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FORECASTING INDUSTRIAL PRODUCTION IN POLAND – A COMPARISON OF DIFFERENT METHODS

Abstract: In this paper we compared the accuracy of a few forecasting methods of the industrial production index in Poland. Naïve forecasts, simple autoregressive models, leading indicator models, factor models as well as joint models were included in the considerations. We used the out-of-sample RMSE and CPA tests as the main measures of the predictions accuracy. We found that three models provided the best predictions in most cases – the models with the PMI index and with the PMI and German IFO indexes as leading indicators as well as joint forecasts.

Keywords: forecasting, industrial production, leading indicators, factor models.

1. Introduction

Accurate and reliable forecasts of the level of economic activity are crucial in making successful business decisions as well as conducting economic policy efficiently. The most popular measure of a country's economic activity is the gross domestic product (GDP). However, this indicator has at least two unpleasant features which restrict its usefulness for decision makers: it is measured on a quarterly basis and there are significant publication lags. In Poland the preliminary information on the GDP dynamics for a given quarter is announced by the Central Statistical Office about two months after the quarter ends. For other countries the delay is somewhat shorter, but in many cases it is still far too long.

For this reason there are complementary measures of a country's economic performance, like the industrial production index (IPI) or business sentiment surveys, to name a few. They are usually published every month with short or even no publication lags. They are also strongly correlated with the GDP which makes them good candidates for leading or coincident indicators for the GDP. Despite these advantages, it is still the GDP that is the measure used most often when one needs to predict the future level of economic activity. Both in the scientific literature and in business and economic policy practice, methods like factor models, leading indicator models, Bayesian VARs and joint models are considered to be the most successful tools for short term DGP prediction. However, very little is known about the forecasting performance of these methods applied to other measures of the level of economic activity.

In this paper we partially fill this gap and compare the prediction abilities of these methods in the case of the forecasting of the industrial production index in Poland. To be more precise, we take autoregressive models, a few leading indicator models, factor models and joint models and check their point forecasting performance compared to simple naïve forecasts. As a forecasting performance measure we use out-of-sample root mean square error. We also check how successful the methods are in predicting directions of changes of the IPI. Since we base our study of the series of realized forecasts we also employ conditional predictive ability test (CPA) [Giacomini, White 2006] to exclude the possibility that the differences in the forecasting performances observed in the sample are caused by pure chance.

We think that our study is important for a few reasons. Despite the fact that industrial production accounts only for about one third of the Polish GDP, it is widely considered to be a reliable indicator of the overall economic activity level. This fact can easily be seen by the extensive comments of business analysts triggered every month by the publication of the IPI data. Moreover, for many companies with strong connections to the industrial sector, the IPI forecasts can be more important than the GDP predictions. It is also well known that accurate IPI forecasts can improve the quality of the GDP predictions [see Parigi, Golinelli 2007].

The study is also important from the methodological point of view. The statistical properties of the IPI series are very different from its counterparts for the GDP. As industrial production is reported on a monthly basis, a relatively higher fraction of its variability can be attributed to factors that are at least weakly connected to the overall economic activity level, like, for example, weather conditions. Therefore it is important to check if the same prediction methods work well in the case of the IPI.

Last but not least, we think that comparing the prediction accuracy of different models is more reliable when using the IPI series than the GDP data. This is due to the simple fact that the IPI series are significantly longer and therefore we could generate more forecasts. This idea was, for example, used in the work of [Siliverstovs, van Dijk 2003], who used the IPI data to test interval forecasting performance of various linear, nonlinear and structural change models.

Our study is closely related to a recent work of [Bulligan, Golinelli and Parigi 2010], who analyzed the forecasting abilities of different methods regarding the Italian IPI series. In their study they included ARIMA models, static and dynamic factor models and coincident indicator models for aggregated and disaggregated data. These are very similar methods to those included in our study, but they considered them in a greater variety. The authors concluded that the coincident indicator models based on the consumption of electricity [see also Bodo, Signorini 1987] clearly outperform other methods as far as short term forecasts were concerned.

