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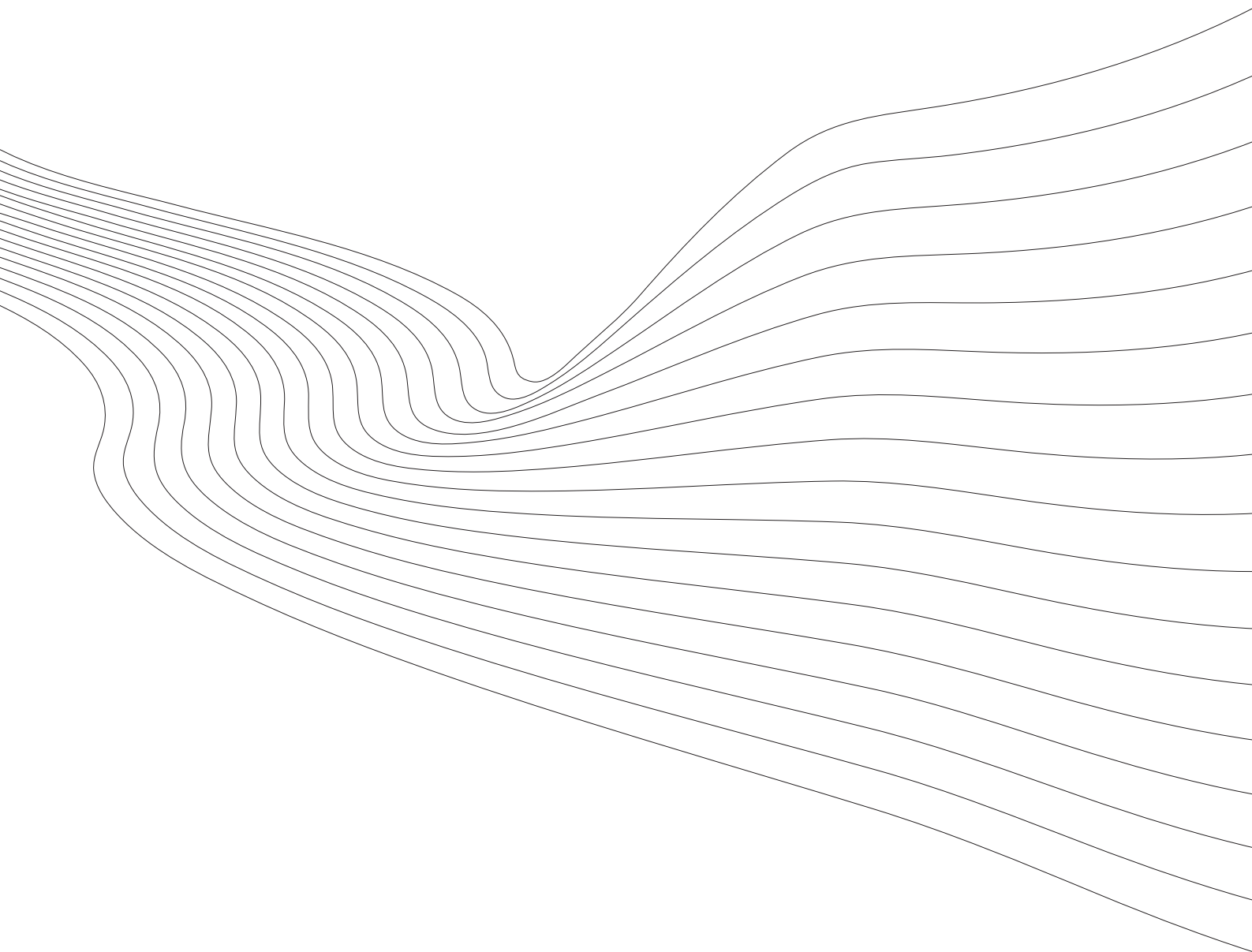
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KOF Working Papers

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Assessing Predictive Content of the KOF Barometer in Real Time*

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Abstract

We investigate whether the KOF Barometer—a leading indicator regularly released by the KOF Swiss Economic Institute—can be useful for short-term out-of-sample prediction of year-on-year quarterly real GDP growth rates in Switzerland. We find that the KOF Barometer appears to be useful for prediction of GDP growth rates. Even the earliest forecasts, made seven months ahead of the first official GDP estimate, allow us to predict GDP growth rates more accurately than forecasts based on an univariate autoregressive model. At every subsequent forecast round as new monthly releases of the KOF Barometer become available we observe a steady increase in forecast accuracy.

Keywords: Leading indicators, forecasting, Bayesian model averaging, Switzerland

JEL code: C53, C22.

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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—usually measured by GDP—stems from the fact that quarterly GDP data are only available with a significant delay. In case of the United States such delay is about one month after the end of the reference quarter and in the European countries GDP data are released with delay of about two months. Moreover, as practice shows, the first release of GDP data often undergoes (substantial) revisions made by statistical agencies as more complete information becomes available later.

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 the coincident/leading indicators (both quantitative and qualitative) that are readily available to decision makers and whose publication precedes that of quarterly GDP data, or any other data of interest. The quantitative indicators are either macroeconomic or financial variables. A typical example of the quantitative coincident indicators are industrial production, total personal income less transfer payments, total manufacturing and trade sales, and employees on nonagricultural payrolls, available at the monthly frequency, that were used in Stock and Watson (1988) to construct a coincident index model. The qualitative indicators are constructed on basis of business and consumer tendency surveys and they reflect an assessment of the current situation as well as recent and expected developments as perceived by businessmen and consumers, respectively.

In this paper, we investigate the usefulness of the leading indicator (the KOF Barometer) for short-term forecasting of GDP growth rates in Switzerland. The multi-sectoral KOF Barometer is regularly released on the monthly basis by the KOF Swiss Economic Institute. The principal use of the KOF Barometer is to provide a snapshot of the current economic situation well ahead of the first official release of the quarterly growth rates of real GDP, typically published after two months of the end of a reference quarter. The reference time series is the real GDP observed at the quarterly frequency released by the Swiss State Secretariat for Economic Affairs (Seco). Our aim is to assess predictive value¹ of the KOF Barometer by comparing predictions of GDP growth rates produced with the model that includes the KOF Barometer against those produced with a benchmark univariate autoregressive model. To this end, we compare accuracy of forecasts made starting as early as seven months ahead of the first official publication for a reference quarter. Furthermore, we capitalize on the fact that the KOF Barometer is released at the end of each month and, subsequently, produce the sequence of forecasts that precede the first official release by six, five, four, three, and two months; such that, the last forecast is made at the very end of a reference quarter. In addition to verifying the presence of the predictive value of the BTS, this sequential approach to forecasting allows us to address questions like, 1) Do earliest forecasts have any predictive value of GDP growth rates?, 2) How quickly improvement in forecast accuracy takes place as additional information is incorporated into forecasting equation, or at which forecast horizon additional information results in largest marginal increase in forecast accuracy? 3) Has the predictive content of the KOF Barometer been affected by the current

¹According 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”.

crisis?

Our study contributes to the literature in the following two ways. First, it is worth mentioning that despite of the widespread use of business tendency surveys in forecasting of either GDP or manufacturing/industrial growth rates (e.g., see Abberger, 2007; 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*), in most cases, the forecasts are made using the latest-available data. The importance of using real-time 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 forecasting properties of leading indicator models is still limited as collection of such databases is rather a formidable task. In sum, the question on predictive value of leading indicators is far from being resolved as there is a rather limited number of studies that address this question in real time. Therefore, additional studies further investigating this question are needed. Hence, the main contribution of our study to the forecasting literature is that we provide an additional empirical piece of work that utilizes the real-time approach in assessing predictive value of leading indicators—constructed from business tendency surveys—for short-term forecasting of GDP growth rates.

