Do Surveys Help in Predicting GDP: A Real-Time Evidence for Switzerland

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Abstract

We investigate whether the KOF Economic Barometer–a leading indicator constructed using business tendency surveys collected at the KOF Swiss Economic Institute at ETH Zurich–can be useful for short-term out-of-sample prediction of quarterly year-on-year real GDP growth rates in Switzerland. Using the real-time data sets consisting of the historical vintages of GDP data and the KOF-Barometer, we find that the KOF-Barometer appears to be very 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.

Keywords: Leading indicators, forecasting, Switzerland

JEL code: C53, C22.

1 Introduction

Various decision-making institutions face a great deal of uncertainty regarding not only the future developement 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 usually released with delay of about six weeks. Moreover, as practice shows, first releases of GDP data often undergo (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. Especially now the recent economic crisis has raised interest again in this timely source of information.

In Switzerland, one of the most closely monitored leading indicators of economic activity is the KOF Economic Barometer regularly released by the KOF Swiss Economic Institute at ETH Zurich. The monthly releases of the KOF-Barometer are widely reflected both in the popular and specialized press, although the interpretation and significance that should be attached to the newly released numbers often are not immediately evident. This paper provides a rigorous analysis of the predictive ability of the KOF-Barometer in forecasting the quarterly year-on-year growth rates of real GDP in Switzerland that are officially released with a publication lag of about two months after the end of a reference quarter. We compare forecasting performance of the KOF-Barometer to the that of the following benchmark forecasts: forecasts generated by a univariate autoregressive model and forecasts published by the Consensus Economics Inc. The former benchmark model allows us to disentangle predictive content of the KOF-Barometer from historical information contained in the GDP time series itself. Despite its simplicity, it is widely acknowledged in the literature that these simple autoregressive models often produce such forecast accuracy that for more elaborated econometric models is often quite difficult to improve upon. The latter benchmark forecasts are used in order to pit forecasting performance of the KOF-Barometer with the predictions of seasoned and skilled professional forecasters that in their judgement may use additionally available information and/or may use information provided by newly released values of the KOF-Barometer in a more sophisticated way than we pursue in this paper.

We perform our forecasting exercise in a real-time setting. For this purpose, we constructed a real-time dataset consisting of all historical *quarterly* vintages released by the State Secretariat of Economic Affairs (SECO) of the quarterly year-on-year growth rates of real GDP and of all historical *monthly* vintages of the KOF Economic Barometer starting from April 2006 when the newly constructed KOF Economic Barometer based on the multisectoral design has been introduced (Graff, 2006, 2010). It means that when making our forecasts we strictly use only information that was known to a forecaster in a respective period. For example, in January 2010 in order to predict the GDP growth rate in the second quarter of 2010 one had to use the latest available vintage of GDP data that was released by SECO in December 2009. Given the publication lag, this vintage contains the latest GDP observation for the third quarter of 2009. For the KOF-Barometer it implies that one has to use the corresponding vintage released in January. Since the KOF-Barometer has a zero publication lag, its last available value is also for January 2010.

Our study contributes to the literature in the following manner. 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 evaluation of forecasting performance of leading indicators is conducted in a so-called *pseudo* real time, i.e., using the latest available and revised 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 Amato and Swanson (2001) and 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 study 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, using Switzerland as an example.

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 firms' surveys 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 (2010) 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. In 1998, it underwent a slight modification. It has been published in the latter form 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, 2010). Graff (2010) 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 (2010) is that a distinction between real-time and latest available data is clearly made in constructing and using barometer in out-of-sample forecasting. However, while coming close to simulating forecasting exercise in real time, Graff (2010) does not take into account that during the selected forecast period not only the KOF-Barometer but also the sequentially released GDP vintages undergo (substantial) revisions (Cuche-Curti et al., 2008). Hence by utilizing for forecast generation the latest available figures for the reference time series as they were known in the end of the chosen forecast period, Graff (2010) is likely to overstate forecasting accuracy of the leading indicator (Diebold and Rudebusch, 1991; Amato and Swanson, 2001; Croushore, 2005). Graff (2010) also reports a significant improvement in forecast accuracy of the newly designed 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 clearly available to forecasters behind the design of the old KOF-Barometer back in 1976.

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 survey 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, although we address a similar question as in Graff (2010) and Müller and Köberl (2008a) our study distinguishes itself from these two papers at least in one important aspect. 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 means that the composition of the KOF-Barometer has not been subjected to pre-selection bias using information for the whole forecast period that was not available to a forecaster in real time. Due to our real-time forecasting setup where we use preliminary and unrevised data in the form they were available to a forecaster in the past we also avoid the critism of biasing our results in favour of the leading indicator, as it has been often observed in *ex post* evaluation of forecasting performance of the leading indicators based on the revised data (Diebold and Rudebusch, 1991; Amato and Swanson, 2001; Croushore, 2005).

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). The leading indicator of economic activity in Switzerland is the KOF-Barometer. 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 the second quarter of 2010; i.e., the latest quarter for which the data have been officially released to date. Since we aim at predicting GDP growth rates released at the first official publication, we employ the real-time dataset of all GDP releases starting with the historical vintage released in March 2006; i.e., the latest vintage available to a forecaster in April 2006. Given the publication lag, this vintage contains the last GDP observation for the fourth quarter of 2005.

4 Forecast timing and econometric model

In this section we describe the setup of our forecasting exercise. We are interested in forecasting the quarterly year-on-year GDP growth rate in a target quarter $\tau + 1$. We exploit the following conjectural information flow that is relevant for predicting economic activity in a quarter of interest, see Figure 1. In the figure, $\tau + i$ denotes quarters with $i = -1, 0, 1, 2$ and the Roman numerals indicate months of the respective quarters. SECO releases GDP vintages in the beginning of the third month in each quarter. The publication lag comprises one quarter implying that the first GDP estimate for a quarter $\tau + j$ is released in a quarter $\tau + j + 1$ with $j = -2, -1, 0, 1$. We denote such vintage as $\text{GDP}_{(\tau+j,\tau+j+1)}$. The KOF-Barometer is released at the end of each month and it has no publication lag. $\text{KOF}_{\tau+k^M}$ with $k = 0, 1$ stands for vintages of the KOF-Barometer that are released in the end of each month M=I, II, III in the respective quarters.

We distinguish between the following six forecast rounds—each exploiting arrival of new information in a form of releases of the KOF-Barometer and/or GDP figures. Let $\Omega^r_{\tau+k}$ with $k = 0, 1$ be an information set available to a forecaster at each forecast round $r = 1, 2, ..., 6$ in a respective quarters τ and $\tau + 1$.

Then, $\Omega_\tau^1 = \{\text{GDP}_{(\tau-2,\tau-1)}; \text{KOF}_{\tau^{\text{I}}}\}$, $\Omega_\tau^2 = \{\text{GDP}_{(\tau-1,\tau)}; \text{KOF}_{\tau^{\text{II}}}\}$, $\Omega_\tau^3 = \{\text{GDP}_{(\tau-1,\tau)}; \text{KOF}_{\tau^{\text{III}}}\}$, $\Omega_{\tau+1}^4 = \{\text{GDP}_{(\tau-1,\tau)}; \text{KOF}_{\tau+1^{\text{I}}}\}$, $\Omega_{\tau+1}^5 = \{\text{GDP}_{(\tau,\tau+1)}; \text{KOF}_{\tau+1^{\text{II}}}\}$, and $\Omega_{\tau+1}^6 = \{\text{GDP}_{(\tau,\tau+1)}; \text{KOF}_{\tau+1^{\text{III}}}\}$. The generated round-specific forecasts of quarterly year-on-year GDP growth rate in a target quarter $\tau + 1$ are compared with actual values released in a vintage $\text{GDP}_{(\tau+1,\tau+2)}$ one quarter later.

At every forecast round GDP growth for the target quarter is predicted in three steps. First, in cases when the last available values of the KOF-Barometer are either for the first or second month of a quarter—this happens at the first, second, fourth, and fifth forecast rounds—we use univariate autoregressive models to produce forecasts of the values of the KOF-Barometer in order to fill up the rest of the quarter. The lag length is automatically selected by the Schwarz Information Criterion (SIC).

Second, since the KOF-Barometer is released at monthly frequency and the GDP growth rate is a quarterly time series, one has to convert the original KOF-Barometer to the quarterly frequency. This conversion is achieved by assuming that the value of the KOF-Barometer actually recorded (or forecast in the first step) for the last month of a quarter is representative for the whole quarter[1].

