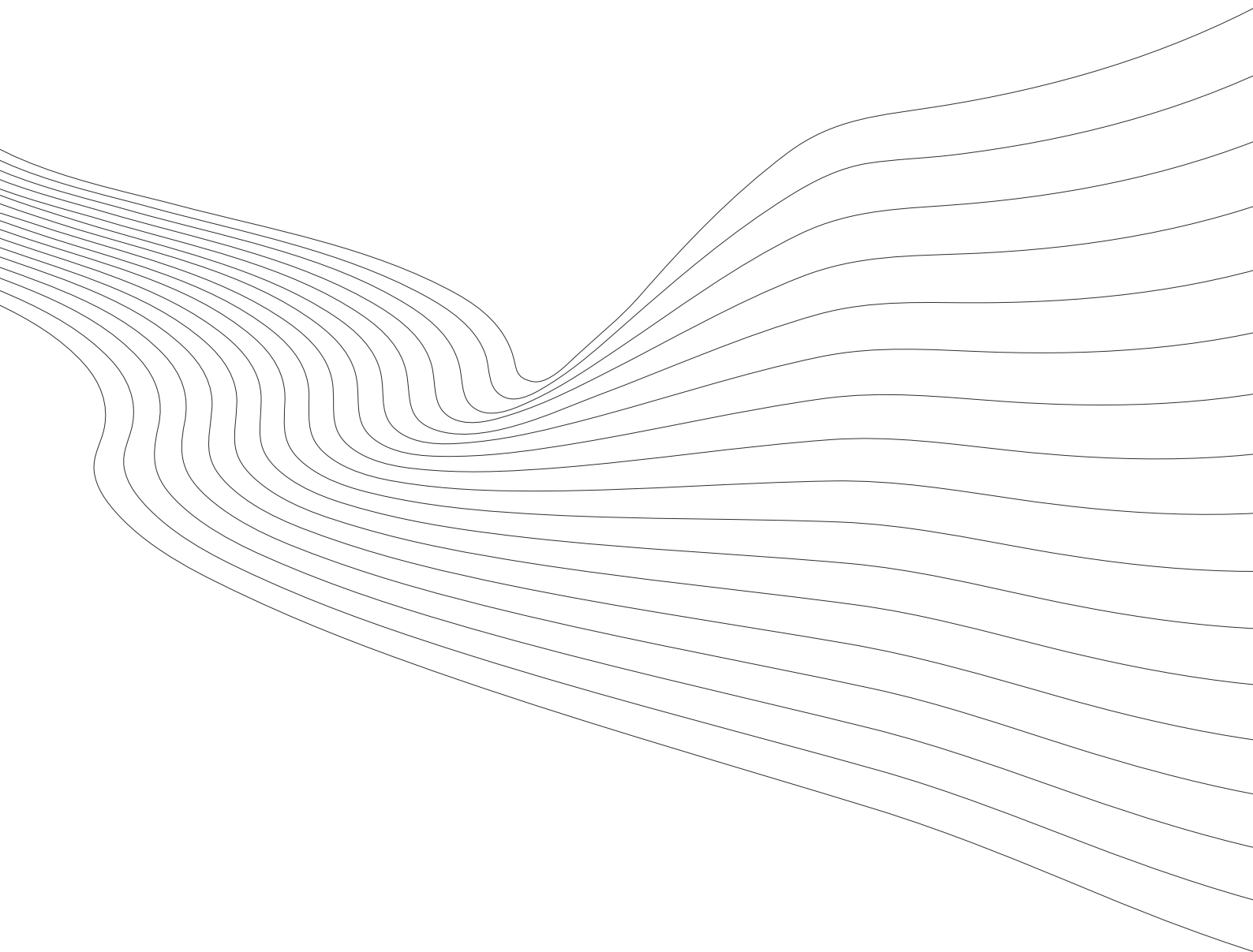# KOF

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Assessing Forecasting Performance of Business Tendency Surveys
during the Great Recession: Evidence for Russia

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Abstract

This study investigates usefulness of business tendency surveys in industrial sector for out-of-sample prediction of growth of industrial production in Russia. A special attention is paid to performance of survey-augmented models during the recent Great Recession 2008/2009. Using the real-time data vintages of the index of industrial production in Russia we conclude that the use of surveys positively contributes to boosting forecast accuracy of industrial production compared with forecasts based on a benchmark univariate autoregressive model.

Keywords: The Great Recession, business tendency surveys, forecasting, model selection, Autometrics, Russia

JEL code: C53, E37.

