Evaluating Short-Run Forecasting Properties of the KOF Employment Barometer for Switzerland in Real Time *

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Abstract

This study investigates the usefulness of the business tendency surveys collected at the KOF institute for short-term forecasting of employment in Switzerland aggregated in the KOF Employment Barometer. We use the real time dataset in order to simulate the actual predictive process using only the information that was available at the time when predictions were made. We evaluate the presence of predictive content of the KOF Employment Barometer both for nowcasts that are published two months before the first official release and for one-quarter ahead forecasts published five months before the first official release. We find that inclusion of the KOF Employment Barometer leads to substantial improvement both in in-sample as well as, more importantly, in out-of-sample prediction accuracy. This conclusion holds both for nowcasts and one-quarter ahead forecasts.

Keywords: Business tendency surveys; Forecasting; Real-time data; Bayesian model averaging; Employment

JEL code: C11, C22, C53, E24.

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1 Introduction

Various decision-making institutions face a great deal of uncertainty regarding not only the future discourse of the economy but also regarding its current stance. The uncertain knowledge about the current state of economic activity stems from the fact that usually relevant economic data are only available with a significant delay. Up to date, a significant body of literature has evolved that attempts to reduce the uncertainty about current and future developments in economy by relying on coincident/leading indicators constructed on the basis of business (and/or consumer) tendency surveys. Business and consumer tendency surveys reflect an assessment of the current situation as well as recent and expected developments as perceived by businessmen and consumers, respectively. Due to the fact that their publication precedes that of economic data, they are readily available to decision makers and hence can be useful for an early assessment of the stance of the economy.

In this article, we investigate the usefulness of the business tendency surveys (BTS) collected at the KOF Swiss Economic Institute for short-term forecasting of employment in Switzerland. More specifically, we use the KOF Employment Barometer calculated on the basis of 19 various employment-related business survey indicators. The reference time series is the growth rates of the full-time equivalent total employment. Our aim is to assess predictive value[1] of the KOF Employment Barometer by comparing predictions of growth rates of employment produced with the model that includes the KOF Employment Barometer against those produced with a benchmark univariate autoregressive model. To this end, we compare accuracy of nowcasts made at the end of the current quarter as well as accuracy of one-quarter ahead forecasts measured against the first official release of the quarterly growth rates of total employment. The Swiss Statistical Agency releases total employment figures about two months later after the end of the reference quarter. This implies that our nowcasts precede the first official publication by two months and our one-quarter ahead forecasts—by five months.

Our study contributes to the literature in the following three ways. First, it is worthwhile mentioning that despite of the widespread use of business tendency surveys in forecasting, in most cases, the target variables for which forecast are made are either GDP or manufacturing/industrial growth rates (e.g., see Abberger, 2007a; Hansson et al., 2005; Lemmens et al., 2005; Balke and Petersen, 2002; Lindström, 2000; Kauppi et al., 1996; Öller and Tallbom, 1996; Bergström, 1995; Markku and Timo, 1993; Öller, 1990; Hanssens and Vanden Abeele, 1987; Teräsvirta, 1986; Zarnowitz, 1973, *inter alia*). At the same time, the use of BTS for forecasting of employment growth rates has received a disproportionately little attention. To the best of our knowledge, there are only two academic studies that specifically address predictive content of BTS for forecasting employment. As early as in 1958, Hartle (1958) summarized the accuracy of employment predictions derived from the Employment Forecast Survey collected on behalf of the Canadian government for the period from 1946 until 1957. Unfortunately, it proved that these predictions were of questionable value and, as noted in Hartle (1958, p. 389), "...there [were] only weak grounds for expecting that the predictions could have been made substantially more reliable in the future." On these grounds further employment predictions with

[1] According to Okun (1962, p. 218), "A variable has predictive value if it makes a positive contribution to the accuracy of forecasting as an addition to other available information".

the Employment Forecast Survey indexes was discontinued. More recently, Abberger (2007b) investigated whether qualitative business surveys collected at the Ifo Institute for Germany can be used for assessment of employment changes. To this end, various approaches including non-parametric regression methods, error correction models, and Probit models were used. In contrast to the negative conclusion reached in Hartle (1958), Abberger (2007b, p. 258) finds that "All methods indicate that the survey results are very useful for assessing actual employment changes, and they show that the survey-based indicator leads the actual employment by between two and four months". As it stands, the evidence on predictive value of BTS for employment remains inconclusive and anecdotal. Hence, there is a need for more case studies addressing this issue. This defines motivation for our study, which contributes to the literature by assessing the usefulness of BTS for short-run forecasting of employment growth rates in Switzerland. Naturally, our study represents the first attempt to carry out such exercise using the Swiss business tendency surveys.

Our further contribution to the literature constitutes the use of the real-time data set, i.e., for every point of time, we constructed data vintages of employment that reflect the available information at time of forecasting. The importance of using real-time data instead of latest-available data has been already emphasized in numerous studies as it has been shown, for example, by Diebold and Rudebusch (1991) and, more recently, by Croushore (2005) that the favorable conclusions on forecasting properties of leading indicator indexes obtained using latest-available data may be substantially weakened or even reversed when forecasting exercise is replicated using real-time data sets. Despite of advantages from using real-time data, their use in assessing the forecasting properties of leading indicator models is still limited as collection of such databases is rather a formidable task. Taking into account that Abberger (2007b) carries out his exercise with latest-available data, our study distinguishes itself by utilizing the real-time approach in assessing predictive value of business tendency surveys for employment.

Finally, we employ the Bayesian model averaging framework instead of relying on a single-best model approach based either on minimization of some information criteria or a more sophisticated model selection procedures, like PcGets advocated in Hendry and Krolzig (2001), that is still a rather standard practice while forecasting with leading indicator models, e.g., see a seminal study of Stock and Watson (2002) or a more recent study such as Golinelli and Parigi (2008). Advantages of Bayesian model averaging are well documented in practice (e.g., see Hoeting, Raftery, and Volinsky, 1999). In forecasting context, such an approach allows us to incorporate the following three types of uncertainty in the models forecasts: error term uncertainty, parameter uncertainty, and model selection uncertainty. Observe that predictions based on a single model typically accommodate only the first and, at best, the second sources of uncertainty. At the same time, the third type of uncertainty is typically ignored in a single-best model approach. However, we believe that accounting for model selection uncertainty is especially important when dealing with real-time data vintages that often undergo (substantial) revisions inducing both changes in temporal dependence structure of a time series of interest as well as changes in interdependence structure between the variables.

Our main findings suggest that inclusion of the KOF Employment Barometer results in substantial improvement both in in-sample as well as, more importantly, in out-of-sample prediction accuracy. This conclusion holds both for nowcasts and one-quarter ahead forecasts. For example, for nowcasts, the values of the RMSFE and the MAFE criteria recorded for the autoregressive distributed lag model are lower by 26% and 33% than those values of the benchmark autoregressive model. For one-quarter ahead forecasts, the improvement is much more pronounced—the corresponding reductions in the values of the RMSFE and the MAFE criteria are 52% and 54%.

The rest of the paper is structured as follows. Section 2 describes the data used in our predictive exercise. The econometric model utilized in our study is described in Section 3. Section 4 discusses in-sample estimation results as well as results of the out-of-sample predictions. The final section concludes.

2 Data

The reference time series is the total employment expressed in full-time equivalent released at the quarterly frequency by the Swiss Statistical Agency (BFS) [code: TS21555100]. We aim to forecast the year-to-year quarterly growth rates of total employment by means of the KOF Employment Barometer which is constructed using the 19 various employment-related business tendency survey indicators in different industries. The KOF Employment Barometer has been constructed as the weighted average of the survey indicators involved, where the weights are defined as the respective employment shares in the sectors under investigation. The characteristic feature of the KOF Employment Barometer is that during the period of investigation the number of industries involved has gradually increased from three to nine industries. The respective information on the changing composition of the KOF Employment Barometer is provided in Table 1, where column *Coverage* reports a percentage share of employment in sectors incorporated in the KOF Employment Barometer in total employment. Observe that this coverage increased from about 35% in 1994 to about 85% at the present. This column also demonstrates the importance of services sector (labeled as 'DLU') in Swiss economy. Unfortunately, in this sector the employment-related questions are only available since 2006Q4. Another important feature of our barometer is the presence of both monthly and quarterly survey indicators. However, to the former group belong only surveys collected in industrial 'IMT' and retail trade 'DHU' sectors. In aggregating from monthly to quarterly frequency we assumed that all monthly observations are available for a given quarter and the simple averaging of the respective values has been used for this purpose. The rest of surveys are collected at quarterly frequency. The full list of the respective survey indicators is given in Table 2, which presents the latest composition of the barometer. For each sector we assigned an equal weight to the questions regarding assessment of current employment and its prospects for next three months. Observe that due to the fact for such sectors as construction, banking, and architects/engineers the question regarding the current employment assessment was not included in the respective questionaires it was substituted with assessment of current business situation. Similarly, the indicator on future employment prospects in hotels/restraurants has been substituted with expectations on future sales.