They also found strong evidence that the factor models generated better forecasts than the ARIMA models. However our work differs from this study in at least one important point. While Bulligan, Golinelli and Parigi forecasted one month production changes, we work with yearly production growth rates. Therefore we are able to smooth out some variations that are not connected to the general trends in the economic activity levels.

It should also be mentioned that there has been a long tradition of using the IPI series for forecasting business cycle turning points [see Maher 1957; Stekler 1961; Bruno, Lupi 2004]. Bruno and Lupi [2003] used national business surveys data together with VAR models for predicting the Euro area IPI. A similar idea was employed by Zizza [2002].

The paper is organized as follows. In the first chapter we briefly introduce the forecasting methods used in the study. Then we discuss the method of comparison of the prediction accuracy of the different methods. Finally we present the results.

2. Description of the models

2.1. Leading indicator models

There are two strands of research regarding the leading indicator models in the literature. The traditional approach looks for single variables that are able to predict accurately the changes of the variable of interest [see for example Estrella, Mishkin 1998; McGuckin, Ozyildirim, Zarnowitz 2000]. The more recent approach looks for synthetic leading variables that are extracted from large datasets [see Bai, Ng 2008]. Since the latter method is very similar to forecasting with the factor models, in the paper we use the traditional approach.

After some preliminary tests, we chose three variables as leading indicators: manufacturing Purchasing Managers' Index PMI for Poland published by HSBC and Markit, the survey on general business tendency climate in manufacturing in Poland conducted by the Central Statistical Office, and the IFO Expectations Index for Germany. All three variables are based on questionnaires sent to companies every month. The PMI values are published at the end of the month of interest. The results of the business tendency climate survey are announced in the middle of the month and the IFO index is published near the end of the month. As a result, at the end of the current month, the values of all three variables are known. Therefore the measures are not only useful for the IPI forecasting but also for nowcasting. The PMI and IFO indexes are well known leading indicators of the level of economic activity and their values are carefully followed by managers and policy makers. This is not the case for the business tendency climate survey. However, we decided to include this measure into our study since the survey is conducted in a similar way to the other two indexes and its values are easily available. We incorporated the IFO index since we believe that the economic activity level in Germany – the main trading partner of Poland – would be a good predictor of the economic performance of our country.

For every leading indicator and every horizon h we estimate a set of forecasting equations of the form:

$$IPI_{t+h} = \alpha + \sum_{i=1}^{n_{IPI}} \beta_i IPI_{t-i} + \sum_{i=0}^{n_{LI}} \gamma_i LI_{t-i} + \xi_{LI,t+h}, \quad (1)$$

where: LI stands for one of the leading indicator variables, a, β_i and γ_i are parameters and x_{LI} represents the error term. For nowcasting we set $h = 0$. The model is estimated with the ordinary least squares method. For every horizon h and every leading indicator variable the model with the smallest value of the Bayesian Information Criterion is chosen for forecasting.

We also consider the forecasting equation with two variables – IFO and PMI (PMI + IFO). They seem to perform better then the business tendency climate survey variable. The equation has the following form:

$$IPI_{t+h} = \alpha + \sum_{i=1}^{n_{IPI}} \beta_i IPI_{t-i} + \sum_{i=0}^{n_{PMI}} \gamma_i PMI_{t-i} + \sum_{i=0}^{n_{IFO}} \varphi_i IFO_{t-i} + \xi_{LI2,t+h}. \quad (2)$$

2.2. Factor models

Using factor models for forecasting has gained a wider popularity in the last two decades, as large databases that contain several hundred variables have become easily available to the research community [Stock, Watson 1998]. Forecasting with factor models basically consists of two steps. First, the factors are extracted from a large set of economic variables and then they are used for forecasting purposes.