1 Introduction

There is an increasing demand for accurate forecasting of industrial production in Russia, as the Russian economy enters a post-transition phase characterised by increasingly pronounced business cycle fluctuations. Traditionally dating of business cycle phases is based on GDP data. However, due to publication lags and subsequent revisions an accurate determination of turning points is only possible with substantial time delays. Hence, in the short run much more attention is paid to indicators available with shorter publication lags and at higher frequency, e.g. industrial production. In Russia this indicator is available at monthly frequency and is released in the following after the reference month. Furthermore, industrial output reacts very quickly to changes in economic conditions, and much earlier than those changes will be reflected in published GDP data. These two features explain why industrial production is widely used as a concident indicator of economic activity and allows timely monitoring of the course of the economy.

In our paper we investigate whether it is possible to use business tendency surveys, that are available even earlier than industrial figures, in order to make accurate forecasts of growth of industrial output in Russia. There are a number of various forecasts of industrial output in Russia produced by state agencies (e.g. Ministry of Economic Development) as well as by private companies and other think tanks. However, the way these forecasts are computed is not always transparent and publicly available. Our approach, however, is based on a sound econometric foundation that is transparent and therefore can be easily replicated. We were somewhat surprised by the fact that forecasting of industrial output so far received a rather negligent attention in the Russian scientific literature. Searching publications for the last 10 years we found only one study (Frenkel et al., 2002) where this important issue is addressed.

Our paper contributes to the forecasting literature in the following ways. First, as mentioned above, we determine predictive content of business tendency surveys for forecasting industrial output in Russia. To this end we use a formal statistical model selection procedure *Autometrics* (Doornik, 2009a). This model selection procedure is a further development of what became widely known as a general-to-specific approach of the London School of Economics (LSE). The advantages of using this automatic model selection procedure are documented in Castle et al. (2011, for example). It allows us to be agnostic about data, and let the data speak for itself.

Secondly, a special attention is devoted to forecasting industrial output during the recent Great Depression 2008/2009, when the world economy was hit by a very strong adverse shock. We find that this shock was well reflected in enterprise surveys, resulting in largest gains in forecast accuracy around turning points when compared to a simple autoregressive benchmark model; i.e. exactly where we expect it to happen. It is also important to emphasise that we use real-time vintages of

industrial production. This allows us to closely simulate information set available to forecasters in the past.

The rest of the paper is structured as follows. Section 2 describes the data, followed by section on econometric methodology. In Section 4 results of our out-of-sample exercise are presented. The final section concludes.

2   Data

The data on index of industrial production (IIP) were taken from official publications of the Russian Federal State Statistics Service (www.gks.ru). The data are usually released with the publication lag of two weeks in the middle of next month. The dependent variable of our interest is the monthly year-on-year growth rate of industrial output in Russia. In order to simulate historical flow of information as it was publically available in the past, we employ real-time data vintages of IIP.

Business tendency surveys in industry are provided by the Business Surveys Department at the Gaidar Institute for Economic Policy (IEP). The Business Surveys Department at the IEP regularly sends out questionnaires to managers of about 1100 enterprises, representing all industries and regions in the Russian Federation. In 2011 the questionnaires were filled out by respondents from which 28% were directors, 36% — deputy directors, 24% — heads of economic departments, and remaining 12% were at lower managing positions. Much effort is devoted to maintaining regular and personalised contact with respondents. The return rate is about 65-70%. The following aspects of firms' economic performance are covered: demand, production, prices, employment (monthly frequency), capacity utilisation and factors hindering production (quarterly frequency), competition and market share (semi-annual frequency), investment, competitiveness, financial situation (annual frequency), and expansion plans to new markets and factors hindering entrance to new markets (bi-annual frequency).

These survey data are typically released in the end of current month (around 25th day of month). We don't have all the real-time vintages of survey indicators, but acknowledging the fact that surveys undergo at worst very minor revisions we can vary well replicate their actual availability in the past by truncating them in an appropriate manner.[1] Our choice of survey indicators is shown in Table 1. There are questions regarding actual and expected changes in production, prices, demand for produced goods, and stocks of finished goods. The main criteria for choosing these indicators was their availability at monthly frequency and sufficient length.[2]

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[1]These minor revisions occur due to the fact that respondents send their answers by conventional post. Counting those mails that arrive after initial publication results in slightly revised indicators. The magnitude of revisions is in the range of 1-1.5 percentage point of reported figures.

