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Abstract. In this paper, we forecast employment growth for Germany with data for the period from November 2008 to November 2015. Hutter and Weber (2015) introduced an innovative unemployment indicator and evaluate the performance of several leading indicators, including the Ifo Employment Barometer, to predict unemployment changes. Since the Ifo Employment Barometer focuses on employment growth instead of unemployment developments, we mirror the study by Hutter and Weber (2015). It turns out that in our case, and in contrast to their article, the Ifo Employment Barometer outperforms their newly developed indicator. Additionally, consumers' unemployment expectations and hard data such as new orders exhibit a high forecasting accuracy.

Keywords: survey data; employment forecasts; model confidence set
JEL-Classification: C52; C53; E24; E27; J00

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1 Introduction

Labor market forecasting receives less attention in literature on this topic than standard macroeconomic variables such as gross domestic product (GDP) or industrial production (IP). There is, however, a small but growing body of literature that focuses specifically on labor market variables like unemployment figures or employment growth.[1] The existing studies for Germany all have one purpose in common: they either evaluate new or established survey indicators for forecasting labor market outcomes.[2] Recently, the study by Hutter and Weber (2015) compares a newly developed and innovative indicator for forecasting unemployment changes with the accuracy of rather 'traditional' indicators. The new indicator (called IAB-Labor Market Barometer – here: LMB), based on the assessments of the CEO of each regional entity of the Federal Employment Agency (FEA), produces lower forecasting errors in comparison to the Ifo Employment Barometer (IEB) or new orders in manufacturing. Since the IEB is a leading indicator for employment growth instead of unemployment changes, our paper largely mirrors the study by Hutter and Weber (2015) and evaluates the same indicators as in their article on employment growth in Germany. We find that the IEB performs better in terms of forecasting employment growth compared to the newly developed LMB.

But how does our study differ from the existing literature for Germany? An early contribution is the study by Abberger (2007). We use the same target series that he applied, as well as the IEB. But our study mainly differs from his because he didn't set up a pseudo out-of-sample exercise. A much closer study to ours is that of Henzel and Wohlrabe (2014). The two authors also distinguish between the IEB and the LMB, but focus on cross-correlations exclusively. To the best of our knowledge, there is only the study by Lehmann and Weyh (2016) left with which we can compare our analysis. They evaluate the question on employment expectations from the Harmonized EU Business and Consumer Survey to forecasting employment growth for 15 European states separately, including Germany. Our paper primarily differs from Lehmann and Weyh (2016) in two respects: firstly, we use monthly employment data instead of quarterly information; and secondly, we compare the accuracies of the IEB and the LMB, as well as other indicators.

[1] Studies that evaluate unemployment forecasts include Claveria *et al.* (2007) or Martinsen *et al.* (2014).

[2] In contrast to these studies, Weber and Zika (2013) evaluate whether sectoral disaggregated employment forecasts improve the accuracy of the aggregate of total employment. For the short-term forecasts they do indeed find a significant improvement via disaggregation.

2 Data and Forecasting Approach

2.1 Target Series

In our study we distinguish between two target series. Firstly, the study features total employment (incl. apprentice, judges, officials and soldiers) for Germany that can be downloaded from the website of the Federal Statistical Office. Secondly, we use the largest subgroup of the total figures: employees that are subject to social security. This series is available from the Federal Employment Agency. Both series are seasonally-adjusted and available in monthly frequency until November 2015. We additionally make usage of two ways to transform the data into stationary series: growth rates to the same month of the previous year (year-on-year (yoy) growth) and growth rates to the previous month (month-on-month (mom) growth). Thus, we end up with four different target series.

2.2 Indicators

To come as close as possible to the study by Hutter and Weber (2015), we use the same indicators as they did (the IEB, the LMB, consumers' unemployment expectations, inflation, nominal new orders in manufacturing and registered vacancies). We, however, add three more indicators: a modified IEB, real new orders in manufacturing and industrial production. Registered vacancies, new orders in manufacturing and industrial production are standard in the literature and need no more explanations. Inflation is measured as the harmonized index of consumer prices.

The remaining four indicators are calculated from survey results. From the EU consumer survey, we can extract consumers' unemployment expectations. Here participants are asked how unemployment in their home country will develop in the next 12 months. They have five options for answering this question and we use the balances reported by the EU. The IAB-Labor Market Barometer (LMB) is based on responses from the CEOs of the FEA's regional entities. They are asked every month how they expect unemployment to develop in their district in the next 3 months. As for the EU-indicator mentioned above, the experts have five possible answers to this question. Hutter and Weber (2015) recommend using an adjusted version of the LMB. We, however, cannot access the micro data and therefore have to use the indicator provided on their homepage.[3] The Ifo Employment Barometer (IEB) results from a monthly survey among enterprises. Each firm in the survey is asked about their employment expectations for the next 3 months. In contrast to the previous surveys, the firms only have three possible answers to choose from. We also base our exercise on balances. The IEB, however, enters the exercise in two different ways. Firstly, it enters in its current version, covering all branches of the German economy; and secondly, we use the

[3] For more details on the indicator see Delfs *et al.* (2013) or Hutter and Weber (2015). The data can be retrieved here: `http://www.iab.de/en/daten/arbeitsmarktbarometer.aspx`.

version in which it was published until December 2011. The earlier version only covers the branches of manufacturing, construction, wholesale trade and retail sales. Since the IEB focuses more on employment subject to social security than on total employment, we will evaluate the four target series described above.

