Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

ifo Working Papers

Forecasting employment in Europe: Are survey results helpful?

Robert Lehmann
Antje Weyh

Ifo Working Paper No. 182

June 2014

Ifo Working Paper No. 182

Forecasting employment in Europe: Are survey results helpful?

Abstract: In this paper we evaluate the forecasting performance of employment expectations for employment growth in 15 European states. Our data cover the period from the first quarter 1998 to the fourth quarter 2012. With in-sample analyses and pseudo out-of-sample exercises, we find that for most of the European states considered, the survey-based indicator model outperforms common benchmark models. It is therefore a powerful tool for generating more accurate employment forecasts. We observe the best results for one quarter ahead predictions that are primarily the aim of the survey question. However, employment expectations also work well for longer forecast horizons in some countries.

Keywords: Employment forecasting, European business survey, employment expectations, Granger causality

JEL Code: E27, J00, J49

Robert Lehmann*
Ifo Institute – Leibniz-Institute
for Economic Research
at the University of Munich e.V.
Branch Dresden
Einsteinstr. 3
01069 Dresden, Germany
Phone: +49(0)351/26476-21
lehmann@ifo.de

Antje Weyh
Institute for Employment Research
Regional IAB Office Saxony
Paracelsusstr. 12
09114 Chemnitz, Germany
Phone: +49(0)371/9118-642
antje.weyh@iab.de

* Corresponding author.

1. Motivation

Business and consumer surveys have become a widely accepted source in the field of macroeconomic forecasting. Because of their rapid availability, qualitative survey results are useful tools for the assessment of the economic constitution. Several groups, such as politicians, employers and researchers, are interested in early information about the course of an economy that is not available from secondary data bases. Additionally and in contrast to such quantitative data, survey results do not suffer from major revisions, which make them a powerful tool for economic forecasting.

There is a large body of literature dealing with the forecasting performance of survey-based indicators. Whereas most studies evaluate the predictive power of these indicators for rather standard economic variables, such as gross domestic product (see, e.g., Hansson *et al.*, 2005; Abberger, 2007a), industrial production (see, e.g., Hanssens and Vanden Abeele, 1987; Fritsche and Stephan, 2002; Croux *et al.*, 2005) or inflation (see, e.g., Ang *et al.*, 2007), analyses for labor market variables are scarce. We fill this gap with our paper. We use qualitative information from the *Joint Harmonised EU Programme of Business and Consumer Surveys*, i.e., employment expectations for three months ahead (*EEXP*), to forecast employment growth[1] on a quarterly basis for 15 European states in the period from 1998Q1 to 2012Q4. We test the forecasting performance of *EEXP* with Granger causality tests as well as pseudo out-of-sample exercises for every country considered in this study. The results show that for most of the countries, *EEXP* is an efficient indicator to forecast employment growth in the short-term (one quarter ahead). Despite the fact that employment expectations can be seen as a short term indicator, we also test the forecasting performance for longer horizons up to four quarters. As expected, the indicator loses its power with increasing forecast horizons. However, for some countries a model including our indicator also significantly beats the benchmark in the long run. For Bulgaria, Hungary and Slovakia, a model that includes *EEXP* has no higher forecast accuracy in comparison to our chosen benchmark models, no matter the forecast horizon considered.

We contribute to the existing literature in several ways. First, we systematically analyze the forecasting performance of a survey-based leading indicator (employment expectations) for employment growth. Interestingly, only five studies have addressed the forecasting properties of similar survey-based qualitative indicators for employment growth of single states. For Canada, an early attempt is the study by Hartle (1958). He used data from the Employment Forecast Survey, where industrial establishments in Canada were asked to forecast their own future employment for the next three and six months and then studies whether it is possible to forecast employment for the Canadian industrial sector more accurately with these firm-specific forecasts. He concluded that these survey results are not able to pro-

[1] We have to mention that studies that evaluate survey results for the prediction of the unemployment rate exist (see, e.g., Claveria *et al.*, 2007; Österholm, 2010; Hutter and Weber, 2013; Martinsen *et al.*, 2014).

vide reliable forecasts for employment change in the Canadian industry. The study of dos Santos (2003) examined the relationship between a large amount of qualitative indicators (among them employment expectations) and several different macroeconomic variables for Portugal. Through a cross-correlation analysis, employment expectations were statistically associated with the annual growth rate of employment in some sectors (e.g., the industrial sector) with a lead of up to two quarters. More recent studies are those from Abberger (2007b) for Germany and Siliverstovs (2013) as well as Graff *et al.* (2012) for Switzerland. Abberger (2007b) analyzed whether employment expectations gained from the monthly Ifo business survey in Germany (Ifo Employment Barometer[2]) can serve as a leading indicator for annual employment changes. Applying three approaches (smoothing techniques, error correction models and probit estimates), he found that the survey-based indicator has a lead of two to four months and is able to date turning points in employment growth. For Switzerland, Siliverstovs (2013) used the KOF Employment Barometer[3] provided by the KOF Swiss Economic Institute to evaluate whether this survey-based indicator improves in-sample and out-of-sample forecast accuracy of Swiss employment. He found that the barometer has predictive power for nowcasts and one-quarter ahead predictions. The study by Graff *et al.* (2012) confirmed these results by showing that the KOF Employment Barometer as well as a survey-based indicator obtained by the Federal Statistical Office of Switzerland are able to predict employment one quarter ahead. With the exception of Hartle (1958), all the other studies found an improvement in the accuracy of employment forecasts by using survey results.

The second contribution of our paper is the examination of forecast improvement by employment expectations for a multitude of European states. Most of the studies either analyzed the Euro area as an aggregate (see Claveria *et al.*, 2007) or just one single state (see Hansson *et al.*, 2005; Österholm, 2010; Martinsen *et al.*, 2014, for Sweden or Norway). Only the study of Croux *et al.* (2005) analyzed the capability of production expectations in forecasting industrial production for 12 European states. We add to the existing literature by studying the predictive content of employment expectations for employment growth in 15 European countries separately. To the best of our knowledge, this has not been documented in the literature.

Our third contribution is that we do not focus on one single sector (e.g., industry) when forecasting employment. This paper uses the survey results from the industrial sector, construction and retail trade together to evaluate the forecasting power for total employment growth. Both in-sample (Granger causality) and out-of-sample properties (root mean squared forecast errors in comparison to benchmark models) are discussed in our analyses.

Fourth, we add to the existing literature on survey results in giving a deeper understanding

[2]The data are periodically updated and available at *http://www.cesifo-group.de/ifoHome/facts/Time-series-and-Diagrams/Zeitreihen/Reihen-Beschaeftigungsbarometer.html.*

[3]A description as well as new press releases can be found at *http://www.kof.ethz.ch/en/surveys.*

on how qualitative information work for macroeconomic forecasting or rather for one specific macroeconomic variable. As was stated in Croux *et al.* (2005), business tendency surveys are expensive as well as time-consuming. In order to justify the different questions of this time consuming and expensive survey, the results should have some predictive power for macroeconomic variables. Since the results for several macroeconomic aggregates are mixed, Claveria *et al.* (2007) concluded that it is not clear why some indicators are able to predict specific macroeconomic variables whereas others cannot. Our paper adds to this discussion by evaluating the forecast performance of employment expectations so that we are able to explain a piece of this apparent puzzle.

The paper is organized as follows. In Section 2, we present our data and the empirical setup along with some descriptive statistics as well as statistic properties of the data. By using in-sample approaches and out-of-sample methods, Section 3 discusses our results in detail. Section 4 concludes.

2. Data and Empirical setup

2.1. Data

The European Commission collects monthly survey results within their *Joint Harmonised EU Programme of Business and Consumer Surveys* for a multitude of European states. This program is harmonized across the countries in terms of questions and methods. It comprises establishments from different sectors (industry, construction, retail trade and services).[4] We excluded the results from the service sector because the time series is too short for our purpose. In the end, we used qualitative information from the industrial sector, construction and retail trade for the period from January 1998 to December 2012. Due to some further data restrictions (e.g., missing employment data), we eliminated some countries so that the following European states remain in our sample: Austria, Belgium, Bulgaria, Czech Republic, Estonia, Finland, France, Germany, Hungary, Italy, Netherlands, Portugal, Slovakia, Sweden and United Kingdom. These 15 states cover almost 82% of the gross domestic product and more than 74% of EU-27-employment in 2011.

For our analysis, the question of interest is: "How do you expect your firm's employment to change over the next 3 months?" (i.e., employment expectations [*EEXP*]). The respondents have three possibilities to answer this question: (+) increase, (=) remain unchanged and (-) decrease. In line with the literature, we assessed the forecasting power of "balances" (for a critical discussion, see Croux *et al.*, 2005; Claveria *et al.*, 2007, and the references therein). These balances are expressed as differences between the weighted share of firms

[4]The aim of the European Commission is to keep the sample representative for each month. To ensure this, sample updates are necessary on occasion due to, e.g., start-ups or bankruptcies. However, the samples for the business survey are very stable in each state. Additional details on the sample composition can be found in European Commission (2007).

whose employment will increase and the weighted share of those who expect that their total employment level will decrease. The weights, therefore, are based on the size of the firms (see European Commission, 2007). All firms with a response "remain unchanged" are not considered.

Since our target variable (employment) is not available on a monthly basis, we had to transform the balances into quarterly data. To obtain quarterly survey results, we calculated a three-month average (*EEXP_av*). To verify our results, we additionally used the third month of each quarter (*EEXP_tm*). All the survey results are provided with or without seasonal adjustment. In line with the literature, we chose seasonal-adjusted data to measure the cyclical movement of employment during the year. In order to summarize the balances from the three different sectors (industry, construction and retail trade) to one single indicator, we applied time-varying weights obtained from quarterly employment figures for every sector and single state.