In the paper we take one of the simplest and most popular approaches [Stock, Watson 1998; Baranowski, Leszczyńska, Szafrański 2010]. As far as the first step is concerned, we use the static version of the principal component analysis PCA. Given a $N \times K$ dimensional matrix $\mathbf{Z}$ of the explanatory variables we look for a $K \times K$ loading matrix $\mathbf{L}$ and $N \times K$ matrix of factors $\mathbf{F}$ that satisfy $\mathbf{Z} = \mathbf{F} \times \mathbf{L}$, where the factors (the columns of the matrix $\mathbf{F}$) are independent and sorted in such a way, that the first factor explains the highest possible share of variation of $\mathbf{Z}$, the second factor explains the highest possible share of variation of $\mathbf{Z}$ unspanned by the first factor, etc. Because of missing observations at the beginning and at the end of the sample, we also employ the Expectation Maximization algorithm [see Stock, Watson 1998]. It fills the empty entries recursively using only full rows as a point of departure. There are other methods of factors extraction, like the dynamic PCA or generalized principal components, and some studies suggest that they can outperform the static PCA [Eickmeier, Ziegler 2006; but see also Baranowski, Leszczyńska, Szafrański 2010]. However we did not explore this possibility further in this paper.

In the second step the forecasting equation is built. Likewise in the leading indicator models we opt for direct h-step forecasts:

$$IPI_{t+h} = \alpha + \sum_{i=1}^{n_{IPI}} \beta_i IPI_{t-i} + \sum_{i=1}^{n_F} \tilde{\mathbf{a}}_i' \mathbf{F}_{t-i}^k + \xi_{F,t+h}, \quad (3)$$

where $\mathbf{F}_t^k$ is a matrix consisting of the first k columns of $\mathbf{F}$ and $\boldsymbol{\gamma}_i$ are the corresponding vectors of parameters. To be in line with the leading indicator models, we also employ BIC for choosing the optimal number of factors k and lags n_{IPI} and n_F simultaneously. In an extensive simulation study [Acedański 2012] showed that this criterion tends to select models with good forecasting performance compared to many alternative approaches.

There is a subtle difference in timing convention between equations (1) and (3). For nowcasting in (1) a contemporaneous relationship between the IPI and the leading indicators should be estimated, since the IPI is published with about a one month lag compared to the leading indicators. This is not the case for the factor models however, since only few variables from the matrix $\mathbf{Z}$ are published earlier than the IPI . Therefore even if we set $h = 0$, we have to use lagged values of $\mathbf{F}_t^k$ for estimating the forecasting equation.

We utilize a relatively small set of 36 preselected exogenous variables. However, as Boivin and Ng (2006) showed, increasing the number of variables may not lead to better predictions. In fact in their study, a model with only 40 prescreened variables performed no worse than a model with the full 147 series. In our database we included variables that should be related to the industrial production dynamics and have a correlation coefficient with other series which is less than 0.95. The series covers such areas as the business climate in manufacturing, construction and trade, the labour market, national accounts, financial results of companies, international trade, the level of economic activity in Germany among others. Most variables are expressed as yearly growth rates and missing values of the quarterly series are linearly interpolated. The exact description of the database is given in the appendix.

2.3. Other models

Two methods are proposed as benchmarks. First, we use the naïve forecasts where we assume that $IPI_{t+h} = IPI_t$. We also employ simple autoregressive models of the first, second or third order depending on the value of the BIC criterion. Finally, we calculate joint forecasts as a mean value of AR, PMI, PMI + IFO and factor model predictions.

3. Research methodology

As we already mentioned earlier, we use change of the industrial production volume in a given month relative to the same month in a previous year as a prediction variable. However, since the IPI is strongly affected by weather conditions as well as the number of working days among other factors, neither taking yearly changes alone nor using seasonality procedures, do not smooth out all the IPI fluctuations that are unrelated with the business cycle. To solve the problem at least partially we take the following formula for calculating the yearly indices:

$$IPI_{t+12/t} = \sqrt{IPI_{t/t-1}} \cdot IPI_{t+1/t} \cdot IPI_{t+2/t+1} \cdot \ldots \cdot IPI_{t+11/t+10} \cdot \sqrt{IPI_{t+12/t+11}} \ . \tag{4}$$

This simple transformation halves the conditional standard deviation of the series from 5.3% per month to 2.5% and increases its autocorrelation from 0.69 to 0.92. Both series – raw 12-month indices and their smoothed version – are illustrated in Figure 1.