In the third step, the forecasts are made. In this step, we utilize two basic strategies for generating multi-period forecasts: a direct approach and an iterated approach[2].

First, we describe a direct forecasting approach. Forecasts for a target quarter $\tau + 1$ conditional on a relevant information set $\Omega_{\tau+1-k}^r$ is generated using the following AutoRegressive Distributed Lag (ARDL) model:

$$\begin{aligned} \widehat{Y}^r_{\tau+1|\Omega^r_{\tau+1-k}} &= \alpha_0 + \sum_{i=h}^{5} \alpha_i Y^r_{\tau+1-i} + \sum_{j=k}^{5} \beta_j \tilde{X}^r_{\tau+1-j}, \qquad (1) \\ & h = 3 \text{ for } r = 1, \quad h = 2 \text{ for } r = 2,3,4, \text{ and } h = 1 \text{ for } r = 5,6 \\ & k = 1 \text{ for } r = 1,2,3 \text{ and } k = 0 \text{ for } r = 4,5,6, \end{aligned}$$

where Y_τ^r is the year-on-year quarterly growth rates[3] of real GDP observed in quarter τ for a GDP vintage available in a forecast round r, with $r = 1, 2, ..., 6$. $\tilde{X}_\tau^r$ is the KOF-Barometer transformed to quarterly

[1] As an alternative conversion method is to use average of monthly values of the KOF-Barometer as the representative for the whole quarter. This approach yielded at best very similar forecasting performance and for the sake of saving space is not reported.

[2] The previous literature pointed out that the iterated approach produces more efficient parameter estimates than the direct approach, but the latter method is more robust to model misspecification. Given the ambiguity regarding true data generating process, the choice of either method is empirical one (Marcellino et al., 2006).

[3] In order to match the values of the dependent variable with those published by the SECO, we calculate Y_τ^r by exact formula for obtaining year-to-year growth rates from levels of the reference time series. Denoting the levels of a quarterly time series z_t, the year-to-year growth rates are $(z_t - z_{t-4})/z_{t-4} * 100$.

frequency as described in the previous two steps. The model parameters are estimated using data in the window terminating at quarter $\tau + 1 - h$.

The following univariate autoregressive model serves as a benchmark model:

$$\widehat{Y}^r_{\tau+1|\Omega^r_{\tau+1-k}} = \alpha_0 + \sum_{i=h}^{5} \alpha_i Y^r_{\tau+1-i}. \tag{2}$$

Next, we describe an iterative forecasting approach. Denote y^r_τ as the quarterly growth rate[4] of real GDP observed in a particular quarter for a GDP vintage available for a forecast round r, with $r = 1, 2, ..., 6$. The corresponding forecasting model is as follows:

$$\widehat{y}^r_{\tau+1|\Omega^r_{\tau+1-k}} = \alpha_0 + \sum_{i=1}^{5} \alpha_i \widehat{y}^r_{\tau+1-i|\Omega^r_{\tau+1-k}} + \sum_{j=k}^{5} \beta_j \tilde{X}^r_{\tau+1-j} + \gamma' SEAS_{\tau+1}, \tag{3}$$

where $\widehat{y}^r_{\tau+1-i|\Omega^r_{\tau+1-k}} = y^r_{\tau+1-i}$ if $i \geq h$ and $SEAS_\tau$ is the vector of seasonal dummies. The coefficients are estimated using data in the window terminating in a quarter $\tau + 1 - h$.

Once forecasts of quarterly growth rates are computed we convert them to year-on-year growth rates as follows:

$$\widehat{Y}^r_{\tau+1|\Omega^r_{\tau+1-k}} = \left(\prod_{i=0}^{3} \left(1 + \frac{\widehat{y}^r_{\tau+1-i|\Omega^r_{\tau+1-k}}}{100} \right) - 1 \right) * 100 \quad \widehat{y}^r_{\tau+1-i|\Omega^r_{\tau+1-k}} = y^r_{\tau+1-i} \text{ if } i \geq h. \tag{4}$$

For the iterative method, we employed another benchmark autoregressive model based on Equation (3) with the imposed zero restriction on all β_j coefficients:

$$\widehat{y}^r_{\tau+1} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \widehat{y}^r_{\tau+1-i} + \gamma' SEAS_{\tau+1} + \varepsilon^r_{\tau+1-h}. \tag{5}$$

Equations (1), (2), (3), and (5) represent general specifications. When making forecasts, an optimal lag augmentation has been selected by minimizing the Schwarz Information Criterion.

We illustrate the presented notation with the following example of predicting GDP growth rate in the target quarter 2010Q2 in the first forecast round $r = 1$ implying that $h = 3$ and $k = 1$[5]. For a direct

[4] We calculate y^r_τ by exact formula for obtaining quarterly growth rates from levels of the reference time series. Denoting the levels of a quarterly time series z_t, the quarterly growth rates are $(z_t - z_{t-1})/z_{t-1} * 100$.

[5] For notational simplicity, we omit the statement that forecasts are conditional on the relevant information set Ω^1_{2010Q1}.

forecasting method we have:

$$\widehat{Y}^1_{2010Q2} = f(Y^1_{2009Q3}, Y^1_{2009Q2}, ..., Y^1_{2008Q3}; \tilde{X}^1_{2010Q1}, ..., \tilde{X}^1_{2009Q1}). \tag{6}$$

For an iterative forecasting method we chain one-step ahead forecasts as follows:

$$\begin{aligned}
\widehat{y}^1_{2009Q4} &= f(y^1_{2009Q3}, y^1_{2009Q2}, ..., y^1_{2008Q3}; \tilde{X}^1_{2009Q3}, ..., \tilde{X}^1_{2008Q3}), \\
\widehat{y}^1_{2010Q1} &= f(\widehat{y}^1_{2009Q4}, y^1_{2009Q3}, ..., y^1_{2008Q4}; \tilde{X}^1_{2009Q4}, ..., \tilde{X}^1_{2008Q4}), \\
\widehat{y}^1_{2010Q2} &= f(\widehat{y}^1_{2010Q1}, \widehat{y}^1_{2009Q4}, ..., y^1_{2009Q1}; \tilde{X}^1_{2010Q1}, ..., \tilde{X}^1_{2009Q1}).
\end{aligned}$$

$$\widehat{Y}^1_{2010Q2} = \left(\left(1 + \frac{\widehat{y}^1_{2010Q2}}{100}\right) * \left(1 + \frac{\widehat{y}^1_{2010Q1}}{100}\right) * \left(1 + \frac{\widehat{y}^1_{2009Q4}}{100}\right) * \left(1 + \frac{y^1_{2009Q3}}{100}\right) - 1\right) * 100. \tag{7}$$

Last but no least, for estimation of model parameters we use rolling estimation window of a fixed size. Given real-time availability of the data, the initial estimation window for the first forecast round when predicting the growth rate in 2006Q3 is 1993Q4—2005Q4. For the second, third, and fourth forecast rounds, the initial estimation window is 1993Q4—2006Q1, and for the fifth and sixth rounds—from 1993Q4 until 2006Q2. For the next target quarter 2006Q4 we shift the respective estimation windows by one quarter forward, i.e., we use the estimation windows 1994Q1—2006Q1, 1994Q1—2006Q2, and 1994Q1—2006Q3 for the rounds 1, 2-4, and 5-6, respectively, etc.

5 Results

In this section we describe obtained results of both in-sample and out-of-sample tests of model comparison. First, consider the in-sample evidence. The latest available vintages of the both time series of interest (adjusted to have the same mean and range) are displayed in Figure 2. For the most of the observation period—with exception of year 1994—the KOF-Barometer shows itself as a truly leading indicator. It appears to lead most of the turning points in GDP growth rates and, more importantly, it timely reacts to the current recession.

In the first step of in-sample model comparison, we follow Amato and Swanson (2001) by presenting results of standard Granger causality tests. The null hypothesis is that the KOF-Barometer does not

Granger cause GDP growth rate in Switzerland. For every round-specific estimation window we performed a sequence of the Wald tests addressing the joint significance of the coefficients $\forall \beta_j = 0$ in Equations (1) and (3) for direct and iterative forecasts, respectively. The corresponding p-values are reported in Table 1 in the upper and lower panels in columns GC. The null hypothesis of no Granger causality can be decisively rejected for every round-specific estimation window. In the second step, we compared competing models in terms of the Schwarz Information Criterion (Granger et al., 1995) presented in Table 2. According to the SIC, the ARDL model should be preferred to the corresponding benchmark models in *all* and in *all but few* cases for direct and iterating forecasting approaches, respectively.