As already mentioned, our variable of interest is the development of employment in 15 EU countries. A source for comprehensive quarterly employment figures are national accounts of single states. Eurostat makes these data available for all member states of the European Union plus Norway and Switzerland. In addition to the total sum of employment, data for 10 branches of the economy are provided.[5] All the data are seasonally adjusted and transformed into quarter-on-quarter (qoq) growth rates to display the cyclical movement of employment. This transformation is very suitable because the firms were asked about their employment development within the next three months.

In addition to total employment (*EMP*), we also used employment in those sectors for which we had survey results (*MEMP*). Hence, our second variable *MEMP* is the difference of total employment minus agriculture, forestry, fishing and advanced services.[6] The variable *MEMP* comprises almost 50% of the total employment for all states in this sample and therefore a large part of the private sector economy. To summarize, we analyzed the forecast accuracy of employment expectations for employment growth on a quarterly basis from 1998Q1 to 2012Q4 for 15 European states.

2.2. Descriptive results

To illustrate the structure and development, Figure 1 shows the qoq growth rate of *MEMP* as well as employment expectations *EEXP_av* for each of the 15 European states.[7] On the left y-axis, *MEMP* (gray bars) is displayed, while the right y-axis illustrates *EEXP_av*,

[5] The code of the corresponding time series is: *namq_nace10_e*. All the data can be downloaded free of charge under *http://epp.eurostat.ec.europa.eu/portal/page/portal/eurostat/home*. The data used in this paper were downloaded on July 31, 2013.

[6] Advanced services comprise the sectors information and communication, financial services, real estate, scientific and administrative services, public administration as well as arts and other service activities. For more details on the specific sectors, see Eurostat (2008).

[7] Table 4 in the Appendix shows the typical descriptive results for all considered series.

shown as a black and continuous line. The x-axis represents the sample period (1998Q1 to 2012Q4). Employment expectations seem to serve as an indicator for predicting employment growth and hence a high heterogeneity exists between the considered European states. *EEXP_av* seems to be a good predictor for Scandinavian states (Finland and Sweden) and large European economies, such as France and Germany; for Bulgaria or Hungary one can see a completely different trend or follow-up movement of *EEXP_av*, which is in total contrast to the question of the survey.

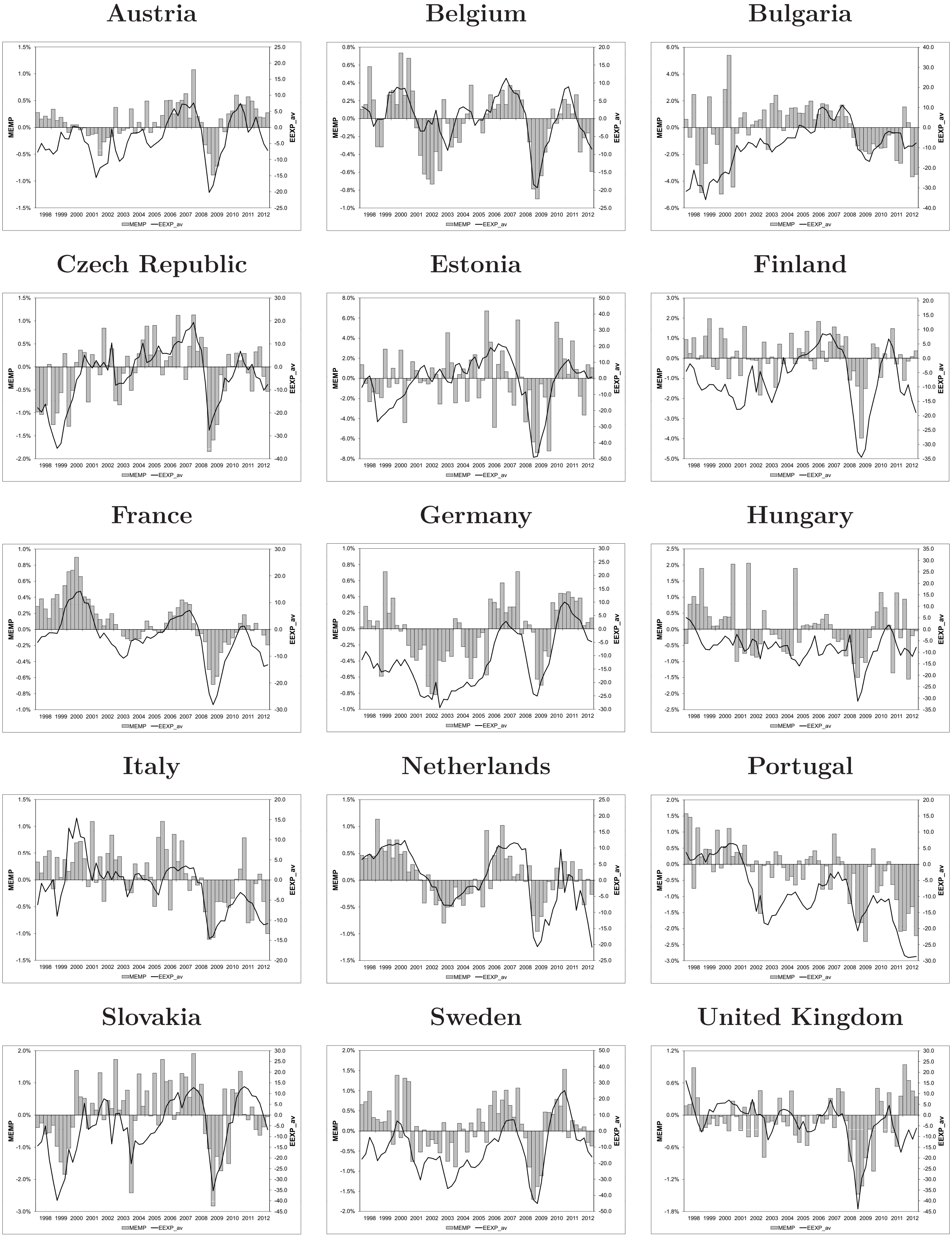
To underpin our idea that in most cases *EEXP_av* could serve as a predictor for *MEMP*, we first examined standard cross-correlations between the two variables. We calculated simple correlation coefficients for all European states in our sample by holding *MEMP* fixed and and applied a lag or lead to the indicator (*EEXP_av*) by four quarters (see Figure 2). To compare the results across all states, the pictures have identical scales for the y-axis (correlation coefficient). In addition, we highlight the correlation coefficient observed by lag one since the question of *EEXP_av* aims at a leading character of the indicator by one quarter. However, the highest correlation coefficients between *EEXP_av* and *MEMP*, with the exception of Bulgaria, Finland, Hungary and Italy, were observed for the contemporaneous consideration of the two series. One possible explanation could be the aggregation from monthly to quarterly data. Moreover, this is not a problem at all since it shows that the indicator could also be used for nowcasts as well. Additionally, the still large correlation coefficients for higher lags than one quarter suggest that the indicator can also be an adequate predictor for larger forecasting horizons in comparison to the benchmark. Altogether, the *EEXP_av* series has leading characteristics for *MEMP*.[8] We observed the strongest linear relationship between *MEMP* and the first lag of *EEXP_av* for France, followed by Germany and Austria. The weakest relation was found for Bulgaria, Hungary and Estonia. One would have expected this from Figure 1. For these three countries, the strongest relationship between the two variables was found for a lead of one or two quarters, i.e., the *EEXP_av* seems to follow the *MEMP*. To sum up, the correlation analyses also show that *EEXP_av* could serve as a potential indicator for predicting *MEMP* in most of the countries and possibly for different forecasting horizons other than only one quarter.

2.3. Empirical setting

Next to the simple analyses of correlation coefficients, potential leading characteristics of the single employment expectation series has to be ensured with more elaborate methods. As a first step, we applied standard Granger causality tests (in-sample analysis) to check whether *EEXP* is basically helpful to describe employment growth. To check the forecasting performance of *EEXP*, we present pseudo out-of-sample exercises in a second step.

[8] The same holds for the series *EEXP_tm*.

Figure 1: Development of *MEMP* and *EEXP_av* for each European state



Source: European Commission, Eurostat, author's calculations and illustrations.

Figure 2: Cross-correlations between *MEMP* and *EEXP_av* for each European state

Note: Calculations are based on the whole sample (1998Q1–2012Q4).

Source: European Commission, Eurostat, author's calculations and illustrations.

2.3.1. In-sample analyses

A necessary condition to test Granger causality is stationarity of the time series considered. To give a broad and reliable picture of stationarity, we applied two different tests: the Ng-Perron (NP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Whereas the NP test states a unit root under the null, the KPSS test is applied against stationarity. Whenever a series has no unit root, the NP test should reject the null. Since the KPSS test is a test on stationarity, it should not reject the null hypothesis. We chose these two different tests for three reasons: First, the widely used Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test have different properties within finite samples, thus they can produce misleading results. Second, the ADF test and the PP test also have low power against $I(0)$ alternatives when the series is close to $I(1)$. In such cases the NP test performs much better (Ng and Perron, 2001). In other words, the NP test is much more accurate when time series are nearly integrated of order one. Third, the KPSS test is applied since it is a stationarity test instead of a unit root test. It proposes a stationary time series under the null hypothesis and is therefore a complement against the NP test. With the KPSS and NP tests, we can distinguish between series that are stationary and series that contain a unit root.

In the first step, the NP test and the KPSS test are applied to the levels of the series (qoq). We performed the tests in two ways: (i) only with a constant and (ii) with a constant and a linear trend. Whenever a series is not stationary in levels, we test the first differences in a second step.