We perform our forecasting exercise in real time, i.e., at each of our forecasting vintages we strictly use only the information on employment as it was available at the time of forecast origin. For this purpose, we employ the vintages of the real-time data on total employment as well as its sectoral components starting from the fourth quarter of 2004 and ending at the fourth quarter of 2008. The last data vintage 2008Q4 is used purely for forecast evaluation purposes, as it includes the first official release of employment figures for 2008Q3. This implies that the forecast sample is from 2004Q4 until 2008Q3 for nowcasts and from 2005Q1 until 2008Q3—for one-step ahead forecasts, yielding 16 and 15 prediction points, respectively. The relatively short forecast sample is largely justified by the changing composition of the indicators that enter in the KOF Employment Barometer. In this respect it merits a mention that the surveys covering employment outlook in the rather important service sector ('DLU') only appear in the barometer earliest in 2006Q4. Hence, by employing the current forecast sample, we attempt to strike a balance between a choice of starting the forecasting exercise as early as in 2006Q4, i.e., evaluating the forecasting properties of the KOF Employment Barometer in its most recent form, and a choice of extending the forecast sample several years earlier. In the former case, we significantly shorten the forecast period, whereas in the latter case in evaluating the forecast accuracy we risk to put too much weight on the forecasts made ignoring developments in the service sector. All the time series have been downloaded from the KOF Database.

3 Model

For our nowcasting and forecasting purposes we use the autoregressive distributed lag (ARDL) models in the following form:

$$Y_\tau = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{\tau-p} + \sum_{j=0}^{q} \beta_j X_{\tau-q} + \varepsilon_\tau \tag{1}$$

and

$$Y_\tau = \alpha_0 + \sum_{i=2}^{p} \alpha_i Y_{\tau-p} + \sum_{j=1}^{q} \beta_j X_{\tau-q} + \varepsilon_\tau, \tag{2}$$

respectively. In these equations, Y_τ is the year-to-year quarterly growth rates of total employment observed in quarter τ. X_τ is the KOF Employment Barometer computed in quarter τ. The structure of these two equations implies that the current growth rates of total employment is projected on own past values and the contemporaneous and past values of the KOF Employment Barometer in equation (1) and on own past values and the past values of the KOF Employment Barometer in equation (2). ε_τ is a disturbance term satisfying usual model assumptions.

In general, an ARDL equation allows 2^k combinations of regressors, where k is the number of regressors except the constant term, which is always retained in estimation. Given such a multitude of equation specifications, we chose to conduct our exercise using the Bayesian model averaging (BMA) approach, rather than concentrating on a 'single-best' model approach. The BMA approach allows us to incorporate three following sources of uncertainty while making now- and forecasts: error term uncertainty, parameter uncertainty, and model selection uncertainty. Observe that predictions based on a single-model approach typically accommodate only the first and, at best, the second sources of uncertainty. Assessment of model uncertainty and, henceforth, its incorporation in the prediction process, *per definition*, is ruled out in the latter approach. The equation parameters have been estimated using the Monte Carlo Markov Chain simulation algorithm, which allows us easily to produce the finite-sample predictive densities, rather than those based on the asymptotic approximation. On the basis of these predictive densities, the point- as well as the interval forecasts of the total employment growth rates can be readily calculated for the current and the next quarters.

The BMA approach allows us to consider either all possible combinations of the regressors in our predictive exercise or to concentrate out a subset of the most likely models. According to the former approach, for model comparison one has to evaluate posterior probabilities for all the possible combinations of lags of Y and X. This may require a significant computational time. To get around this, we followed Madigan and Raftery (1994) and applied an approach of model selection based on Occam's window. According to this approach we exclude "(a) models that are much less likely than the most likely model-say 20 times less likely, corresponding to a BIC (or BIC') difference of 6; and (optionally) (b) models containing effects for which there is no evidence-that is, models that have more likely submodels nested within them. The models that are left are said to belong to Occam's window, a generalization of the famous Occam's razor, or principle of parsimony in scientific explanation. When both (a) and (b) are used, Occam's window is said to be strict, and when only (a) is used it is said to be symmetric" (Raftery, 1995, p. 146). One can adjust the severity of model selection procedure by changing ratio in (a), and/or apply a strict rather than symmetric Occam's window.

4 Results

4.1 Estimation results for the full-sample: Equations (1) and (2)

Tables 3 and 4 present the BMA results using a symmetric Occam's window for now- and forecasts produced using Equations (1) and (2), respectively, for the longest estimation sample, covering 1993Q4—2008Q3, available at the latest vintage 2008Q4. For both equations, we use the maximum ratio of 20 for excluding models in Occam's window[2]. Together with the model specifications selected in the Occam's window, the following information is reported in columns of these two tables: the column *Frequency* indicates the inclusion frequency of a regressor in model specifications, and the columns *Mean* and *SD* reported means and standard deviations of the respective posterior distributions of the model coefficients.

For nowcasting equation (1), altogether 30 have been selected. The first two models have the posterior probability of 0.169 and 0.148. For the remaining 28 models, the reported posterior probability is below 7%. Altogether, this finding indicates a rather large model specification uncertainty, which, in turn, justifies the usage of the BMA approach. Observe that the two models with the highest posterior probability have the following regressors: $[Y_{\tau-1}, X_\tau]$—for Model 1 and $[Y_{\tau-1}, X_\tau, X_{\tau-1}]$—for Model 2, apart from the intercept and the impulse dummy variable $d94q2$ that takes the value of one in 1994Q2 and zero otherwise. Also notice that the first lag of the dependent variable $Y_{\tau-1}$ and the contemporaneous value of the KOF Employment Barometer X_τ appear in every of 30 model specifications within the selected Occam's window, as indicated by the value of 100 % per cents in the *Frequency* column in Table 3. This result suggests that the information

[2]Bayesian Model Averaging was carried out using the **BMA** package for R. Estimation of model parameters was carried out using the **MCMCpack** package for R. All optional parameters for these two packages were left at their default values.

from the business tendency surveys that is aggregated in the KOF Employment Barometer is useful for in-sample prediction of the employment growth rates in the current quarter. It remains to see whether this encouraging conclusion will hold also for predictions (nowcasts) made out of sample. Another encouraging result is that the first lag of the KOF Employment Barometer $X_{\tau-1}$ appears in second best model (Model 2). Moreover, its significance is also emphasized by rather high inclusion frequency of 48.5%, as reported in the *Frequency* column in Table 3. This suggests that the KOF Employment Barometer may be useful not only for nowcasts but also for one-quarter ahead forecasts made out of sample.

Similar conclusions may also be reached upon examining the estimation results of the forecasting equation (2), presented in Table 4. Note that the number of model specifications selected for this equation is 21, that is somewhat lower than that for Equation (1). The model with the highest posterior probability of 0.232 has the following regressors: $[Y_{\tau-2}, X_{\tau-1}]$, apart from the intercept and the impulse dummy variable $d94q2$.[3] Moreover, observe that the lagged values of the KOF Employment Barometer apppear in every of 21 model specifications selected in the Occam's window, as reported in the *Frequency* column in Table 4. All in all, this allows us to conclude that the KOF Employment Barometer has rather high informative in-sample content regarding the developments of the Swiss employment in the next quarter. Again, it remains to see whether this encouraging conclusion will hold also for predictions (one-quarter ahead forecasts) made out of sample.

4.2 Out-of-sample predictions

In this subsection, we discuss the results of the out-of-sample forecasting exercises that are summarized in Tables 6 and 7 for nowcasts using the ARDL equation (1) and its only autoregressive part, respectively, and in Tables 8 and 9 for one-step ahead forecasts using the ARDL equation (2) and the corresponding autoregressive model. In these four tables all the necessary information on estimation sample period, forecast quarters, nowcasts, actual values as reported in first official release of employment figures, nowcast errors, the lower and upper bounds of the 95% predictive interval as well as the results of the BMA including the number of models selected in the Occam's window, the maximum and minimum posterior probabilities of the models in the Occam's window is presented. Comparison of the prediction accuracy of the ARDL model that includes both the values of the KOF Employment Barometer and the own lags of the growth rates of total employment with that of the purely autoregressive model, which includes only the lags of the dependent variable, allows us to assess the usefulness of the KOF Employment Barometer for short-run forecasting of total employment.

In this respect, we would like to reiterate that for evaluation purposes we use the real-time dataset of both the KOF Employment Barometer as well as the growth rates of total employment as the corresponding vintages of these variables were available at times now- and forecasts were made. For example, both nowcast and one-step ahead forecast for 2008Q3 were made using the corresponding vintages of data as available in 2008Q3 and in 2008Q2, respectively. This means that for appropriate data vintages the parameters of the

[3]The impulse dummy is needed to accommodate an outlier in actual employment growth rate in 1994Q2 that is not matched in the barometer time series, see Figure 1.