Next, we present the results of out-of-sample forecasting exercise performed in real time. We believe that ability of a leading indicator to predict GDP growth rate out of sample is a more informative test regarding causation between the two time series of interest. As noted in Ashley et al. (1980, p. 1149): "In our view the out-of-sample forecasting performance ... provide the best information bearing on hypotheses about causation." Table 2 summarizes our findings for direct [the upper panel] and for iterative [the lower panel] forecasts. We have computed two measures of forecast accuracy for every forecast round: Root Mean Squared Forecast Error (RMSFE) and Mean Absolute Forecast Error (MAFE).

Based on evidence presented in Table 2 several observations can be made. First, the ARDL model produces more accurate forecasts than the univariate model. For every forecast round, the corresponding RMSFE and MAFE ratios are below one. Second, the most sizeable improvement in forecast accuracy takes place at the first and fourth forecast rounds; i.e., when a new value of the KOF-Barometer is released in the first month of a new quarter. Thirdly, the most accurate forecasts occurs at $h = 1$; i.e., when the first estimate of GDP growth rate in the previous quarter is incorporated in the forecast information set.

The superiority of ARDL-forecasts over the simple benchmark models is further illustrated in Figures 3 and 4 as well as in Figures 5 and 6. Figures 3 and 4 present respective AR-/ARDL-forecasts and actual values of the first-released GDP growth rates. In Figures 5 and 6 the difference in absolute forecast errors of the AR- and ARDL models is displayed. Bars above the zero line indicate that for a given quarter an ARDL-forecast is more accurate than a corresponding AR-forecast. Bars below the zero line indicate the opposite. The superior accuracy of ARDL-forecasts over those of the AR model are clearly visible for the first forecast round that precedes an official release of data by seven months. In this round the ARDL model produced more accurate forecasts in all but three quarters. The rest of panels reveal that the model augmented with the leading indicator performed generally better in forecasting not only during the pre-crisis period but also during initial phase of the recession.

In order to assess whether reported differences in forecast accuracy are statistically significant we employ the testing framework of Giacomini and White (2006). Their testing approach "... is well suited for comparing methods based on nested models or on different modeling and estimation techniques" (Giacomini and White, 2006, p. 1564) as long as forecasts are produced using a limited memory forecasting methods like ones based on a rolling estimation window. We apply their approach to testing for unconditional equal predictive ability and for forecast encompassing. As argued in Giacomini and White (2006, p. 1557), the test statistic of unconditional equal predictive ability is identical to that proposed in Diebold and Mariano (1995). Hence we refer to it as the Diebold-Mariano (DM) test statistic. We test for forecast encompassing using the test statistic suggested in Harvey et al. (1998), which is closely related to the Diebold-Mariano test statistic[6]. In order to account for the fact that the forecast sample is rather small we follow suggestion of Harvey et al. (1997) and apply the small-sample correction for both test statistics of interest.

The results of both formal testing procedures are reported in Table 2. The results of the test of unconditional equal predicitve ability suggest that even though gains in forecast accuracy brought by the KOF-Barometer are substantial, one has to use higher significance levels in order to the reject the corresponding null hypothesis. At the usual 5% or 10% significance levels we are able to reject the null hypothesis on for forecast round $r = 1, 4$; i.e., when the reduction in forecast accuracy measures exceeds 40%. Our finding is consistent with simulation results reported in Ashley (2003, p. 235) that for a forecast sample size of 10 or 20 observations the improvement in mean square forecasting error to be statistically "...significant at the 5% level one model's forecast error variance needs to be two to three times smaller than the other!". (Ashley, 1998, p. 664) argues that given that post-sample forecasting is rather stringent test one should be satisfied with reductions in MSFE and MAFE that appear to be significant at 10% or even 20% levels.

The corresponding p-values of the forecast encompassing tests are reported in the column HNL-test in Table 2. The null that the AR-model forecasts encompass the ARDL-model forecasts can be rejected at the 10% significance level in most cases for direct and in all cases for iterated forecasts. This is consistent with the superior performance of the ARDL-model both in sample and out of sample. The more interesting hypothesis

[6]Although (Giacomini and White, 2006) does not provide an explicit example of testing for encompassing, their framework allows for that as mentioned in Comment 6 on p. 1555. The loss differential needs to be replaced with an appropriate function of forecast errors as shown in Harvey et al. (1998).

is whether the ARDL-model forecasts encompass the AR-model forecasts. The null of encompassing in this direction can not be rejected at the usual significance levels. Consequently, we conclude that encompassing holds in one direction only, with the ARDL-model forecasts encompassing the AR-model forecasts.

For our final assessment of predictive content of the KOF-Barometer we use the quarterly consensus forecasts published by the Consensus Economics Inc. These are based on regular surveys of professional forecasters and provide another benchmark forecasts published in real time. The consensus now-/forecasts are released once per quarter, shortly after the official release of GDP. Such timing corresponds to the second (next-quarter forecasts) and fifth (current-quarter forecasts) rounds in our forecasting setting. The corresponding consensus now-/forecasts along with the first-available GDP growth rate estimates are shown in Figure 7. In terms of RMSFE and MAFE, the Consensus Forecasts did worse than the model with the KOF-Barometer. For the consensus forecasts for the next quarter RMSFE(MAFE) is 1.152(0.914) which exceeds RMSFE(MAFE) reported for the ARDL-forecasts for $r = 2$: for direct forecasts we have 1.143(0.877) and for iterative forecasts—0.914(0.740), see Table 2. For consensus nowcasts RMSFE(MAFE) is 0.807(0.662) which also exceeds RMSFE(MAFE) reported for the ARDL-forecasts for $r = 5$: for direct forecasts—0.505(0.374) and for iterative forecasts—0.630(0.518). Observe that accuracy of consensus nowcasts is very similar to that produced by the AR-model for $h = 1$.

6 Conclusion

In this paper we investigate whether the KOF Economic Barometer is useful for short-term forecasting of quarterly year-on-year real GDP growth rates in Switzerland. We employ both direct and iterative methods to produce forecasts. We perform our analysis using the real-time vintages of both time series. The forecast sample is 2006Q3—2010Q2. For each forecast quarter we produce a sequence of forecasts taking into account conjectural flow of information in the form of new releases of the KOF-Barometer and/or GDP data. Our first forecast round is about seven months ahead of the first GDP release by SECO. Our sixth and last forecast round precedes an official GDP data releaese by about two months. We compare forecast accuracy of models with the leading indicator against univariate autoregressive model forecasts as well as forecasts published by Consensus Economics Inc.

Our main findings are as follows. The model with the KOF-Barometer displays superior performance over the univariate autoregressive models both in- and out of sample. For all estimation windows, we could decisively reject the null hypothesis that the KOF-Barometer does not Granger cause GDP growth rates. The results based on the Schwarz Information Criterion also indicate that the model with the KOF-Barometer should be prefered to the univariate model. In out-of-sample forecast comparison the model with the KOF-Barometer provide a substantial improvement in forecast accuracy over the corresponding benchmark model for all forecast rounds. The reported ratios of RMSFE and MAFE of the model with the leading indicator and of the univariate model are below one. The largest relative improvement in forecast accuracy takes place at the first and fourth forecast round for which we observe reduction in measures of forecast accuracy of about 40%. In absolute terms, the largest forecast accuracy of the model with the leading indicator is achieved at the fifth (and sixth) forecast round for direct forecasting approach.

Application of the formal statistical tests for equal predictive ability suggests that reduction in forecast accuracy measures is significant only if one uses somewhat higher significance levels, e.g., the 10% or even the 20% level. A finding that consistent with the simulation results reported in Ashley (1998, 2003) for a comparatively small forecast evalutation periods like ours. The results of the forecast encompassing test suggest that encompassing holds in one direction only, with the ARDL-model forecasts encompassing the AR-model forecasts. We also find that on average the ARDL-model produces smaller forecast errors than consensus forecasts published by Consensus Economics Inc. 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 short-term forecasting of the GDP growth rates up to seven months prior to an official release.

References

Abberger, K. (2007). Forecasting quarter-on-quarter changes of German GDP with monthly business tendency survey results. Ifo Working paper 40, Ifo Institute for Economic Research at the University of Munich.

Amato, J. D. and N. R. Swanson (2001). The real-time predictive content of money for output. *Journal of Monetary Economics 48*(1), 3 – 24.

Ashley, R. (1998). A new technique for postsample model selection and validation. *Journal of Economic Dynamics and Control 22*(5), 647–665.