[2]A potential candidate is a question regarding employment, but because it is available at the monthly frequency

The original indicators are shown in Figure 1. All variables except `IEP_Q5_S`, denoting estimated demand for production goods, display a seasonal pattern of a varying degree. In order to remove seasonality in those variables we transform them using the 12-th order difference. The variable `IEP_Q5_S` is retained in its original form. Transformed variables are shown in Figure 2 and display no seasonality.

3 Econometric approach

Since we are interested in determined whether survey data have had any predictive content regarding slowdown of industrial activity in Russia during the period of the Great Recession, we set the forecast evaluation sample from 2008(1) until 2011(7). For each month in this evaluation sample we compute one-, two-, three-, and four-step ahead forecasts using the following model specification:

$$y_{t+h-1}^v = \alpha + \sum_{i=1}^{p-(h-1)} \beta_i y_{t-i}^v + \gamma' \mathbf{X}_t + \epsilon_{t+h-1}, \tag{1}$$

where y_t^v denotes a vintage of the year-on-year growth rate in IIP that was available in the month forecast was made, and $\mathbf{X}_t = (x_{1t}, x_{2t}, ..., x_{nt})'$ is a $n \times 1$ vector of survey indicators.[3] Observe that the maximum autoregressive lag length is set to four, $p = 4$. The benchmark model is a univariate autoregressive model of the following form:

$$y_{t+h-1}^v = \alpha + \beta_i y_{t-1}^v + \epsilon_{t+h-1}, \tag{2}$$

resembling Equation (2) but without indicator variables. We compare forecast accuracy of the competing models with respect to the first release of year-on-year growth of industrial production. This is mainly because of revisions of initial estimates of IIP growth in Russia are rather rare and, naturally, first releases gain much more attention than revised data available with a substantial time delay.

Horizon-specific out-of-sample forecasts are obtained using a rolling window allowing for 36 months for parameter estimation. The horizon-specific models are respecified and its parameters are re-estimated each time a new observation is added to estimation sample. For example, a one-step ahead forecast of IIP growth in 2008(1) is computed in using information available in that month; i.e. an IIP vintage released in this month with the last observation for 2007(12) and surveys $\mathbf{X_t}$ with the last observation available for the current month. Correspondingly, models parameters are estimated using sample 2005(1)—2007(12). The next one-step ahead forecast is made for 2008(2),

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since 2009(1) we did not selected it in our study.

[3]We chose to present results based on a parsimonious model specification where no further lags of indicators were allowed. Allowing for more general lag structure did not result in any systematic improvement in forecast accuracy.

using an IIP vintage and survey variables released in this month. The relevant estimation sample is then from 2005(2) until 2008(1).

In a similar fashion two-step ahead forecasts are produced. For example, in order to produce a two-step forecast for 2008(1) we employ information available in 2007(12), allowing us to estimate model parameters using sample 2004(12)—2007(11), and use them in order to produce a forecast for 2008(1). The next two-step ahead forecast is made for 2008(2), using an IIP vintage and survey variables released in 2008(1). The relevant estimation sample is then from 2005(1) until 2007(12). We continue making two-step ahead forecasts until we reach the final month in our forecast evaluation sample, 2011(7). The described procedure straightforwardly extends to three- and four-step ahead forecasts.

Last but not least, since we selected eight survey indicators, inserting all of them at once may result in model overfitting and subsequent deterioration of forecast accuracy. In order to circumvent this problem we utilise the automatic model selection procedure *Autometrics*, that is an integral part of the econometric modelling software OxMetrics (Doornik, 2009b). *Autometrics* is the comprehensive model selection procedure based on general-to-specific approach, where various practical aspects of modelling economic variables is automated. In particular, automated model selection addresses such issues as testing for model mis-specification, testing for structural breaks and model encompassing (for more details, see Doornik, 2009a). By choosing this approach to model selection we remain agnostic about the choice of variables for forecasting and let the data speak for itself.

4   Results

Results of out-of-sample forecasting exercise are presented in Table 2. The ARDL model with selected regressors by the *Autometrics* produces uniformly lower values of the RMSFE for all forecast horizons. While at the one-month ahead forecast horizon the improvement over the benchmark model, given in (2), is rather small, for longer forecast horizons incorporating information from surveys results in much more substantial gain in forecast accuracy, up to 38% reduction in RMSFE. Results of Clark and West (2007) test of equal predictive accuracy between nested model indicate that gains in forecast accuracy are statistically significant at the usual singnificance levels.