ARDL and the AR models were estimated using the sample periods from 1993Q4 till 2008Q2 for nowcasts and from 1993Q4 till 2008Q1 for one-step ahead forecasts, as implied by the lag structures of equations (1) and (2). Correspondingly, the values of regressors as they were available in 2008Q3 for nowcasts and in 2008Q2 for one-step ahead forecasts were used for prediction. The now- and forecasts produced with the help of the ARDL and the AR models are compared with the first official release of total employment, which they precede by two and five months.

As discussed in more detail below, the overall results are very encouraging. According to Table 5, where the descriptive statistics of the real-time forecast errors is presented, inclusion of the KOF Employment Barometer either in nowcasting equation (1) or in forecasting equation (2) results in a substantial improvement in forecast accuracy compared to the performance of the benchmark AR model. For nowcasts, the values of the RMSFE and the MAFE criteria recorded for the autoregressive distributed lag model are by 26% and 33% lower than those values of the benchmark autoregressive model. For one-quarter ahead forecasts, the improvement is much more pronounced—the corresponding values are 52% and 54% for the RMSFE and the MAFE criteria. As expected, the RMSFE and the MAFE are higher for one-step ahead forecasts than those for nowcasts both for the ARDL and for the AR models. Based on the MAFE, we expect an average prediction error of about 0.2 and 0.25 for nowcasts and one-step ahead forecasts, respectively, made by the ARDL model, and the corresponding average prediction error of about 0.3 and 0.55—for the AR model.

Furthermore, the now- and forecast errors of the AR model seem to be downwards biased, whereas the average values of the nowcast and forecast errors of the ARDL model are rather close to zero. The former fact contributes substantially to larger values of the RMSFE and the MAFE criteria recorded for the AR model. Also the prediction errors of the ARDL model are more close to be normally distributed than those of the AR model. For the AR model the null hypothesis of normality can be rejected at the 10% significance level due to rather high values of the excess kurtosis, whereas for the ARDL model the corresponding null hypothesis cannot be rejected at the usual significance levels. The histogram of the prediction errors and the estimated density are displayed in Figure 10.

The real-time nowcasts together with the 95% predictive interval produced by the ARDL and the AR models and the actual values of the growth rates of total employment are displayed in Figures 2 and 3, respectively. On the one hand, the ARDL nowcasts track the actual values quite closely and the actual values never fall out of the predictive interval. On the other hand, the AR nowcasts seem to be systematically downwards biased. Also, the AR predictive interval is much wider than that of the ARDL model, as shown in Figure 4. The bar-plot of the nowcast errors together with the actual values is displayed in Figure 5. With a few exceptions, the nowcast errors made by the ARDL model are always lower (in absolute value) than those made by the AR model.

The real-time one-step ahead forecasts together with the 95% predictive interval produced by the ARDL and the AR models and the actual values of the growth rates of total employment are displayed in Figures 6 and 7, respectively. As in case of nowcasts, the ARDL forecasts track the actual values much more closely than the forecasts made by the AR model, which systematically underpredicts the actual values. Also the AR predictive interval is much wider than that of the ARDL model, as shown in Figure 8. The bar-plot of the one-step ahead forecast errors together with the actual values is displayed in Figure 9. The one-step ahead forecast errors of the ARDL model for all periods except for 2005Q2 are always lower (in absolute value) than those made by the AR model.

4.3 Conclusion

In this paper we evaluated the usefulness of the KOF Employment Barometer, derived from the business tendency surveys collected at the KOF Swiss Economic Institute, for out-of-sample prediction of the growth rates of (full-time equivalent) total employment in Switzerland. In particular, we capitalize on the fact that the business tendency surveys, reflecting current and future employment expectations of the firms in the current quarter, are available at least two months ahead of the first official release of the Swiss Statistical Agency (BFS). We conduct our exercise in real time, i.e., at each forecast origin we strictly use the only information that was available to a forecaster at that time. For this purpose, we constructed the real-time database that contains all the first official employment data vintages as released by the BFS starting from 2004Q4 till 2008Q3. The data vintages cover both the total employment figures as well as employment broken down by sectors. We use these sectoral employment data as the weights in constructing the KOF Employment Barometer in real time. We evaluate the presence of predictive content of the KOF Employment Barometer both for nowcasts that are published two months before the first official release and for one-quarter ahead forecasts published five months before the first official release.

We produce now- and forecasts of the employment growth rates for the current and the next quarters with help of the autoregressive distributed lag (ARDL) models cast in the Bayesian Model Averaging framework. In doing so, we avoid an, often arbitrary, choice of a single best model and integrate model selection uncertainty in making out-of-sample predictions. We compare the predictive accuracy of the ARDL model that includes both the values of the KOF Employment Barometer as well as the lags of the dependent variable with that of the benchmark autoregressive (AR) model from which the values of the KOF Employment Barometer are omitted.

Our main findings are as follows. The KOF Employment Barometer does have an informative content which can be used in order to accurately predict the growth rates of total employment both for a current quarter as well as for a next quarter. More specifically, inclusion of the KOF Employment Barometer either in nowcasting equation (1) or in forecasting equation (2) results in a substantial improvement in forecast accuracy compared to the performance of the benchmark AR model. For nowcasts, the values of the RMSFE and the MAFE criteria recorded for the autoregressive distributed lag model are by 26% and 33% lower than those values of the benchmark autoregressive model. For one-quarter ahead forecasts, the improvement is much more pronounced—the corresponding values are 52% and 54% for the RMSFE and the MAFE criteria. We expect the average prediction error of about 0.2 and 0.25 for nowcasts and one-step ahead forecasts, respectively, made by the ARDL model compared with the corresponding average prediction error of about 0.3 and 0.55—for the AR model. We also find a substatntial evidence for systematic underpredictions of the AR model, which largerly disappears when the KOF Employment Barometer is included either in the nowcasting or in the forecasting equation.

The ARDL model produces not only more accurate point forecasts but also more accurate interval forecasts than those produced by the pure AR model. The 95% predictive intervals of the former model are much much narrow than those of the latter model, but, at the same time, the actual value never falls out of the 95% bounds of the ARDL predictive interval.

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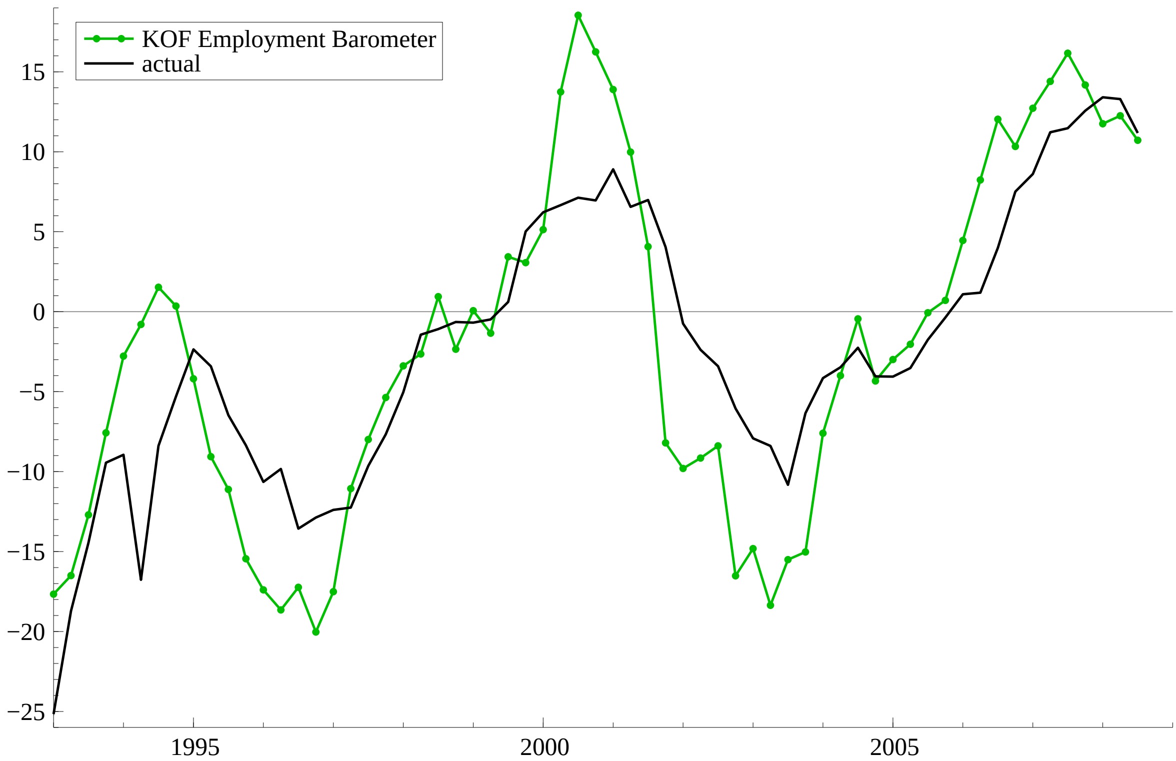

Figure 1: Employment (year-on-year growth rates) and KOF Employment Barometer: Latest-available data; Time series are adjusted to have the same mean and range