Secondly, 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.

The rest of the paper is structured as follows. Section 2 relates the present paper to earlier research on forecasting the Swiss GDP using the tendency surveys. Section 3 describes the data used in our predictive exercise. The econometric model utilized in our study is described in Section 4. Section 5 discusses results of out-of-sample predictions. The final section concludes.

2 Literature review

In Switzerland, Business Tendency Surveys are collected at the KOF Swiss Economic Institute at the Swiss Federal Institute of Technology (ETH), Zurich. Consequently, most of the research involving BTS has been done at KOF. An interested reader may consult the following studies: Jacobs and Sturm (2009), Köberl and Lein (2008), Müller and Köberl (2008b), Müller, Wirz, and Sydow (2008), Rupprecht (2008), Schenker (2008), Graff and Etter (2004), and Etter and Graff (2003). However, there are only two studies—Graff (2009) and Müller and Köberl (2008a)—that are directly related to our study as they evaluate predictive value of business tendency surveys for Swiss GDP.

At the KOF Swiss Economic Institute, assessing of the current economic situation with tendency surveys has a long tradition. The first version of the KOF Barometer was developed in 1976 and its slightly modified version in 1998 has been published until March 2006. Since April 2006, the traditional KOF Barometer has been substituted with the new KOF Barometer based on the multi-sectoral design (Graff, 2006, 2009). Graff (2009) compares predictive accuracy of the old KOF Barometer with that of a new one for the forecast period from 2003Q1 until 2006Q2. The most interesting feature of Graff (2009) is that a distinction between real-time and latest-available data is clearly made in construction and using the constructed barometer in out-of-sample forecasting. However, while coming close to simulating forecasting exercise in real time, Graff (2009) utilizes for forecast comparison the latest-available figures for the reference time series of real GDP as they were known in 2006Q3. This fact may somewhat bias the reported results when compared with those that could have been obtained in a genuine real-time exercise; i.e., when real-time vintages for both time series of a leading indicator and a reference time series are utilized. Graff (2009) reports a significant improvement in forecast accuracy of the new KOF Barometer over the traditional one. This, however, might be at least partly explained by the fact that the components of the new KOF Barometer have been pre-selected using the information for the whole forecast period that was not available to a forecaster had he made his predictions in real time.

Müller and Köberl (2008a) suggest a novel approach to using BTS for forecasting of GDP growth rates that is based on semantic cross validation analysis of firms' answers to BTS questionnaires. The main feature of the approach of Müller and Köberl (2008a) is that the constructed indicator is available in real time, undergoes no revisions, and it is based on a single indicator rather than on pooling information from several indicators as done in case of the KOF Barometer. However, in contrast to the KOF Barometer that is released every month, the indicator of Müller and Köberl (2008a) is only available at a quarterly frequency. Müller and Köberl (2008a) present the results of an out-of-sample forecasting exercise suggesting that their approach to constructing a leading indicator is useful for out-of-sample forecasting of GDP growth rates, but, again, the latest-available GDP data have been used in evaluating the predictive value of this semantic indicator. Nevertheless, it must be added that the semantic approach to GDP forecasting is an ongoing endeavor and at present real-time forecasts are regularly released every quarter since 2007Q4. Due to the fact that Müller and Köberl (2008a) suggest a rather different way to construct a leading indicator we view their approach to GDP forecasting complementary to ours rather than substitutive. Future research will

shed more light on comparative advantages of these two approaches, provided that there will be a sufficient amount of real-time forecasts.

In sum, while we address a similar question as in Graff (2009) and Müller and Köberl (2008a) our study distinguishes itself from those two papers at least in two important aspects. First of all, we conduct our exercise in real time; i.e., using real-time vintages both for the KOF Barometer as well as for the GDP growth rates. This also means that the composition of the KOF Barometer has not been subject to pre-selection using information for the whole forecast period that was not available in real time. Secondly, Graff (2009) and Müller and Köberl (2008a) utilize a single-best model approach in forecasting of GDP growth rates, whereas we employ a Bayesian model averaging framework allowing us to take into account two additional sources of uncertainty omitted from either of these two studies: parameter estimation as well as, more importantly, model selection uncertainties.

3 Data

The reference time series is the real GDP observed at the quarterly frequency released by the Swiss State Secretariat for Economic Affairs (Seco)[code: TS41808000] being forecast with the KOF Barometer [code: TS12130800]. Both time series were downloaded from the KOF Database. We conduct the exercise in real time. For this purpose, we employ the vintages of the KOF Barometer starting with the earliest vintage released in April 2006. This implies that we can use the KOF Barometer for earliest prediction of GDP growth rates starting with the forecast for the third quarter of 2006. We end our forecasting exercise in 2009Q3; i.e., the latest quarter for which the data has been officially released to date. Since we aim predicting the GDP growth rates released at the first official publication, we employ the real-time dataset of all GDP releases starting with the fourth quarter of 2005.

4 Model

Since the Seco releases GDP figures in the beginning of the third month in each quarter; i.e., two months later after the end of the reference quarter, and since the KOF Barometer is published at the end of every month, we have opted for the following forecast timing setup, see Table 1. Table 1 illustrates our sequential approach to making forecasts of GDP growth rates subject to availability of both KOF Barometer and of GDP figures in real time. Our first GDP forecast for the target quarter $\tau + 1$ is made in the beginning of the second month of the previous quarter τ when the values of the KOF Barometer are available for the first months of the current quarter τ . At this moment, the GDP figure is only available for the quarter $\tau - 2$. The second forecast round takes place in the beginning of the third month of quarter τ when the GDP figure for the previous quarter $\tau - 1$ are released. The dark-gray color correspondingly illustrates for which months and quarter(s) both the barometer and the GDP values are available at each forecast round. Similarly, we make the third and the fourth forecasts when our information set has been increased by the values of the KOF Barometer for the third month of the quarter τ and for the first months of the quarter $\tau + 1$, respectively.

Observe that the fifth and the final sixth forecasts are made when information set increases not also because of the respective values of the KOF Barometer for the second and the third months of the quarter $\tau + 1$ but also due to newly published GDP figures for the quarter τ . In sum, we produce the sequence of six forecasts for every quarter accounting for data availability at the end points of our sample. This means that our first forecast precedes the first official release of GDP data by seven months and our last forecast—by two months.

Such asynchronous release of the GDP data as well as of the KOF Barometer implies that we have a missing end-point problem. We overcome this feature of our data set by shifting the whole time series of the KOF Barometer forward to cover all months of the target quarter $\tau + 1$. In this way, we estimate model parameters for the sample for which both values of GDP and of the indicator are available and use the future values of the indicator that now are available for the target quarter in order to obtain out-of-sample forecasts. In Table 1 we show the months for which we shift the KOF Barometer at each forecast round by light-gray color.

The model that corresponds to such a solution of the missing end-point problem is the autoregressive distributed lag (ARDL) model in the following form:

$$Y_\tau = \alpha_0 + \sum_{i=i^*}^p \alpha_i Y_{\tau-p} + \sum_{j=0}^q \beta_j X_{\tau-q} + \varepsilon_\tau, \quad (1)$$

where Y_τ is the year-to-year quarterly growth rates of real GDP observed in quarter τ . We calculate Y_τ by taking the fourth-order difference of the logarithmic transformation of the reference time series. X_τ is an appropriate quarterly aggregation of monthly values of the KOF Barometer $X_{\tau,t}$ for $t = 1, 2, 3$; first, we shift forward the values of the KOF Barometer as described above; second, we keep observations corresponding to the last month of each calendar quarter. Observe that the index i^* takes values of three for the first forecast round, two—for the second, third, and fourth forecast rounds, and it takes value of one for the fifth and the last, sixth, forecast rounds, reflecting the availability of GDP data for the respective forecast rounds. ε_τ is a disturbance term satisfying usual model assumptions.