Actual values of first releases of year-on-year growth of industrial production together with h-step ahead forecasts from Equations (1) and (2) are shown in Figures 3—6 for $h = 1, 2, 3, 4$, respectively. Consistent with results reported in Table 2, forecast gains from using surveys are easily noticeable at longer forecast horizons. The largest forecast gains are observed soon after turning points; i.e. when positive IIP growth changes to negative and back to positive growth. It

is also worthwhile mentioning that in the period preceding the crisis and in the post-crisis period both competing models produce generally similar forecast accuracy. We interpret this fact that surveys are mostly useful in times when the economy is hit by a large (in this case, adverse) shock affecting all industrial sectors at once.

An additional information on the usefulness of separate indicators for predicting IIP growth is contained in Table 3. In this table the frequency with which indicators are chosen is displayed. The absolute leaders are survey questions `IEP_Q5_S` and `D12IEP_Q11_S`, corresponding to assessment of current demand and expected changes in demand in the next 2-3 months. The former variable is more informative at the shorter horizons, whereas the latter—at the longer horizons. This is consistent with our expectations. The survey questions `D12IEP_Q1_S` and `D12IEP_Q6_S` are chosen not that often and hence their contribution is relatively small.

5 Conclusion

In this study we investigated the usefulness of business tendency surveys for predicting growth of industrial output in Russia. Our main finding is that the surveys positively contribute to boosting forecast accuracy compared to a benchmark autoregressive model. The largest gains occur at longer- rather than at shorter forecast horizons. We also find that a shock of considerable size is necessary to be reflected in surveys leading to a significant increase forecast accuracy. As a result, incorporation of information from surveys for out-of-sample forecasting mostly pays off around turning points, i.e. when the sign of growth changes. The period of the recent Great Recession is used in order to illustrate our findings.

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Table 1: Survey questions

Question regarding	Label	Transformation
Changes in production with respect to last month	IEP_Q1_S[a]	$(1 - L^{12})$
Changes in demand with respect to last month	IEP_Q3_S	$(1 - L^{12})$
Changes in prices with respect to last month	IEP_Q4_S	$(1 - L^{12})$
Current demand	IEP_Q5_S	none
Current stocks of finished goods	IEP_Q6_S	$(1 - L^{12})$
Expected changes in production in next 2-3 months	IEP_Q9_S	$(1 - L^{12})$
Expected changes in demand in next 2-3 months	IEP_Q11_S	$(1 - L^{12})$
Expected changes in prices in next 2-3 months	IEP_Q12_S	$(1 - L^{12})$

[a] The letter 'S' indicates that the balance (saldo) computed as difference between shares of positive and negative answers is used.

Table 2: Forecasting results: 2008(1)—2011(7)

	RMSFE			Clark and West (2007)
	AR	ARDL	Ratio	p-value
$h = 1$	4.239	3.998	0.94	[0.014]
$h = 2$	6.542	4.506	0.69	[0.033]
$h = 3$	8.322	5.151	0.62	[0.012]
$h = 4$	8.816	6.449	0.73	[0.007]

Table 3: Selection frequency of indicators

Indicator	$h = 1$	$h = 2$	$h = 3$	$h = 4$	Total
D12IEP_Q1_S	8	0	2	2	12
D12IEP_Q3_S	7	0	14	5	26
D12IEP_Q4_S	7	10	3	2	22
IEP_Q5_S	26	15	22	10	73
D12IEP_Q6_S	5	0	1	3	9
D12IEP_Q9_S	7	2	2	11	22
D12IEP_Q11_S	1	27	22	21	71
D12IEP_Q12_S	5	12	3	13	33