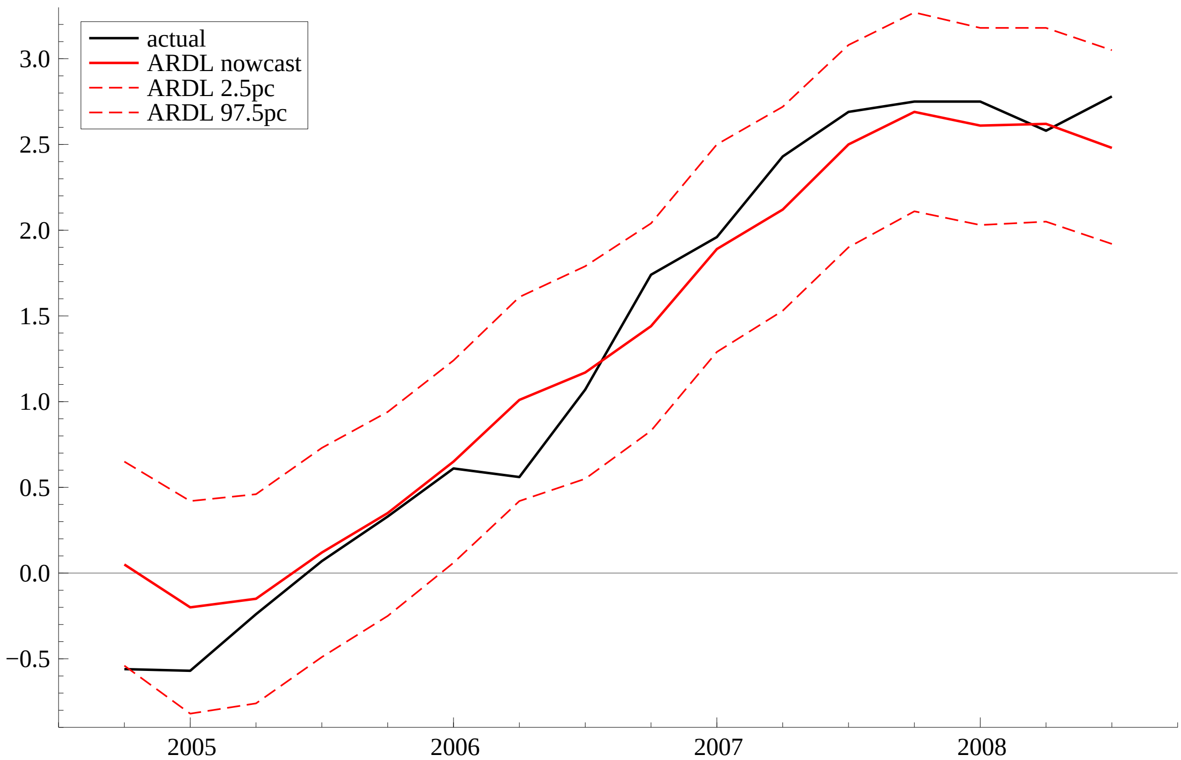

Figure 2: Nowcasts with ARDL: Real-time actual values, nowcasts, 95% predictive interval

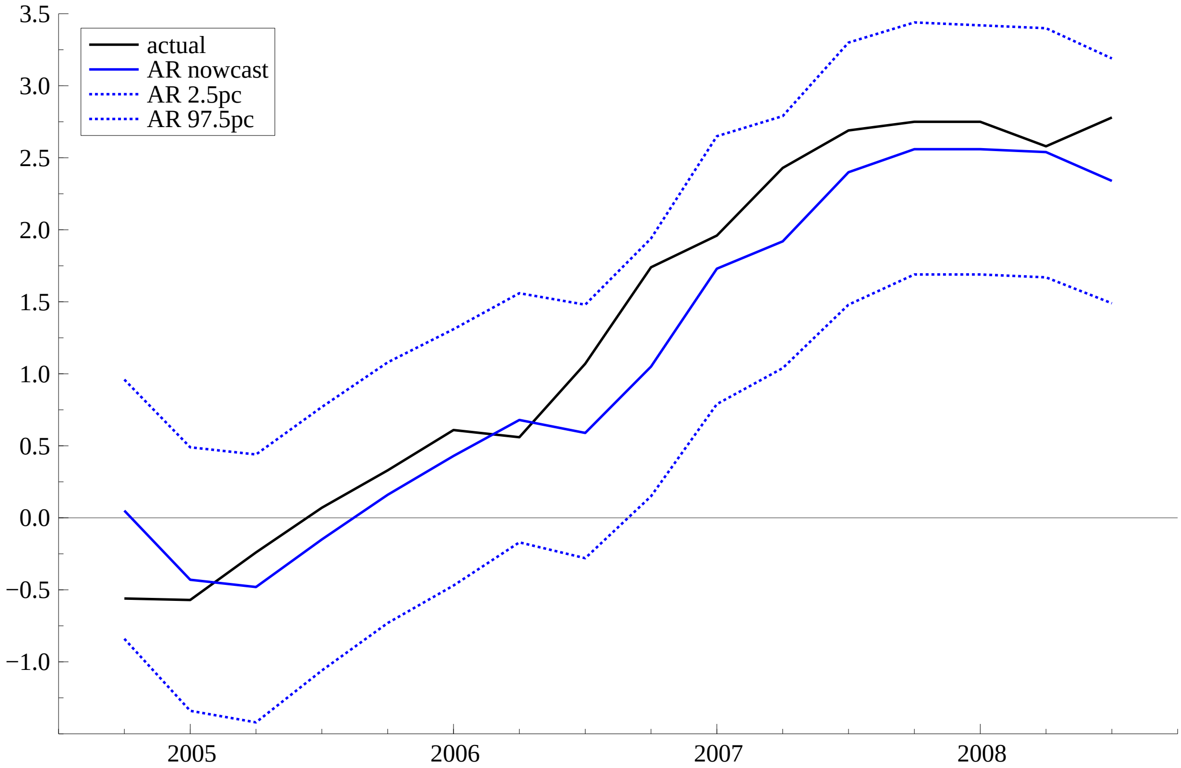

Figure 3: Nowcasts with AR: Real-time actual values, nowcasts, 95% predictive interval