Ashley, R. (2003). Statistically significant forecasting improvements: How much out-of-sample data is likely necessary? *International Journal of Forecasting 19*(2), 229–239.

Ashley, R., C. W. J. Granger, and R. Schmalensee (1980). Advertising and aggregate consumption: An analysis of causality. *Econometrica 48*(5), pp. 1149–1167.

Balke, N. S. and D. Petersen (2002). How well does the Beige Book reflect economic activity? Evaluating qualitative information quantitatively. *Journal of Money, Credit and Banking 34*(1), 114–136.

Bergström, R. (1995). The relationship between manufacturing production and different business survey series in Sweden 1968-1992. *International Journal of Forecasting 11*(3), 379–393.

Croushore, D. (2005). Do consumer-confidence indexes help forecast consumer spending in real time? *The North American Journal of Economics and Finance 16*(3), 435–450.

Cuche-Curti, N., P. Hall, and A. Zanetti (2008). Swiss GDP revisions: A monetary policy perspective. *Journal of Business Cycle Measurement and Analysis 4*(2), 183–214.

Diebold, F. X. and R. S. Mariano (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics 13*(3), 253–63.

Diebold, F. X. and G. D. Rudebusch (1991). Forecasting output with the composite leading index : A real-time analysis. *Journal of the American Statistical Association 86*(415), 603–610.

Doornik, J. A. (2007). *Object-Oriented Matrix Programming Using Ox.* London: Timberlake Consultants Press and Oxford: www.doornik.com.

Etter, R. and M. Graff (2003). Estimating and forecasting production and orders in manufacturing industry from business survey data: Evidence from Switzerland, 1990-2003. *Swiss Journal of Economics and Statistics 139*(4), 507–553.

Giacomini, R. and H. White (2006). Tests of conditional predictive ability. *Econometrica 74*(6), 1545–1578.

Graff, M. (2006). Ein multisektoraler Sammelindikator für die Schweizer Konjunktur. *Schweizerische Zeitschrift für Volkswirtschaft und Statistik 142*, 529–577.

Graff, M. (2010). Does a multi-sectoral design improve indicator-based forecasts of the GDP growth rate? Evidence for Switzerland. *Applied Economics 42*(21), 2579–2781.

Graff, M. and R. Etter (2004). Coincident and leading indicators of manufacturing industry: Sales, production, orders and inventories in Switzerland. *Journal of Business Cycle Measurement and Analysis 1*(1), 109–113.

Granger, C. W. J., M. L. King, and H. White (1995). Comments on testing economic theories and the use of model selection criteria. *Journal of Econometrics 67*(1), 173 – 187.

Hanssens, D. M. and P. M. Vanden Abeele (1987). A time-series study of the formation and predictive performance of EEC production survey expectations. *Journal of Business & Economic Statistics 5*(4), 507–519.

Hansson, J., P. Jansson, and M. Löf (2005). Business survey data: Do they help in forecasting GDP growth? *International Journal of Forecasting 21*(2), 377–389.

Harvey, D. I., S. J. Leybourne, and P. Newbold (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting 13*(2), 281–291.

Harvey, D. I., S. J. Leybourne, and P. Newbold (1998). Tests for forecast encompassing. *Journal of Business & Economic Statistics 16*(2), 254–59.

Jacobs, J. P. and J.-E. Sturm (2009). The information content of KOF indicators on Swiss current account data revisions. *Journal of Business Cycle Measurement and Analysis 2008*(2), 35–57.

Kauppi, E., J. Lassila, and T. Terasvirta (1996). Short-term forecasting of industrial production with business survey data: Experience from Finland's great depression 1990-1993. *International Journal of Forecasting 12*(3), 373–381.

Köberl, E. and S. M. Lein (2008). The NAICU and the Phillips Curve - An approach based on micro data. Working paper 08-211, KOF Swiss Economic Institute, ETH Zurich.

Lemmens, A., C. Croux, and M. G. Dekimpe (2005). On the predictive content of production surveys: A pan-European study. *International Journal of Forecasting 21*(2), 363–375.

Lindström, T. (2000). Qualitative survey responses and production over the business cycle. Working Paper Series 116, Sveriges Riksbank (Central Bank of Sweden).

Marcellino, M., J. H. Stock, and M. W. Watson (2006). A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of Econometrics 135*(1-2), 499–526.

Markku, R. and T. Timo (1993). Business survey data in forecasting the output of Swedish and Finnish metal and engineering industries: A Kalman filter approach. *Journal of Forecasting 12*(3-4), 255–271.

Müller, C. and E. Köberl (2008a). Business cycle measurement: A semantic identification approach using firm level data. Working paper 08-212, KOF Swiss Economic Institute, ETH Zurich.

Müller, C. and E. Köberl (2008b). The speed of adjustment to demand shocks: A Markov-chain measurement using micro panel data. Working paper 07-170, KOF Swiss Economic Institute, ETH Zurich.

Müller, C., A. Wirz, and N. Sydow (2008). A note on the Carlson-Parkin method of quantifying qualitative data. Working paper 07-168, KOF Swiss Economic Institute, ETH Zurich.

Öller, L.-E. (1990). Forecasting the business cycle using survey data. *International Journal of Forecasting 6*(4), 453–461.

Öller, L.-E. and C. Tallbom (1996). Smooth and timely business cycle indicators for noisy Swedish data. *International Journal of Forecasting 12*(3), 389–402.

Rupprecht, S. M. (2008). When do firms adjust prices? Evidence from micro panel data. Working paper 07-160, KOF Swiss Economic Institute, ETH Zurich.

Schenker, R. (2008). Comparing quantitative and qualitative survey data. Working paper 07-169, KOF Swiss Economic Institute, ETH Zurich.

Teräsvirta, T. (1986). Model selection using business survey data: Forecasting the output of the Finnish metal and engineering industries. *International Journal of Forecasting 2*(2), 191 – 200.

Zarnowitz, V. (1973). A review of cyclical indicators for the United States: Preliminary results. NBER Working Papers 0006, National Bureau of Economic Research, Inc.

Table 1: In-sample model comparison: direct vs multi-step forecasts

Direct forecasts

Forecast quarter	Forecast round 1			2			3			4			5			6		
	GC[a]	SIC[b] ARDL	SIC[b] AR	GC	SIC ARDL	SIC AR	GC	SIC ARDL	SIC AR	GC ARDL	SIC AR	SIC ARDL	GC AR	SIC ARDL	SIC AR	GC	SIC ARDL	SIC AR
2006Q3	0.000	0.387	0.797	0.000	0.380	0.664	0.000	0.380	0.664	0.000	0.450	0.664	0.002	-0.087	-0.041	0.002	-0.088	-0.041
2006Q4	0.000	0.384	0.825	0.000	0.286	0.665	0.000	0.287	0.665	0.000	0.364	0.665	0.001	-0.142	-0.060	0.001	-0.142	-0.060
2007Q1	0.000	0.339	0.840	0.000	0.289	0.659	0.000	0.290	0.659	0.000	0.360	0.659	0.001	-0.145	-0.070	0.001	-0.144	-0.070
2007Q2	0.000	0.354	0.821	0.000	0.178	0.610	0.000	0.180	0.610	0.000	0.251	0.610	0.000	-0.321	-0.099	0.000	-0.321	-0.099
2007Q3	0.000	0.217	0.810	0.000	0.021	0.615	0.000	0.021	0.615	0.000	0.080	0.615	0.001	-0.341	-0.216	0.001	-0.343	-0.216
2007Q4	0.000	-0.025	0.814	0.000	0.159	0.698	0.000	0.159	0.698	0.000	0.157	0.698	0.000	-0.419	-0.212	0.000	-0.419	-0.212
2008Q1	0.000	-0.066	0.866	0.000	-0.050	0.700	0.000	-0.048	0.700	0.000	-0.039	0.700	0.000	-0.452	-0.176	0.000	-0.452	-0.176
2008Q2	0.000	-0.151	0.877	0.000	-0.199	0.659	0.000	-0.199	0.659	0.000	-0.158	0.659	0.000	-0.465	-0.162	0.000	-0.465	-0.162
2008Q3	0.000	-0.257	0.884	0.000	-0.223	0.661	0.000	-0.222	0.661	0.000	-0.186	0.661	0.000	-0.440	-0.237	0.000	-0.437	-0.237
2008Q4	0.000	-0.459	0.863	0.000	-0.185	0.586	0.000	-0.181	0.586	0.000	-0.142	0.586	0.000	-0.519	-0.223	0.000	-0.519	-0.223
2009Q1	0.000	-0.251	0.857	0.000	-0.210	0.592	0.000	-0.212	0.592	0.000	-0.172	0.592	0.000	-0.461	-0.136	0.000	-0.461	-0.136
2009Q2	0.000	-0.248	0.878	0.000	-0.138	0.674	0.000	-0.139	0.674	0.000	-0.153	0.674	0.000	-0.452	-0.047	0.000	-0.453	-0.047
2009Q3	0.000	-0.168	0.932	0.000	-0.066	0.801	0.000	-0.070	0.801	0.000	-0.108	0.801	0.000	-0.730	-0.333	0.000	-0.729	-0.333
2009Q4	0.000	-0.100	1.076	0.000	-0.006	0.751	0.000	-0.006	0.751	0.000	-0.136	0.751	0.000	-0.750	-0.326	0.000	-0.752	-0.326
2010Q1	0.000	-0.017	1.122	0.000	-0.013	0.774	0.000	-0.019	0.774	0.000	-0.141	0.774	0.000	-0.706	-0.286	0.000	-0.706	-0.286
2010Q2	0.000	-0.029	1.167	0.000	0.027	0.813	0.000	0.027	0.813	0.000	-0.120	0.813	0.000	-0.712	-0.340	0.000	-0.712	-0.340