Table entries denote number of months in the estimation sample 2008(1)—2011(7) when a corresponding indicator was retained in the forecasting model, see Equation (1).
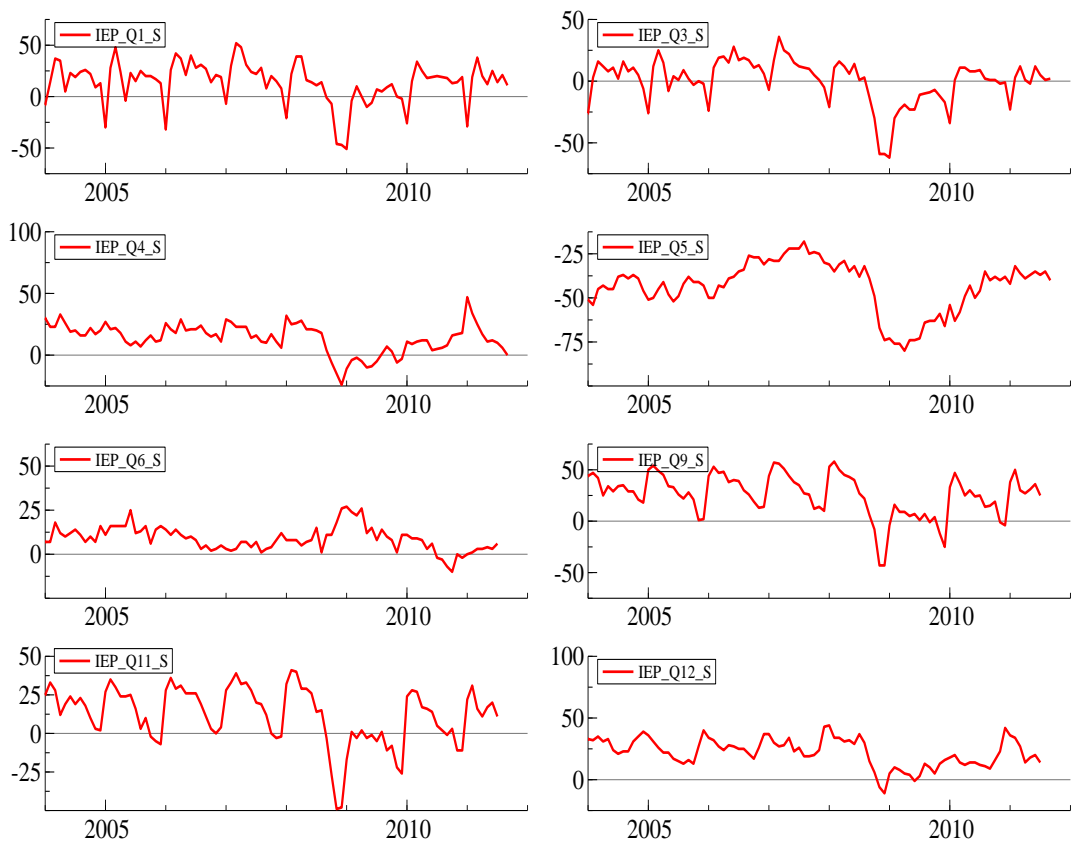
Figure 1: Original survey questions, see Table 1 for description.
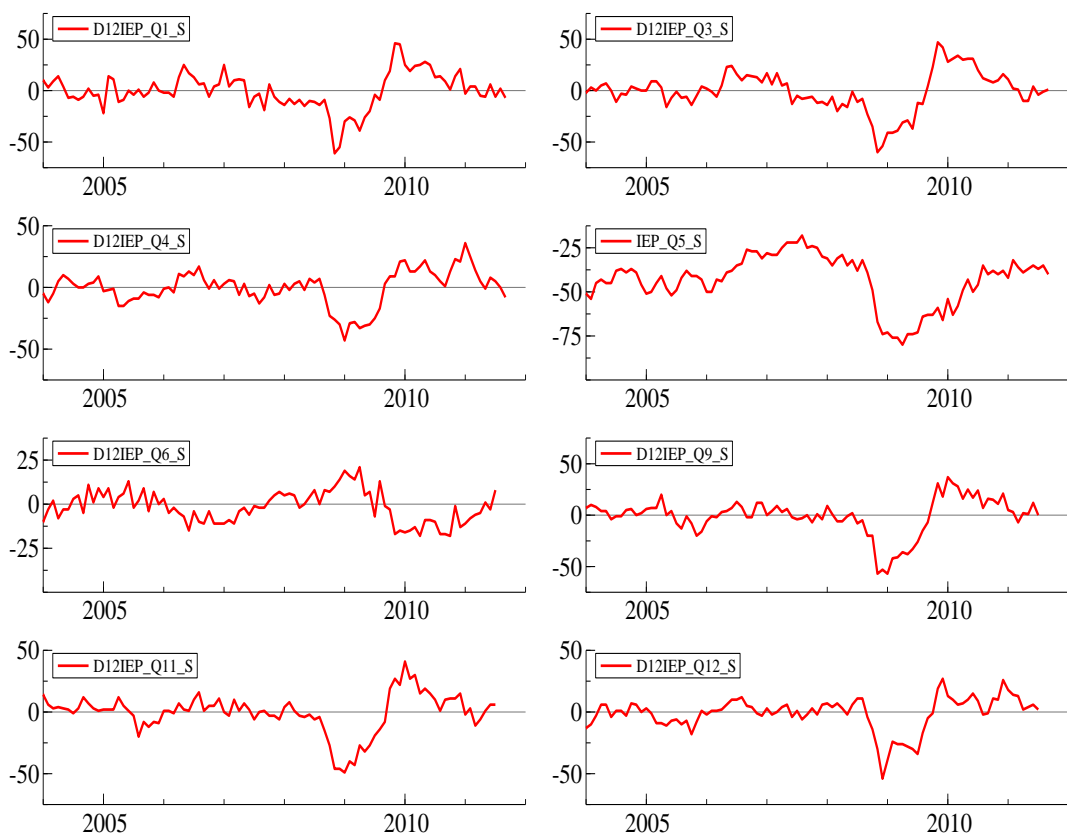