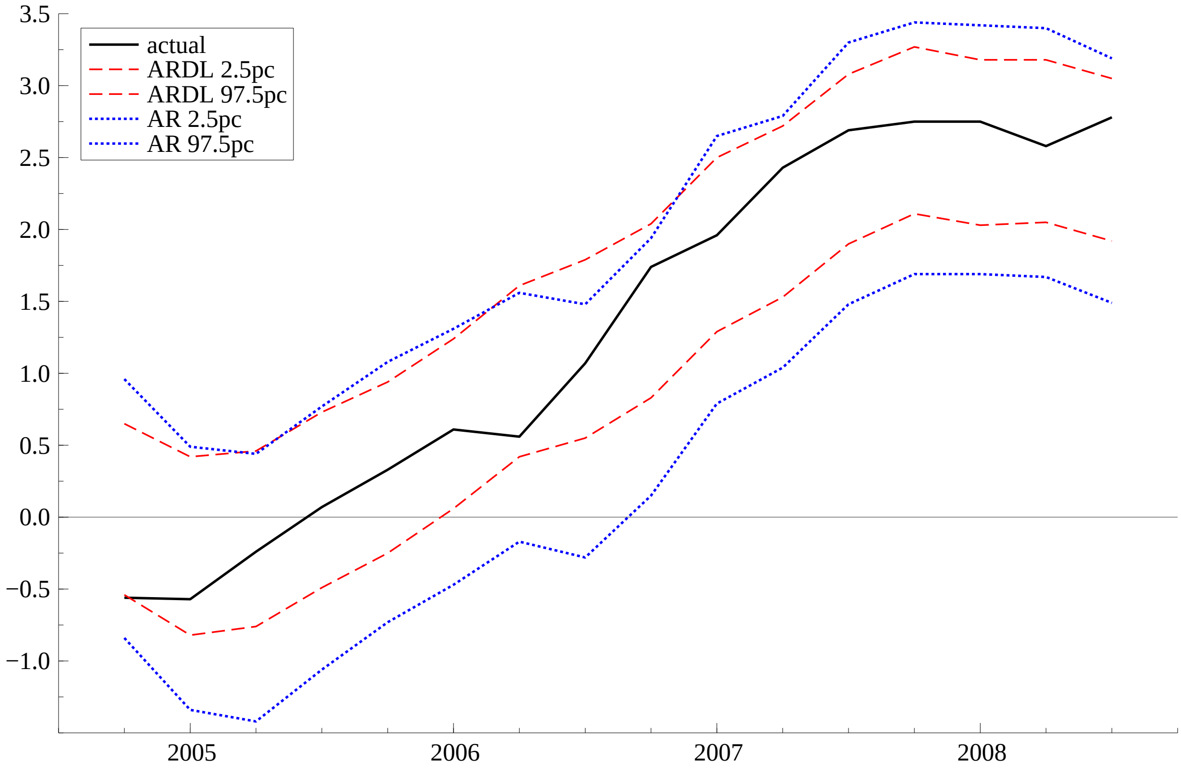

Figure 4: Nowcasts ARDL vs AR: Real-time actual values, 95% predictive intervals

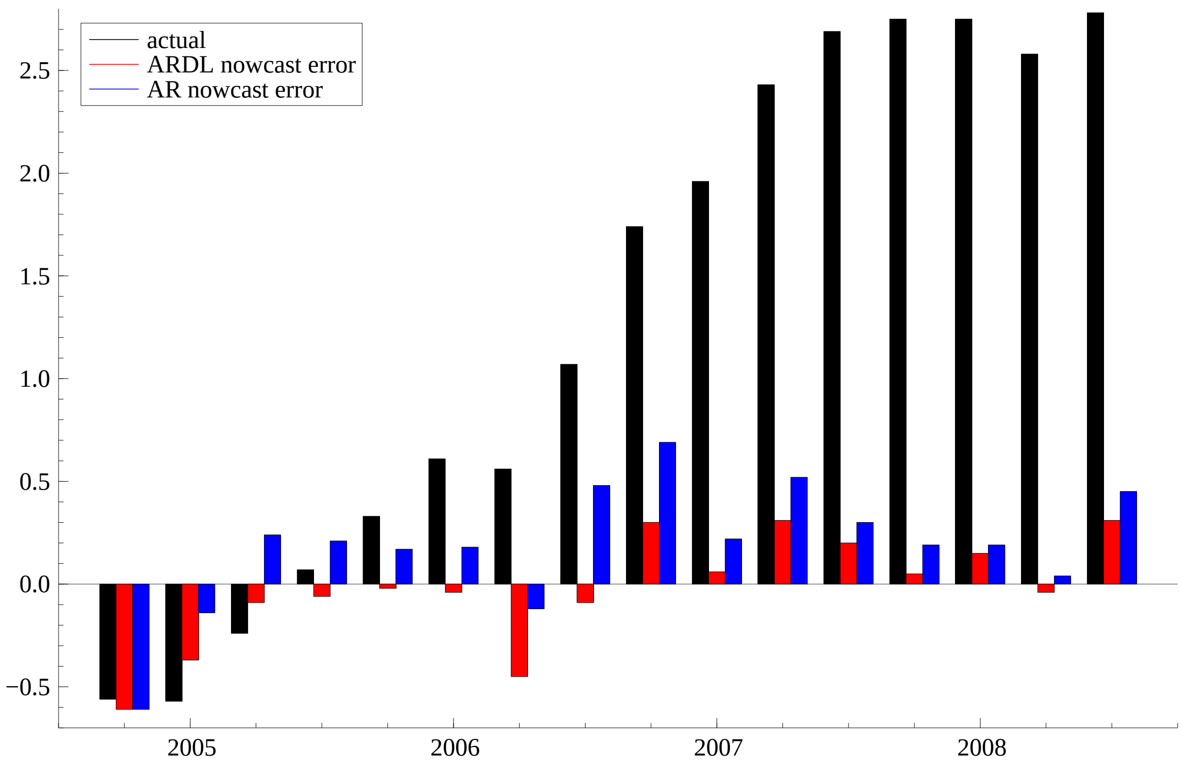

Figure 5: Nowcasts ARDL vs AR: Real-time actual values, nowcast errors

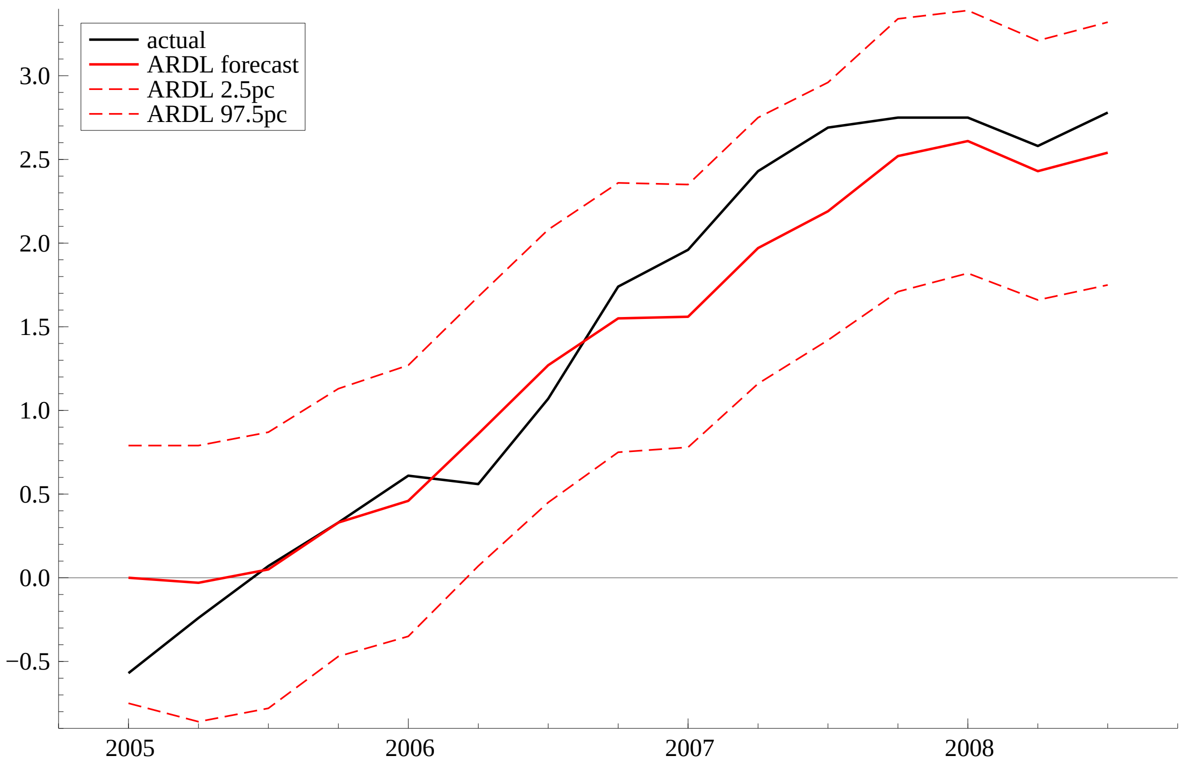

Figure 6: Forecasts with ARDL: Real-time actual values, nowcasts, 95% predictive interval

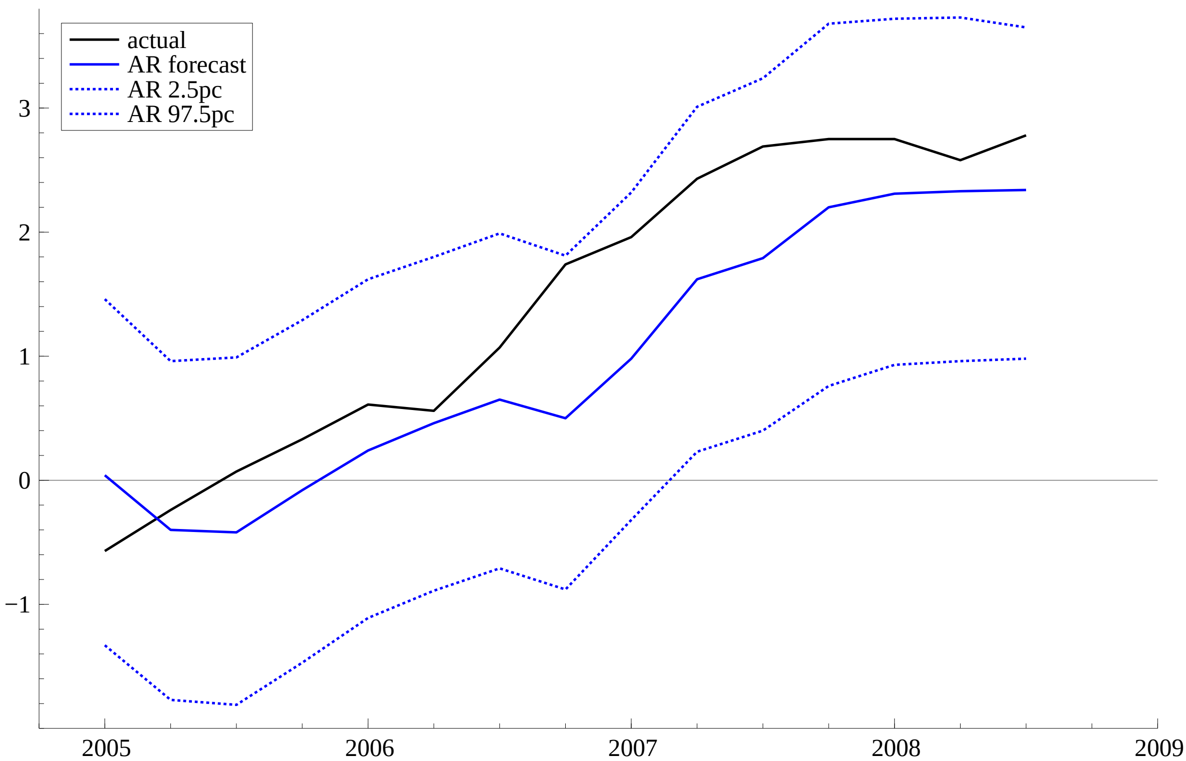

Figure 7: Forecasts with AR: Real-time actual values, nowcasts, 95% predictive interval