As a benchmark model we chose the following univariate autoregressive model which is naturally nested in the ARDL model above:

$$Y_\tau = \alpha_0 + \sum_{i=i^*}^p \alpha_i Y_{\tau-p} + \varepsilon_\tau. \quad (2)$$

It retains the same structure as Equation (1) but excludes values of the leading indicator. By comparing the forecasts produced by the model with the leading indicator with those produced by such a benchmark model, we can evaluate both in-sample as well as out-of-sample predictive content of the KOF Barometer.

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 uncer-

tainty, 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 GDP growth rates can be readily calculated.

Another advantage of the BMA procedure is that it allows one to evaluate the informative content of the leading indicator in the current setup as follows. If the leading indicator has a low in-sample explanatory power than models involving this indicator will receive a rather low posterior probability. This implies that models without the KOF Barometer will be assigned higher posterior probability than models with the leading indicator. The opposite is, of course, possible. If the KOF Barometer has a large predictive content for the reference time series, then models with that indicator will dominate model specifications without this indicator in terms of the assigned posterior probability.

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.

5 Results

In this section we present our estimation results addressing the following three questions regarding the out-of-sample predictive ability of the chosen leading indicator:

1. Do earliest forecasts have any predictive value of GDP growth rates?
2. How quickly improvement in forecast accuracy takes place as additional information is incorporated in forecasting equation, or at which forecast horizon additional information results in largest marginal increase in forecast accuracy?
3. Has forecasting ability of the model with the KOF Barometer been affected by recent crises?

However, before addressing these three questions presented above we first report in-sample estimation results based on the BMA procedure using the symmetric Occam’s window². A typical output of the BMA procedure is reported in Table 2. The estimation sample used in the sixth forecast round corresponds to the period from 1993(4) until 2009(2). The forecast quarter is 2009(3). According to the forecasting scheme described in Table 1, at this forecast round the values of the KOF Barometer are available up to the last month of the third quarter of 2009 and the GDP data are available until 2009(2). As seen, a total number of 17 models have been selected into the Occam’s window with the maximum and minimum posterior probability of 0.301 and 0.015. The model with the highest posterior probability turns out to be the most parsimonious model with the following regressors: own lags of the dependent variable $Y_{t-1}, Y_{t-4}, Y_{t-5}$ and the contemporaneous value of the KOF Barometer X_t , justifying leading-indicator properties of the KOF Barometer. Furthermore, according to the inclusion frequency the contemporaneous value of the KOF Barometer has been retained in every of the selected 17 models; another fact illustrating potential relevance of the KOF-Barometer for short-term forecasting of GDP growth rates in Switzerland.

In Table 3 we report the summary of the BMA for every forecast round and every forecast quarter, generalizing the estimation results reported in the previous paragraph for a single forecast quarter and a single forecast round. In order to save space we report number of models selected in symmetric Occam’s window, model maximum and minimum posterior probabilities, and, most importantly, inclusion probability of the contemporaneous value of the KOF Barometer in the selected models in Occam’s window. Observe that with exception of the first forecast round³, we generally observe decreasing model selection uncertainty (measured either by a number of models selected into Occam’s window or model maximum posterior probability) for a given forecast quarter due to additional information added into forecasting equation in the form of newly released values of the GDP and the KOF Barometer. It is rather remarkable that in all but three cases reported in Table 3 the inclusion probability of the contemporaneous value of the KOF Barometer X_t is 100%, i.e., it has been retained in every model selected in Occam’s window practically for all forecast rounds and all forecast quarters. This strongly indicates that the KOF Barometer possesses leading-indicator properties, based on in-sample evidence at least. Of course, the next task is investigating whether this encouraging conclusion also holds in out-of-sample forecasting exercise.

In order to answer the first posed question on how far in future can we forecast using the KOF Barometer we computed the root mean squared forecast errors (RMSFE) for the both models estimated with and without the barometer. The corresponding RMSFE along with some basic descriptive statistics of the observed forecast errors are reported in Table 4 for the whole forecast sample, 2006(3)–2009(3). As seen, for all forecast rounds, the model with the KOF Barometer yields a sizable improvement in forecast accuracy over that reported for the univariate model. In fact, depending on a forecast round, the corresponding ratio

²Bayesian 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. The maximum ratio of 20 for excluding models in Occam’s window has been used.

³A rather small number of models selected into the Occam’s window at the first forecast round e.g. compared to that for the second forecast round can be explained by the fact that the forecast model employed for the first round is smaller than that employed for the second forecast round. The former model has only three own lags of the dependent variable $Y_{t-3}, Y_{t-4}, Y_{t-5}$ whereas the other model has four lags— $Y_{t-2}, Y_{t-3}, Y_{t-4}, Y_{t-5}$, reflecting the availability of GDP data in real time, see Section 4 and Table 1 for model specification and timing setup.

of the RMSFE of the ARDL model to that of the AR model varies between 0.56 and 0.72, implying an improvement in forecast accuracy up to 44% in terms of RMSFE. It is also worthwhile mentioning that the corresponding ratio for the earliest forecast round is solid 0.59, implying that substantial gains in forecast precision can be achieved by using the model with the KOF Barometer as early as seven months before the official release of GDP data. As expected, we observe further increase in forecast accuracy with every forecast round as new information in terms of both GDP and the KOF Barometer values is incorporated in every sequential forecast round. Thus, for the ARDL model the RMSFE falls from 1.21 reported for the first forecast round to 0.58 in the last sixth forecast round. For the univariate AR model the corresponding values of the RMSFE are 2.06 and 0.87, respectively. The model with the KOF Barometer produces also lower maximum forecast error than that observed for the AR model and the forecasts of the former model appear to be less biased than those of the latter model, although we observe a tendency of both models to overpredict actual GDP growth rates. The forecasts of both the ARDL and AR models along with the corresponding 95% predictive intervals as well as the actual realizations of the real GDP quarterly year-on-year growth rates are reported in Figures 1–6 for each forecast round.

The information reported in Table 4 also allows us to address the second question at which forecast round the largest improvement in forecast accuracy is achieved. The column labeled as “Marginal improvement” reports the relative reduction in RMSFE at a given forecast round compared to the previous forecast round. Unsurprisingly, for the AR model we observe that reduction in RMSFE only occurs at the second and fifth forecast rounds when, according to Table 1, an update of the GDP takes place. On the contrary, for the ARDL model we observe reduction in RMSFE at each sequential forecast round, indicating that incorporation of more recent values of the KOF Barometer (as well as of the GDP data) into the forecasting equation results in gradual improvement in forecast accuracy. The largest marginal reduction in relative RMSFE by 28% and 44% for both ARDL and AR models, respectively, occurs at the fifth forecast round, i.e., about three months before an official release.

