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Latent factor growth models for forecasting Polish GDP growth, inflation and unemployment using survey data

Abstract

In this paper a novel application of latent factor growth models is applied to responses to the manufacturing industry tendency survey conducted by the Research Institute for Economic Development, Warsaw School of Economics. An approach based on a common factor was assumed to explain variation in time response to specific questions drawn from the survey questionnaire. It was demonstrated that responses to questions relating to general economic situation in Poland, inflation and employment were explained by a latent growth factor, which was confirmed by RMSEA. Using cross-correlation and an ARIMAX model, it was shown that slopes obtained from latent factor growth models could be applied to forecasting or at least nowcasting of GDP growth and unemployment rate. Survey data of the type described clearly offer potential for refinement of economic projections and it is hoped that this work might stimulate further discussion of the methodology based on latent factor growth modeling for forecasting main macroeconomic time series.

Keywords: latent factor growth modelling, forecasting, GDP growth, inflation, unemployment

JEL classification: C38, C53, E37

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1. Introduction

There is a large body of literature on application of survey data to forecasting the main macroeconomic time series (Darne, 2008; Dudek & Walczyk, 2004; Rünstler & Sédillot, 2003). Some articles concentrate on the forecasting benefit from factor analytical approach (Baranowski *et al*., 2010; Boivin & Ng, 2006; Reijer, 2012; Stock & Watson, 2002), but most of them only uses time series data from national accounts. Although survey data can be useful in forecasting, particularly in the short term (Bańbura *et al*., 2010; Białowolski *et al*., 2014a), only a few authors have applied tendency survey data to the task (Białowolski *et al*., 2014b; Frale *et al*., 2010; Hansson *et al*., 2005; Kaufmann & Scheufele, 2013). When survey data has been used, however, it has mostly been limited to aggregate statistics (balances). Such an approach might lead to several potential errors. Firstly, since balances result from arbitrary aggregation of survey question responses, it is implied that differences in difficulty between the various survey response categories are predetermined and not estimated. Secondly, a value attributed to a response category might evolve with time, a phenomenon which should be compensated for during estimation. Further, it is possible that responses might vary according to sample composition, even if proper weighting is applied.

The variation of response to a single question over time, as demonstrated by a given respondent in a tendency survey, has never been investigated to explain how it might be associated with a latent growth factor. Responses to such questions that prove to be related to a common time dependent latent force would clearly highlight meaningful items for future use in forecasting. Additionally, variation of a latent growth factor has never been tested as a predictor for variation in a macroeconomic time series and its potential lead properties. The main objectives of the study were therefore as follows:

1. To test the possibility of constructing a well-fitted latent growth curve model using a set of indicators from the manufacturing industry questionnaire, i.e., general economic situation, price changes or employment predictions.
2. To test the results as predictors for GDP growth, inflation or unemployment rate.

This paper, accordingly, reports two innovations. To the best of our knowledge, it describes the first attempt to establish whether in tendency surveys respondent answers to a question over a given period can be treated as a reflection of a particular factor. Secondly, the paper describes how this data can be used to predict the unexplained part of GDP growth, inflation rate changes and unemployment rate fluctuations using a latent factor growth model based on tendency survey data.

Following these objectives, the paper first covers the time series analysis of GDP growth, unemployment rate and inflation in Poland. Datasets used for forecasting the macro-indicators are then described, together with basic descriptive statistics for their associated questions. Subsequently, the fit of the latent growth curve model to responses from the manufacturing industry survey is computed. Using ARIMA models, the results are applied to shed light on the unexplained part of GDP growth, inflation and unemployment in Poland.

2. GDP growth, inflation and unemployment in Poland

The Central Statistical Office provides figures for GDP growth in Poland on a quarterly basis. Inflation and unemployment rates are announced monthly. However, with respect to unemployment a competing measure developed from the labor force survey methodology is also reported quarterly. Figure 1 presents the evolution of GDP growth, unemployment rate (measured using the labor force survey methodology) and inflation for the period 1996-2014 in Poland.

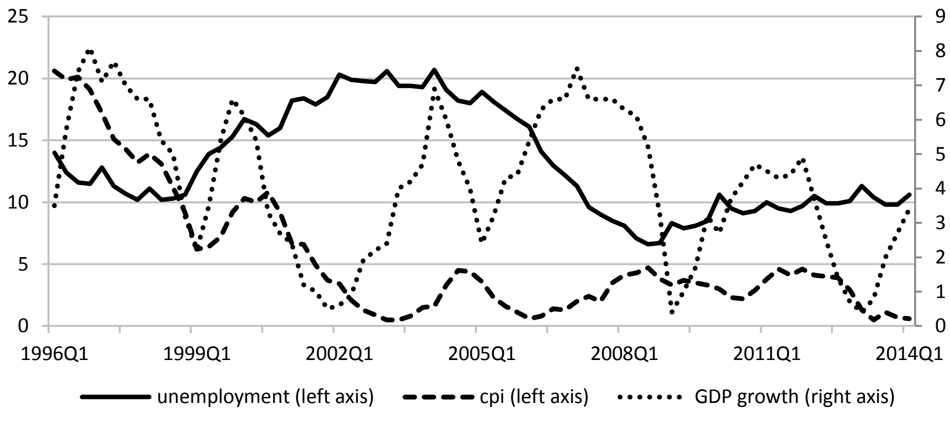

Figure 1. GDP growth, inflation and unemployment in Poland.