Table 1: Results of the unit root tests for *MEMP* and *EEXP_av*

Country	**MEMP**					**EEXP_av**				
	KPSS		NP		Δ	KPSS		NP		Δ
	Const.	Trend	Const.	Trend		Const.	Trend	Const.	Trend	
Austria			**					***	***	
Belgium			***	*				***	***	
Bulgaria	*	***			X	**	***			X
Czech Republic		**	***	**			**			X
Estonia			**	*				***	*	
Finland			***	***				***	**	
France	**		**	***				***	***	
Germany			***	**		*	*	***	***	
Hungary	*		***	***		*		*		
Italy	*	*	***	***		**		*		X
Netherlands			*		X	*				X
Portugal	***		**	***		**			***	X
Slovakia		**	***	*		*		**		X
Sweden			***	***				***	***	
United Kingdom			***	***		**			***	

Note: Calculations are based on the whole sample (1998Q1–2012Q4). The Ng-Perron (NP) test states a unit root under the null hypothesis. The Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) has stationarity under the null hypothesis. For the KPSS and the NP tests, only test statistics and critical values are available. We therefore use asterisks to show whether the null can be rejected or not. In all cases we first tested stationarity in levels (qoq qrowth rate or balances). If the levels turned out to be non-stationary, we then tested first differences of the variables. The column Δ presents the decision on the transformation of the variables. An **X** indicates that first differences are applied. ***, ** and * indicate the rejection of the null hypothesis at the 1%, 5% and 10% significance level.

Table 1 presents the unit root test results for *MEMP* and *EEXP_av*.[9] and shows that most of the series are stationary in levels, although the results of the tests are not always consistent with each other. In such cases, we decided whether the series is stationary or not by all means with the NP test, because the KPSS test could suffer from a finite sample bias. Table 1 also shows which series have to be transformed. This is indicated by an X in column Δ. After the transformation into first differences, all series are stationary.

Granger causality is commonly used to show whether an indicator has some leading characteristics for a specific target variable.[10] It is also possible to check whether feedback effects between the two series are present (Granger, 1969). This is the case whenever an indicator variable explains the target variable and vice versa. In the worst case, the target variable has a leading character for the indicator and not the other way around (reverse Granger causality). To test for (reverse) Granger causality, we estimated the following two equations:

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j x_{t-j} + \varepsilon_{1,t} \ , \tag{1}$$

$$x_t = \sum_{j=1}^{q} \gamma_j x_{t-j} + \sum_{i=1}^{p} \delta_i y_{t-i} + \varepsilon_{2,t} \ . \tag{2}$$

The qoq growth rate of either *MEMP* or *EMP* is denoted with y_t. Employment expectations, either as the three-month average (*EEXP_av*) or the last value of the quarter (*EEXP_tm*), are defined as x_t. We allow a maximum of four lags for p and q in Equations (1) and (2).

We first tested whether all four lags of the indicator (x_t) have a significant effect on the target variable y_t. Under the null hypothesis "employment expectations (x_t) do NOT Granger cause employment growth (y_t)". If the null is rejected, then *EEXP* is able to explain our variable of interest (*MEMP*, *EMP*). Then, in a second step, the reverse way is tested with the null hypothesis "employment growth does NOT Granger cause employment expectations". If this hypothesis is rejected, then *MEMP* or *EMP* can explain *EEXP*. From the Granger causality tests, four different cases emerge: (i) *EEXP* only Granger causes employment growth, (ii) there are feedback effects between the two series, (iii) *MEMP* or *EMP* only Granger causes *EEXP* and (iv) there is no relationship. As already mentioned, the third case is the worst. Whenever case (iii) occurs, employment expectations are probably not a suitable predictor for employment growth. The same holds for the fourth event. In case (i) and (ii), *EEXP* can probably be used as an indicator to forecast employment growth, i.e., y can be better forecasted with the additional information of x. It is well known that the Granger concept has some weaknesses (see, e.g., Lütkepohl, 2005). It is often argued that data transformation, such as first differences or the elimination of a trend, go along with a loss of information. This loss causes the Granger concept not to be able

[9] The results of the unit root tests for *EMP* and *EEXP_tm* can be found in Table 5 in the Appendix. For these two variables, the stationarity tests yield relatively similar results as for *MEMP* and *EEXP_av*.

[10] So it is by no means a test on causality between two variables or on the exogeneity of a series.

to distinguish between long-term and short-term relationships between variables. However, we are not interested in long-term or short-term movements between series but rather to check the survey-based indicator's ability to forecast employment. Another weakness of Granger causality originates from the specification of Equations (1) and (2): The results of the Granger causality tests may be sensitive due to the maximum lag length of p and q. We tested different specifications of p and q with fairly robust results. We also checked the necessary assumptions (e.g., homoscedasticity or no autocorrelation) to estimate the models in Equations (1) and (2) and found that these assumptions are predominantly fulfilled. As our focus is not on short-term or long-term relationships and as we debilitate the second main criticism, the Granger concept seems to be an adequate approach for our purpose.

2.3.2. Out-of-sample examination

Forecast model

To generate our pseudo out-of-sample forecasts, we employ an autoregressive distributed lag (ADL) model

$$y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{j=1}^{q} \gamma_j x_{t+1-j} + \varepsilon_t \ , \tag{3}$$

where y_{t+h} is the h-step-ahead forecast of either *MEMP* or *EMP* and x_t represents the employment expectations *EEXP*. The forecast horizon h is defined in the range of $h \in \{1, 2, 3, 4\}$ quarters. We allow, as in the in-sample analyses, a maximum of four lags for our target variable (p) and the employment expectations (q). The optimal lag length is determined by the Bayesian Information Criterion. Robinzonov and Wohlrabe (2010) showed for Germany that choosing either a recursive approach or a rolling window can lead to different forecasting results. Thus, we generated our forecast in both ways. The initial estimation period for Equation (3) ranges from 1998Q1 to 2004Q4 ($T_E = 28$). The period is then expanded successively by one quarter with a new specification of the model. The rolling window approach serves as a robustness check for our results obtained from the recursive approach.[11] It uses a fixed window, which is successively moved forward by one quarter; the first forecast for y_t is calculated for 2005Q1 and the last for 2012Q4. To avoid a prediction of the indicator x_t or the dependent variable y_t itself, we implement the ADL model in a direct-step fashion. This means that y_{t+h} is directly explained with lagged values of the dependent variable and the indicator. This results in the same number of forecasts ($T_F = 32$) for every forecast horizon h. More details on direct-step forecasting can be found in Robinzonov and Wohlrabe (2010). As the benchmark model, we chose a common AR(p) process.

[11] Whenever breaks in the time series are present, the rolling window approach is preferable. An expanding window is suitable when there are no breaks in the series or the whole cyclicality of the series should be captured. The recursive approach then leads to more precise estimates of the parameters (Weber and Zika, 2013).

Forecast evaluation

To evaluate the forecast accuracy of our different models, we first have to calculate forecast errors from our exercises. Let $\widehat{y}_{t+h}$ denote the h-step-ahead forecast produced at time t, then the resulting forecast error is defined as $FE_{t+h} = y_{t+h} - \widehat{y}_{t+h}$. The corresponding forecast error of our benchmark model is FE^{ARp}_{t+h}. To assess the performance of an indicator-based model, we calculate the root mean squared forecast error (RMSFE) as the loss function. For the h-step-ahead indicator-based forecast, the RMSFE is

$$RMSFE_h = \sqrt{\frac{1}{T_F}\sum_{n=1}^{T_F}\left(FE_{t+h,n}\right)^2}\,. \tag{4}$$

The RMSFE for the benchmark model is $RMSFE^{ARp}_h$. To decide whether employment expectations perform, on average, better than the autoregressive process, we calculate the relative RMSFE between the indicator model and the benchmark

$$rRMSFE_h = \frac{RMSFE_h}{RMSFE^{ARp}_h}\,. \tag{5}$$

Whenever this ratio is smaller than one, the indicator-based model performs better than the benchmark. Otherwise, the AR(p) process is preferable. Nonetheless, calculating this ratio does not clarify whether the forecast errors of the indicator-based model and the benchmark are statistically different from each other. To check this, we first apply the test proposed by Diebold and Mariano (1995). Under the null hypothesis, the test states that the expected difference in the MSFE equals zero. With our notation, this gives

$$H_0 : E\left[\left(FE^{ARp}_{t+h}\right)^2 - \left(FE_{t+h}\right)^2\right] = E\left[MSFE^{ARp}_{t+h} - MSFE_{t+h}\right] = 0\,. \tag{6}$$

In other words, the null hypothesis states that the AR(p) is the data generating process. Adding an indicator to this process can then cause a typical problem of nested models. The larger model – with our survey-based indicator – therefore introduces a bias through estimating model parameters that are zero within the population. Thus, the AR(p) process nests the indicator model by setting the parameters of the indicator to zero. As stated by Clark and West (2007), this causes the MSFE of the larger model to be biased upwards since redundant parameters have to be estimated. As a result, standard tests, such as the one proposed by Diebold and Mariano (1995), loose their power. On this account, we follow the literature (e.g., Weber and Zika, 2013) and apply the adjusted test statistic by Clark and West (2007)

$$CW_h = \sqrt{\frac{1}{\widehat{V}(a_{t+h})T_F}}\sum_{t=1}^{T_F}\left(\underbrace{MSFE^{ARp}_{t+h} - \left[MSFE_{t+h} - \left(FE_{t+h} - FE^{ARp}_{t+h}\right)^2\right]}_{a_{t+h}}\right)\,, \tag{7}$$

with $\widehat{V}(a_{t+h})$ as the sample variance of a_{t+h} and $\left(FE_{t+h} - FE_{t+h}^{ARp}\right)^2$ as the adjustment term. After this adjustment, standard critical values from the Student's t-distribution with $T_F - 1$ degrees of freedom can be used to decide whether forecast errors are statistically significant from each other.