Finally, in order to address the third question on whether forecasting ability of the model with the KOF Barometer has been changed during the current crisis compared to that observed in the pre-crisis period. The relevant information is presented in Table 5 where we report RMSFE computed over the rolling window of eight quarters rather than for the whole forecast period as displayed in Table 4 above. Several observations can be made. First, similarly to the results observed for the whole forecast period, for a given rolling forecast window we observe a steady increase in forecast accuracy with each forecast round as more timely information is incorporated into forecasting equation; this equally refers to the ARDL as well as the univariate AR model. Secondly, for the first four forecast rounds both for the ARDL and AR models we observe a sharp deterioration in forecast accuracy starting from the rolling window 2007(1)–2008(4) compared to that observed for two previous rolling windows 2006(3)–2008(2) and 2006(4)–2008(3). A further decrease in forecasting accuracy takes place for the next rolling window 2007(2)–2009(1). The associated deterioration in forecast accuracy could be explained by relatively large forecast errors in quarters 2008(4) and 2009(1) as reflected in Figures 1–6. For the last two rolling windows for these four forecast rounds the magnitude of RMSFE largely remains stable. Thirdly, for the last two forecast rounds for the ARDL

model we observe increase in RMSFE starting from the rolling window 2007(1)–2008(4) which stabilizes at the window 2007(3)–2009(2). The evolution of RMSFE for each rolling window and forecast round is graphically summarized in Figure 7. All in all, we can conclude that the magnitude of RMSFE observed for the pre-crisis period has increased about two times compared to the period that also includes the current crisis. However, this increase in RMSFE took place proportionally both for the ARDL and AR models such that the ratio of RMSFE of these two models has been affected to a much smaller degree and depending on evaluation window and forecast round takes values in the interval from 0.48 till 0.74 as shown in the lower panel of Table 5. These values of the relative RMSFE are compatible with those observed for the whole forecast period reported in Table 4.

6 Conclusion

In this paper we investigate whether the leading-indicator model based on the KOF Barometer which is regularly published by the KOF Swiss Economic Institute on a monthly basis has any predictive power that can be used for short-term forecasting of year-on-year quarterly real GDP growth rates in Switzerland well ahead of the official data release by the Swiss State Secretariat for Economic Affairs (Seco). The forecasting accuracy of the model with the KOF Barometer has been compared to a benchmark univariate autoregressive model. Since the KOF Barometer is based on the business tendency surveys collected at the KOF, we also investigate a more general question whether surveys, that are based on qualitative or “soft” data, are useful for a quantitative short-run prediction of the so-called “hard” data. To this end, we produced a sequence of forecasts for every quarter during the forecast sample from 2006(3) until 2009(3). We start with the first forecast made about seven months ahead of GDP release by Seco, followed by the second forecast that precedes GDP release by six months, etc., till the final sixth forecast made about two months ahead of the first official GDP estimate. The important feature of our forecasting exercise is that at every forecast vintage we employ the real-time data set that could have been available to a forecaster at the respective time in the past. The real-time data set constructed for this purpose includes all real-time vintages of GDP data as well as of the KOF Barometer.

Our main findings are as follows. First, the model with the KOF Barometer provides a substantial improvement in forecast accuracy over the benchmark model as far as seven months ahead of the official data release. Second, at every subsequent forecast round we observe increase in forecast accuracy as reflected in steadily declining values of RMSFE criterion. The value of RMSFE for a model with the KOF Barometer decreases from 1.21 achieved at the first forecast round till 0.58—at the last sixth forecast round. This has to be compared to the corresponding values attained by the autoregressive model: 2.06 and 0.87, for the first and sixth forecast rounds, respectively. The largest increase in forecast accuracy, however, is achieved at the fifth forecast round; i.e., about three months ahead of an official data release. Third, during the period of current crisis we find that the forecasting ability of the model with a leading indicator has deteriorated in absolute value. Using the rolling window for computation of RMSFE, we find that for the leading-indicator model inclusion of the quarters when the current crisis has been unfolding resulted in twice as large values of

RMSFE compared to that reported for the pre-crisis period. At the same time, we would like to emphasize that forecast accuracy produced by the benchmark model has also deteriorated to a similar degree such that in relative terms the forecasting performance of the model with the KOF Barometer remained relatively unaffected by recent economic crisis.

All in all, based on the reported results of our forecast exercise the KOF Barometer possesses a definite predictive content that can be used for early forecasts as well as nowcasts of the GDP growth rates up to seven months prior to an official release.

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Table 1: Data release schedule in real time

Forecast round	Quarter Month	$\tau - 1$			τ			$\tau + 1$		
		I	II	III	I	II	III	I	II	III
1	KOF Barometer									
	GDP									
2	KOF Barometer									
	GDP									
3	KOF Barometer									
	GDP									
4	KOF Barometer									
	GDP									
5	KOF Barometer									
	GDP									
6	KOF Barometer									
	GDP									

Notes: Table describes the sequence of forecasts for the target quarter $\tau + 1$. The first forecast is made in the beginning of the second month of the quarter τ , when values of the KOF Barometer are available for the first month of the quarter τ . At this time the GDP data are only available for the quarter $\tau - 2$. The dark-gray color in the table indicates that both the KOF Barometer and the GDP are available up to the corresponding month and the quarter. Given the publication lag of about two months of the GDP, the earliest forecast precedes the official release by seven months. The second forecast round takes place in the beginning of the third month of the quarter τ , when values of the KOF Barometer are available for the second month of the quarter τ . At this time the GDP data for the quarter $\tau - 1$ becomes available. The next forecast takes place in the beginning of the first month of the quarter $\tau + 1$, when the value of the KOF Barometer is already known for the last month of the quarter τ , etc. The light-gray color indicates the missing end points that are filled with values of the KOF Barometer time series by shifting it forward in order to conform with specification of the ARDL equation (1).

Table 2: Results of the BMA procedure (symmetric Occam’s window), 1993(4)–2009(2), Forecast round 6

Regressors	Inclusion frequency ^a	EV ^b	SD ^c	Model						
				1	2	3	4	5	6	7
Incpt	100	-0.37	0.19	-0.37	-0.33	-0.34	-0.42	-0.38	-0.40	-0.35
Y_{t-1}	100	0.80	0.12	0.74	0.88	0.93	0.71	0.72	0.73	0.75
Y_{t-2}	44.6	-0.11	0.16	.	-0.19	-0.36
Y_{t-3}	19	0.04	0.11	.	.	0.26
Y_{t-4}	100	-0.43	0.13	-0.44	-0.36	-0.53	-0.45	-0.44	-0.45	-0.43
Y_{t-5}	100	0.44	0.10	0.44	0.42	0.46	0.45	0.45	0.45	0.44
X_t	100	0.62	0.11	0.64	0.61	0.61	0.63	0.57	0.65	0.64
X_{t-1}	8.8	0.01	0.07	0.12	.	.
X_{t-2}	10.4	0.01	0.06	.	.	.	0.10	.	.	.
X_{t-3}	8.4	0.01	0.05	0.03	.
X_{t-4}	6.1	0.00	0.03	-0.03
X_{t-5}	6.1	0.00	0.04
nVar				4	5	6	5	5	5	5
R^2				0.850	0.856	0.864	0.851	0.851	0.850	0.850
BIC				-102.816	-101.585	-100.615	-99.245	-99.085	-98.736	-98.732
Post. Prob.				0.301	0.163	0.100	0.051	0.047	0.039	0.039

Regressors	Model									
	8	9	10	11	12	13	14	15	16	17
Incpt	-0.38	-0.37	-0.40	-0.41	-0.35	-0.37	-0.36	-0.41	-0.41	-0.36
Y_{t-1}	0.74	0.74	0.84	0.86	0.86	0.88	0.88	0.89	0.91	0.90
Y_{t-2}	.	.	-0.20	-0.22	-0.19	-0.19	-0.20	-0.37	-0.38	-0.36
Y_{t-3}	.	0.02	0.26	0.25	0.26
Y_{t-4}	-0.45	-0.45	-0.37	-0.37	-0.36	-0.38	-0.37	-0.54	-0.53	-0.53
Y_{t-5}	0.44	0.45	0.43	0.43	0.42	0.42	0.42	0.47	0.47	0.47
X_t	0.64	0.65	0.60	0.63	0.53	0.61	0.62	0.60	0.63	0.55
X_{t-1}	0.12	0.11
X_{t-2}	.	.	0.13	0.13	.	.
X_{t-3}	.	.	.	0.11	0.09	.
X_{t-4}	0.05	.	.	.
X_{t-5}	0.02	0.06
nVar	5	5	6	6	6	6	6	7	7	7
R^2	0.850	0.850	0.859	0.858	0.858	0.857	0.857	0.866	0.865	0.864
BIC	-98.702	-98.694	-98.375	-98.122	-97.900	-97.635	-97.561	-97.449	-96.945	-96.842
Post. Prob.	0.039	0.038	0.033	0.029	0.026	0.023	0.022	0.021	0.016	0.015

Notes:

^a Denotes inclusion frequency of each regressor in the models retained in the symmetric Occam’s window, see equation (1).
^{b,c} EV and SD stand for “Expected Value” and “Standard Deviation” of the posterior distribution of the model parameters.