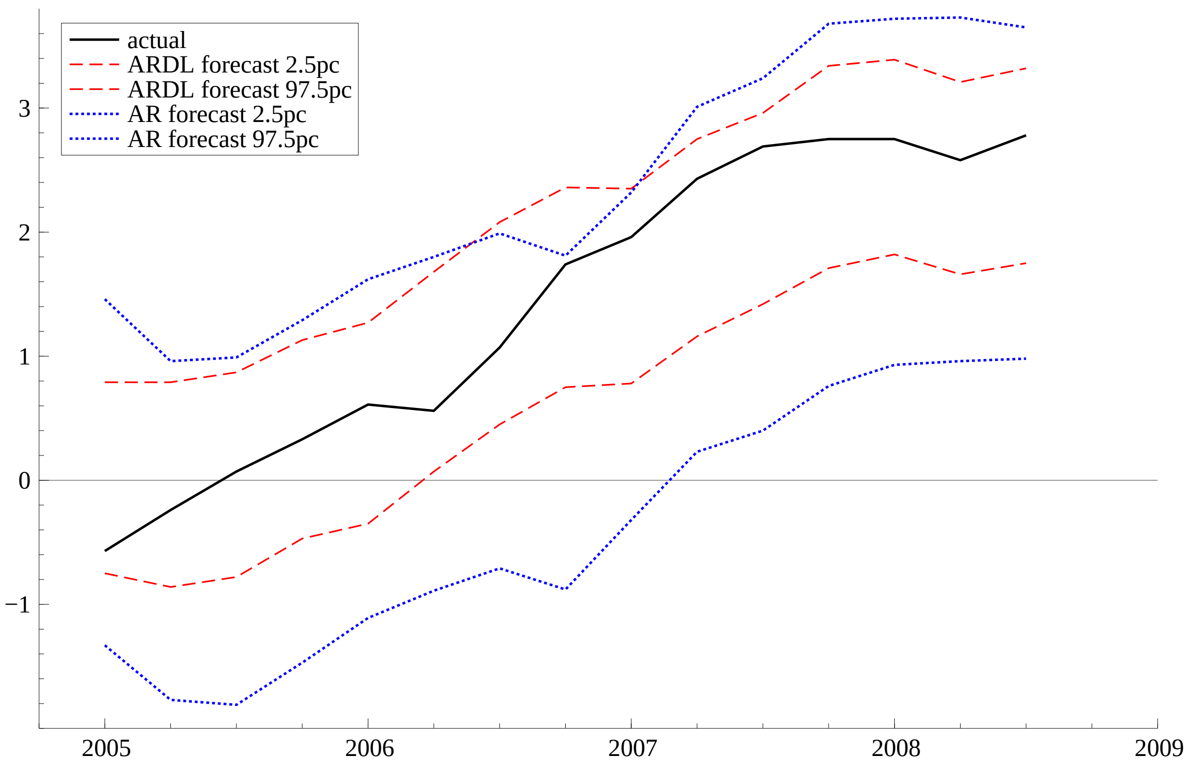

Figure 8: Forecasts ARDL vs AR: Real-time actual values, 95% predictive intervals