3. Results

The figures and cross-correlations in Section 2.2 have shown that employment expectations in most of the countries could serve as a potential indicator for predicting employment. Only for a few of the observed countries (e.g., Bulgaria or Hungary) was a leading character of *EEXP_av* unlikely. In order to analyze the forecasting performance of employment expectations, the following two subsections present the results of our in-sample and out-of-sample analyses. We discuss the forecasting performance of *EEXP_av* for *MEMP* and *EMP*. Tables with results for *EEXP_tm* can be found in the Appendix.

3.1. Results of the in-sample analyses

Do employment expectations deliver some additional information to forecast employment growth? In most of the cases, they do. The results for *MEMP* are shown in the upper part of Table 2. The lower part of the table comprises the Granger causality results for *EMP*. Column two shows the test results for Granger causality from employment expectations to employment growth (*EEXP_av* $\rightarrow$ *MEMP* or *EMP*). Column three presents this information in reverse (*MEMP* or *EMP* $\rightarrow$ *EEXP_av*). All numbers represent p-values. The last column shows whether the indicator has leading characteristics (+), whether feedback effects between the two series are present (FB) or whether the indicator has no predictive content or there is no relationship at all (X).

In most of the countries considered, employment expectations serve as a leading indicator. For *MEMP*, *EEXP_av* probably does not deliver additional information in Hungary, Slovakia or the United Kingdom. In the United Kingdom, no relationship between the two series exists, whereas in Hungary and Slovakia, employment growth serves as an indicator for *EEXP_av*. Feedback effects are evident for two countries (Czech Republic and Germany). Interestingly, for Bulgaria where we suspected no relationship from descriptive statistics, employment expectations do Granger cause employment growth.

For *EMP*, the results are inferior to those for *MEMP*. In fewer cases compared to *MEMP*, employment expectations have additional information to forecast total employment. Overall, the results changed for Bulgaria, the Czech Republic, Germany and Italy. There, employment expectations provide no additional information to improve forecasting of total employment. For Hungary and the United Kingdom, the results for *EMP* are in line with those for *MEMP*. In contrast, feedback effects are now present for Slovakia. Turning to *EEXP_tm*,

Table 2: Granger causality results for *MEMP*, *EMP* and *EEXP_av*

Country	MEMP		
	EEXP_av → MEMP	MEMP → EEXP_av	Result
Austria	0.000	0.267	+
Belgium	0.003	0.385	+
Bulgaria	0.002	0.367	+
Czech Republic	0.035	0.084	FB
Estonia	0.001	0.118	+
Finland	0.002	0.542	+
France	0.000	0.225	+
Germany	0.002	0.092	FB
Hungary	0.487	0.036	X
Italy	0.035	0.446	+
Netherlands	0.001	0.308	+
Portugal	0.017	0.504	+
Slovakia	0.159	0.078	X
Sweden	0.005	0.640	+
United Kingdom	0.232	0.784	X
Country	**EMP**		
	EEXP_av → EMP	EMP → EEXP_av	Result
Austria	0.011	0.047	FB
Belgium	0.070	0.183	+
Bulgaria	0.260	0.202	X
Czech Republic	0.126	0.229	X
Estonia	0.001	0.220	+
Finland	0.002	0.900	+
France	0.002	0.057	FB
Germany	0.104	0.128	X
Hungary	0.427	0.242	X
Italy	0.189	0.955	X
Netherlands	0.000	0.269	+
Portugal	0.039	0.648	+
Slovakia	0.033	0.018	FB
Sweden	0.012	0.892	+
United Kingdom	0.119	0.707	X

Note: Calculations are based on the whole sample (1998Q1–2012Q4). The table presents p-values from the Granger causality test. *Acronyms:* +, *EEXP*, only Granger causes employment growth (case [i]); FB, feedback effects are present (case [ii]); X, employment growth Granger causes *EEXP* (case [iii]) or no relationship (case [iv]).

the third month of each quarter as representative serves as a leading indicator as well.

To summarize, the in-sample analyses revealed potential forecasting information from employment expectations for nearly all countries in our sample. However, we found differences between our two target variables *MEMP* and *EMP*. We suggest that it is important which sectors are asked as possibly our indicators is less able to reproduce the cyclical movement of total employment. Adding the employment expectations of the service sector to our indicator may solve this puzzle. To examine whether *EEXP_av* produces lower forecast errors than a benchmark model and to underpin the statements from our in-sample analyses, we conducted pseudo out-of sample exercises in the following section.

3.2. Results of the pseudo out-of-sample analyses

Are employment expectations able to produce lower forecast errors in comparison to a common benchmark model? The answer is yes, for most of the countries in our sample. Table 3 presents the pseudo out-of-sample results for all 15 European states, produced with a recursive estimation window.[12] We divided the table into two parts *MEMP* and *EMP*. Each column represents the forecasting outcome for a specific forecast horizon, ranging from one to four quarters for *MEMP* and *EMP*. For each single country, we added the forecasting performance of six different models: (i) AR(p) is the chosen benchmark, (ii) an AR(1) process, (iii) the in-sample mean (ISM), (iv) a Random Walk (RW)[13] and finally (v) and (vi) the outcomes from employment expectations (*EEXP_av*, *EEXP_tm*). Each entry in the rows *AR(p) in %* illustrates one single $RMSFE_h^{ARp}$ of the benchmark model in percentage points. These figures are separated from the other results for each country with dashed lines. The other numbers in Tables 3 and 7 are the model-specific $rRMSFE_h$, i.e., the $RMSFE$ of each model compared to the benchmark. Asterisks typically denote significant differences between the forecast errors based on the outcome of the Clark-West test.

As expected from descriptive statistics and the in-sample analyses, employment expectations seem to be able to predict employment growth more accurately than a simple benchmark model. Compared to the other three possible benchmarks (AR(1), ISM, and RW) this conclusion holds as well. The best results can be found for short-term forecasts with a forecasting horizon of one quarter ahead ($h = 1$). This is straightforward because the survey-based indicators used here are short-term indicators by construction. Firms were asked to provide a statement about their expected employment development for the next three months. However, some noteworthy exceptions exist. For Austria, Estonia, France, Germany and Sweden, the indicator model produced significantly lower forecast errors for longer forecast horizons, i.e., the ADL model is significantly better than the benchmark for $h > 1$. These are the countries with the best relative performance of employment expectations in terms of $rRMSFE$.

Table 3: Out-of-sample results (recursive) for *MEMP* and *EMP*

Model	**MEMP**				**EMP**			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
				Austria				
AR(p) in %	0.352	0.379	0.475	0.483	0.229	0.294	0.309	0.330
AR(1)	0.972	0.987**	0.923*	0.974***	0.957	0.919*	0.978*	0.971*
ISM	1.177	1.105	0.895	0.885	1.249	0.990	0.953	0.898*
RW	1.120	1.332	1.139	1.294	1.273	1.223	1.336	1.363

Continued on next page...

[12] The results from the rolling window are presented in Table 7 in the Appendix.

[13] The ISM is defined as $y_{t+h} = \overline{y}$, representing the sample average of the estimation window. The Random Walk prediction is simply the last known value of the target variable $y_{t+h} = y_{t-1}$.

Table 3: Out-of-sample results (recursive) for *MEMP* and *EMP* – continued

Model	**MEMP**				**EMP**			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
EEXP_av	0.831**	0.956*	0.962**	1.005	0.934**	0.935**	1.033	1.082
EEXP_tm	0.921**	1.038	0.940**	1.026	0.948***	0.949**	0.964**	1.056
				Belgium				
AR(p) in %	0.235	0.311	0.339	0.348	0.157	0.199	0.237	0.248
AR(1)	0.997	0.968*	1.000	0.997	0.988*	0.997	0.992	0.994
ISM	1.412	1.083	1.003	0.982**	1.452	1.161	0.990	0.948**
RW	1.414	1.320	1.439	1.453	1.378	1.441	1.406	1.419
EEXP_av	0.938**	0.974***	1.286	1.747	0.931**	0.921***	1.107	1.217
EEXP_tm	0.882**	1.005	1.070	1.376	0.920**	0.974**	1.085	1.151
				Bulgaria				
AR(p) in %	1.104	0.973	1.092	1.127	0.465	0.447	0.441	0.425
AR(1)	1.157	0.993	1.108	1.009	0.971	1.094	0.992	1.034
ISM	1.113	1.263	1.112	1.078	1.058	1.089	1.103	1.164
RW	1.912	1.598	0.962*	1.323	1.435	1.154	2.013	1.412
EEXP_av	1.214	1.764	1.667	1.766	1.009	1.035	0.934***	1.078
EEXP_tm	1.264	1.879	1.906	1.915	1.021	1.060	0.874***	1.131
				Czech Republic				
AR(p) in %	0.627	0.721	0.719	0.736	0.443	0.538	0.547	0.561
AR(1)	0.988	0.995	1.016	1.036	1.005	1.000	1.002	1.027
ISM	1.155	1.021	1.033	1.013	1.259	1.057	1.055	1.040
RW	1.389	1.325	1.373	1.387	1.249	1.220	1.288	1.324
EEXP_av	0.983**	1.003	0.978	0.941	0.977*	1.034	1.022	0.998
EEXP_tm	0.994	0.982	0.987*	0.955*	0.997	0.996	0.985	1.013
				Estonia				
AR(p) in %	3.675	3.818	3.848	3.721	1.863	2.112	1.901	2.050
AR(1)	0.976	0.953*	0.935**	0.968	0.962	0.932**	1.008	0.998
ISM	0.973	0.941*	0.928*	0.966*	1.036	0.923**	1.029	0.962*
RW	1.492	1.136	1.127	1.471	1.318	1.076	1.344	1.360
EEXP_av	0.835**	0.876**	0.971*	0.961	0.868**	0.860**	1.008	0.916
EEXP_tm	0.810**	0.857**	1.001	1.050	0.828*	0.853**	1.000	0.911
				Finland				
AR(p) in %	1.131	1.168	1.172	1.176	0.725	0.712	0.723	0.731
AR(1)	1.000	0.996**	0.999	0.999	1.006	0.981**	0.990	0.993
ISM	0.995	0.971**	0.971	0.971**	0.963	0.987	0.979*	0.969*
RW	1.272	1.307	1.395	1.380	1.116	1.351	1.440	1.559
EEXP_av	0.893**	1.041	1.032	1.037	0.838*	0.928**	1.071	1.177
EEXP_tm	0.958	1.021	1.069	1.053	0.845*	0.935**	1.059	1.100
				France				
AR(p) in %	0.128	0.132	0.148	0.136	0.120	0.126	0.125	0.123
AR(1)	0.958	0.997	0.943*	0.975	0.959	0.990	0.999	0.999
ISM	1.012	0.989	0.882*	0.959	0.983	0.940	0.951	0.968

Continued on next page...