Source: own computation based on Central Statistical Office's data.

With respect to GDP, considerable fluctuations occurred in the growth during the period 1996-2014. Until 1998, the growth was observed much above the potential level, which is commonly assumed to be 4% *per annum*.

The sudden decline was associated with the ‘Asian and Russian crises’ occurring in 1997 and 1998, respectively. By the end of 1999, the growth rate had returned to high levels but the Polish economy was hit in early 2000 by considerable budgetary problems, and growth abruptly declined. For the entire 2001-2002 period, the Polish economy suffered and the growth rate was below the potential. After 2004, the situation improved, with only a mild downturn at the turn of 2005. The Polish economy, after flourishing in the 2005-2008 period, was hit by the financial crisis at the end of 2008. Growth rates started to improve again in 2010 and 2011. However, another slowdown has been observed since 2013.

With respect to inflation, considerable transition has been observed since the beginning of the 1990s. At the beginning of the transition period, inflation was very high, followed by a period of disinflation, characteristic for the transforming economies (Henry & Shields, 2004). Disinflation in Poland continued until 1999. At the turn of the millennium, there was a brief upswing in the rate, but the subsequent economic crisis led to further reduction in the rate of consumer price growth. Initial economic improvement from 2004 stimulated inflation but restrictive monetary policy over that period again forced inflation down in 2006. The following two years 2007-2008 were associated with economic growth rates of 7%, which inevitably led to a rise in inflation (as the growth rate was around 3 pp. above the potential level of growth). Higher inflation rates dropped along with the onset of the financial crisis at the end of 2008. In 2009-2013, inflation rates fluctuated around the National Bank of Poland 2.5% target but only after an initial slide into the deflationary zone.

As regards unemployment, reduced cyclical activity has been observed during the past two decades. Unemployment rate, after dropping to ca. 10% following the first transition shock, started to rise after the outburst of the ‘Asian and Russian crises’. By the end of 1999, the growth rate had again risen to high levels but unemployment was affected by hysteresis and remained at around 20%. Only after growth rates started to exceed 4-5% did unemployment start to decline; in the period 2006-2008 dropping to ca. 8%. With the onset of the financial crisis, unemployment rates started to rise but, despite the severity of the crisis, total increase in the period 2009-2014 was just ca. 2 pp.

Fluctuations in GDP growth, inflation and unemployment in the past two decades provide a promising basis for forecasting using survey data owing to its considerable observed variability. However, the significant contribution of intrinsic autoregressive processes observed in quarterly macroeconomic aggregates requires analysis before results from a latent factor growth model can be used to forecast dynamics. This is first justified, as according to Clements & Hendry (1998, p. 14), 'survey information can be a useful adjunct within formal models (...) rather than as a substitute for econometric systems'. So, the starting point is investigation of the time series properties using integrated autoregressive moving-average models (ARIMA). A second justification ties with wording of the survey questions used to predict macro-indicator changes. Their wording directly refers to a 'change' and not 'a state', so it seems most appropriate to apply the information they generate to analysis of differenced macro-indicators and not reference series directly.

The approach used in this study follows the standard Box-Jenkins approach to modelling stochastic processes (Greene, 2003). It can be summarized in the following steps (Greene, 2003, p. 620):

(1) transformation of data to obtain stationary time series;
(2) estimation of an ARIMA model;
(3) verification of the residual properties;
(4) application of the model to forecasting.

Investigation of time-series properties is based on autoregressive specifications. In the scope of the analysis, the general-to-specific approach is applied. As Welfe (2003, p. 210) indicates, this approach guarantees a proper structure for the model. In this paper, the final structure of the autoregressive model is derived in two steps. First, using the Augmented Dickey-Fuller test (ADF), the series of GDP growth, inflation and unemployment are tested for a unit root. Then, the best model is selected with application of the BIC to each series[1].

The ADF test is designed to establish whether the hypothesis of the unit root can be rejected; testing for H0 – there is a unit root, versus H1 – there is an autocorrelation coefficient lower than one. This led to the conclusion that H0 could not be rejected at a 5% significance level for any of the series investigated (for results see Appendix 2)[2]. The same procedure was applied to the differenced time series. However, the H0 hypothesis was rejected in all cases, which indicated that GDP growth, unemployment and inflation could be treated as I(1) processes. Then, a set of competing models with ARIMA

[1] A similar model selection pattern is applied by Ang *et al*. (2007).
[2] Due to the disinflation still continuing in the late 1990s (Białowolski *et al*., 2011) in the inflation series, and the ADF test was performed with inclusion of possible trend.

specification was estimated[3]. The selected models were of the form (Table 1)[4]:

Table 1. Final ARIMA model specifications for the GDP growth, inflation and unemployment rate.

GDP growth	$\Delta GDP_t = \underset{(0.091)}{.410} \Delta GDP_{t-1} + \varepsilon_t$
Inflation	$\Delta INF_t = \underset{(0.139)}{-.265} + \underset{(0.155)}{.661} \Delta INF_{t-1} + \mu_t$ $\mu_t = \varepsilon_t \underset{(0.180)}{-.128} \varepsilon_{t-1} \underset{(0.125)}{-.429} \varepsilon_{t-4}$
Unemployment	$\Delta UNE_t = \underset{(0.074)}{.771} \Delta UNE_{t-4} + \mu_t$ $\mu_t = \varepsilon_t \underset{(0.128)}{+.348} \varepsilon_{t-1}$

Source: own calculations in Stata.