All nine indicators have different ranges in availability. The shortest time series, which also defines our forecasting exercise, is the LMB, running from November 2008 until January 2016. With the exception of the survey indicators that enter the following regression in levels, all variables are transformed into year-on-year growth rates.

2.3 Forecasting Models and Evaluation

As possible benchmarks, we apply three different types of models: (i) a random walk, (ii) the in-sample mean and (iii) an $AR(2)$ process with a constant, determined by the AIC. As indicator models, we add each of the nine indicators to the $AR(2)$ process separately. So we have the same twelve models as Hutter and Weber (2015) for each of the four target series.[4]

Our initial estimation period ranges from November 2008 to December 2010. Since our observation period is pretty short, we apply an expanding window approach. In each iteration, the window is thus enlarged by one month. We consider forecasts for 1, 3 and 6 months ahead. The forecasts are produced in a direct-step fashion, i.e., the models are adjusted in such a way that we do not have to forecast missing indicators within the horizon. Another advantage of the direct-step is that we produce the same number of forecasts for each forecast horizon (here: 59, January 2011 to November 2015). In order to keep the exercise realistic, we also account for publication lags. Whereas the survey indicators have no publication lag, vacancies and inflation have a publication delay of one month. With two lags, the longest publication lag is observable for new orders and industrial production.

Besides calculating ratios of the root mean squared forecasts errors ($RMSFE$) between the indicator models and the $AR(2)$ process, we evaluate our twelve models via the so called Model Confidence Set (MCS) by Hansen *et al.* (2011). From a bunch of models the MCS chooses the optimal ones with the best performance within a 5% confidence range. One advantage of the MCS is that we do not have to specify a specific benchmark model.

3 Results

Our forecasting exercise reveals interesting insights (see Table 1). We observe very clear differences in forecasting accuracy between the target variables and their specific transformations. Basically, yoy growth rates show higher $RMSFEs$ than mom growth rates. Mom growth rates, however, show larger variances and are thus harder to predict.

[4]Hutter and Weber (2015) consider even more models. In our application, however, these models do not perform well so that we skip these below.

Table 1: Results for each target series and forecasting horizon

Total employment (year-on-year growth)						
	RMSFE-Ratio			MCS		
Model	$h = 1$	$h = 3$	$h = 6$	$h = 1$	$h = 3$	$h = 6$
Random Walk	0.884	1.010	1.008	X		
In-sample Mean	5.138	3.137	1.912			
LMB	0.898	0.930	0.943			
IEB	0.884	0.851	0.863	X		
IEB2011	0.843	**0.814**	**0.831**	X	X	X
EUCS-UNEMP	0.896	**0.830**	**0.841**	X	X	X
Vacancies	0.911	**0.821**	**0.808**	X	X	X
HCPI	1.024	1.009	1.000			
New Orders (real)	**0.807**	0.874	0.863	X		
New Orders (nom.)	**0.802**	0.865	0.854	X		
Industrial Production	**0.795**	0.853	0.857	X		X
$RMSFE$ $AR(2)$ in p.p.	0.095	0.166	0.296			

Total employment (month-on-month growth)						
	RMSFE-Ratio			MCS		
Model	$h = 1$	$h = 3$	$h = 6$	$h = 1$	$h = 3$	$h = 6$
Random Walk	1.247	1.144	1.180		X	
In-sample Mean	1.031	1.179	1.115	X	X	X
LMB	0.999	1.010	0.922	X	X	X
IEB	0.948	1.032	0.949	X	X	X
IEB2011	0.926	**0.988**	0.932	X	X	X
EUCS-UNEMP	0.970	1.034	1.023	X	X	
Vacancies	0.950	**0.982**	0.948	X	X	X
HCPI	1.023	1.051	1.049		X	
New Orders (real)	**0.913**	1.008	**0.884**	X	X	X
New Orders (nom.)	**0.907**	1.000	**0.876**	X	X	X
Industrial Production	**0.892**	**0.939**	**0.897**	X	X	X
$RMSFE$ $AR(2)$ in p.p.	0.058	0.052	0.058	X	X	