Iterated forecasts

	GC	SIC ARDL	SIC AR	GC	SIC ARDL	SIC AR	GC	SIC ARDL	SIC AR	GC ARDL	SIC AR	SIC ARDL	GC AR	SIC ARDL	SIC AR	GC	SIC ARDL	SIC AR
2006Q3	0.003	-0.254	-0.160	0.003	-0.268	-0.169	0.003	-0.268	-0.169	0.002	-0.250	-0.169	0.005	-0.197	-0.167	0.005	-0.195	-0.167
2006Q4	0.003	-0.242	-0.140	0.004	-0.209	-0.137	0.004	-0.206	-0.137	0.006	-0.162	-0.137	0.008	-0.174	-0.174	0.008	-0.173	-0.174
2007Q1	0.005	-0.173	-0.109	0.007	-0.181	-0.147	0.007	-0.179	-0.147	0.010	-0.136	-0.147	0.008	-0.174	-0.174	0.008	-0.172	-0.174
2007Q2	0.001	-0.341	-0.184	0.001	-0.376	-0.212	0.001	-0.375	-0.212	0.001	-0.341	-0.212	0.001	-0.377	-0.232	0.001	-0.377	-0.232
2007Q3	0.001	-0.390	-0.184	0.000	-0.424	-0.206	0.000	-0.424	-0.206	0.000	-0.393	-0.206	0.001	-0.176	-0.061	0.001	-0.175	-0.061
2007Q4	0.000	-0.476	-0.183	0.001	-0.181	-0.034	0.001	-0.181	-0.034	0.001	-0.150	-0.034	0.001	-0.186	-0.063	0.001	-0.185	-0.063
2008Q1	0.000	-0.468	-0.155	0.000	-0.504	-0.185	0.000	-0.504	-0.185	0.000	-0.493	-0.185	0.000	-0.471	-0.150	0.000	-0.472	-0.150
2008Q2	0.000	-0.474	-0.217	0.000	-0.445	-0.141	0.000	-0.445	-0.141	0.000	-0.435	-0.141	0.000	-0.471	-0.168	0.000	-0.471	-0.168
2008Q3	0.000	-0.412	-0.116	0.000	-0.442	-0.143	0.000	-0.442	-0.143	0.000	-0.443	-0.143	0.000	-0.403	-0.192	0.000	-0.404	-0.192
2008Q4	0.000	-0.531	-0.139	0.000	-0.455	-0.164	0.000	-0.452	-0.164	0.000	-0.411	-0.164	0.000	-0.424	-0.163	0.000	-0.425	-0.163
2009Q1	0.000	-0.422	-0.136	0.000	-0.424	-0.135	0.000	-0.425	-0.135	0.000	-0.393	-0.135	0.000	-0.366	-0.078	0.000	-0.365	-0.078
2009Q2	0.000	-0.394	-0.104	0.000	-0.323	-0.048	0.000	-0.324	-0.048	0.000	-0.345	-0.048	0.000	-0.380	-0.026	0.000	-0.379	-0.026
2009Q3	0.000	-0.288	-0.056	0.000	-0.316	-0.032	0.000	-0.316	-0.032	0.000	-0.345	-0.032	0.000	-0.586	-0.359	0.000	-0.585	-0.359
2009Q4	0.000	-0.294	-0.008	0.003	-0.428	-0.328	0.003	-0.428	-0.328	0.000	-0.550	-0.328	0.000	-0.609	-0.361	0.000	-0.611	-0.361
2010Q1	0.002	-0.426	-0.317	0.001	-0.512	-0.348	0.001	-0.518	-0.348	0.000	-0.619	-0.348	0.000	-0.614	-0.325	0.000	-0.614	-0.325
2010Q2	0.002	-0.508	-0.377	0.001	-0.482	-0.346	0.001	-0.482	-0.346	0.000	-0.589	-0.346	0.000	-0.620	-0.349	0.000	-0.621	-0.349

Notes:
The table presents the outcome of in-sample evaluation of the competing models. For each forecast quarter, XXX were calculated using real-time data vintages for every estimation sample using round-specific model specifications shown in Equations

[a] "GC" stands for Granger Causality. The respective column entries are marginal significance levels (p-values) for the null hypothesis that the KOF-Barometer does not Granger cause the real GDP growth rate. (1) and (3) for direct and for iterative forecasts, respectively.

[b] The respective column entries are the minimized values of the Schwarz Information Criterion (SIC) reported for the ARDL and AR models shown in Equations (1)—(2) and (3)—(5) for direct and for iterative forecasts, respectively.

Table 2: Evaluation of forecast performance: AR- vs ARDL models

Direct forecasts

Forecast round	Forecast horizon	RMSFE AR	RMSFE ARDL	RMSFE Ratio	DM-test[a]	MAFE AR	MAFE ARDL	MAFE Ratio	DM-test[b]	HNL-test[c] H_0^{AR}	HNL-test[c] H_0^{ARDL}
$r = 1$	$h = 3$	1.910	1.095	0.573	[0.134]	1.505	0.810	0.538	[0.047]	[0.134]	[0.563]
$r = 2$	$h = 2$	1.370	1.143	0.834	[0.600]	0.998	0.877	0.878	[0.723]	[0.107]	[0.363]
$r = 3$	$h = 2$	1.370	1.018	0.743	[0.373]	0.998	0.794	0.795	[0.511]	[0.087]	[0.488]
$r = 4$	$h = 2$	1.370	0.725	0.529	[0.130]	0.998	0.562	0.563	[0.089]	[0.072]	[0.618]
$r = 5$	$h = 1$	0.779	0.505	0.648	[0.224]	0.586	0.374	0.638	[0.126]	[0.099]	[0.822]
$r = 6$	$h = 1$	0.779	0.499	0.641	[0.212]	0.586	0.362	0.617	[0.102]	[0.089]	[0.824]

Iterated forecasts

Forecast round	Forecast horizon	RMSFE AR	RMSFE ARDL	RMSFE Ratio	MDM-test	MAFE AR	MAFE ARDL	MAFE Ratio	MDM-test	HNL-test H_0^{AR}	HNL-test H_0^{ARDL}
$r = 1$	$h = 3$	1.731	0.994	0.574	[0.078]	1.407	0.731	0.520	[0.024]	[0.072]	[0.700]
$r = 2$	$h = 2$	1.180	0.914	0.775	[0.398]	0.907	0.740	0.817	[0.487]	[0.079]	[0.477]
$r = 3$	$h = 2$	1.180	0.912	0.773	[0.382]	0.907	0.743	0.820	[0.512]	[0.072]	[0.471]
$r = 4$	$h = 2$	1.180	0.689	0.584	[0.164]	0.907	0.564	0.623	[0.100]	[0.093]	[0.778]
$r = 5$	$h = 1$	0.822	0.630	0.766	[0.264]	0.655	0.518	0.791	[0.358]	[0.065]	[0.789]
$r = 6$	$h = 1$	0.822	0.619	0.752	[0.235]	0.655	0.510	0.778	[0.320]	[0.059]	[0.858]

Notes:

[a] The column reports marginal significance levels (p-values) for the null hypothesis that the true MSFE is zero. We use the Diebold-Mariano test statistics modified as suggested in Harvey et al. (1997). The loss is quadratic and the truncation lag for the Newey-West estimator is $h - 1$, where h is the forecast horizon. The critical values are obtained using the Student's t distribution with $P - 1$ degrees of freedom, where P is the size of the forecast evaluation period 2006Q3—2010Q2.