Although most variability of the time series of interest can be accounted for by autoregressive processes without inclusion of additional variables, fitted models appeared to be poor predictors for turning points, thus offering potential for augmentation with other variables. As Mueller states (1963, p. 902): 'expectations are not merely a projection of recent trends but are influenced by current perceptions and news received', which implies that there is a room for expectation about the economy to enhance the forecasting power of models. The following parts of the article will describe testing of whether there would have been sufficient additional information in the data from the manufacturing sector to improve forecasts by inclusion of valid latent growth factor means from selected questions.

3. Proxies for basic macro-indicators in tendency surveys

The standardized questionnaire for tendency surveys in manufacturing recommended by the European Commission (2006) comprises questions to assess the general economic situation, price and employment forecasts. In questions referring to prices and employment, firms are requested to provide an assessment of their own situation, while in the general economic situation

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[3] Models are estimated by application of the general-to-specific approach – starting from a specification with one- and four-quarter lags in the auto-regression (see Appendix 2). Only models with zero constant terms are specified and estimated – as a direct consequence of the Augmented Dickey-Fuller test for the time series of GDP dynamics.

[4] In all models ΔX_t represents change in the series 'X' between quarter *t* and *t* - 1.

predictions, a macro-assessment is made. Nevertheless, in all cases, information about the economy can be aggregated from individual data. Responses are all scored on a 3-point Likert-type scale (Appendix 1). The forecast horizon for questions is limited to 3-4 months, which suggests rather short-term usefulness of the data.

The survey is conducted monthly by the Research Institute for Economic Development, Warsaw School of Economics. The data from this study have already been used in research articles (Adamowicz, 2013; Białowolski *et al*., 2007; Drozdowicz-Bieć, 2012). However, for the purposes of the analysis, only information from the first month of each quarter was used. The time span of the analysis covered 64 quarters, from the 2nd quarter 1997 to the 1st quarter 2013. The average number of responses was 538 with a maximum of 1,043 in the 2nd quarter 1997 and a minimum of 333 in the 3rd quarter 2007. The average response rate was approximately 30%. In the manufacturing tendency survey, results are also presented as balances. And since a three point scale is used for all questions, the balances are calculated in line with the formula $BAL = f_1 - f_3$, where f_i represents the fraction of respondents who selected *i*-th option (see Appendix 1).

3.1. GDP growth proxies

The balance of the general economic situation forecasts that might serve as a proxy for GDP growth are shown in Figure 2. They are plotted against the actual GDP growth.

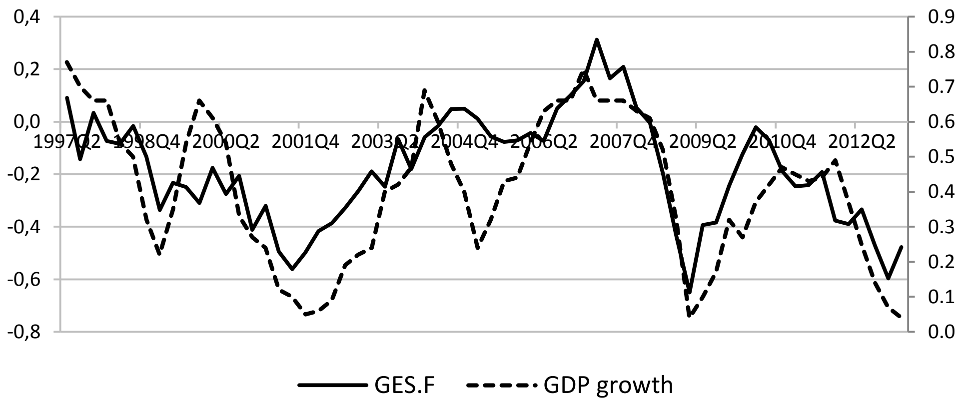

Figure 2. The balance of general economic situation forecasts.

Source: own computation.

There is a clear, parallel tendency between the series. The correlation was highly significant, while the GDP growth and the general economic situation forecasts were correlated with a level of 0.782.

3.2. Inflation and unemployment proxies

Unemployment and inflation proxies from the manufacturing firm tendency survey were also plotted as balances against their reference macroeconomic indicators (Figure 3).

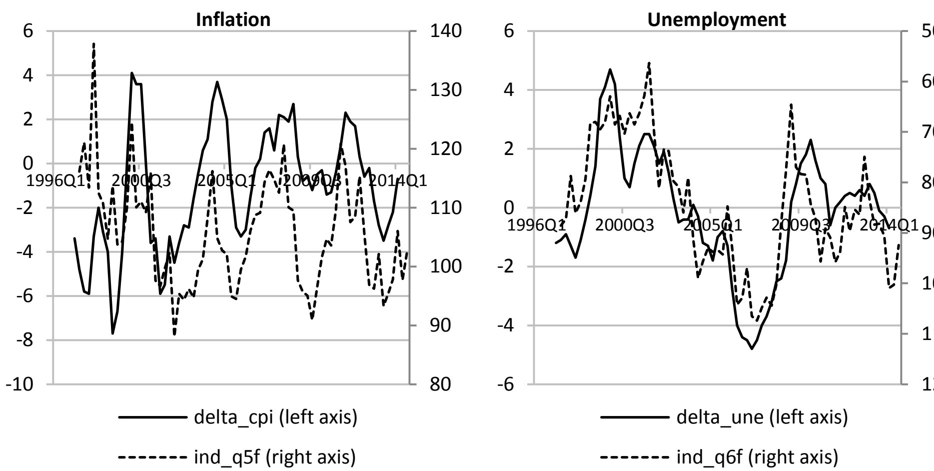

Figure 3. The balances of price change forecasts (vs. inflation change) and employment expectations (vs. unemployment rate change).