Table 3: Summary of the BMA procedure (symmetric Occam's window), all forecast rounds

Forecast quarter	Forecast round 1				Forecast round 2			
	Number of models ^a	Posterior probability ^b		Inclusion frequency (X_t) ^c	Number of models	Posterior probability		Inclusion frequency (X_t)
		max	min			max	min	
2006(3)	20	0.226	0.014	100	58	0.107	0.005	100
2006(4)	26	0.213	0.011	100	49	0.120	0.006	100
2007(1)	26	0.212	0.011	100	39	0.146	0.008	100
2007(2)	22	0.237	0.013	100	42	0.137	0.007	100
2007(3)	22	0.241	0.012	100	39	0.147	0.007	100
2007(4)	19	0.266	0.017	100	65	0.070	0.004	100
2008(1)	26	0.246	0.014	100	62	0.079	0.004	100
2008(2)	26	0.240	0.013	100	55	0.095	0.005	100
2008(3)	24	0.264	0.016	100	55	0.099	0.005	100
2008(4)	25	0.253	0.013	100	44	0.137	0.007	100
2009(1)	24	0.238	0.014	100	45	0.118	0.006	100
2009(2)	25	0.235	0.012	100	38	0.165	0.008	100
2009(3)	24	0.265	0.014	100	66	0.064	0.003	100
	Forecast round 3				Forecast round 4			
	Number of models	Posterior probability		Inclusion frequency (X_t)	Number of models	Posterior probability		Inclusion frequency (X_t)
		max	min			max	min	
2006(3)	45	0.121	0.006	100	29	0.199	0.010	100
2006(4)	40	0.133	0.007	100	19	0.285	0.016	100
2007(1)	35	0.158	0.008	100	17	0.305	0.019	100
2007(2)	36	0.153	0.008	100	18	0.296	0.015	100
2007(3)	31	0.175	0.009	100	17	0.316	0.018	100
2007(4)	42	0.144	0.008	100	23	0.243	0.013	100
2008(1)	41	0.149	0.008	100	23	0.244	0.012	100
2008(2)	28	0.209	0.011	100	17	0.300	0.021	100
2008(3)	28	0.218	0.011	100	17	0.322	0.019	100
2008(4)	19	0.328	0.017	100	12	0.399	0.024	100
2009(1)	20	0.325	0.017	100	12	0.399	0.024	100
2009(2)	12	0.415	0.021	100	10	0.439	0.030	100
2009(3)	35	0.163	0.008	100	22	0.297	0.015	100
	Forecast round 5				Forecast round 6			
	Number of models	Posterior probability		Inclusion frequency (X_t)	Number of models	Posterior probability		Inclusion frequency (X_t)
		max	min			max	min	
2006(3)	26	0.262	0.013	100	12	0.380	0.022	100
2006(4)	18	0.316	0.016	100	13	0.381	0.019	100
2007(1)	17	0.326	0.017	100	12	0.396	0.020	100
2007(2)	13	0.360	0.019	100	11	0.408	0.023	100
2007(3)	13	0.355	0.018	100	14	0.343	0.019	100
2007(4)	13	0.355	0.018	100	14	0.341	0.019	100
2008(1)	8	0.465	0.065	100	8	0.473	0.066	100
2008(2)	8	0.466	0.064	100	8	0.474	0.065	100
2008(3)	8	0.499	0.065	100	10	0.394	0.051	88.5
2008(4)	8	0.504	0.065	100	11	0.383	0.020	88.8
2009(1)	8	0.505	0.065	100	9	0.435	0.024	97.6
2009(2)	8	0.501	0.064	100	8	0.462	0.059	100
2009(3)	14	0.314	0.025	100	17	0.301	0.015	100

Notes:

^a Denotes number of models selected in symmetric Occam's window.

^b Denotes maximum and minimum of assigned posterior probabilities of the models retained in the symmetric Occam's window.

^c Denotes inclusion frequency of the contemporaneous values of the KOF Barometer X_t in the models retained in the symmetric Occam's window, see equation (1).

Table 4: Forecast results: ARDL vs AR model, 2006(3)–2009(3)

Forecast round	RMSFE			Max forecast error		Mean forecast error		Marginal improvement ^b	
	ARDL	AR	Ratio ^a	ARDL	AR	ARDL	AR	ARDL	AR
1	1.21	2.06	0.59	3.14	4.24	-0.19	-0.33	.	.
2	1.07	1.56	0.68	2.65	3.86	-0.12	-0.31	-0.12	-0.24
3	0.99	1.56	0.64	2.46	3.86	-0.13	-0.31	-0.07	0
4	0.87	1.56	0.56	2.05	3.86	-0.09	-0.31	-0.12	0
5	0.62	0.87	0.72	1.36	2.04	-0.10	-0.22	-0.28	-0.44
6	0.58	0.87	0.67	1.20	2.04	-0.14	-0.22	-0.07	0

Notes:

^a Denotes ratio of the RMSFE of the ARDL model to that of the AR model.

^b Denotes relative marginal improvement in the RMSFE at a given forecast round compared to that of the previous forecast round.

Table 5: Forecast results: ARDL vs AR model, rolling forecast sample

ARDL	Forecast round					
Rolling forecast evaluation window	1	2	3	4	5	6
2006(3)–2008(2)	0.66	0.62	0.57	0.59	0.38	0.35
2006(4)–2008(3)	0.66	0.57	0.50	0.46	0.29	0.28
2007(1)–2008(4)	0.90	0.78	0.73	0.65	0.48	0.45
2007(2)–2009(1)	1.43	1.20	1.11	0.97	0.56	0.52
2007(3)–2009(2)	1.46	1.17	1.10	0.97	0.74	0.67
2007(4)–2009(3)	1.47	1.26	1.17	1.01	0.74	0.69

AR	Forecast round					
Rolling forecast evaluation window	1	2	3	4	5	6
2006(3)–2008(2)	1.21	0.90	0.90	0.90	0.50	0.50
2006(4)–2008(3)	1.18	0.93	0.93	0.93	0.56	0.56
2007(1)–2008(4)	1.44	1.25	1.25	1.25	0.82	0.82
2007(2)–2009(1)	2.06	1.83	1.83	1.83	1.07	1.07
2007(3)–2009(2)	2.39	1.92	1.92	1.92	1.06	1.06
2007(4)–2009(3)	2.48	1.89	1.89	1.89	1.05	1.05

ARDL/AR	Forecast round					
Rolling forecast evaluation window	1	2	3	4	5	6
2006(3)–2008(2)	0.55	0.69	0.63	0.65	0.74	0.69
2006(4)–2008(3)	0.56	0.61	0.54	0.49	0.52	0.50
2007(1)–2008(4)	0.63	0.62	0.58	0.52	0.58	0.54
2007(2)–2009(1)	0.69	0.65	0.61	0.53	0.52	0.48
2007(3)–2009(2)	0.61	0.61	0.58	0.50	0.70	0.63
2007(4)–2009(3)	0.59	0.67	0.62	0.54	0.71	0.66

Notes:

Table entries are RMSFE reported for the rolling window for each forecast round for the ARDL and AR models in the upper and middle panels, respectively. The ratio of RMSFE of the ARDL to that of the AR model is reported in the lower panel.