Figure 2: Transformed survey questions, see Table 1 for description.
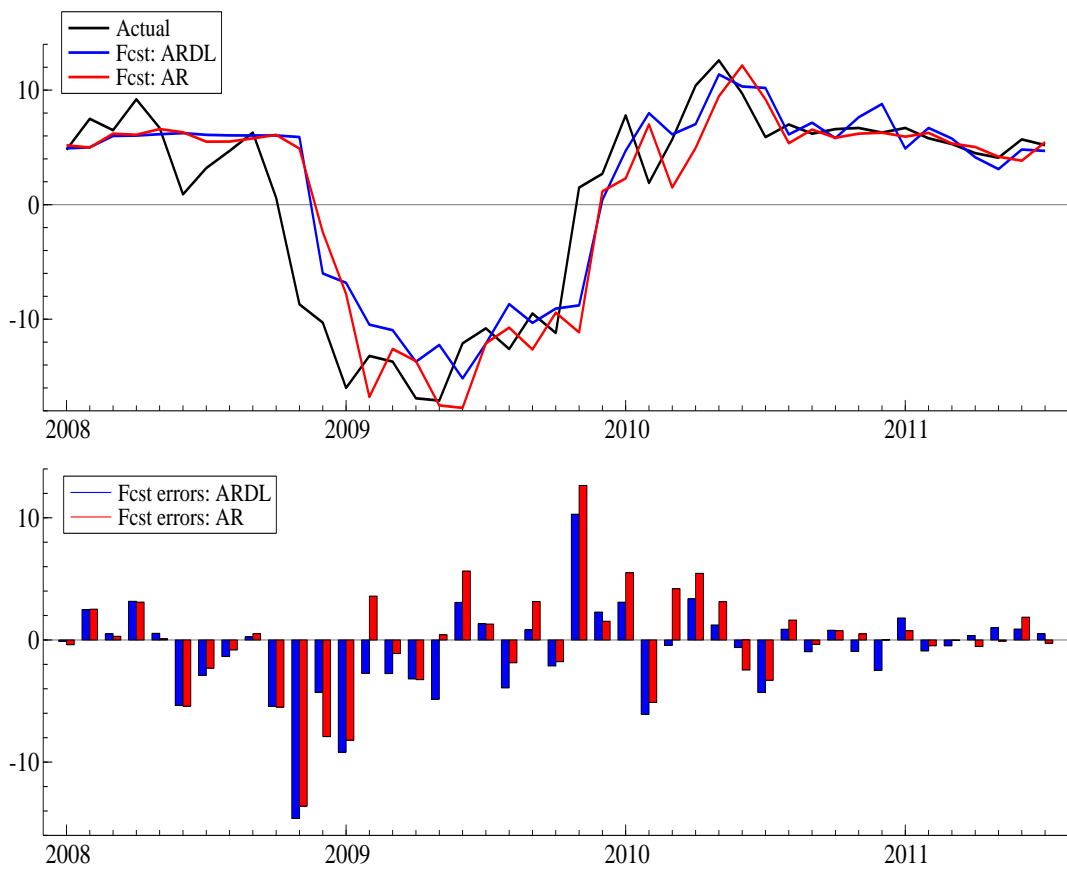
Figure 3: Index of industrial production, monthly year-on-year growth: Actual values (first released), one-step ahead forecasts from the benchmark AR model and from the ARDL model with surveys.
