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Working Paper

The R-word index for Switzerland

KOF Working Papers, No. 304

Provided in Cooperation with:

KOF Swiss Economic Institute, ETH Zurich

Suggested Citation: Iselin, David; Siliverstovs, Boriss (2012) : The R-word index for Switzerland, KOF Working Papers, No. 304, ETH Zurich, KOF Swiss Economic Institute, Zurich, <https://doi.org/10.3929/ethz-a-007319025>

This Version is available at:

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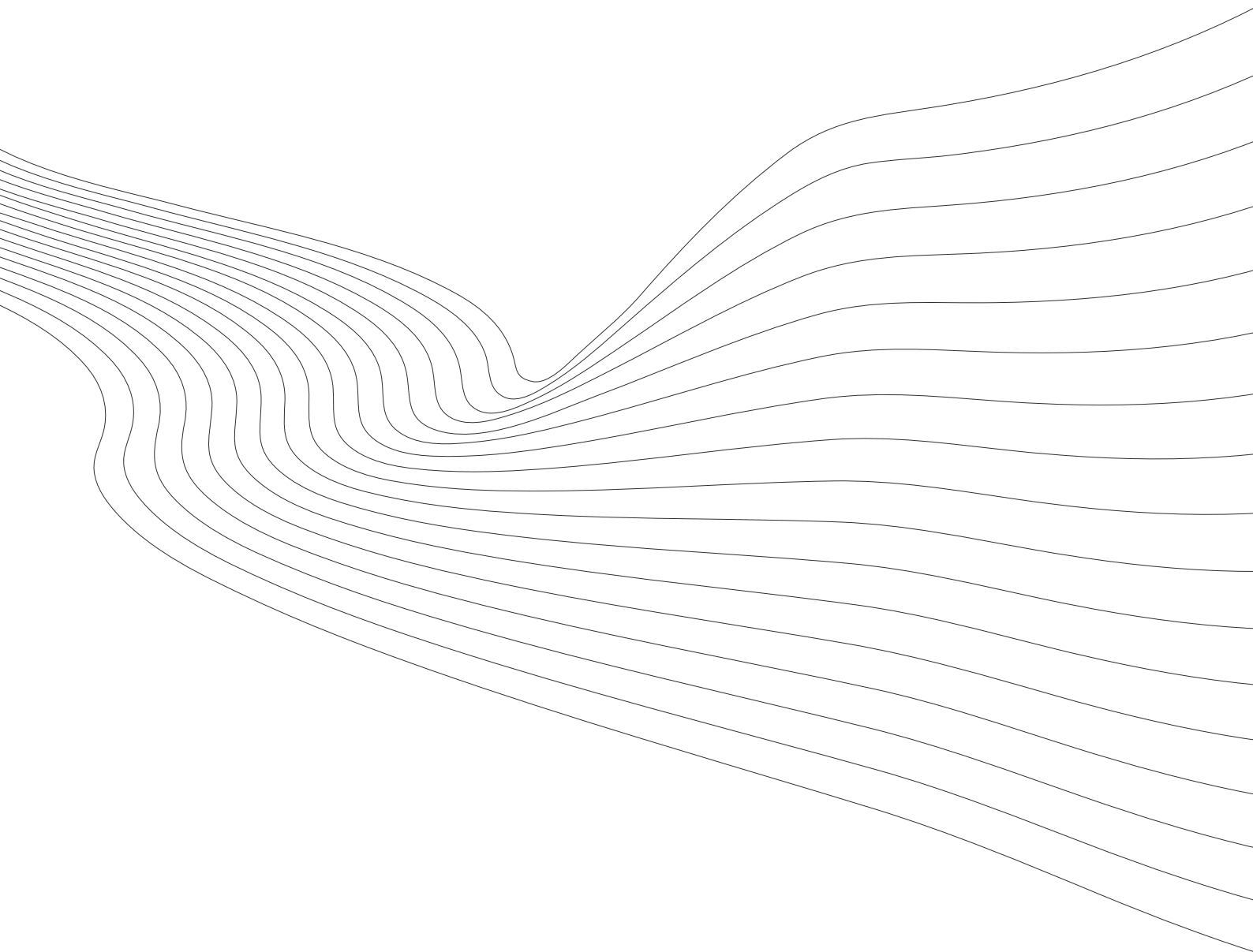
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KOF Working Papers