Source: own computation.

There is clear parallelism between the tendency survey series and their respective macro-indicators. Although, the correlation coefficient between the consumer price index and price forecasts is only 0.25, company price expectations correlate high with changes in the level of inflation (0.56). Company employment forecasts also correlate better with changes in the unemployment rate. Correlation between the series is 0.791 and is highly significant.

4. The latent factor growth model as a verification tool for forecasting indicators

Latent factor growth models are often used in psychology to research the sequence of the development of certain psychological characteristics. The approach has never, however, been applied to either business or consumer tendency survey data. Due to their specification, as in the approach based on balances, results allow tracking of changes in perception of the economy (in its specific domains) by firms participating in a survey. Due to the fact that estimation is based on the responses made by each respondent over time, it is possible to compensate for variation resulting from changes in sample structure. The tool allows validity testing for a concept, which in this case was the pattern of response to a certain question over time. The latent factor growth model would generate invalid model fit estimates if a group of firms developed either an upward or downward bias with respect to the estimated growth path.

Latent factor growth models are also a means to address the measurement problem for invariance in longitudinal studies, which has been rarely addressed (Brown, 2006) and to the best of our knowledge, never, in tendency surveys data research. Absence of such an approach might lead to potential problems comparing results, unchecked for equivalence. Chan (1988) indicates three possible types of change that might occur in repeated measurement: *alpha*, *beta* and *gamma*. The *alpha* change, which is the only one that allows inter-temporal comparability, takes place when the concept remains stable but its assessment changes. The *beta* and *gamma* change preclude comparability of the values as either measurement scales of items change (*beta*) or even the whole factor structure changes (*gamma*). In order to ensure that only the *alpha* change was present in this tendency survey dataset, latent factor growth models were applied and their fit tested.

4.1. Specification of latent factor growth models

In a latent factor growth model, responses to each specific question are assumed to be driven by two latent factors. One factor corresponds to the random intercept which indicates that for each respondent there is a randomly distributed starting point for assessment from a given question. Future responses by each respondent are additionally driven by a latent factor associated with changes in an economy. In order to obtain a good fit for the model, each respondent must assess economic conditions within the framework of the survey questions according to the prevailing economic situation, state of inflation or unemployment (freely estimated period specific factor loading ensures this). Consequently, response to a specific question over a given period is modeled as a linear function of their sentiment at the individual level in the area addressed by the question. The maximum likelihood model is simultaneously estimated from information sampled at all survey times.

In the approach taken – the latent factor growth model – responses to a single indicator in the domain of a firms' forecasts are assumed to be driven by a latent phenomenon over time. With latent factor growth models based on a single indicator there is only one specification possible. The estimated structure of the model following a single question over *T* time measurement periods can be represented by the following scheme[5].

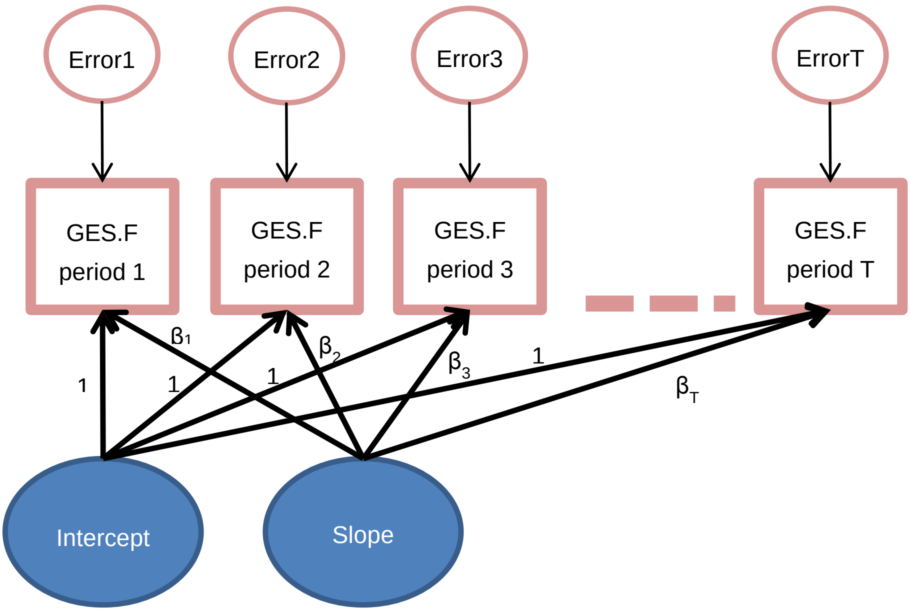

Figure 4. Latent factor growth model with single indicator.