[b] The column reports marginal significance levels (p-values) for the null hypothesis that the true MAFE is zero. The loss is absolute and the truncation lag for the Newey-West estimator is $h - 1$, where h is the forecast horizon. We use the modified Diebold-Mariano test statistics suggested in Harvey et al. (1997). The critical values are obtained using the Student's t distribution with $P - 1$ degrees of freedom, where P is the size of the forecast evaluation period 2006Q3—2010Q2.

[c] Outcome of the forecast encompassing test of Harvey et al. (1998). The columns report marginal significance levels (p-values) for the null hypotheses H_0^{AR} that the AR-model forecasts encompass those of the ARDL model and H_0^{ARDL} that the ARDL model forecasts encompass those of the AR model. The truncation lag for the Newey-West estimator is $h - 1$, where h is the forecast horizon. The critical values are obtained using the Student's t distribution with $P - 1$ degrees of freedom, where P is the size of the forecast evaluation period 2006Q3—2010Q2.

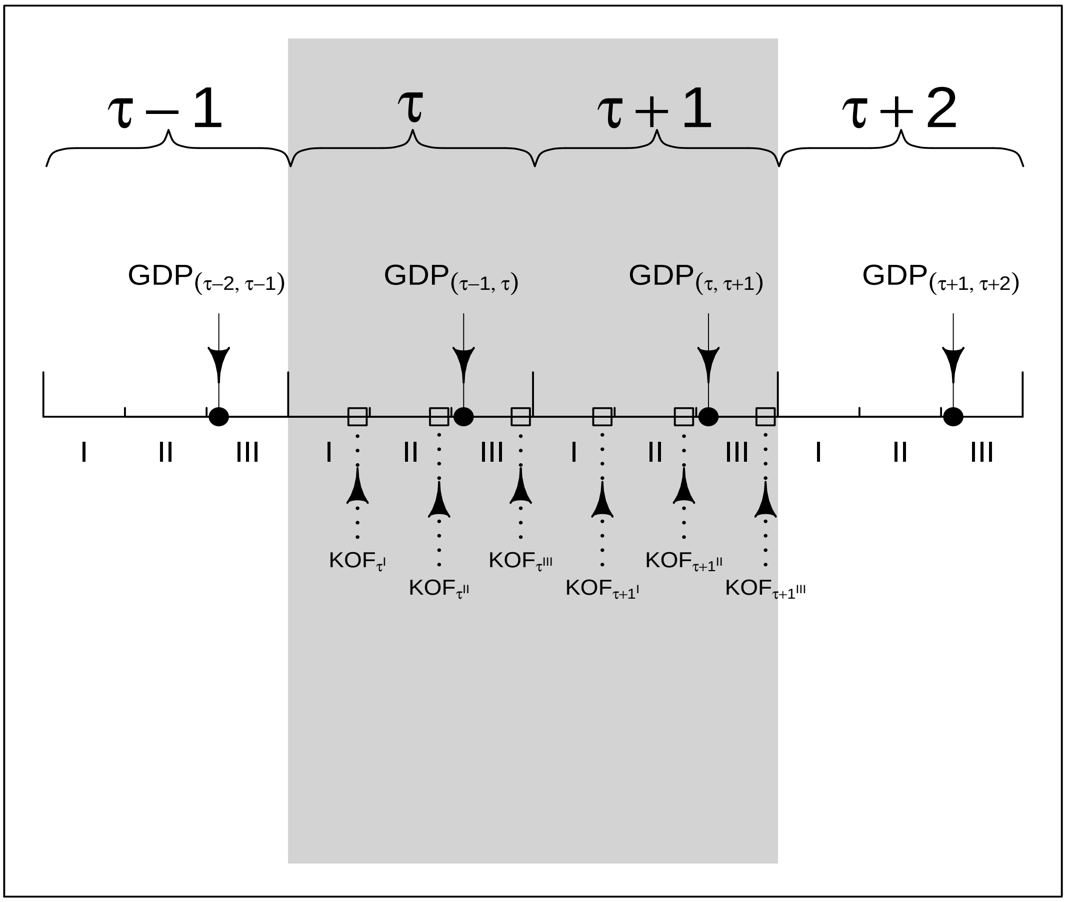

Figure 1: Conjectural information flow.
[*Notes*: $\tau + i$ denotes quarters with $i = -1, 0, 1, 2$. The Roman numerals indicate months of the respective quarters. $\mathrm{GDP}_(\tau + j, \tau + j + 1)$ denotes GDP vintages released by SECO in quarter $\tau + j + 1$ that have observations up to quarter $\tau + j$, with $j = -2, -1, 0, 1$. $\mathrm{KOF}_\tau + k^M$ with $k = 0, 1$ stands for vintages of the KOF-Barometer that are released in the end of each month M=I, II, III in the respective quarters. Let Ω^r be an information set available to a forecaster at each forecast round $r = 1, 2, ..., 6$. Then, $\Omega^1 = \{\mathrm{GDP}_{(\tau-2,\tau-1)}; \mathrm{KOF}_{\tau^{\mathrm{I}}}\}$, $\Omega^2 = \{\mathrm{GDP}_{(\tau-1,\tau)}; \mathrm{KOF}_{\tau^{\mathrm{II}}}\}$, $\Omega^3 = \{\mathrm{GDP}_{(\tau-1,\tau)}; \mathrm{KOF}_{\tau^{\mathrm{III}}}\}$, $\Omega^4 = \{\mathrm{GDP}_{(\tau-1,\tau)}; \mathrm{KOF}_{\tau+1^{\mathrm{I}}}\}$, $\Omega^5 = \{\mathrm{GDP}_{(\tau,\tau+1)}; \mathrm{KOF}_{\tau+1^{\mathrm{II}}}\}$, and $\Omega^6 = \{\mathrm{GDP}_{(\tau,\tau+1)}; \mathrm{KOF}_{\tau+1^{\mathrm{III}}}\}$. All the round-specific forecasts of GDP growth rate for the target quarter $\tau + 1$ are compared with the first estimate of GDP growth rate in this quarter released in the vintage $\mathrm{GDP}_{(\tau+1,\tau+2)}$.]

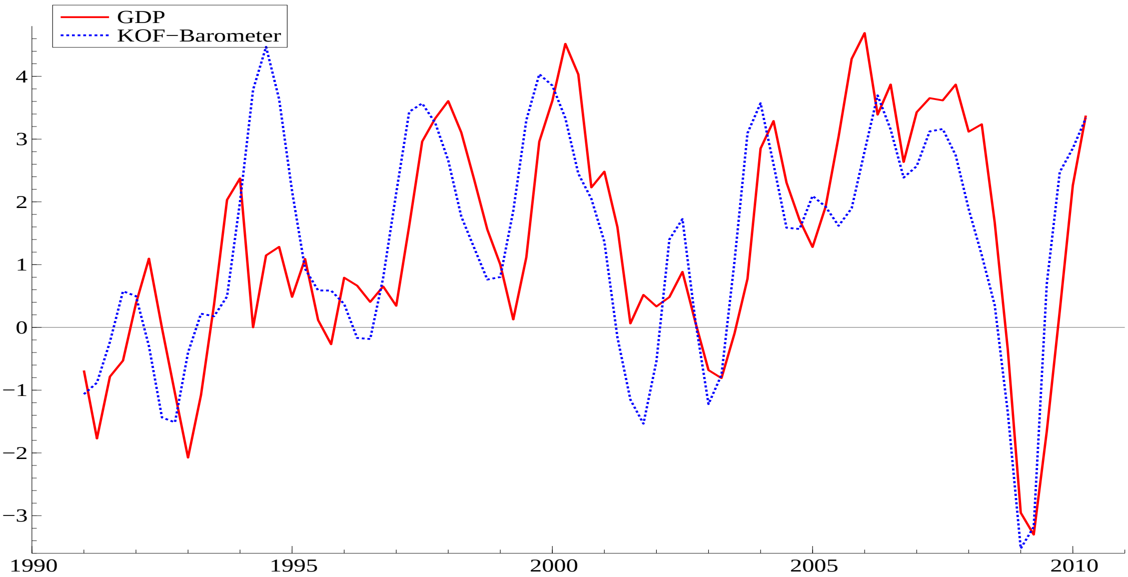

Figure 2: Actual values of the quarterly year-on-year real GDP growth rates (vintage released on 02.09.2010) and KOF-Barometer (released on 27.08.2010, only values of last month in each quarter are reported): Both time series adjusted to have the same mean and range.