Employment subject to social security (year-on-year growth)						
	RMSFE-Ratio			MCS		
Model	$h = 1$	$h = 3$	$h = 6$	$h = 1$	$h = 3$	$h = 6$
Random Walk	**0.870**	1.020	1.026	X		
In-sample Mean	6.330	4.025	2.527			
LMB	0.880	0.935	0.944	X	X	X
IEB	**0.871**	0.897	0.899	X	X	X
IEB2011	**0.874**	**0.882**	**0.879**	X	X	X
EUCS-UNEMP	0.951	**0.892**	**0.888**	X	X	X
Vacancies	0.981	**0.889**	**0.864**	X	X	X
HCPI	1.022	1.021	1.018			
New Orders (real)	0.878	0.934	0.923	X	X	X
New Orders (nom.)	0.898	0.942	0.926	X	X	X
Industrial Production	0.921	0.951	0.941	X	X	X
$RMSFE$ $AR(2)$ in p.p.	0.145	0.241	0.419			

Employment subject to social security (month-on-month growth)						
	RMSFE-Ratio			MCS		
Model	$h = 1$	$h = 3$	$h = 6$	$h = 1$	$h = 3$	$h = 6$
Random Walk	1.167	1.117	1.136			
In-sample Mean	1.158	1.346	1.269			
LMB	1.023	1.074	0.988		X	X
IEB	**0.927**	0.974	0.965	X	X	X
IEB2011	**0.924**	0.945	0.952	X	X	X
EUCS-UNEMP	0.959	**0.931**	**0.899**	X	X	X
Vacancies	0.940	0.933	0.940	X	X	X
HCPI	1.033	1.056	1.057			
New Orders (real)	0.940	0.937	**0.898**	X	X	X
New Orders (nom.)	**0.935**	**0.921**	**0.894**	X	X	X
Industrial Production	0.951	**0.929**	0.928	X	X	X
$RMSFE$ $AR(2)$ in p.p.	0.088	0.078	0.087			

Note: The table presents the $RMSFE$-Ratios for each forecast horizon and target variable. Each target series is separated from the others by a double line. The $RMSFE$ of the respective autoregressive benchmark of order two is presented in percentage points (p.p.) at the end of each target series block. The three best $RMSFE$ for each forecast horizon and target series are set in **boldface**. An X indicates that the specific model is included in the Model Confidence Set (MCS). *Abbreviations:* LMB...IAB-Labor Market Barometer; IEB...Ifo Employment Barometer; IEB2011...Ifo Employment Barometer, version 2011 and earlier; EUCS-UNEMP...EU Consumer Survey, unemployment expectations; HCPI...Harmonized consumer price index.

Hard data like new orders (either in real or nominal terms) and industrial production are very good predictors for all target series and forecast horizons. Additionally, these indicators also get selected into the MCS in almost all cases. The role of vacancies, which are commonly seen as one of the best predictor for the labor market, can be confirmed in our setting. We find only a small number of cases where vacancies are not among the best three performing models in terms of $RMSFE$. The opposite holds for the consumer price index: there is no case where the HCPI beats the autoregressive benchmark.

But how do the chosen survey indicators perform? As expected, they do a very good job. And the story by Hutter and Weber (2015) reverses if we look at employment growth instead of unemployment changes: the Ifo Employment Barometer (IEB) performs better in almost all cases than the IAB-Labor Market Barometer (LMB) and is more frequently selected into the MCS. Thus, the IEB should be used to forecast employment growth instead of the LMB. Whenever it comes to predicting unemployment changes, one should opt for the LMB, as shown by Hutter and Weber (2015). Another interesting finding is that the IEB in its earlier version (IEB2011) produces lower forecasting errors than the latest version. The inclusion of services may deteriorate the forecasting properties of the survey series. A look at the responses of consumers reveals that their unemployment expectations for the next 12 months (EUCS-UNEMP) offer stiff competition for the IEB, especially if we look at year-on-year growth rates. Thus, the EU survey results for consumers also provide a very good indicator for forecasting employment growth in Germany.

4 Conclusion

Our study follows the approach by Hutter and Weber (2015) and uses the newly developed IAB-Labor Market Barometer to forecasting employment growth instead of unemployment changes. Whereas this new indicator focuses on unemployment, the Ifo Employment Barometer is a predictor for employment growth. We find that the Ifo indicator performs better in terms of forecasting employment than the IAB indicator. Additionally, hard data such as vacancies or new orders are tough competitors in terms of forecast accuracy.

Next to the academic advice to intensively study the forecasting performance of different model types and indicators for labor market outcomes, we focus on the practical issues raised by our paper. A large number of indicators can be used to forecast different macroeconomic variables. However, it is not always clear which indicator should be focused on for which target series. This is a more pressing issue for labor market outcomes than GDP. In this respect, our paper offers some hints as to which indicator works for employment growth, instead of unemployment changes.

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