Source: own compilation.

The model can be formally described with the following equation:

$$IND.GES.F_{i,t} = Intercept_t + \beta_t Slope_i + \varepsilon_{i,t}, \tag{1}$$

where $IND.GES.F_{i,t}$ represents the respondent's response to the question regarding the general economic situation, $Intercept_i$ is a realization of the latent variable *Intercept* for the *i*-th respondent, $Slope_i$ is the realization of

[5] Subsequently, we present a specification for a latent factor growth model of general economic sentiment, which serves as the proxy of GDP growth. The same logic applies to price and employment predictions.

the latent variable $Slope$ for the i-th respondent, β_t are period specific parameters, which are associated with the time evolution of the forecast concept and finally $\varepsilon_{i,t}$ is the measurement error for respondent i in period t. To ensure identification of the model and to establish metrics for the latent variable $Slope$, two coefficients from the set of $\{\beta_t\}_{t=1,..,T}$ need to be fixed[6]. Additionally, $E(\boldsymbol{\varepsilon}^t) = \mathbf{0}$ and $\mathrm{cov}(Intercept, Slope)$ are freely estimated to ensure that response to changes in the economic environment can be associated with the initial state[7]. Since, in the manufacturing industry tendency survey, responses to all questions are made on a three point scale, estimation procedures were employed for a categorical (non-continuous) variable. Thus, thresholds for switching between categories are estimated, the implication being that, for the i-th respondent, scoring on latent variables $Intercept_i^*$ and $Slope_i^*$, their answers are determined by:

$$\begin{gathered} \forall_{t\in 1,\ldots,T} IND.GES.F_{i,t}{}^* = m, \\ \text{if} \\ v_{m-1}^t < Intercept_t{}^* + \beta_t Slope_i{}^* + \varepsilon_{i,t}{}^* < v_m^t. \end{gathered} \tag{2}$$

In equation (2), m represents the m + 1-th answer category for the categorical indicator variable *IND.GES.F*, which can have values ranging from 0 to 2 and v_m^t represents the m-th estimate threshold for the variable *IND.GES.F*[8].

The goodness-of-fit is the most common approach to proof of validity for a latent factor's role in period-to-period changes in mean response to a specific question. Of the most frequently used fit estimates - the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) and Standardised Root Mean Square Residuals (SMRM) – figures in this study were drawn solely from RMSEA. For latent factor growth curve models, especially since the process evolves over time, incremental model fit indices like CFI and TLI could be not justified as they are based on null models, in which it is assumed that the average value of responses is the same for all periods. A rule has been developed for each of these descriptive fit statistics based on simulation

[6] Most often $\beta_1 = 0$ and $\beta_2 = 1$.
[7] This being true at the micro level.
[8] It should be stated that two thresholds are predefined: $v_{p,0}^t = -\infty$ and $v_{p,M_v+1}^t = +\infty$.

results (Chou & Bentler, 1995; Kaplan, 2009). According to the rule for RMSEA, acceptable values should be below 0.08 (Browne & Cudeck, 1993)[9]. An adequate fit must be obtained from the latent growth curve model for answers to a specific question to meet the criterion for validity.

4.2 Model estimation

In the Manufacturing Sector Tendency Survey, three latent factor growth models were estimated for assessment of economic performance in areas of interest. They corresponded to the questions selected for analysis, *IND.GES.F*, *IND.PRA.F* and *IND.EMPL.F*, to which responses were treated as endogenous. Estimation on the full sample was possible (from the 2nd quarter 1997 to 1st quarter 2013) in all cases, owing to the panel nature of the study. All models proved to be well fitted with respect to RMSEA (see Table 2).

Table 2. RMSEA goodness-of-fit statistic for estimated models.

Manufacturing survey	RMSEA
Model for general economic situation expectations (*IND.GES.F*)	0.013
Model for price forecasts (*IND.PRA.F*)	0.012
Model for employment forecasts (*IND.EMPL.F*)	0.014

Source: own calculations in Mplus.

Of the models estimated based on the manufacturing industry data, the best fit was observed for the model predicting price change. Nevertheless, differences were small. Comparison of slopes between the latent factor growth model and simple balances can shed light on validity of the latter commonly used estimates in forecasting. Comparisons for questions related to the GDP growth, inflation forecasts and unemployment expectations are shown in Figure 5.

As can be easily observed, results using both approaches (balances and latent factor growth model) are similar but differences are visible in the data from manufacturers. Correlation between slopes and balances for *IND.GES.F* is almost perfect – 0.987, but correlation, although significant, is lower between balances and slopes for price expectations (*IND.PRA.F*) and employment (*IND.EMPL.F*). The coefficient for price expectations was estimated at 0.717 but for employment forecasts only 0.245, which stimulated

[9] For further discussion on model fit see Steenkamp & Baumgartner (1998), Hu & Bentler (1999), Marsh *et al*. (2004) and Davidov (2008).

inclusion of both slopes and balances in the following forecasting exercise to assess their predictive validity.