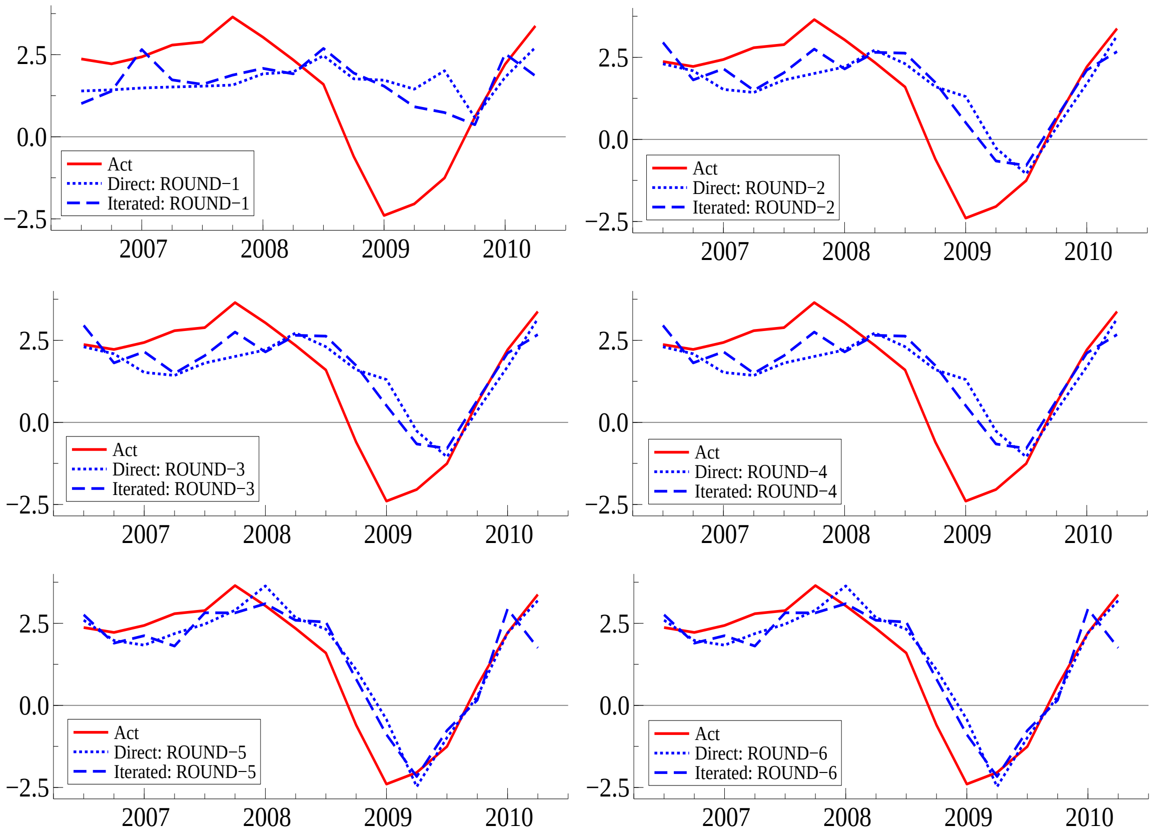

Figure 3: Quarterly year-on-year real GDP growth rates: Actual (first release) and AR-model forecasts (dotted line—direct forecasts and dashed line—iterated forecasts)

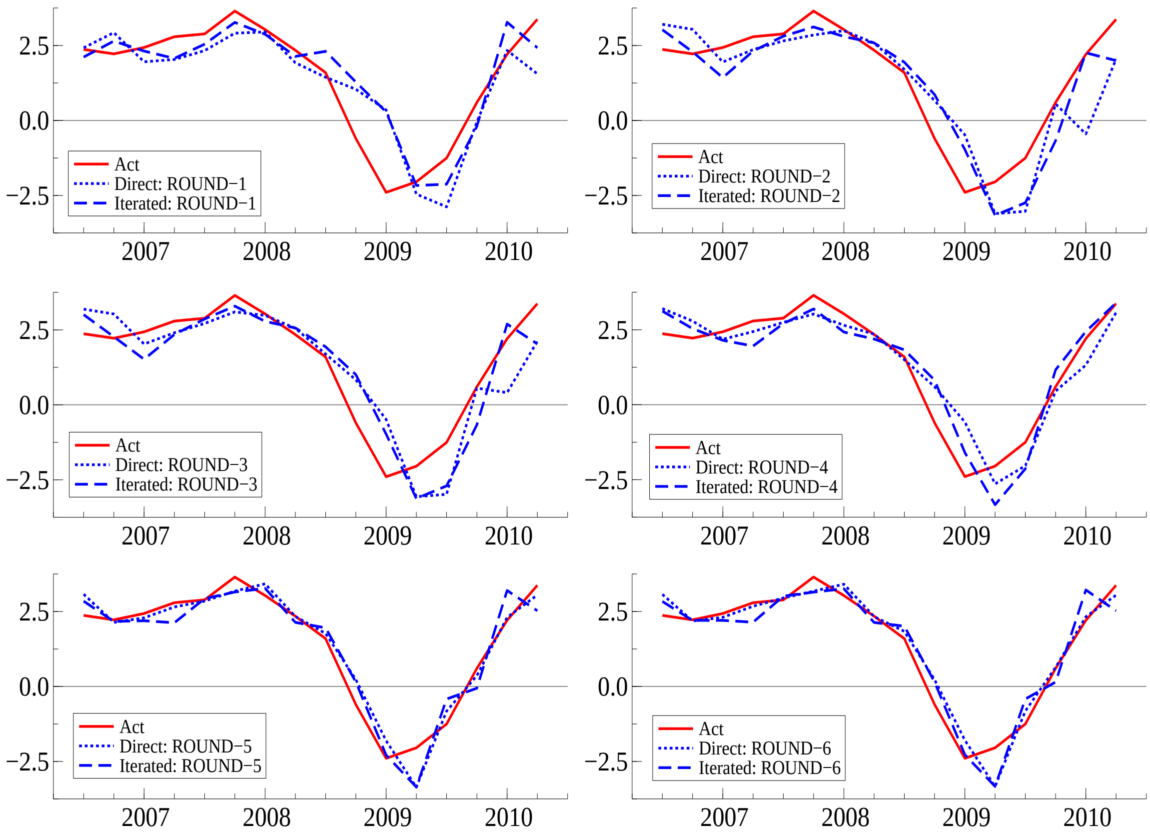

Figure 4: Quarterly year-on-year real GDP growth rates: Actual (first release) and ARDL-model forecasts (dotted line—direct forecasts and dashed line—iterated forecasts)