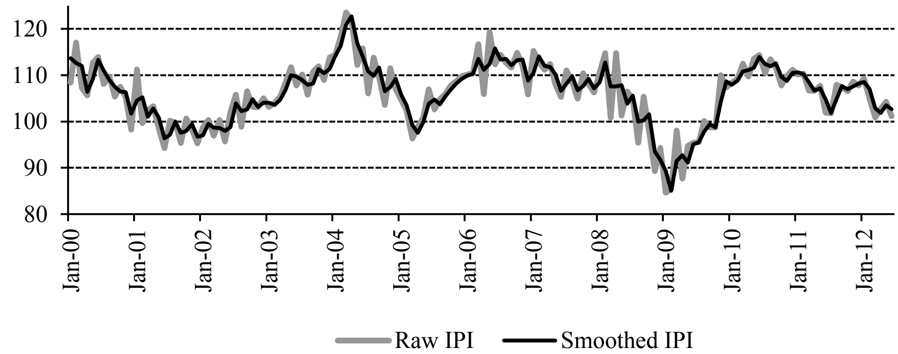

Figure 1. Raw and smoothed IPI

Source: own calculations.

Our database covers the period 1M2000 to 6M2012 for the IPI and the factor variables and to 7M2012 for the leading indicators. Overall we have 150 monthly observations. In a baseline study we take 60-month-long rolling subsamples which are utilized for estimating the models and forecasting. For every horizon $h = 0, 1, 3, 6$ months we calculate the out-of-sample RMSE. We also check if the models are able to correctly predict directions of changes by calculating a fraction of the subsamples where the sign of the predicted change differs from the sign of the true index change. Finally, we apply the CPA test of Giacomini and White [2006] to exclude the possibility that the differences in the forecasting performances observed in the sample are caused by pure chance. We use the unconditional version of the test which compares models' general predictive abilities regardless of any additional information.

4. Comparing the predictions accuracy

Table 1 contains RMSE in our baseline study with 84 forecasts for each method and each horizon. In the table we have first the two benchmarks method – naïve and AR models – then four leading indicator models (three single variable models – survey of the general business climate in manufacturing, PMI and IFO and one with two variables – PMI + IFO). Finally, there are the results for the factor models and for the joint forecasts.

As far as nowcasting is concerned (h = 0) the lowest RMSE is associated with the joint forecasts – 2.2% per month. One obtains only a slightly higher value – 2.26% – taking the PMI as the leading indicator. This variable, however, outperforms the others in 1-month-ahead forecasting. For 3 and 6-month horizons it is the two variables leading indicator model (PMI + IFO) that delivers the most accurate predictions. It should also be noticed that both the business climate survey based models and, especially, the factor models, perform very poorly for the longer horizons and even for the short horizons they are unable to beat the naïve forecasts. This is also the case for the AR models that slightly underperform the naïve forecasts regardless of the horizon.

Table 1. RMSE for the baseline study, T = 60 months (in %)

Horizon	Naïve	AR	Survey	PMI	IFO	PMI+IFO	Factor	Joint
$h = 0$	2.59	2.61	2.75	2.26	2.48	2.33	2.58	**2.20**
$h = 1$	3.60	3.77	3.63	**2.68**	3.08	2.76	3.97	2.78
$h = 3$	5.25	5.56	5.18	3.76	4.05	**3.68**	8.46	4.33
$h = 6$	7.34	7.33	7.49	5.63	5.79	**5.07**	8.81	5.50

Source: own calculations.

Table 2. Predicted sign inconsistency for the baseline study (in %)

Horizon	Naïve	AR	Survey	PMI	IFO	PMI+IFO	Factor	Joint
$h = 0$	100,0	47,0	39,8	**30,1**	38,6	32,5	33,7	**30,1**
$h = 1$	100,0	46,3	39,0	**29,3**	35,4	32,9	42,7	30,5
$h = 3$	100,0	41,3	41,3	32,5	33,8	**31,3**	50,0	33,8
$h = 6$	100,0	36,4	35,1	28,6	28,6	**26,0**	48,0	28,6

Source: own calculations.