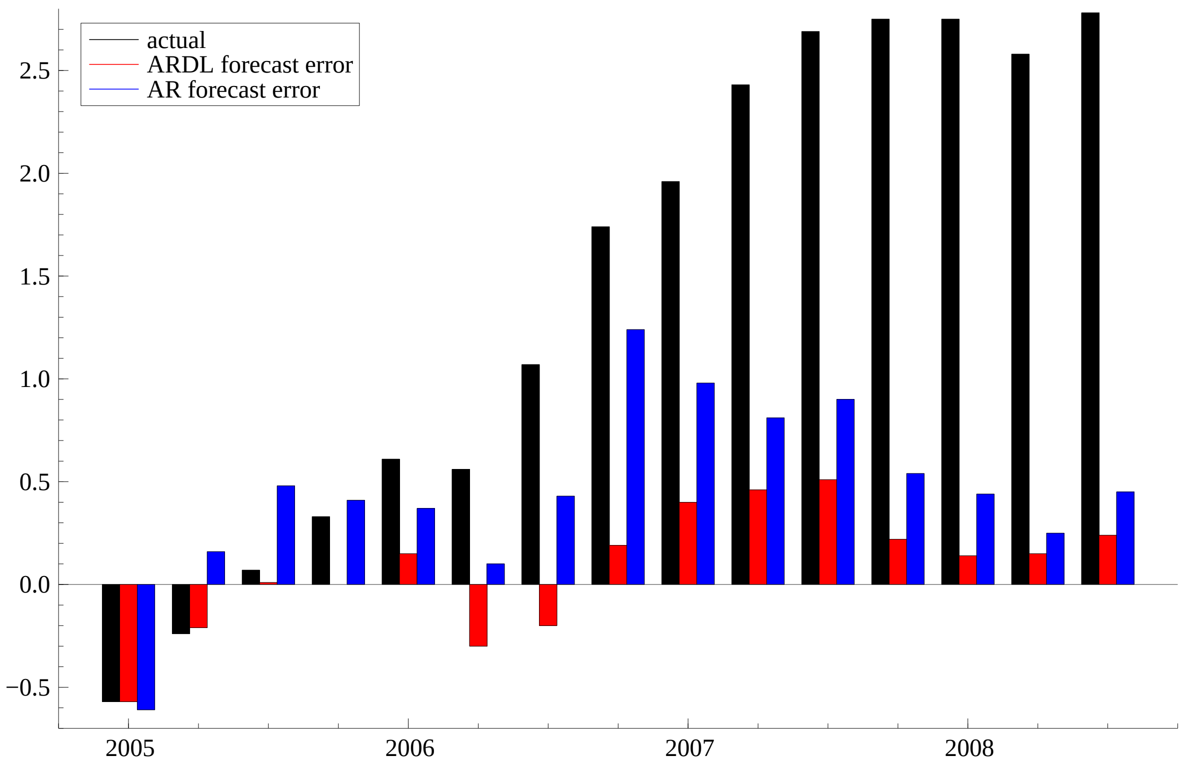

Figure 9: Forecasts ARDL vs AR: Real-time actual values, forecast errors

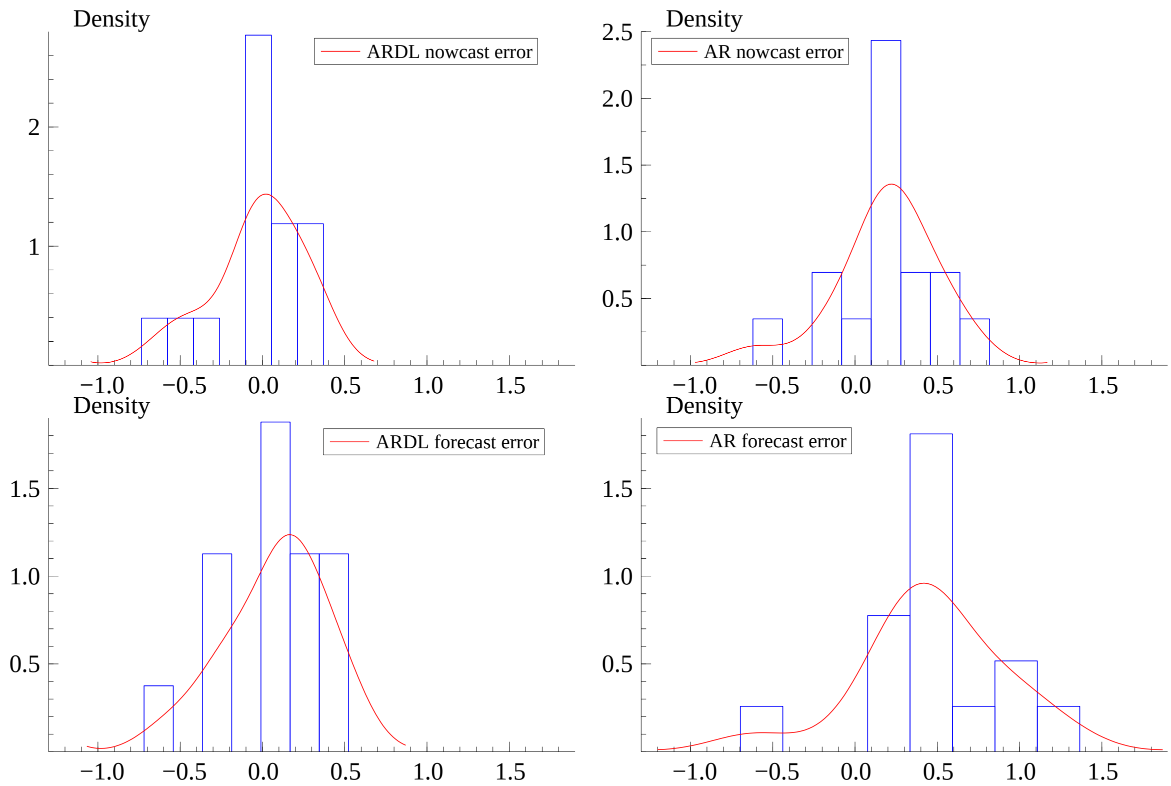

Figure 10: ARDL vs AR: Real-time nowcast and forecast errors

Table 1: KOF Employment Barometer: Changes over time

Period	Sectors covered[a]	No. of indicators	Coverage[b] (in %)
1991Q3-1994Q1	IMT,GGT,GHU	6	35.2
1994Q2-1994Q3	IMT,GGT,GHU,DHU	8	44.0
1994Q3-1996Q1	IMT,GGT,GHU,DHU,BAT	10	53.4
1996Q2-2000Q1	IMT,GGT,GHU,DHU,BAT,AIT	11	52.6
2000Q2-2001Q2	IMT,GGT,GHU,DHU,BAT,AIT,BT	14	56.0
2001Q3-2006Q3	IMT,GGT,GHU,DHU,BAT,AIT,BT,VT	17	55.3
2006Q4-2008Q3	IMT,GGT,GHU,DHU,BAT,AIT,BT,VT,DLU	19	84.6

[a] ‘IMT’ stands for manufacturing, ‘GGT’ — hotel and restaurants, ‘GHU’ — wholesale trade, ‘DHU’ — retail trade, ‘BAT’ — construction, ‘AIT’ — architects and engineers, ‘BT’ — banking, ‘VT’ — insurance, ‘DLU’ — services. All employment is expressed in full-time equivalent.

[b] Reports a share of sectoral employment covered in KOF Employment Barometer in total employment.

Table 2: KOF Employment Barometer: Components

Sector	Label	Indicator	Weight[a]
Manufacturing	IMT	Current employment assessment	50%
		Employment expectations for next 3 months	50%
Hotels/restraurants	GGT	Current employment assessment	50%
		Sales expectation for next 3 months	50%
Wholesale trade	GHU	Current employment assessment	50%
		Employment expectations for next 3 months	50%
Retail trade	DHU	Current employment assessment	50%
		Employment expectations for next 3 months	50%
Construction	BAT	Current business situation assessment	50%
		Employment expectations for next 3 months	50%
Architects/engineers	AIT	Current business situation assessment	50%
		Employment expectations for next 3 months	50%
Banking	BT	Frontoffice assessment of current situation	25%
		Backofffice assessment of current situation	25%
		Employment expectations for next 3 months	50%
Insurance	VT	Current employment assessment	50%
		Employment expectations for next 3 months	50%
Services	DLU	Current employment assessment	50%
		Employment expectations for next 3 months	50%

[a] Denotes weights assigned for each survey question within each sector.

Table 3: ARDL Equation (1), BMA: Symmetric Occam's window (Ratio 20), 1993Q4-2008Q3

	Frequency (%)	Posterior distribution Mean	SD	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8	model 9	model 10
Incpt	100	0.356	0.061	0.314	0.353	0.395	0.387	0.365	0.347	0.399	0.345	0.400	0.331
$Y_{\tau-1}$	100	0.585	0.077	0.644	0.591	0.508	0.564	0.579	0.578	0.556	0.603	0.540	0.604
$Y_{\tau-2}$	5.4	0.001	0.020	.	.	.	.	.	.	.	.	.	.
$Y_{\tau-3}$	10.1	-0.007	0.034	.	.	.	.	.	.	-0.113	.	.	.
$Y_{\tau-4}$	7.8	0.002	0.023	.	.	.	.	.	.	.	.	.	0.033
$Y_{\tau-5}$	23.2	0.018	0.043	.	.	0.065	.	.	0.055	0.126	.	.	.
X_{τ}	100	0.043	0.012	0.049	0.033	0.038	0.054	0.049	0.054	0.035	0.046	0.039	0.051
$X_{\tau-1}$	48.5	0.012	0.015	.	0.023	0.025	.	.	.	0.029	.	0.020	.
$X_{\tau-2}$	6.8	0.000	0.003	.	.	.	.	.	.	.	0.009	.	.
$X_{\tau-3}$	10.7	0.001	0.005	.	.	.	.	0.010	.	.	.	.	.
$X_{\tau-4}$	9.4	-0.001	0.006	.	.	.	.	.	.	.	.	.	.
$X_{\tau-5}$	13.7	0.002	0.005	.	.	.	0.009	.	.	.	.	0.007	.
$d94q2$	100	-2.130	0.300	-2.152	-2.195	-2.041	-2.140	-2.145	-2.019	-1.966	-2.161	-2.181	-2.110
nVar				3	4	5	4	4	4	6	4	5	4
R^2				0.965	0.967	0.968	0.966	0.966	0.965	0.970	0.965	0.967	0.965
BIC				-188.04	-187.77	-186.12	-185.89	-185.65	-185.61	-185.15	-184.99	-184.66	-184.53
Post. Prob.				0.169	0.148	0.065	0.058	0.051	0.050	0.040	0.037	0.031	0.029

For the estimation window [1993Q4-2008Q3], 30 models were selected, but only the best 10 models are presented (cumulative posterior probability = 0.677).

Table 4: ARDL Equation (2), BMA: Symmetric Occam's window (Ratio 20), 1993Q4-2008Q3

	Frequency	Posterior distribution		model	model	model	model	model	model	model	model	model	model
	(%)	Mean	SD	1	2	3	4	5	6	7	8	9	10
Incpt	100	0.547	0.071	0.533	0.568	0.578	0.513	0.575	0.504	0.516	0.504	0.526	0.536
$Y_{\tau-2}$	98.7	0.390	0.128	0.378	0.451	0.264	0.503	0.330	0.418	0.403	0.416	0.387	0.367
$Y_{\tau-3}$	36.2	-0.083	0.135	.	-0.259	.	-0.114	.	.	.	.	.	.
$Y_{\tau-4}$	12.8	-0.011	0.063	.	.	.	.	-0.196	.	.	.	.	0.009
$Y_{\tau-5}$	52.2	0.087	0.106	.	0.182	0.098	.	0.234	.	.	.	.	.
$X_{\tau-1}$	100	0.087	0.010	0.083	0.089	0.089	0.080	0.089	0.086	0.091	0.083	0.082	0.083
$X_{\tau-2}$	7.7	-0.001	0.005	.	.	.	.	.	.	-0.011	.	.	.
$X_{\tau-3}$	8.2	-0.001	0.004	.	.	.	.	.	-0.009	.	.	.	.
$X_{\tau-4}$	7.7	0.000	0.003	.	.	.	.	.	.	.	-0.006	.	.
$X_{\tau-5}$	7.2	0.000	0.003	.	.	.	.	.	.	.	.	-0.001	.
$d94q2$	100	-2.270	0.440	-2.414	-2.127	-2.157	-2.499	-2.081	-2.445	-2.431	-2.439	-2.419	-2.401
nVar				3	5	4	4	5	4	4	4	4	4
R^2				0.933	0.941	0.936	0.935	0.939	0.934	0.934	0.934	0.933	0.933
BIC				-150.24	-149.58	-148.46	-147.42	-147.37	-146.71	-146.63	-146.47	-146.17	-146.17
Post. Prob.				0.232	0.166	0.095	0.057	0.055	0.040	0.038	0.035	0.030	0.030

For the estimation window [1993Q4-2008Q3], 21 models were selected, but only the best 10 models are presented (cumulative posterior probability = 0.779).