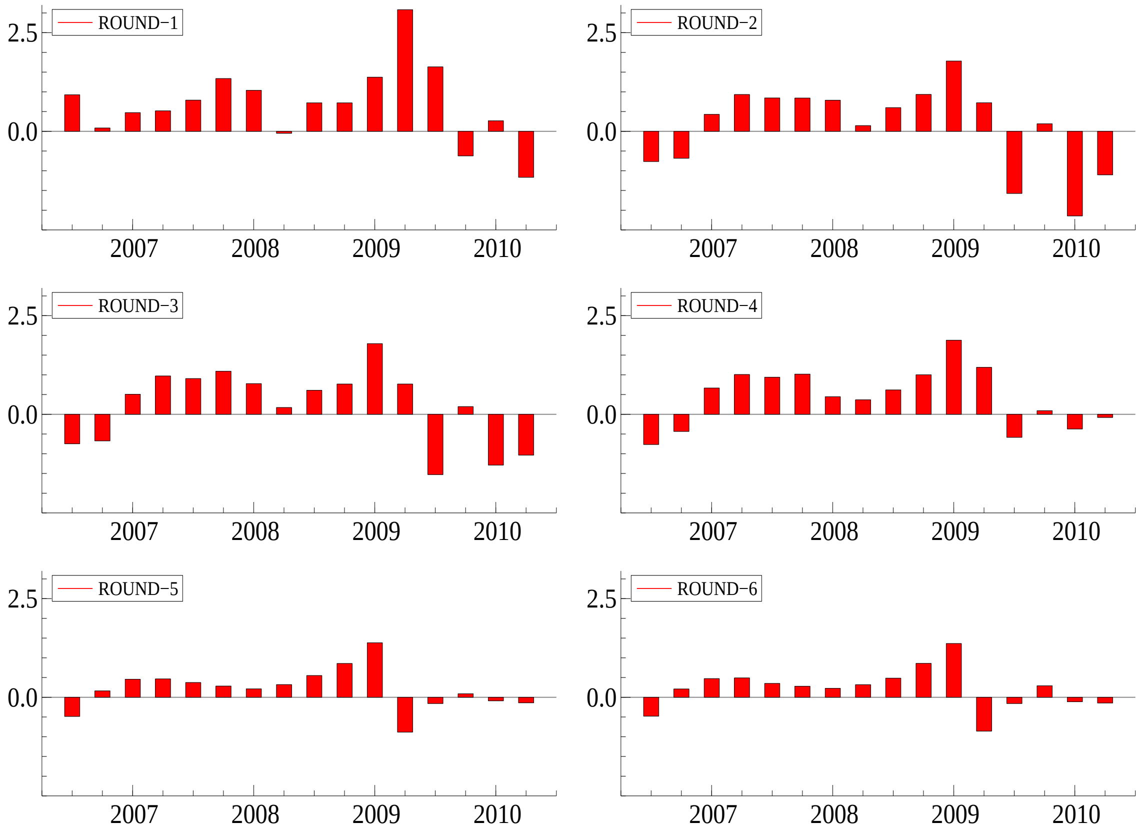

Figure 5: Direct forecasts: Difference in absolute forecast errors of AR- and ARDL models. [*Notes*: Each of the panels contains a plot of the absolute forecast error from the AR model (i.e., without the KOF-Barometer) minus the absolute forecast error from the ARDL model (i.e., with the KOF-Barometer). Bars above the line indicate quarters for which the AR model produced larger forecast errors than the ARDL model. Bars below the line indicate the opposite. All forecasts are constructed using real-time data sets, and forecast comparison is based on first-released actual data.]

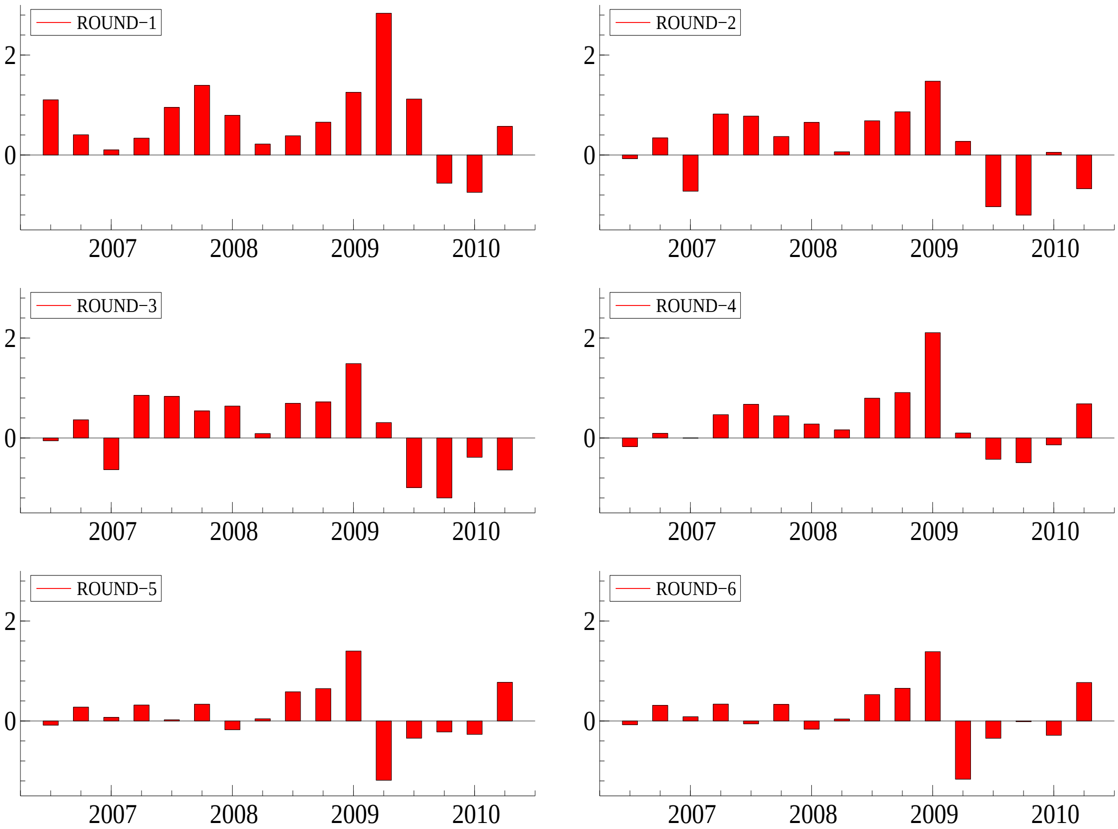

Figure 6: Iterated forecasts: Difference in absolute forecast errors of AR- and ARDL models. [*Notes*: Each of the panels contains a plot of the absolute forecast error from the AR model (i.e., without the KOF-Barometer) minus the absolute forecast error from the ARDL model (i.e., with the KOF-Barometer). Bars above the line indicate quarters for which the AR model produced larger forecast errors than the ARDL model. Bars below the line indicate the opposite. All forecasts are constructed using real-time data sets, and forecast comparison is based on first-released actual data.]

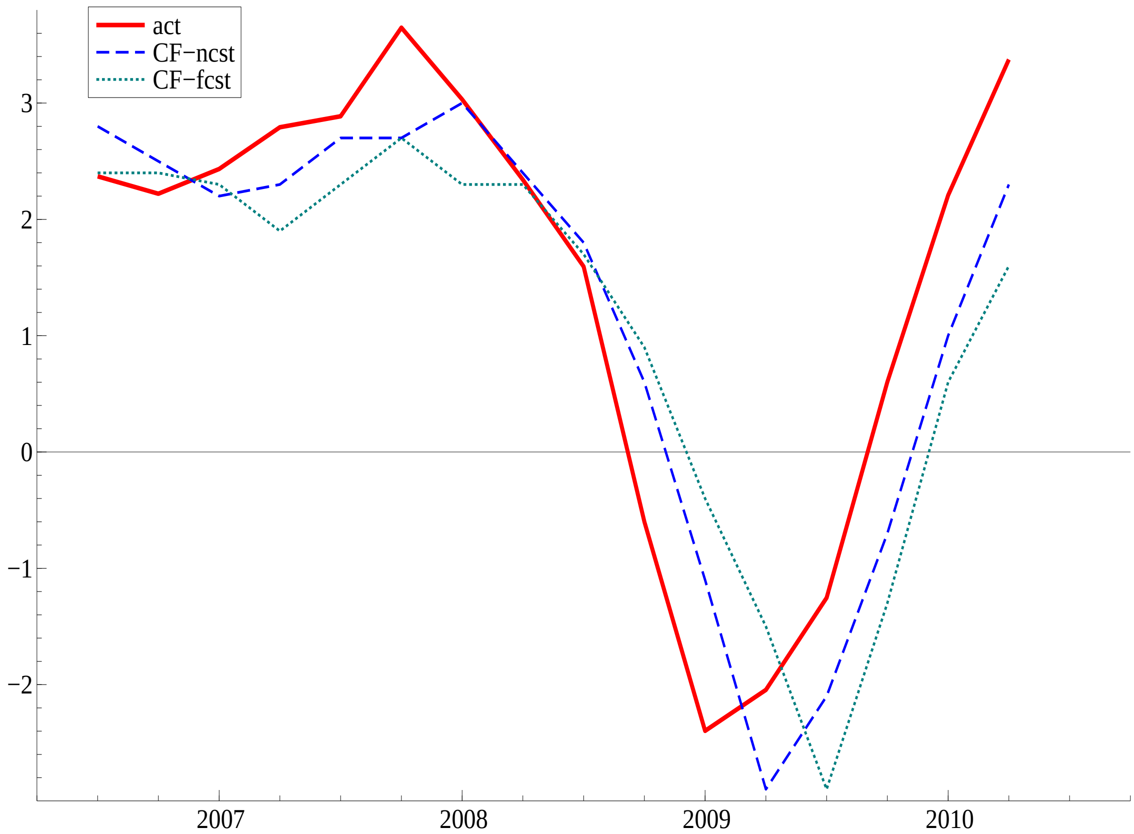

Figure 7: Quarterly year-on-year GDP growth rates: One-step ahead forecasts (dotted line) and nowcasts (short dashed line) released by the Consensus Economics Inc. as well as first-released actual data (solid line).