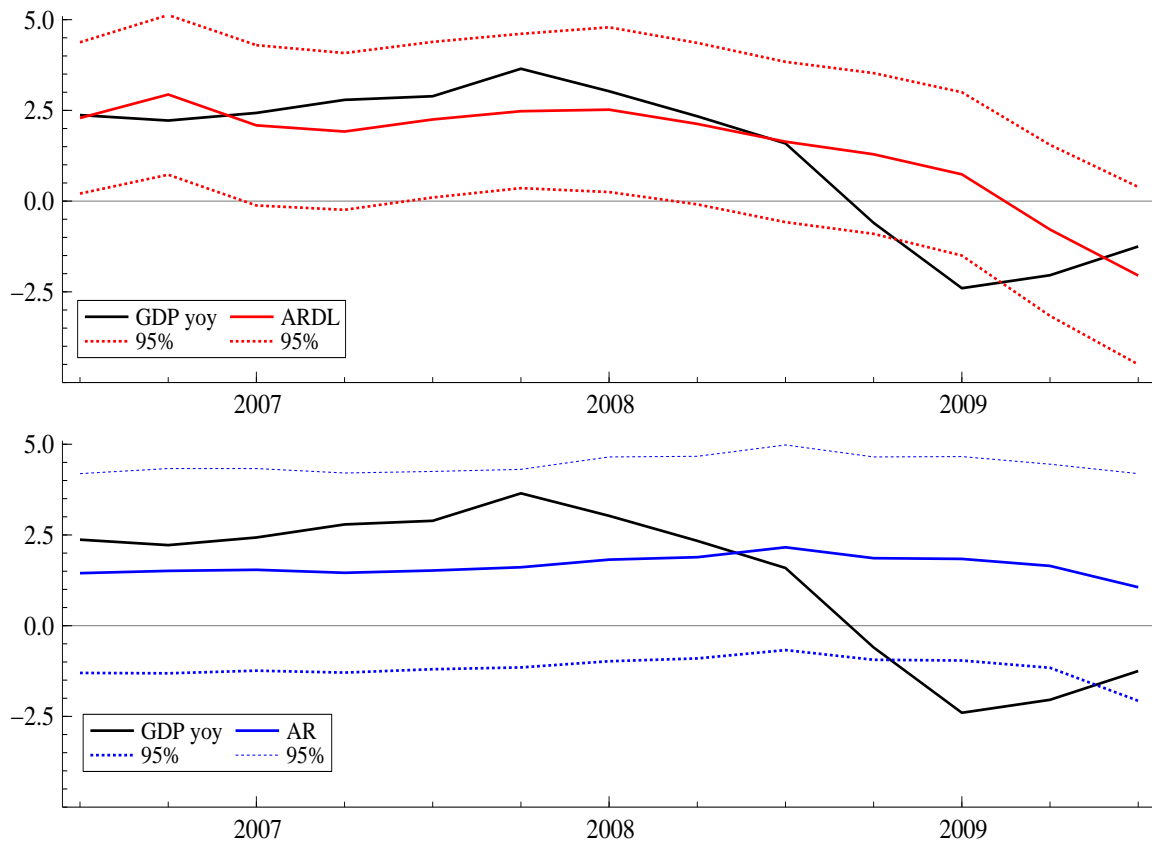


Figure 1: Forecast round 1: (Upper panel) Forecasts of the ARDL model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release); (Lower panel) Forecasts of the AR model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release)

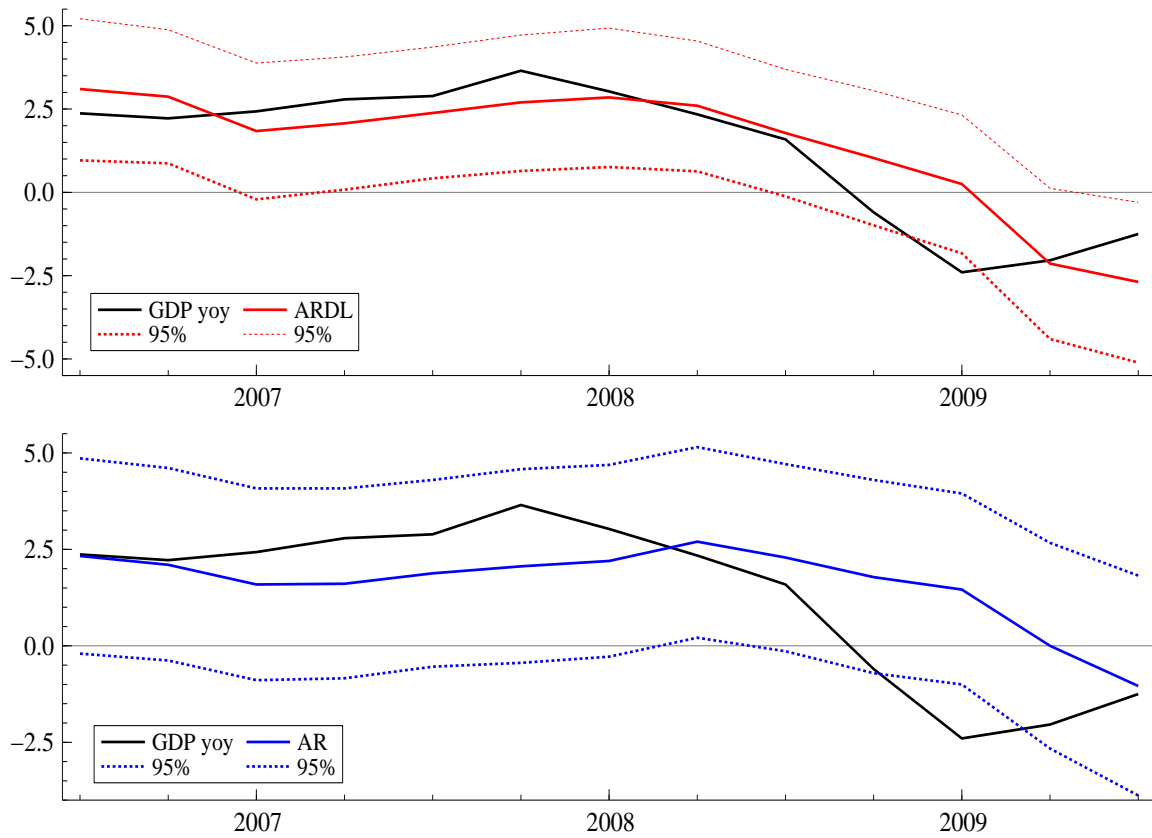


Figure 2: Forecast round 2: (Upper panel) Forecasts of the ARDL model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release); (Lower panel) Forecasts of the AR model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release)