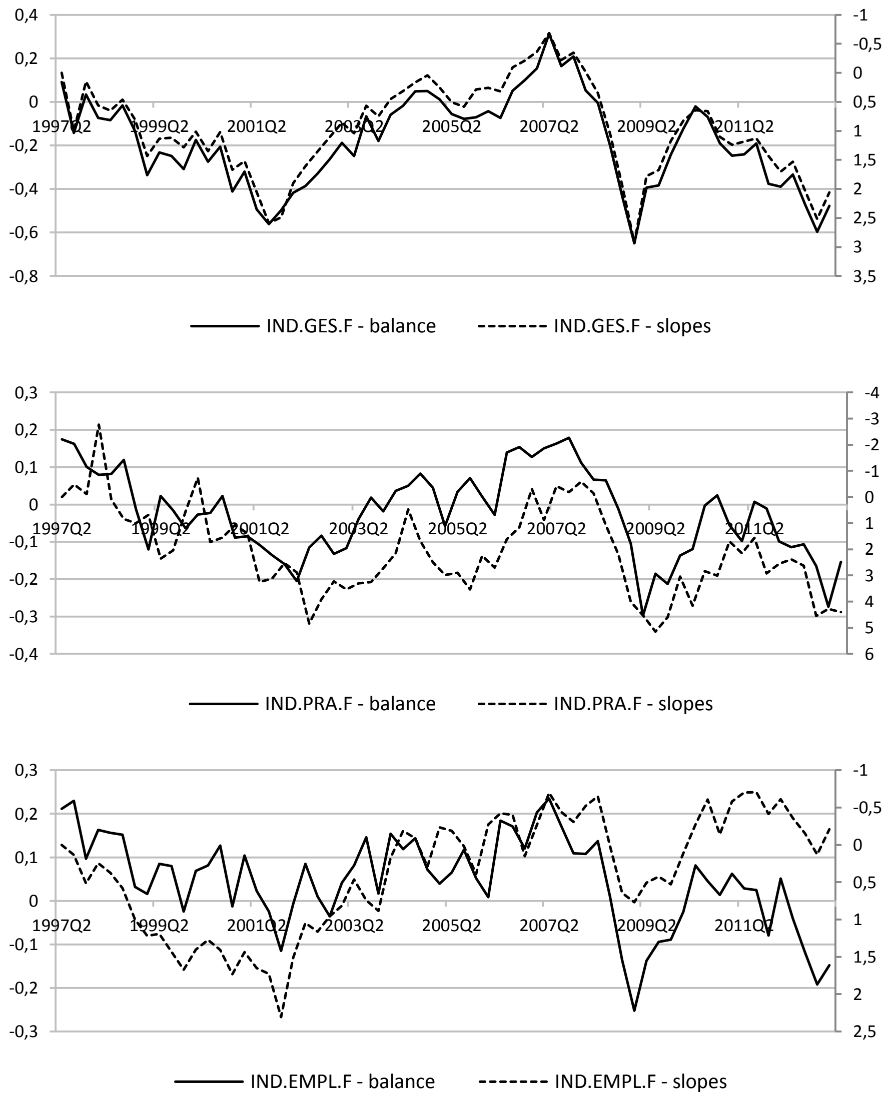

Figure 5. Balances and slopes from the latent factor growth model for questions addressing general economic situation forecasts, inflation expectations and unemployment forecasts.

Source: own computation.

5. Forecasting GDP, inflation and unemployment

Validity of the latent concept underlying the data is an important prerequisite but the key issue in the forecasting of the reference series is applicability of results from the latent factor growth model. The first test, in such a situation, is on the lead properties with respect to the reference series. In order to test its lead properties, it was challenged using Polish yearly growth rates for GDP, inflation change and unemployment evolution.

The estimated cross correlations indicate significant correlation between slopes and the reference series. With respect to GDP growth, the best correlation between estimated slopes and the reference series was observed with a one-quarter lead, i.e., estimated slopes from the latent factor growth model, correlated best, at 0.801, with the values for GDP growth reported by the Central Statistical Office in the following quarter. However, differences between the correlations for the coincident and those observed for one-quarter leading values were very small. Owing to this, a decisive character (lead or lag) for the slopes could not be identified. Lower, but still significant correlations were obtained between slopes from the latent factor growth model for IND.PRA.F and inflation. The highest correlation of 0.645 was for a two-quarter lead. Investigation of the relationship between employment forecasts (IND.EMPL.F) from the latent factor growth model and the actual unemployment rate showed a very strong correlation, 0.746, but for the indicator leading by four quarters.

Table 3. Cross-correlation of the slopes for latent factor growth - GDP growth, inflation change and unemployment change.

Lead(-)/lag(+)	+4	+3	+2	+1	0	-1	-2	-3	-4
IND.GES.F – GDP growth	0.158	0.342	0.526	0.684	0.791	0.801	0.735	0.606	0.487
IND.PRA.F – inflation	0.357	0.363	0.407	0.473	0.558	0.616	0.645	0.618	0.558
IND.EMPL.F – unemployment	0.187	0.291	0.352	0.417	0.510	0.613	0.661	0.695	0.746

Source: own calculations.

The final step of the analysis was to introduce slopes to the time series model and to test its lead-lag properties. Before this could be done, the slopes also required testing for stationarity. The Dickey-Fuller test confirmed that all time-series obtained from the analysis with latent factor growth models could be treated as integrated I(1). Additionally, two out of three series obtained with the balance method were I(1). Only employment forecasts obtained using the standard balance method were I(0). Autoregressive models were subsequently applied to the series, which were transformed or not, depending results from the ADF test.