Table 5: Real-time nowcast and forecast errors: Descriptive statistics

	Nowcast		Forecast	
	ARDL	AR	ARDL	AR
Observations	16	16	15	15
Mean	-0.024	0.188	0.079	0.463
Std.Devn.	0.259	0.295	0.288	0.418
Skewness	-0.693	-0.896	-0.553	-0.539
Excess Kurtosis	-0.177	1.234	-0.293	1.017
Minimum	-0.610	-0.610	-0.570	-0.610
Maximum	0.310	0.690	0.510	1.240
Normality test $\chi^2(2)$	[0.379]	[0.081]	[0.536]	[0.055]
MSFE	0.068	0.122	0.090	0.391
RMSFE	0.260	0.349	0.299	0.625
MAFE	0.197	0.296	0.251	0.546

Table 6: Nowcast results: ARDL model

Estimation sample	Nowcast period	Y_τ	$\widehat{Y}_{\tau\|\tau}$	Predictive interval (95%)	$Y_\tau - \widehat{Y}_{\tau\|\tau}$	Models[a]	Posterior probability Max	Min
1993Q4 –2004Q3	2004Q4	-0.56	0.05	[-0.54, 0.65]	-0.61	21	0.28	0.01
1993Q4 –2004Q4	2005Q1	-0.57	-0.20	[-0.82, 0.42]	-0.37	25	0.17	0.01
1993Q4 –2005Q1	2005Q2	-0.24	-0.15	[-0.76, 0.46]	-0.09	26	0.17	0.01
1993Q4 –2005Q2	2005Q3	0.07	0.12	[-0.49, 0.73]	-0.06	25	0.18	0.01
1993Q4 –2005Q3	2005Q4	0.33	0.35	[-0.25, 0.94]	-0.02	25	0.19	0.01
1993Q4 –2005Q4	2006Q1	0.61	0.65	[0.06, 1.24]	-0.04	24	0.19	0.01
1993Q4 –2006Q1	2006Q2	0.56	1.01	[0.42, 1.61]	-0.45	24	0.20	0.01
1993Q4 –2006Q2	2006Q3	1.07	1.17	[0.55, 1.79]	-0.09	23	0.22	0.02
1993Q4 –2006Q3	2006Q4	1.74	1.44	[0.83, 2.04]	0.30	23	0.23	0.02
1993Q4 –2006Q4	2007Q1	1.96	1.89	[1.29, 2.50]	0.06	23	0.26	0.01
1993Q4 –2007Q1	2007Q2	2.43	2.12	[1.53, 2.72]	0.31	23	0.26	0.01
1993Q4 –2007Q2	2007Q3	2.69	2.50	[1.90, 3.08]	0.20	24	0.24	0.01
1993Q4 –2007Q3	2007Q4	2.75	2.69	[2.11, 3.27]	0.05	36	0.14	0.01
1993Q4 –2007Q4	2008Q1	2.75	2.61	[2.03, 3.18]	0.15	36	0.14	0.01
1993Q4 –2008Q1	2008Q2	2.58	2.62	[2.05, 3.18]	-0.04	36	0.15	0.01
1993Q4 –2008Q2	2008Q3	2.78	2.48	[1.92, 3.05]	0.31	36	0.15	0.01

[a] Denotes a number of models included in Occam's window.

Table 7: Nowcast results: AR model

Estimation sample	Nowcast period	Y_τ	$\widehat{Y}_{\tau\|\tau}$	Predictive interval (95%)	$Y_\tau - \widehat{Y}_{\tau\|\tau}$	Models[a]	Posterior probability Max	Min
1993Q4 –2004Q3	2004Q4	-0.56	0.05	[-0.84, 0.96]	-0.61	9	0.44	0.02
1993Q4 –2004Q4	2005Q1	-0.57	-0.43	[-1.34, 0.49]	-0.14	11	0.34	0.02
1993Q4 –2005Q1	2005Q2	-0.24	-0.48	[-1.42, 0.44]	0.24	11	0.33	0.02
1993Q4 –2005Q2	2005Q3	0.07	-0.15	[-1.06, 0.77]	0.21	11	0.34	0.02
1993Q4 –2005Q3	2005Q4	0.33	0.16	[-0.73, 1.08]	0.17	11	0.35	0.02
1993Q4 –2005Q4	2006Q1	0.61	0.43	[-0.47, 1.31]	0.18	11	0.34	0.02
1993Q4 –2006Q1	2006Q2	0.56	0.68	[-0.17, 1.56]	-0.12	11	0.34	0.02
1993Q4 –2006Q2	2006Q3	1.07	0.59	[-0.28, 1.48]	0.48	11	0.34	0.02
1993Q4 –2006Q3	2006Q4	1.74	1.05	[0.15, 1.94]	0.69	10	0.37	0.03
1993Q4 –2006Q4	2007Q1	1.96	1.73	[0.79, 2.65]	0.22	11	0.37	0.02
1993Q4 –2007Q1	2007Q2	2.43	1.92	[1.04, 2.79]	0.52	10	0.37	0.02
1993Q4 –2007Q2	2007Q3	2.69	2.40	[1.48, 3.30]	0.30	10	0.35	0.02
1993Q4 –2007Q3	2007Q4	2.75	2.56	[1.69, 3.44]	0.19	11	0.30	0.02
1993Q4 –2007Q4	2008Q1	2.75	2.56	[1.69, 3.42]	0.19	11	0.31	0.02
1993Q4 –2008Q1	2008Q2	2.58	2.54	[1.67, 3.40]	0.04	11	0.32	0.02
1993Q4 –2008Q2	2008Q3	2.78	2.34	[1.49, 3.19]	0.45	11	0.32	0.02

[a] Denotes a number of models included in Occam's window.

Table 8: One-step ahead forecast results: ARDL model

Estimation sample	Forecast period	$Y_{\tau+1}$	$\widehat{Y}_{\tau+1\|\tau}$	Predictive interval (95%)	$Y_{\tau+1} - \widehat{Y}_{\tau+1\|\tau}$	Models[a]	Posterior probability Max	Min
1993Q4 –2004Q3	2005Q1	-0.57	0.00	[-0.75, 0.79]	-0.57	10	0.41	0.02
1993Q4 –2004Q4	2005Q2	-0.24	-0.03	[-0.86, 0.79]	-0.21	16	0.35	0.02
1993Q4 –2005Q1	2005Q3	0.07	0.05	[-0.78, 0.87]	0.01	14	0.36	0.02
1993Q4 –2005Q2	2005Q4	0.33	0.33	[-0.47, 1.13]	0.00	14	0.36	0.02
1993Q4 –2005Q3	2006Q1	0.61	0.46	[-0.35, 1.27]	0.15	14	0.36	0.02
1993Q4 –2005Q4	2006Q2	0.56	0.86	[0.07, 1.68]	-0.30	14	0.36	0.02
1993Q4 –2006Q1	2006Q3	1.07	1.27	[0.45, 2.08]	-0.20	13	0.37	0.02
1993Q4 –2006Q2	2006Q4	1.74	1.55	[0.75, 2.36]	0.19	13	0.37	0.02
1993Q4 –2006Q3	2007Q1	1.96	1.56	[0.78, 2.35]	0.40	13	0.37	0.02
1993Q4 –2006Q4	2007Q2	2.43	1.97	[1.16, 2.75]	0.46	12	0.38	0.02
1993Q4 –2007Q1	2007Q3	2.69	2.19	[1.42, 2.96]	0.51	14	0.36	0.02
1993Q4 –2007Q2	2007Q4	2.75	2.52	[1.71, 3.34]	0.22	16	0.33	0.02
1993Q4 –2007Q3	2008Q1	2.75	2.61	[1.82, 3.39]	0.14	21	0.21	0.01
1993Q4 –2007Q4	2008Q2	2.58	2.43	[1.66, 3.21]	0.15	21	0.21	0.01
1993Q4 –2008Q1	2008Q3	2.78	2.54	[1.75, 3.32]	0.24	22	0.21	0.01

[a] Denotes a number of models included in Occam's window.

Table 9: One-step ahead forecast results: AR model

Estimation sample	Forecast period	$Y_{\tau+1}$	$\widehat{Y}_{\tau+1\|\tau}$	Predictive interval (95%)	$Y_{\tau+1} - \widehat{Y}_{\tau+1\|\tau}$	Models[a]	Posterior probability Max	Min
1993Q4 –2004Q3	2005Q1	-0.57	0.04	[-1.33, 1.46]	-0.57	7	0.36	0.05
1993Q4 –2004Q4	2005Q2	-0.24	-0.40	[-1.77, 0.96]	-0.24	8	0.30	0.02
1993Q4 –2005Q1	2005Q3	0.07	-0.42	[-1.81, 0.99]	0.07	8	0.28	0.02
1993Q4 –2005Q2	2005Q4	0.33	-0.08	[-1.47, 1.29]	0.33	8	0.29	0.02
1993Q4 –2005Q3	2006Q1	0.61	0.24	[-1.11, 1.62]	0.61	8	0.30	0.02
1993Q4 –2005Q4	2006Q2	0.56	0.46	[-0.89, 1.80]	0.56	8	0.28	0.02
1993Q4 –2006Q1	2006Q3	1.07	0.65	[-0.71, 1.99]	1.07	7	0.28	0.05
1993Q4 –2006Q2	2006Q4	1.74	0.50	[-0.88, 1.81]	1.74	7	0.29	0.04
1993Q4 –2006Q3	2007Q1	1.96	0.98	[-0.32, 2.32]	1.96	7	0.29	0.04
1993Q4 –2006Q4	2007Q2	2.43	1.62	[0.23, 3.01]	2.43	7	0.33	0.04
1993Q4 –2007Q1	2007Q3	2.69	1.79	[0.40, 3.24]	2.69	7	0.32	0.04
1993Q4 –2007Q2	2007Q4	2.75	2.20	[0.76, 3.68]	2.75	8	0.27	0.01
1993Q4 –2007Q3	2008Q1	2.75	2.31	[0.93, 3.72]	2.75	7	0.28	0.05
1993Q4 –2007Q4	2008Q2	2.58	2.33	[0.96, 3.73]	2.58	7	0.28	0.04
1993Q4 –2008Q1	2008Q3	2.78	2.34	[0.98, 3.65]	2.78	7	0.29	0.04

[a] Denotes a number of models included in Occam's window.