These observations are confirmed when one analyses the fraction of the subsamples in which the predicted sign change differs from the observed one. These results are presented in Table 2. The best models – joint, PMI and PMI + IFO – are able to predict correctly the sign of the change in two out of three cases on average (about 30% of wrong predictions). The sign prediction accuracy tends to increase as the horizon rises.

Finally, Tables 3 and 4 contain the results of the CPA tests for horizons h = 0 and h = 6 months. The tests are conducted for every pair of the models. A value "0" in the tables means that there are no systematic differences in the methods' RMSE at the 0.1 significance level. A value "–1" in a row suggests that a model in that row delivers less accurate forecasts than a model from the corresponding column and the value "1" means the opposite. The last column contains sums of the values in the rows and

Table 3. Results of the CPA pairwise tests for the baseline study and $h = 0$

	Naïve	AR	Survey	PMI	IFO	PMI+IFO	Factor	Joint	**Sum**
Naïve	0	0	0	0	0	0	0	–1	–1
AR	0	0	0	0	0	0	0	–1	–1
Survey	0	0	0	–1	0	0	0	–1	–2
PMI	0	0	1	0	1	1	0	0	3
IFO	0	0	0	–1	0	0	0	–1	–2
PMI + IFO	0	0	0	–1	0	0	0	0	–1
Factor	0	0	0	0	0	0	0	–1	–1
Joint	1	1	1	0	1	0	1	0	**5**

Source: own calculations.

Table 4. Results of the CPA pairwise tests for the baseline study and $h = 6$

	Naïve	AR	Survey	PMI	IFO	PMI+IFO	Factor	Joint	**Sum**
Naïve	0	0	0	–1	0	–1	1	–1	–2
AR	0	0	0	–1	0	–1	0	–1	–3
Survey	0	0	0	–1	0	–1	0	–1	–3
PMI	1	1	1	0	0	0	1	0	**4**
IFO	0	0	0	0	0	0	1	0	1
PMI + IFO	1	1	1	0	0	0	1	0	**4**
Factor	–1	0	0	–1	–1	–1	0	–1	–5
Joint	1	1	1	0	0	0	1	0	**4**

Source: own calculations.

Table 5. RMSE for longer samples, $T = 84$ months

Horizon	Naïve	AR	Survey	PMI	IFO	PMI+IFO	Factor	Joint
$h = 0$	2.69	2.71	2.84	**2.32**	2.57	2.34	2.61	**2.32**
$h = 1$	3.68	3.75	3.51	2.90	3.23	2.89	3.34	**2.86**
$h = 3$	5.56	5.55	5.29	**4.28**	4.65	4.35	5.66	4.34
$h = 6$	7.97	7.32	8.11	6.10	6.45	6.74	8.49	**6.04**

Source: own calculations.

is used for ranking the methods. As one can easily notice, the results also confirm the observations from Table 1. As far as nowcasting is concerned, the joint forecasts and PMI models beat the other methods. For the longer horizons also the PMI + IFO models perform quite well.

The last two tables contain the results of the robustness check exercises with regard to the length of the samples. With 84 observations per sample, the joint and

Table 6. RMSE for shorter samples, $T = 42$ months

Horizon	Naïve	AR	Survey	PMI	IFO	PMI+IFO	Factor	Joint
$h = 0$	2.62	2.95	3.09	2.46	2.64	2.71	2.90	**2.40**
$h = 1$	3.73	4.60	4.50	3.53	3.76	3.58	4.57	**3.49**
$h = 3$	5.53	8.00	7.74	5.54	**5.24**	5.61	7.18	5.42
$h = 6$	**7.70**	12.40	10.83	9.38	10.91	10.03	10.32	8.68

Source: own calculations.

PMI models outperform the other methods for all horizons. As far as the 42-month-length samples are concerned, the joint models provide the highest accuracy for the short horizons. For $h = 3$ the IFO leading indicator model delivers the smallest RMSE and for $h = 6$ it is the naïve forecasts that clearly beat all the alternatives.