Results, using the additional explanatory variables from the equations presented in Table 1, for general economic situation forecasts, inflation forecasts or employment forecasts, when different leads or lags of slope estimates were obtained from the latent factor growth model, are presented in Table 4.

Table 4. Bayesian Information Criterion Values for different lead(-)/lag(+) of the additional explanatory variable in predicting GDP growth, inflation and unemployment.

	IND.GES.F		*IND.PRA.F*		*IND.EMPL.F*			
Lag(+) / lead (-)	slopes (I(1))	balances (I(1))	slopes (I(1) AR(4))	balances (I(1) AR(4))	slopes (I(1) AR(4))	slopes (I(0) AR(1))	balances (I(1) AR(4))	balances (I(0) AR(1))
+2	183.54	183.61	173.86	173.98	138.46	141.91	143.49	142.13
+1	181.81	181.49	173.58	171.83	140.58	143.58	143.58	140.42
0	**176.63**	178.37	170.93	171.26	140.51	142.13	142.38	139.73
-1	180.26	180.79	171.10	170.85	136.91	**135.68**	135.72	138.15
-2	180.31	180.55	167.77	170.46	138.80	138.85	142.50	140.01
Benchmark	178.13	178.13	**166.50**	**166.50**	136.07	136.07	136.07	136.07

Source: own calculations.

Results indicate that ARIMAX models oriented towards predicting macro-variables performed better with respect to BIC in specifications using slopes than their counterparts using balances. However, only in two cases – predictions of the GDP growth and the unemployment rate – did inclusion of information from business tendency surveys result in model improvement, while in the case of inflation the best model proved to be the benchmark without information from tendency surveys. In this case, information from the business tendency survey in the manufacturing industry did not offer any benefit in terms of BIC, not improving the model fit, either with inclusion of estimated slopes or traditional calculated balances. Additionally, although from the analysis of cross-correlations it seemed that a substantial lead might be obtained from models based on tendency survey data, final analysis disproved the case for GDP growth forecasts and provided only marginal proof in the case of unemployment forecasts – a one-quarter lead.

The formula for GDP growth predictions from the superior specification can be described by as follows :

$$\Delta GDP_t = \underset{(0.121)}{0.292}\Delta GDP_{t-1} - \underset{(0.284)}{0.594}\Delta ges\_slopes_t + \varepsilon_t, \tag{3}$$

where ΔGDP_t represents a change in the annual growth rate of GDP between periods t and t - 1, and Δges_slopes_t, a change in the estimate of the slope between periods t and t - 1 for the question about the general economic situation. In the final specification better general economic situation forecasts stimulate the GDP growth, which is confirmed by the coefficient for Δges_slopes_t significant at the 0.05 level.

With respect to the forecasts of unemployment the final model was:

$$\begin{gathered} \Delta UNE_t = \underset{(0.074)}{0.771}\Delta UNE_{t-4} + \underset{(0.264)}{0.929} surp_{t-1} + \mu_t, \\ \mu_t = \varepsilon_t + \underset{(0.128)}{0.348}\varepsilon_{t-1}, \\ surp_t = \Delta une\_slopes_t - 0.445\Delta une\_slopes_{t-4}. \end{gathered} \tag{4}$$

where ΔUNE_t represents a change in the unemployment rate between period t and t - 1, Δune_slopes_t represents a change in the estimate of the slope between period t and t - 1 for the question about employment forecasts and $surp_t$ is the deviation between the actual employment and forecasts generated from the autoregressive model. The results of fitted values are shown in Figure 6.

6. Conclusions

This paper presents a new approach to forecasting GDP, inflation and unemployment. In place of the conventionally used, standard balances, estimates of slopes from latent factor growth models were used to observe changes in the economy, expectations for inflation and unemployment forecasts. Estimates generated from the survey of the manufacturing industry proved very close to actual balances in terms of the growth of GDP but differed from inflation expectations or employment predictions.

Using latent factor growth models it was possible to show that responses relating to questions about the general economic situation, intertemporal price changes and employment forecasts were sufficiently consistent to be used for reliable assessment of manufacturing sector economic forecasts. This implies that changes associated with sample composition did not significantly influence results. Additionally and probably most importantly, inclusion of slope estimates in the ARIMAX model for both the economic growth and the unemployment rate improved the overall fit of the model.