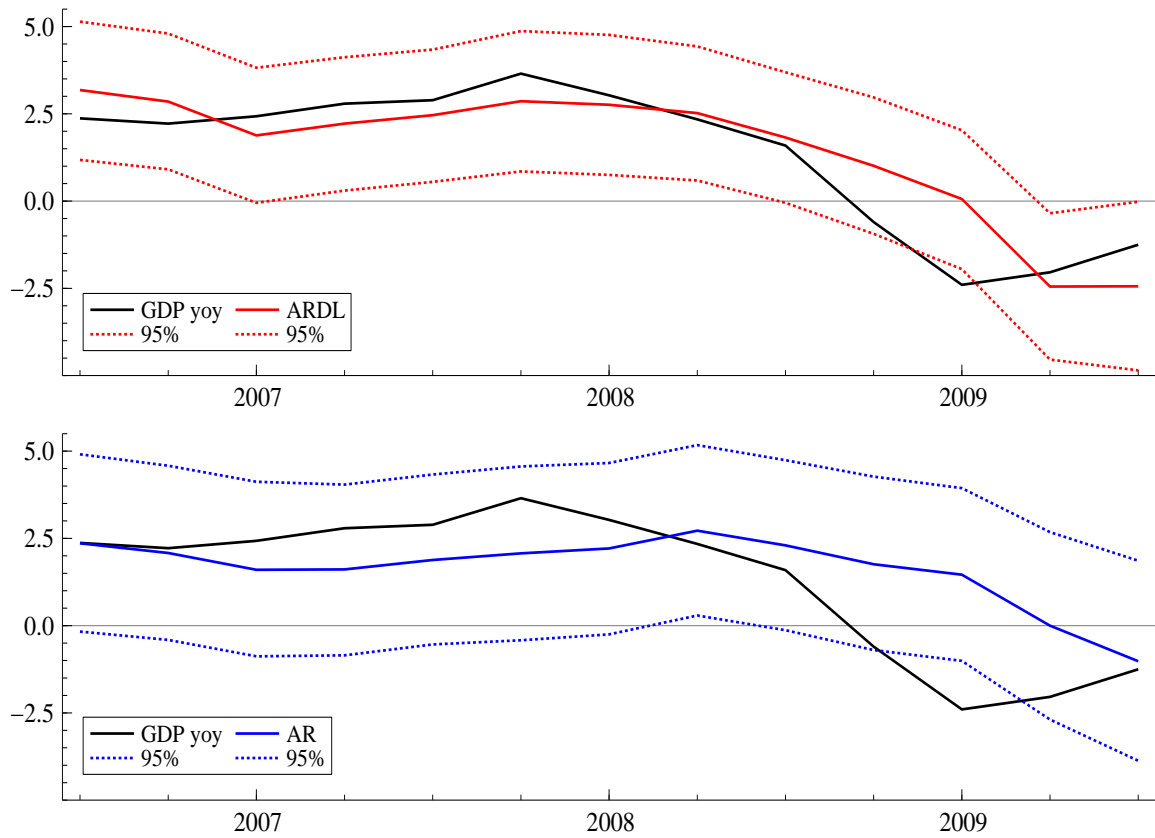


Figure 3: Forecast round 3: (Upper panel) Forecasts of the ARDL model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release); (Lower panel) Forecasts of the AR model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release)

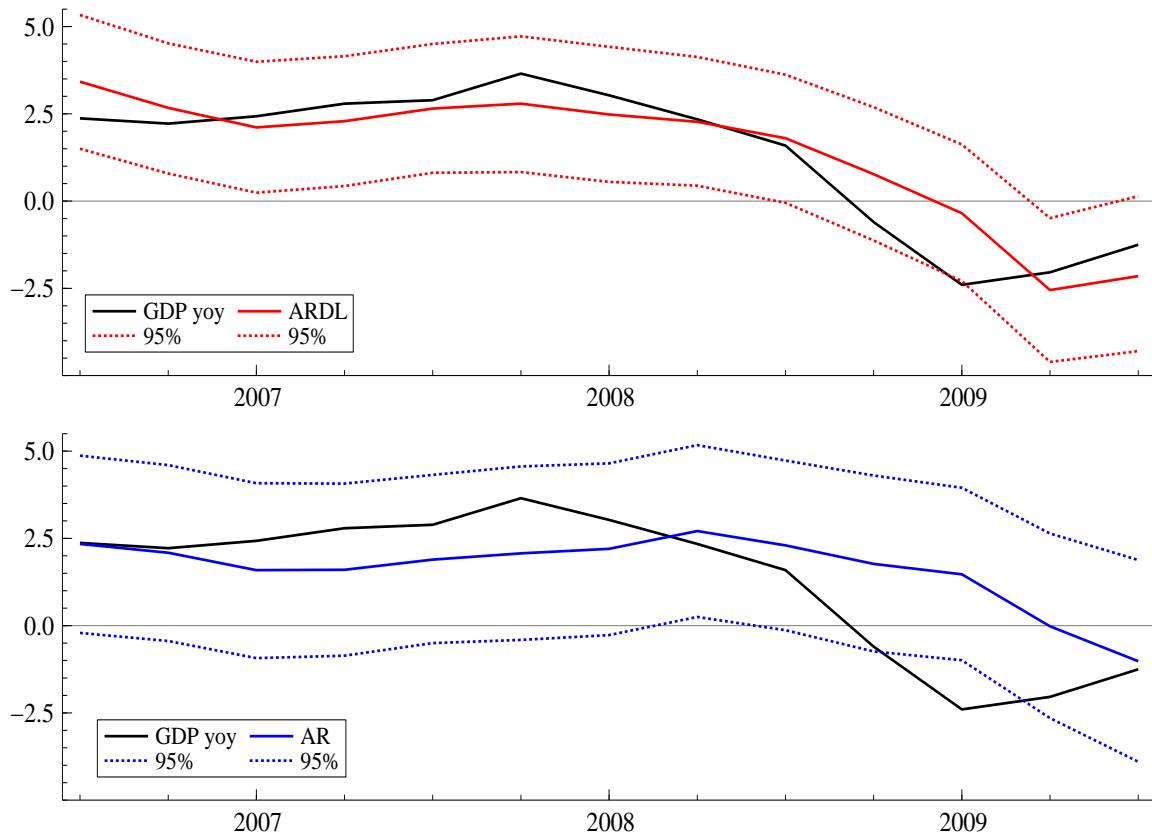


Figure 4: Forecast round 4: (Upper panel) Forecasts of the ARDL model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release); (Lower panel) Forecasts of the AR model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release)

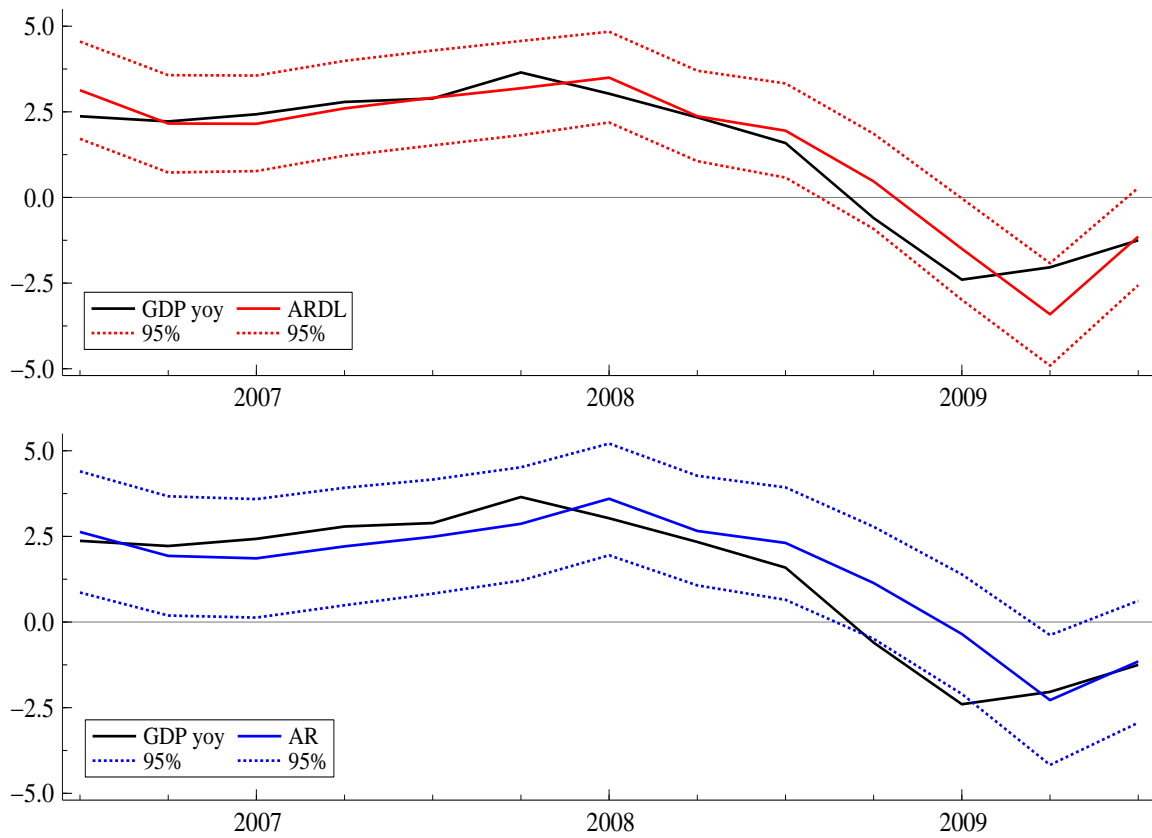


Figure 5: Forecast round 5: (Upper panel) Forecasts of the ARDL model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release); (Lower panel) Forecasts of the AR model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release)