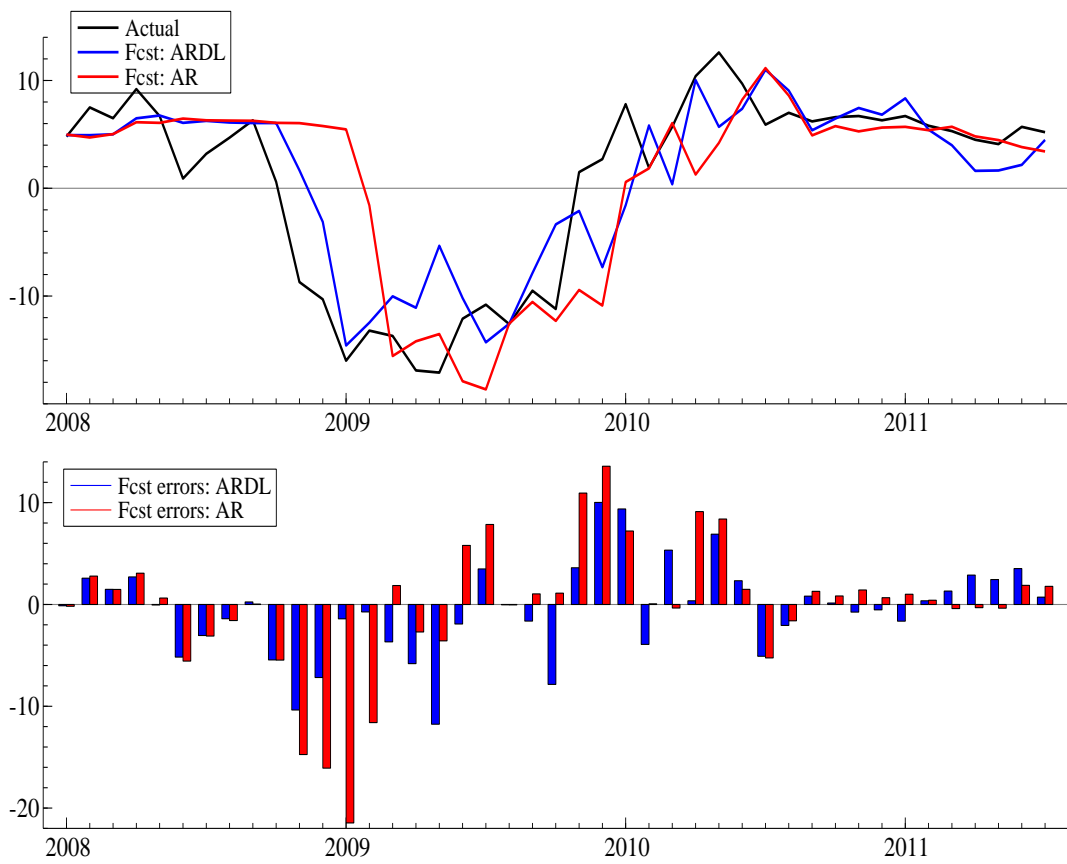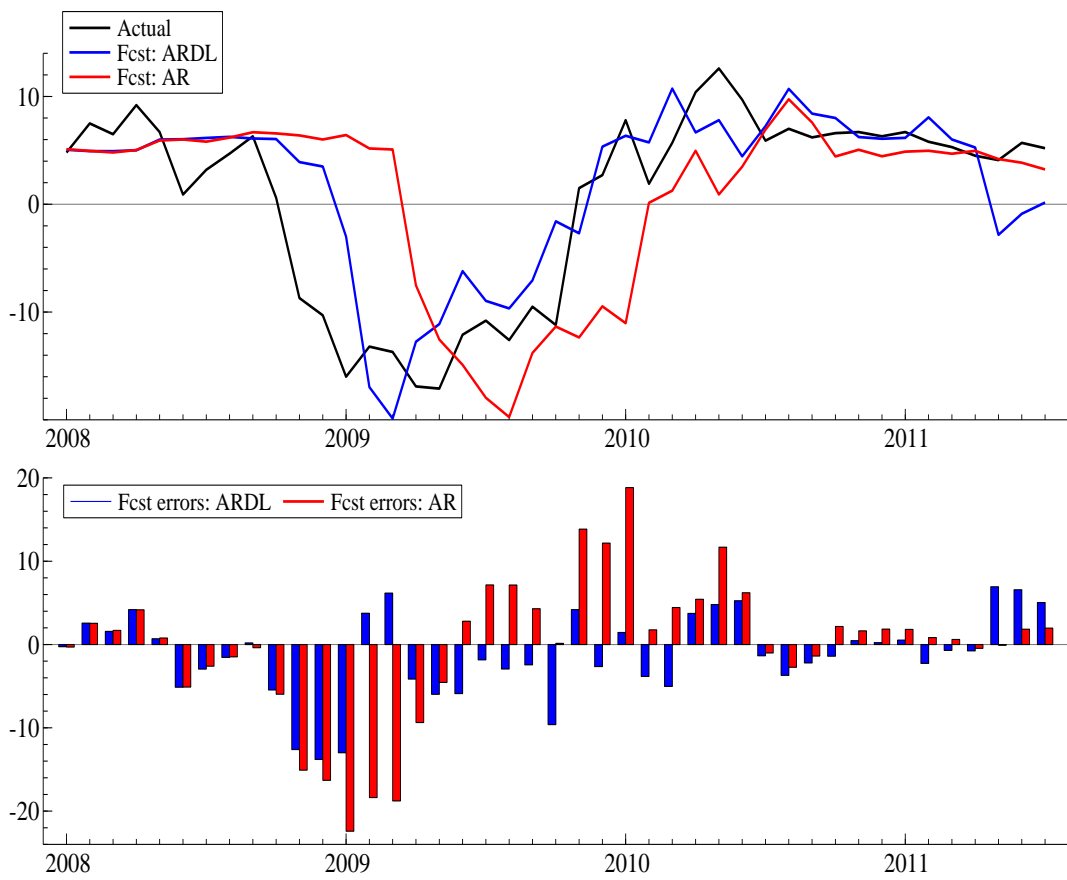
Figure 4: Index of industrial production, monthly year-on-year growth: Actual values (first released), two-step ahead forecasts from the benchmark AR model and from the ARDL model with surveys.