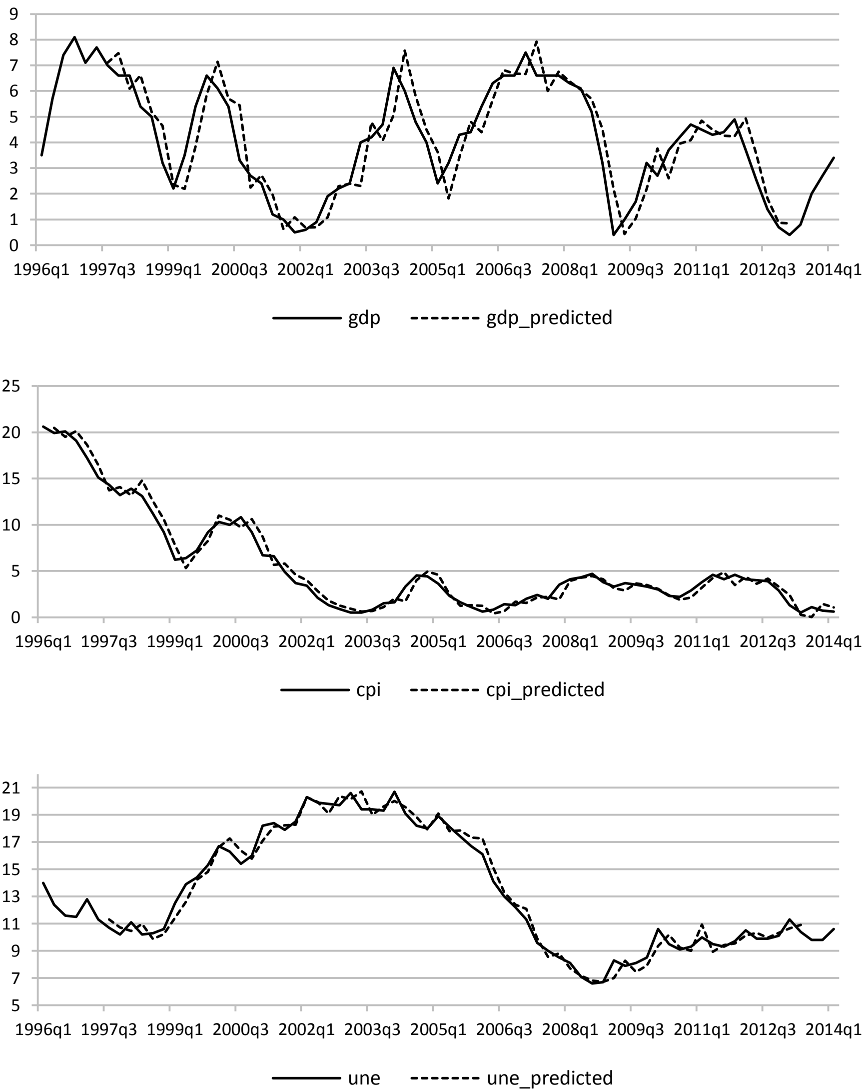

Figure 6. Actual and fitted values for the changes in the GDP growth, inflation (cpi) and the unemployment rate (une) in Poland in the ARIMAX model.

Note: gdp_predicted, cpi_predicted and une_predicted represent final values predicted from the best performing model selected based on the BIC.
Source: own computation using Stata.

Nevertheless, to the best of the author's knowledge, this article describes the first application of latent factor growth models to the forecasting of basic macroeconomic indicators. Hence, it should provide a starting point for further discussion and investigation of its potential applications and the refinement of the methodology. Household and business tendency survey data clearly offer much to explanation of fluctuations in economic processes, but further research is required to validate true indicators for forecasts. The critical test for survey applications always follows when out-of-sample prediction offers the clearest evidence.

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Appendix 1. Selected questions used in the analyses for response categories in the standardized business tendency survey questionnaire

Question number and code	Question wording	Answer categories (representing also scale points)
Q5_F (IND.PRICES.F)	Your selling prices in the forthcoming 3-4 months...	+ will increase = won't change - will decrease
Q6_F (IND.EMPL.F)	Your firm's total employment in the forthcoming 3-4 months...	+ will increase = won't change - will decrease
Q8_F (IND.GES.F)	The general economic situation (irrespectively of the situation of your branch and company) in the forthcoming 3-4 months...	+ will improve = won't change - will deteriorate

Source: *Survey in the manufacturing industry*, Research Institute for Economic Development, Warsaw School of Economics.

Appendix 2. Dickey-Fuller test for a unit root in GDP growth, inflation and unemployment time series

	Test statistic	Critical values			MacKinnon approximate p-value
		1%	5%	10%	
GDP	-2.064	-3.549	-2.912	-2.591	0.2590
ΔGDP	-5.715	-3.551	-2.913	-2.592	0.0000
Inflation + trend	-2.456	-4.102	-3.478	-3.167	0.3506
ΔInflation	-5.036	-3.551	-2.913	-2.592	0.0000
ΔInflation+trend	-5.219	-4.104	-3.479	-3.167	0.0001
Unemployment	-0.860	-3.549	-2.912	-2.591	0.8010
ΔUnemployment	-7.068	-3.551	-2.913	-2.592	0.0000

Source: own calculations.

Appendix 3. Information criteria for models with different lags for AR and MA in the ARIMA model for GDP growth, inflation and unemployment

Table A3.1. Autoregressive model for GDP growth – selection of the best specification according to the BIC.

AR	GDP
1 4	203.5592
1	203.5001
2	215.0236
3	215.4025
4	211.5821
Null	211.6485

Table A3.2 Autoregressive and moving average model for inflation – selection of the best specification according to the BIC.

		MA					
		1,4	1	2	3	4	---
AR	1,4	194.8897	196.8421	196.5849	196.1088	192.175	192.7649
	1	191.8938	199.7824	199.4946	199.1702	187.9038	195.5069
	2	194.829	199.4373	---	213.6393	203.8426	209.4458
	3	196.8083	200.5958	208.408	216.8415	208.3622	212.5704
	4	197.5986	194.1779	203.8969	209.4472	211.8558	208.0108
	---	194.0754	197.2165	204.3562	212.5661	207.6119	208.4515