Table 3: Out-of-sample results (recursive) for *MEMP* and *EMP* – continued

Model	**MEMP**				**EMP**			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
RW	1.490	1.408	1.164	1.215	1.364	1.203	1.406	1.457
EEXP_av	0.809**	0.855**	0.842*	0.912**	0.876*	0.858*	0.916*	0.907**
EEXP_tm	0.762**	0.869**	0.832*	0.898**	0.800	0.825*	0.872*	0.869**
				Germany				
AR(p) in %	0.320	0.357	0.397	0.437	0.210	0.228	0.232	0.264
AR(1)	0.982***	0.990	1.004	0.979**	0.990	0.989	0.997	0.977
ISM	1.249	1.136	1.033	0.947*	1.100	1.028	1.016	0.902*
RW	1.207	1.264	1.255	1.260	1.236	1.189	1.352	1.283
EEXP_av	0.802***	0.816***	0.797***	0.941**	0.931***	0.990***	1.019	1.033
EEXP_tm	0.812***	0.787***	0.762***	0.802***	0.941***	0.959***	1.006	0.933***
				Hungary				
AR(p) in %	0.801	0.789	0.838	0.830	0.617	0.608	0.600	0.637
AR(1)	1.012	1.001	0.982	0.987	0.975*	1.016	1.001	0.951
ISM	1.001	1.020	0.967	0.977	0.970*	0.988*	1.006	0.953
RW	1.180	1.427	1.196	1.295	1.292	1.238	1.530	1.361
EEXP_av	1.145	1.026	1.066	0.962*	1.036	1.113	1.031	1.050
EEXP_tm	1.318	1.040	1.098	1.007	1.077	1.076	1.102	1.121
				Italy				
AR(p) in %	0.587	0.635	0.637	0.583	0.497	0.525	0.602	0.560
AR(1)	1.005	1.003	1.022	0.997	0.997*	0.985*	0.918	0.873
ISM	1.068	0.998	0.999	1.098	1.023	0.977*	0.857**	0.923
RW	1.274	1.154	0.961**	1.132	1.249	1.305	0.967**	0.971**
EEXP_av	0.989	0.979	0.913**	0.961**	0.990	1.021	0.988**	0.991
EEXP_tm	0.913**	0.947**	0.962*	0.980*	1.035	1.030	0.978	0.988
				Netherlands				
AR(p) in %	0.427	0.475	0.494	0.499	0.433	0.520	0.515	0.601
AR(1)	0.969	0.992	0.993	0.991	1.044	0.966*	0.920*	0.996
ISM	1.146	1.015	0.983	0.971	1.162	0.955**	0.958*	0.832
RW	1.320	1.553	1.256	1.408	1.803	1.097	1.491	1.276
EEXP_av	0.935**	1.038	1.105	0.981*	0.980**	1.196	1.107	1.132
EEXP_tm	0.949**	1.039	1.079	1.088	0.960**	1.133	1.000	1.074
				Portugal				
AR(p) in %	0.863	0.934	0.991	1.008	0.699	0.737	0.746	0.716
AR(1)	1.004	1.003	1.004	1.004	1.033	0.996	1.012	1.010
ISM	1.226	1.147	1.093	1.083	1.127	1.079	1.073	1.124
RW	1.118	1.178	1.076	1.076	1.206	1.176	1.006	1.032
EEXP_av	0.952*	0.912*	1.024	1.046	1.056	0.985	0.966	1.014
EEXP_tm	0.946	0.971	0.958	0.989	1.055	0.948	0.947	0.973*
				Slovakia				
AR(p) in %	1.018	0.977	1.099	1.105	0.469	0.530	0.635	0.641
AR(1)	0.981*	0.996	1.003	0.998	1.004	1.004	1.013	1.047

Continued on next page...

Table 3: Out-of-sample results (recursive) for *MEMP* and *EMP* – continued

Model	**MEMP**				**EMP**			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
ISM	1.051	1.105	0.996	0.992	1.322	1.190	1.011	1.013
RW	1.037	1.599	1.346	1.559	1.100	1.345	1.377	1.425
EEXP_av	1.001	0.941*	0.971	0.985	0.988*	0.882**	0.905**	0.982*
EEXP_tm	1.028	1.158	1.266	1.062	1.023	1.078	1.018	1.026
				Sweden				
AR(p) in %	0.647	0.697	0.737	0.758	0.323	0.404	0.488	0.511
AR(1)	0.962*	0.974*	0.993**	0.989	0.949***	0.986*	0.998	1.000
ISM	1.095	1.029	0.983	0.961**	1.404	1.143	0.959	0.924*
RW	1.189	1.305	1.434	1.463	1.320	1.360	1.356	1.409
EEXP_av	0.938***	0.880**	0.952*	0.982**	1.039	0.961**	1.073	1.148
EEXP_tm	0.867***	0.894***	0.986	0.979***	0.977**	1.022	1.070	1.139
				United Kingdom				
AR(p) in %	0.589	0.586	0.586	0.615	0.432	0.435	0.428	0.419
AR(1)	0.935***	0.976	0.997	0.980	0.978	0.968	1.004	1.005
ISM	0.976*	0.989	0.997	0.957	0.939**	0.939**	0.959	0.986
RW	1.125	1.124	1.364	1.393	1.151	1.109	1.410	1.485
EEXP_av	0.989	1.040	1.074	1.000	0.935	1.048	1.083	1.042
EEXP_tm	0.990	1.005	1.077	0.989	0.930	1.001	1.113	0.997

Note: Calculations are based on the whole sample (1998Q1–2012Q4). The table presents the relative root mean squared forecast errors (*rRMSFE*) of the different models and the benchmark. The row AR(*p*) shows the *RMSFE* (in %) for the benchmark model. *ISM*, in-sample mean; *RW*, Random Walk. Asteriks show significant differences between forecast errors due to the Clark-West test. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

What about the countries for which the in-sample analyses suggest that *EEXP* does not serve as an indicator to predict employment?[14] For *MEMP*, the indicator model has a lower forecast accuracy than the benchmark in Bulgaria, Hungary and Slovakia. For these countries we find for almost all forecast horizons that $rRMSFE$ is larger than one. Another candidate with a relatively bad performance of the indicator model, although with a slightly non-significant increase of the forecast accuracy compared to the benchmark, is the United Kingdom. For the most part, the in-sample analyses have indicated correct out-of-sample performance. From Table 3 we can conclude that only small differences between *EEXP_av* and *EEXP_tm* exist. This holds for *MEMP* and *EMP* as well, which is promising since the rapid availability of a firmÂ´s employment expectations delivers a rich source to forecast either total employment or the sector aggregate for most of the countries in our sample.

[14]One would argue that adding an indicator and therefore getting a better in-sample fit for the data has to result in a better out-of-sample performance. This may not be the case (see Chatfield, 1995). Overfitting the model or parameter instabilities (see Rossi and Sekhposyan, 2011) are some explanations why in-sample and out-of-sample performance may differ.

Instead of using an expanding window, we additionally applied a rolling window approach to verify the results and provide another robustness check (see Table 7 in the Appendix). What we first found from the rolling approach is that the relative performance of *EEXP* for *MEMP* is not as effective as with an expanding window. Second, we found that for most countries employment expectations deliver a higher forecast accuracy than the benchmark model in the expanding window approach. Unfortunately, the results differ for the Czech Republic, France, the Netherlands and Portugal. It is possible that the rolling window is not able to capture all the cyclicality in the target series for these countries and therefore the expanding window approach produces the better parameter estimates. Third, differences between *EEXP_av* and *EEXP_tm* are small overall, with only some exceptions (e.g., Finland). To summarize, employment expectations serve as an indicator to predict employment in the short-term for most of the European states in our sample; exceptions are only Bulgaria, Hungary and Slovakia.