Figure 5: Index of industrial production, monthly year-on-year growth: Actual values (first released), three-step ahead forecasts from the benchmark AR model and from the ARDL model with surveys.
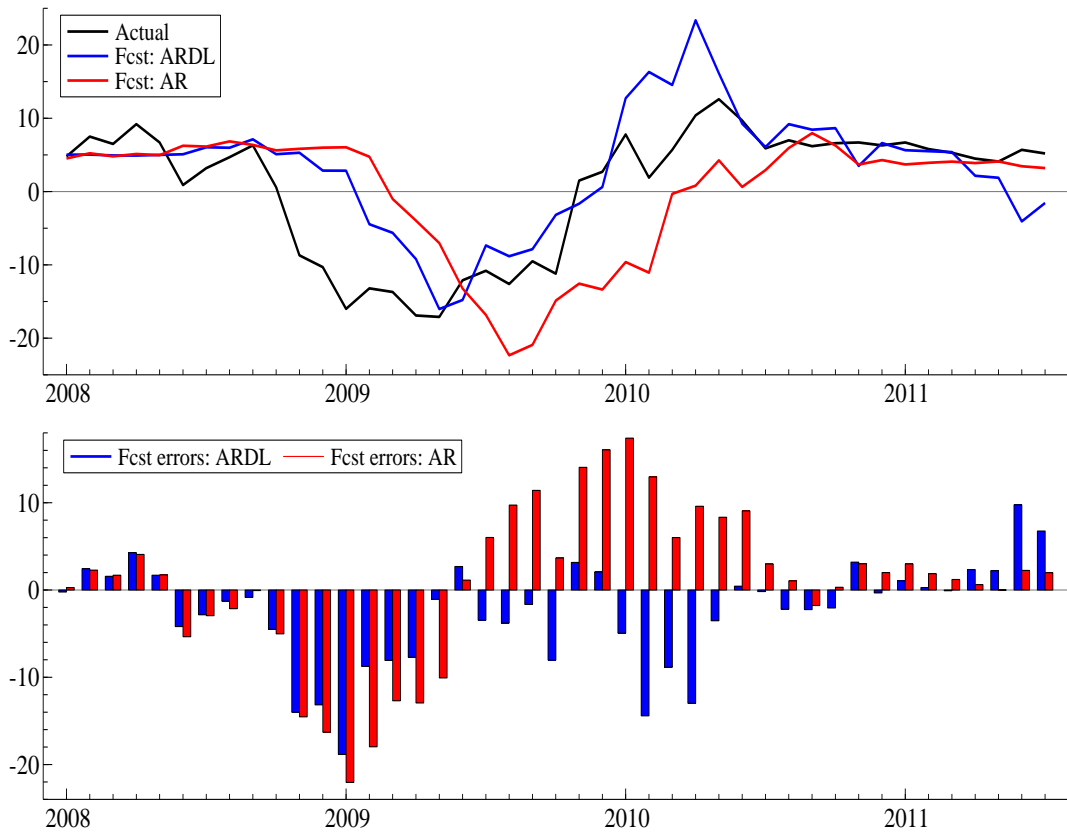
Figure 6: Index of industrial production, monthly year-on-year growth: Actual values (first released), four-step ahead forecasts from the benchmark AR model and from the ARDL model with surveys.