5. Conclusions

In the paper we compared a few methods of prediction the IPI in Poland. We included naïve forecasts, simple autoregressive models, leading indicator models, factor models as well as joint models into the considerations. We found that three models provide the best predictions in most cases – the models with the PMI index and with the PMI and German IFO indexes as leading indicators, as well as joint forecasts consisting of autoregressive model forecasts, PMI and PMI + IFO leading indicator forecasts and factor model forecasts. They usually outperform the other methods regardless of length of the sample and the forecast horizon. Therefore we confirmed the conclusion of Bulligan, Golinelli and Parigi who had also found that the leading indicator models provided the most accurate forecasts of the Italian IPI. However, contrary to that paper, the factor models in our study performed surprisingly poorly and were unable to beat the naïve forecasts in almost every case. We did not conduct an in-depth study of this phenomenon, but we suppose this may result – at least in some part – from either a bad variable selection or using the yearly indices.

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Appendix. The list of variables for the factor models

No	Variable	Lag	Freq.	Unit
1	Average employment in enterprise sector	0	M	1
2	Average employment in enterprise sector – manufacturing	0	M	1
3	Average real monthly gross wages and salaries in enterprise sector	0	M	1
4	WIBOR 3M	–1	M	1
5	Consumer price index	0	M	2
6	WIG20 index	–1	M	1
7	EUR/PLN nominal exchange rate	–1	M	1
8	Money supply M3	0	M	1
9	Price index of sold production of industry	0	M	1
10	Price index of sold production in mining and quarrying	0	M	1
11	Industrial production index in manufacturing	0	M	1
12	Industrial production index in construction	0	M	1
13	New orders in industry	0	M	1
14	Steel production	0	M	1
15	Export in PLN	2	M	1
16	Import in PLN	2	M	1
17	Job offers declared during a month	0	M	1
18	Deposits of nonfinancial corporations	1	M	1
19	Net domestic assets of nonfinancial corporations	1	M	1
20	Sales profitability rate in industry	4	Q	2
21	Cost level indicator in industry	4	Q	2
22	Net turnover profitability rate in industry	4	Q	2
23	Financial liquidity ratio of first degree	4	Q	2
24	Indicator of the general business tendency climate in manufacturing	–1	M	3
25	Forecast of the general economic situation in manufacturing	–1	M	3
26	Forecast of the domestic and abroad orders in manufacturing	–1	M	3
27	Forecast of the production in manufacturing	–1	M	3
28	Indicator of the general business tendency climate in construction	–1	M	3
29	Indicator of the general business tendency climate in trade	–1	M	3
30	Gross domestic product	4	Q	1
31	Gross capital formation	4	Q	1
32	Gross value added in industry	4	Q	1
33	IFO Germany Business Climate	–1	M	3
34	IFO Germany Business Situation	–1	M	3
35	IFO Germany Business Expectations	–1	M	3
36	Industrial production index in Germany	1	M	1

Lag – maximum publication lag in months relative to the IPI; Freq – frequency of series (M – monthly, Q – quarterly); Unit – measurement units (1 – percentage change relative to the same period in previous year; 2 – percentage points; 3 – in levels (for the survey climate measures).

Source: own calculations.

PROGNOZOWANIE PRODUKCJI PRZEMYSŁOWEJ W POLSCE – PORÓWNANIE ALTERNATYWNYCH METOD

Streszczenie: W pracy porównywana jest dokładność różnych metod prognozowania indeksu produkcji przemysłowej w Polsce. W rozważaniach uwzględniane są prognozy naiwne, proste modele autoregresyjne, modele wskaźników wyprzedzających, modele czynnikowe oraz prognozy łączone. Jako miary jakości prognoz wykorzystywane są błędy średniokwadratowe prognoz wygasłych oraz testy CPA. Rezultaty badań porównawczych wskazują, że w większości analizowanych przypadków najlepsze prognozy dawały trzy modele: modele z indeksem PMI oraz z indeksami PMI i niemieckim IFO jako wskaźnikami wyprzedzającymi oraz prognozy łączone.

Słowa kluczowe: prognozowanie, produkcja przemysłowa, wskaźniki wiodące, modele czynnikowe.