3.3. Discussion of the results

Why does the survey-based indicator not work similarly for all countries? The explanation is manifold and beyond the scope of this paper. There are some preliminary explanations that we will briefly discuss. First, in some countries the survey may suffer from non-responsive firms, leading to a large bias that deteriorates the accuracy of survey-based indicators (see Seiler, 2014). For Germany, Seiler and Heumann (2013) showed for the Ifo business climate that the bias is negligible. This may explain why employment expectations work well to forecast employment growth in Germany. Since we were not able to analyze the firm-level data for each European state in such detail, it could be the case that employment expectations are biased in Bulgaria, Hungary and Slovakia because of non-responses, which are the reason why the indicator loses its power to forecast employment growth in these countries. Second, all three countries where a forecasting model with employment expectations do not beat the benchmark (Bulgaria, Hungary and Slovakia) are still seen as transition economies (see EBRD, 2013). A lack of experience or wrongly anticipating future developments may lead to wrong answers from the respondents in these states. Another very simple and third explanation is that labor markets are, of course, not similar between states. We observed a high heterogeneity with country-specific labor market institutions and separate matching processes between firms and the unemployed. This heterogeneity can lead to spreads between employment expectations and observable employment in an economy. Firms may want to fill a vacancy but are not able to get suitable candidates due to, e.g., a low matching efficiency. Fourth, a discussion about the aggregation of firm's responses, e.g., balances, exists in the literature (Croux *et al.*, 2005; Claveria *et al.*, 2007). Next to this discussion about the sheer aggregation of the raw data, several methods exist to transform qualitative indicators into quantitative information. Rather than using the direction of employment change, a quantitative measure extracted from employment expectations may have predictive power for the magnitude of employment change (Claveria *et al.*, 2007). However, our paper gives a first insight into the forecasting performance of survey-based indicators for predicting labor market variables. Follow-up studies may concentrate on these issues.

4. Summary and Conclusion

Survey-based indicators serve as powerful tools to forecast different macroeconomic variables. Since the survey results we used here are immediately available at the end of each month and do not suffer from major revisions, the outcome of specific questions can easily be used to analyze the recent state of the economy. Most of the existing studies in the field of economic forecasting try to evaluate forecasting performance of survey-based indicators for standard macroeconomic variables, such as gross domestic product; articles for labor market variables are scarce. With our paper, we fill this gap in the literature.

We used the results from the *Joint Harmonised EU Programme of Business and Consumer Surveys* to forecast employment growth in Europe. Especially, we concentrated on the question of employment expectations. Our sample consisted of 15 European states, which covered more than 74% of total employment in the EU-27 for the period 1998Q1 to 2012Q4. To evaluate the forecasting performance of employment expectations, we applied in-sample as well as out-of-sample techniques. Some descriptive statistics as well as Granger causality tests indicate that an indicator based on employment expectations can be used to forecast employment growth for most countries in our sample. The out-of-sample examination based on an autoregressive distributed lag model showed that our indicator produces significant lower forecast errors than several benchmark models. Whereas the best relative performance of the indicator model can be found for Austria, Estonia, France, Germany and Sweden, employment expectations have no better predictive information in comparison to the benchmark model for Bulgaria, Hungary and Slovakia.

Our contribution to survey-based forecasting is manifold: We focus on a very important part of an economy, the labor market. We also add to the discussion by Croux *et al.* (2005) that different survey results should have some predictive power for different macroeconomic variables. Here, we contribute by analyzing employment expectations and employment growth. Moreover, we examined the forecasting performance of a survey-based indicator not for the Euro area as a whole but rather for a large number of single states. This gives a broader picture on how survey results work as indicators in different states. As our results highlight, employment expectations are an indicator to forecast employment growth. However, for some countries the indicator fails to improve forecasts in comparison to a simple benchmark model. We provided some preliminary explanations why this result emerges but have left this in-depth analysis for future research.

Acknowledgments: Our special thanks goes to Alfred Garloff and Marcel Thum for their careful reading of our manuscript. We are grateful to Wolfgang Nagl, Michael Weber and seminar participants at the Technische UniversitÃ¤t Dresden for helpful comments and suggestions. We also thank the participants at the meeting of the Regional Research Network from the Institute for Employment Research in November 2013. Comments from the 1st CGDE Doctoral Workshop are also gratefully acknowledged.

References

Abberger, K. (2007a). *Forecasting Quarter-on-Quarter Changes of German GDP with Monthly Business Tendency Survey Results.* Ifo Working Paper No. 40.

— (2007b). Qualitative business surveys and the assessment of employment – A case study for Germany. *International Journal of Forecasting*, **23** (2), 249–258.

Ang, A., Bekaert, G. and Wei, M. (2007). Do macro variables, asset markets, or surveys forecast inflation better? *Journal of Monetary Economics*, **54** (4), 1163–1212.

Chatfield, C. (1995). Model Uncertainty, Data Mining and Statistical Inference. *Journal of the Royal Statistical Society, Series A*, **158** (3), 419–466.

Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predicitve accuracy in nested models. *Journal of Econometrics*, **138** (1), 291–311.

Claveria, O., Pons, E. and Ramos, R. (2007). Business and consumer expectations and macroeconomic forecasts. *International Journal of Forecasting*, **23** (1), 47–69.

Croux, C., Dekimpe, M. G. and Lemmens, A. (2005). On the predictive content of production surveys: A pan-European study. *International Journal of Forecasting*, **21** (2), 363–375.

Diebold, F. X. and Mariano, R. S. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics*, **13** (3), 253–263.

dos Santos, R. H. (2003). *The use of qualitative data for short term analysis.* Banco de Portugal Economic Bulletin September 2003.

EBRD (2013). Transition Report 2013. European Bank for Reconstruction and Development, ISBN 9781898802402.

European Commission (2007). *The Joint Harmonised EU Programme of Business and Consumer Surveys – User Guide.* Directorate General for Economic and Financial Affairs, http://ec.europa.eu/economy_finance/db_indicators/surveys/documents/userguide_en.pdf.

Eurostat (2008). *NACE Rev. 2 - Statistical classification of economic activities in the European Community*. Eurostat Methodologies and Working Papers, ISSN 1977-0375.

Fritsche, U. and Stephan, S. (2002). Leading Indicators of German Business Cycles. *Journal of Economics and Statistics*, **222** (3), 289–315.

Graff, M., Mannino, M. and Siegenthaler, M. (2012). *A real time Evaluation of Employment Forecasts in Switzerland*. KOF Working Papers No. 320.

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, **37** (3), 424–438.

Hanssens, M. and Vanden Abeele, P. M. (1987). A Time-Series Study of the Formation and Predictive Performance of EEC Production Survey Expectations. *Journal of Business & Economic Statistics*, **5** (4), 507–519.

Hansson, J., Jansson, P. and Löf, M. (2005). Business survey data: Do they help in forecasting GDP growth? *International Journal of Forecasting*, **21** (2), 377–389.

Hartle, D. (1958). Predictions Derived from the Employment Forecast Survey. *The Canadian Journal of Economics and Political Science*, **24** (3), 373–390.

Hutter, C. and Weber, E. (2013). *Constructing a New Leading Indicator for Unemployment from a Survey among German Employment Agencies*. IAB-Discussion Paper 17/2013.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Springer-Verlag Berlin Heidelberg.

Martinsen, K., Ravazzolo, F. and Wulfsberg, F. (2014). Forecasting macroeconomic variables using disaggregate survey data. *International Journal of Forecasting*, **30** (1), 65–77.

Ng, S. and Perron, P. (2001). Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power. *Econometrica*, **69** (6), 1519–1554.

Robinzonov, N. and Wohlrabe, K. (2010). Freedom of Choice in Macroeconomic Forecasting. *CESifo Economic Studies*, **56** (2), 192–220.

Rossi, B. and Sekhposyan, T. (2011). Understanding models' forecasting performance. *Journal of Econometrics*, **164** (1), 158–172.

Seiler, C. (2014). On the Robustness of the Balance Statistics with respect to Nonresponse. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, forthcoming.

— and Heumann, C. (2013). Microdata imputations and macrodata implications: Evidence from the Ifo Business Survey. *Economic Modelling*, **35** (September 2013), 722–733.

Siliverstovs, B. (2013). Do Business Tendency Surveys Help in Forecasting Employment? A Real-Time Evidence for Switzerland. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, **2013** (2), 1–20.

Österholm, P. (2010). Improving Unemployment Rate Forecasts Using Survey Data. *Finnish Economic Papers*, **23** (1), 16–26.

Weber, E. and Zika, G. (2013). *Labour market forecasting – Is disaggregation useful?* IAB-Discussion Paper 14/2013.

A. Appendix

Table 4: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.
Austria				
MEMP (in %)	0.122	0.335	-0.888	1.077
EMP (in %)	0.245	0.240	-0.469	0.907
EEXP_av (balances)	-3.366	6.439	-20.199	7.605
EEXP_tm (balances)	-3.544	6.433	-21.306	8.218
Belgium				
MEMP (in %)	-0.035	0.363	-0.899	0.735
EMP (in %)	0.246	0.246	-0.385	0.681
EEXP_av (balances)	0.431	6.461	-19.359	11.281
EEXP_tm (balances)	0.358	6.634	-20.281	10.637
Bulgaria				
MEMP (in %)	-0.100	2.025	-4.961	5.400
EMP (in %)	-0.120	0.937	-2.056	1.410
EEXP_av (balances)	-9.023	11.415	-35.910	11.172
EEXP_tm (balances)	-8.899	11.236	-36.203	9.974
Czech Republic				
MEMP (in %)	-0.081	0.663	-1.843	1.129
EMP (in %)	0.009	0.515	-1.195	1.037
EEXP_av (balances)	-3.687	12.645	-35.491	19.359
EEXP_tm (balances)	-4.018	12.988	-36.829	20.447
Estonia				
MEMP (in %)	-0.082	2.933	-7.394	6.714
EMP (in %)	-0.040	1.581	-4.995	4.222
EEXP_av (balances)	-2.151	15.726	-49.096	21.496
EEXP_tm (balances)	-2.181	16.454	-55.688	23.214
Finland				
MEMP (in %)	0.111	1.026	-3.978	1.973
EMP (in %)	0.242	0.648	-1.688	1.607
EEXP_av (balances)	-7.412	9.797	-34.522	8.581
EEXP_tm (balances)	-7.769	10.521	-36.010	9.866
France				
MEMP (in %)	0.101	0.295	-0.685	0.898
EMP (in %)	0.187	0.272	-0.559	0.694
EEXP_av (balances)	-2.696	8.842	-28.104	14.215
EEXP_tm (balances)	-2.781	9.337	-28.655	15.543
Germany				
MEMP (in %)	-0.026	0.381	-0.819	0.713
EMP (in %)	0.167	0.269	-0.422	0.878
EEXP_av (balances)	-12.189	10.549	-29.429	10.019
EEXP_tm (balances)	-12.275	11.056	-32.631	11.948

Continued on next page...