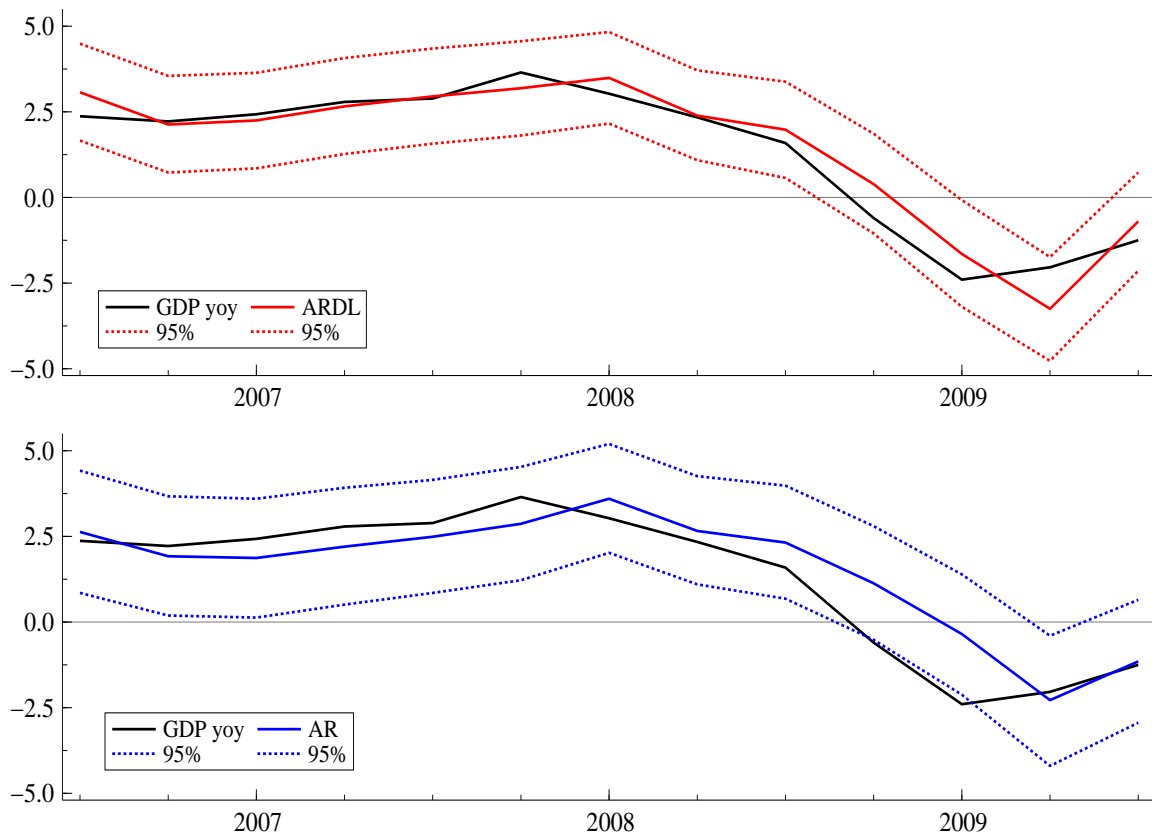


Figure 6: Forecast round 6: (Upper panel) Forecasts of the ARDL model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release); (Lower panel) Forecasts of the AR model with a 95% predictive interval, Actual values of the quarterly year-on-year real GDP growth rates (first release)

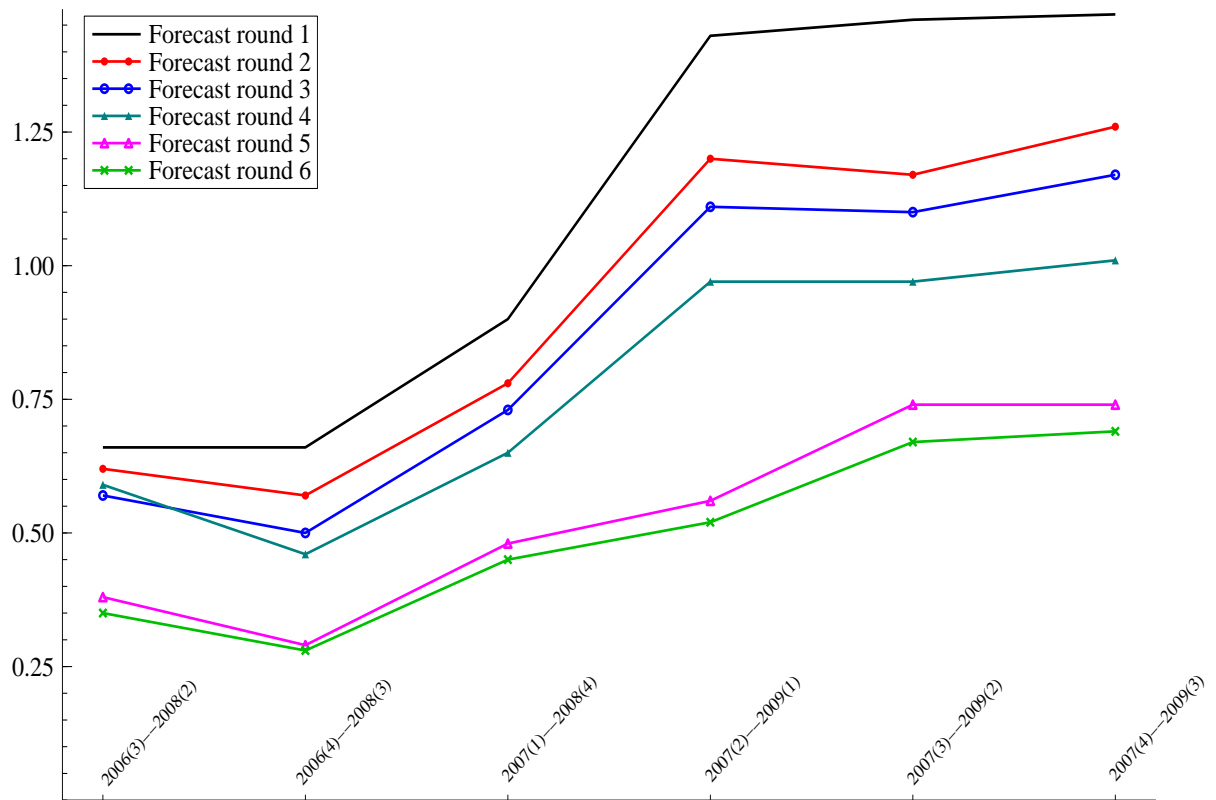


Figure 7: RMSFE evaluated for rolling windows, see Table 5