Table 4: Descriptive statistics – continued

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
		Hungary		
MEMP (in %)	0.019	0.828	-1.554	2.056
EMP (in %)	0.018	0.546	-1.299	1.084
EEXP_av (balances)	-8.070	6.170	-31.346	5.080
EEXP_tm (balances)	-7.942	6.571	-35.301	6.051
		Italy		
MEMP (in %)	0.073	0.519	-1.109	1.093
EMP (in %)	0.186	0.436	-0.862	1.176
EEXP_av (balances)	-1.352	6.272	-14.579	15.371
EEXP_tm (balances)	-1.287	6.375	-16.229	15.210
		Netherlands		
MEMP (in %)	0.070	0.463	-0.954	1.137
EMP (in %)	0.212	0.421	-0.930	1.140
EEXP_av (balances)	0.553	9.236	-20.840	12.348
EEXP_tm (balances)	0.428	9.731	-22.822	12.995
		Portugal		
MEMP (in %)	-0.244	0.903	-2.406	1.571
EMP (in %)	-0.078	0.660	-2.001	1.234
EEXP_av (balances)	-8.810	9.593	-29.009	6.412
EEXP_tm (balances)	-9.118	9.711	-30.216	6.460
		Slovakia		
MEMP (in %)	0.068	1.022	-2.830	1.909
EMP (in %)	0.060	0.653	-1.404	1.944
EEXP_av (balances)	-5.805	13.669	-39.828	13.233
EEXP_tm (balances)	-5.600	14.497	-43.823	14.494
		Sweden		
MEMP (in %)	0.135	0.671	-1.701	1.532
EMP (in %)	0.230	0.437	-1.205	1.067
EEXP_av (balances)	-11.189	15.426	-45.116	25.080
EEXP_tm (balances)	-11.262	15.420	-44.518	27.123
		United Kingdom		
MEMP (in %)	-0.086	0.479	-1.475	0.941
EMP (in %)	0.185	0.326	-0.932	0.687
EEXP_av (balances)	-3.552	9.966	-43.797	16.032
EEXP_tm (balances)	-3.607	10.193	-42.342	15.708

Note: Calculations are based on the whole sample (1998Q1–2012Q4).

Source: European Commission, Eurostat, author's calculations.

Table 5: Results of the unit root tests for *EMP* and *EEXP_tm*

Country	**EMP**					**EEXP_tm**				
	KPSS		NP		Δ	KPSS		NP		Δ
	Const.	Trend	Const.	Trend		Const.	Trend	Const.	Trend	
Austria			***	**				**		
Belgium			***	***				***	***	
Bulgaria		**			X	**	***			X
Czech Republic		**	***	**			**			
Estonia			***	***				***	*	
Finland			***	***				***	**	
France	**		*	***	X			***	***	
Germany		*	***	**		*	*	**	**	
Hungary			***	***		*		**	*	
Italy	**			***		**		**	**	
Netherlands					X	*		**		X
Portugal	***		**	***		**			***	X
Slovakia		*	***	*				**		
Sweden			**	*				***	***	
United Kingdom			***	***		**		**	*	

Note: Calculations are based on the whole sample (1998Q1–2012Q4). The Ng-Perron (NP) test states a unit root under the null hypothesis. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test has stationarity under the null hypothesis. For the KPSS and the NP tests, only test statistics and critical values are available. We therefore use asterisks to show whether the null can be rejected or not. In all cases we first tested stationarity in levels (qoq qrowth rate or balances). If the levels turned out to be non-stationary, we then tested first differences of the variables. The column Δ presents the decision on the transformation of the variables. An **X** indicates that first differences are applied. ***, ** and * indicate the rejection of the null hypothesis at the 1%, 5% and 10% significance level.

Table 6: Granger causality results for *MEMP*, *EMP* and *EEXP_tm*

Country	MEMP		
	EEXP_tm → MEMP	MEMP → EEXP_tm	Result
Austria	0.001	0.226	+
Belgium	0.000	0.407	+
Bulgaria	0.001	0.163	+
Czech Republic	0.007	0.038	FB
Estonia	0.007	0.086	FB
Finland	0.026	0.756	+
France	0.000	0.025	FB
Germany	0.005	0.032	FB
Hungary	0.766	0.290	X
Italy	0.062	0.060	FB
Netherlands	0.003	0.034	FB
Portugal	0.004	0.294	+
Slovakia	0.030	0.751	+
Sweden	0.001	0.762	+
United Kingdom	0.224	0.264	X
Country	**EMP**		
	EEXP_tm → EMP	EMP → EEXP_tm	Result
Austria	0.014	0.163	+
Belgium	0.017	0.750	+
Bulgaria	0.121	0.116	X
Czech Republic	0.016	0.164	+
Estonia	0.001	0.204	+
Finland	0.006	0.971	+
France	0.000	0.401	+
Germany	0.101	0.078	X
Hungary	0.692	0.309	X
Italy	0.020	0.100	+
Netherlands	0.002	0.030	FB
Portugal	0.010	0.461	+
Slovakia	0.001	0.082	FB
Sweden	0.003	0.743	+
United Kingdom	0.014	0.524	+

Note: Calculations are based on the whole sample (1998Q1–2012Q4). The table presents p-values from the Granger causality test. *Acronyms:* +, *EEXP*, only Granger causes employment growth (case [i]); FB, feedback effects are present (case [ii]); X, employment growth Granger causes *EEXP* (case [iii]) or no relationship (case [iv]).

Table 7: Out-of-sample results (rolling) for *MEMP* and *EMP*

Model	MEMP				EMP			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
				Austria				
AR(p) in %	0.381	0.402	0.503	0.530	0.228	0.322	0.371	0.540
AR(1)	0.958	0.982	0.910	0.936	0.995	0.905	0.859	0.698
ISM	1.100	1.066	0.871	0.838*	1.299	0.942	0.835	0.579*
RW	1.034	1.257	1.074	1.179	1.283	1.117	1.115	0.832
EEXP_av	0.822**	1.080	1.125	1.052	1.068	1.045	1.408	1.179
EEXP_tm	0.826**	1.010	1.008	1.123	1.070	1.018	1.311	1.259
				Belgium				
AR(p) in %	0.263	0.341	0.427	0.575	0.176	0.224	0.294	0.411
AR(1)	0.933***	0.983*	0.892*	0.732	0.937**	0.988	0.905	0.746
ISM	1.262	1.001	0.816**	0.613*	1.314	1.063	0.827*	0.597*
RW	1.261	1.204	1.144	0.879*	1.228	1.285	1.132	0.854
EEXP_av	0.915**	1.025	1.114	1.369	1.045	0.925*	1.017	1.158
EEXP_tm	0.854***	0.998***	0.969***	1.163	0.869*	0.919*	1.020	0.990*
				Bulgaria				
AR(p) in %	1.092	0.901	1.287	1.209	0.442	0.463	0.480	0.475
AR(1)	1.155	0.970**	0.961**	0.962**	1.057	1.084	0.917**	0.863***
ISM	1.136	1.377	0.941**	1.005	1.120	1.056	1.020	1.055
RW	1.932	1.726	0.816*	1.233	1.508	1.115	1.850	1.265
EEXP_av	1.001	1.451	1.157	1.075	1.041	1.189	1.425	1.121
EEXP_tm	1.060	1.529	1.551	1.273	1.053	1.114	1.274	1.257
				Czech Republic				
AR(p) in %	0.650	0.825	0.798	0.896	0.459	0.557	0.619	0.726
AR(1)	0.968	0.923	0.940	0.948	0.967	0.976	0.928	0.919*
ISM	1.113	0.895	0.934	0.836	1.218	1.029	0.944	0.815
RW	1.341	1.158	1.236	1.140	1.208	1.180	1.139	1.023
EEXP_av	1.046	0.987	0.955*	0.951	1.092	1.316	0.997	1.197
EEXP_tm	1.066	1.071	1.077	1.027	1.073	1.273	1.120	1.146
				Estonia				
AR(p) in %	3.616	4.156	3.937	4.032	1.867	2.169	2.024	2.246
AR(1)	1.004	0.943	0.933**	0.920*	0.989*	0.966	0.991	0.965*
ISM	1.004	0.883**	0.927**	0.914**	1.058	0.926**	1.001	0.914*
RW	1.516	1.044	1.102	1.358	1.316	1.048	1.263	1.241
EEXP_av	0.872*	0.914*	1.489	1.625	0.930*	0.986*	1.511	1.788
EEXP_tm	0.851*	0.867**	1.292	1.831	0.863*	0.951*	1.384	1.692
				Finland				
AR(p) in %	1.153	1.440	2.130	2.626	0.746	0.730	0.760	0.971
AR(1)	0.986**	0.821*	0.592	0.493	0.984	0.967**	0.946**	0.763
ISM	0.974***	0.790*	0.538	0.438	0.926*	0.956*	0.929**	0.729*
RW	1.248	1.060	0.768	0.618	1.085	1.318	1.368	1.173
EEXP_av	0.823**	0.882**	1.079	0.714	0.824*	1.105	1.318	0.872

Continued on next page...

Table 7: Out-of-sample results (rolling) for *MEMP* and *EMP* – continued

Model	**MEMP**				**EMP**			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
EEXP_tm	1.024	0.968**	0.965*	0.782	0.842*	1.111	1.336	0.858
				France				
AR(p) in %	0.126	0.140	0.155	0.169	0.142	0.158	0.164	0.173
AR(1)	0.971**	0.983	0.956**	0.843*	0.840*	0.836	0.846*	0.782*
ISM	1.038	0.949**	0.855**	0.785*	0.835*	0.759*	0.735*	0.699*
RW	1.511	1.328	1.110	0.978**	1.150	0.960**	1.071	1.035
EEXP_av	1.066	1.316	1.541	0.982***	0.832**	0.850*	1.082	1.018
EEXP_tm	0.925*	1.414	1.316	0.981*	0.760**	0.877*	0.927**	0.894*
				Germany				
AR(p) in %	0.327	0.381	0.435	0.454	0.224	0.252	0.265	0.283
AR(1)	0.984*	0.982	0.999	1.021	0.982	0.974*	1.006	1.007
ISM	1.238	1.091	0.976	0.951*	1.130	1.025	0.994	0.948*
RW	1.178	1.183	1.145	1.213	1.161	1.072	1.186	1.196
EEXP_av	0.872***	0.860***	1.011	1.540	1.036	1.009	1.153	1.333
EEXP_tm	0.913***	0.924**	0.833***	0.889***	0.978***	0.894**	0.924**	1.156
				Hungary				
AR(p) in %	0.901	0.878	0.966	0.940	0.616	0.611	0.630	0.608
AR(1)	0.901*	0.899*	0.857*	0.924*	0.994	1.007	0.969	1.004
ISM	0.856*	0.880*	0.809**	0.829***	0.954*	0.968*	0.944	0.985
RW	1.049	1.282	1.037	1.144	1.294	1.232	1.458	1.425
EEXP_av	1.099	1.190	1.063	1.049	1.171	1.190	1.177	1.348
EEXP_tm	1.217	1.230	1.110	1.006	1.142	1.230	1.217	1.376
				Italy				
AR(p) in %	0.539	0.609	0.595	0.569	0.480	0.545	0.596	0.581
AR(1)	1.004	1.000	1.014	0.981**	0.992	0.927**	0.879*	0.796*
ISM	1.078	0.968*	0.997	1.049	0.981	0.875**	0.802**	0.823*
RW	1.389	1.202	1.030	1.162	1.293	1.258	0.975**	0.935**
EEXP_av	0.992	1.019	1.042	0.990	1.037	1.031	0.994	1.063
EEXP_tm	0.997	1.036	1.066	1.212	1.132	1.021	1.000	1.112
				Netherlands				
AR(p) in %	0.442	0.480	0.506	0.512	0.453	0.552	0.503	0.691
AR(1)	0.945**	0.980	0.982	0.973	1.006	0.914**	0.927**	0.940**
ISM	1.118	1.010	0.970	0.951	1.116	0.900**	0.981**	0.726**
RW	1.276	1.538	1.229	1.371	1.723	1.033	1.526	1.110
EEXP_av	1.018	1.606	1.276	1.237	1.149	1.299	1.296	1.321
EEXP_tm	1.048	1.130	1.309	1.175	1.138	1.140	1.297	1.277
				Portugal				
AR(p) in %	0.840	1.034	1.072	0.942	0.703	0.705	0.762	0.734
AR(1)	0.984	0.915	0.900	0.998	0.968	0.995	0.940	1.011
ISM	1.061	0.879	0.859	0.985	0.973	0.982	0.915*	0.954
RW	1.149	1.065	0.995	1.151	1.198	1.229	0.985*	1.007

Continued on next page...

Table 7: Out-of-sample results (rolling) for *MEMP* and *EMP* – continued

Model	**MEMP**				**EMP**			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
EEXP_av	1.081	0.862*	1.347	1.182	1.034	0.885*	1.308	1.173
EEXP_tm	1.097	0.857**	1.588	1.341	1.008	1.058	1.168	1.344
				Slovakia				
AR(p) in %	1.080	1.054	1.182	1.376	0.447	0.514	0.910	1.504
AR(1)	0.997	0.998	0.959	0.819	1.083	1.095	0.758*	0.509
ISM	1.012	1.053	0.959	0.825	1.406	1.256	0.727*	0.446
RW	0.978**	1.483	1.252	1.253	1.153	1.386	0.960*	0.607
EEXP_av	1.066	0.943*	1.986	1.495	1.031	1.216	1.417	1.154
EEXP_tm	1.328	1.122	2.084	1.444	1.280	1.579	1.653	1.258
				Sweden				
AR(p) in %	0.676	0.754	0.880	0.951	0.329	0.414	0.570	0.585
AR(1)	0.917**	0.953*	0.898*	0.888**	0.948***	0.996***	0.871**	0.903**
ISM	1.059	0.971**	0.846**	0.790**	1.353	1.104	0.820***	0.809***
RW	1.138	1.206	1.202	1.166	1.297	1.326	1.160	1.231
EEXP_av	0.815***	0.944***	1.272	1.805	0.804**	0.972*	1.195	1.472
EEXP_tm	0.888**	1.168	1.524	1.841	0.759**	1.044	1.042	1.456
				United Kingdom				
AR(p) in %	0.549	0.680	0.832	0.898	0.442	0.549	0.510	0.434
AR(1)	1.042	0.859**	0.709*	0.744	0.973	0.782*	0.855*	1.021
ISM	1.058	0.869**	0.720*	0.675*	0.927***	0.757**	0.821*	0.975*
RW	1.206	0.969**	0.961*	0.954	1.124	0.879*	1.184	1.433
EEXP_av	1.046	1.051	0.898*	0.969	0.945*	1.119	1.111	1.360
EEXP_tm	1.020	1.057	1.045	1.010	0.909**	0.975	0.975*	1.083

Note: Calculations are based on the whole sample (1998Q1–2012Q4). The table presents the relative root mean squared forecast errors (*rRMSFE*) of the different models and the benchmark. The row AR(p) shows the *RMSFE* (in %) for the benchmark model. *ISM*, in-sample mean; *RW*, Random Walk. Asteriks show significant differences between forecast errors due to the Clark-West test. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Ifo Working Papers

No. 181 Schinke, C., Government Ideology, Globalization, and Top Income Shares in OECD Countries, June 2014.

No. 180 Benz, S., M. Larch and M. Zimmer, The Structure of the German Economy, May 2014.

No. 179 Meier, V. and H. Rainer, Pigou Meets Ramsey: Gender-Based Taxation with Non-Cooperative Couples, May 2014.

No. 178 Kugler, F., G. Schwerdt und L. Wößmann, Ökonometrische Methoden zur Evaluierung kausaler Effeke der Wirtschaftspolitik, April 2014.

No. 177 Angerer, S., D. Glätzle-Rützler, P. Lergetporer and M. Sutter, Donations, risk attitudes and time preferences: A study on altruism in primary school children, March 2014.

No. 176 Breuer, C., On the Rationality of Medium-Term Tax Revenue Forecasts: Evidence from Germany, March 2014.

No. 175 Reischmann, M., Staatsverschuldung in Extrahaushalten: Historischer Überblick und Implikationen für die Schuldenbremse in Deutschland, März 2014.

No. 174 Eberl, J. and C. Weber, ECB Collateral Criteria: A Narrative Database 2001–2013, February 2014.

No. 173 Benz, S., M. Larch and M. Zimmer, Trade in Ideas: Outsourcing and Knowledge Spillovers, February 2014.

No. 172 Kauder, B., B. Larin und N. Potrafke, Was bringt uns die große Koalition? Perspektiven der Wirtschaftspolitik, Januar 2014.

No. 171 Lehmann, R. and K. Wohlrabe, Forecasting gross value-added at the regional level: Are sectoral disaggregated predictions superior to direct ones?, December 2013.

No. 170 Meier, V. and I. Schiopu, Optimal higher education enrollment and productivity externalities in a two-sector-model, November 2013.

No. 169 Danzer, N., Job Satisfaction and Self-Selection into the Public or Private Sector: Evidence from a Natural Experiment, November 2013.

No. 168 Battisti, M., High Wage Workers and High Wage Peers, October 2013.

No. 167 Henzel, S.R. and M. Rengel, Dimensions of Macroeconomic Uncertainty: A Common Factor Analysis, August 2013.

No. 166 Fabritz, N., The Impact of Broadband on Economic Activity in Rural Areas: Evidence from German Municipalities, July 2013.

No. 165 Reinkowski, J., Should We Care that They Care? Grandchild Care and Its Impact on Grandparent Health, July 2013.

No. 164 Potrafke, N., Evidence on the Political Principal-Agent Problem from Voting on Public Finance for Concert Halls, June 2013.

No. 163 Hener, T., Labeling Effects of Child Benefits on Family Savings, May 2013.

No. 162 Bjørnskov, C. and N. Potrafke, The Size and Scope of Government in the US States: Does Party Ideology Matter?, May 2013.

No. 161 Benz, S., M. Larch and M. Zimmer, The Structure of Europe: International Input-Output Analysis with Trade in Intermediate Inputs and Capital Flows, May 2013.

No. 160 Potrafke, N., Minority Positions in the German Council of Economic Experts: A Political Economic Analysis, April 2013.

No. 159 Kauder, B. and N. Potrafke, Government Ideology and Tuition Fee Policy: Evidence from the German States, April 2013.

No. 158 Hener, T., S. Bauernschuster and H. Rainer, Does the Expansion of Public Child Care Increase Birth Rates? Evidence from a Low-Fertility Country, April 2013.

No. 157 Hainz, C. and M. Wiegand, How does Relationship Banking Influence Credit Financing? Evidence from the Financial Crisis, April 2013.

No. 156 Strobel, T., Embodied Technology Diffusion and Sectoral Productivity: Evidence for 12 OECD Countries, March 2013.