The R-word Index for Switzerland

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June 10, 2012

Abstract

In this study we construct the R(ecession)-word index for Switzerland. To the best of our knowledge, this has never been done before. We evaluate the extent to which the inclusion of the index contributes to more accurate forecasts of GDP growth compared with a benchmark autoregressive model. We perform our forecasting exercise using real-time vintages of GDP data, closely simulating flow of information in the past. We find that inclusion of the R-word index led to statistically significant improvement in forecast accuracy over the benchmark model. Largest improvements in forecast accuracy were observed in the period around the Great Recession.

Keywords: Recession, nowcasting, real-time data, Switzerland

JEL code: C22, C53

*We thank participants at the KOF Brown Bag Seminar at ETH Zurich (May 4, 2012) for their comments. All computations were performed in Ox version 6.10 (Doornik, 2007).

1 Introduction

The news media are, after all, in the business of creating stories that people would like to hear.

G. A. Akerlof and R. J. Shiller,
“Animal Spirits”, 2009

During his tenure as chairman of the Federal Reserve, Alan Greenspan was known to be very fond of unusual measures to predict the economy. One of his favourite was sales of men’s underwear. The sales are usually quite constant, but drop in recessions when men replace them less often [...] (The Economist, 2011a). Greenspan’s underwear indicator is not the only unorthodox indicator for forecasting the ups, and more often downs, of the economy. Another popular indicator is known as ‘Where you Eat’ Index of *The New York Times* 2012.¹ This index takes into account the relative sales trends of different types of restaurants. When people are more optimistic about their finances, they are more likely to eat at restaurants with full service, rather than in fast food chains.

In the early 1990s, the weekly Magazine *The Economist* invented the so called R-word index (The Economist, 2011b). The idea is straightforward: *The Economist* counts how many articles in the two newspapers *Financial Times* and the *Wall Street Journal* used the word ‘recession’ in each quarter.² The higher the number, the worse the (US) economy is doing. Subsequently, in 2001 the *Hypo Vereinsbank* publicly launched the German version of the R-word index.

In our study, we produce for the first time—to our best knowledge—a R-word index for Switzerland. For the construction of our so called Swiss R-word index we conduct a simple keyword search in the Swiss Media Database ‘Schweizerischer Mediendienst (SMD)’. We apply several ways how such an index can be constructed on the basis of information provided by SMD. First, we distinguish between what keywords are used in the search. The more restrictive search is based on joint occurrence of keywords “recession” (“Rezession” in German) and “Switzerland” (“Schweiz” in German) in a newspaper article. This version allows us to select articles that specifically focus on Switzerland. Acknowledging the fact that Switzerland is a small open economy that is deeply integrated in the world economy, we applied a more lax search based on the single keyword “recession”. This version of the R-word index should capture a more general mood regarding economic conditions not only in Switzerland but also worldwide. Secondly, we distinguish by coverage of newspapers, where we look for keywords in question only in one newspaper (*Neue Zürcher Zeitung*) or in all

¹<http://www.nytimes.com/interactive/2012/03/16/business/economy/off-the-charts-Economic-Indicator-Where-You-Eat.html?ref=economy>

²The R-word index started in 1992 with, what was considered at the time, Britain’s quality newspapers. For more information check *The Economist*’s website: <http://www.economist.com>.

newspapers listed in SMD. The *Neue Zürcher Zeitung* is widely regarded as the most influential newspaper in Switzerland, and it is also best known for its economic news coverage.

Our main finding is that the R-word index constructed by counting number of articles in the *Neue Zürcher Zeitung*, where both keywords “recession” and “Switzerland” are mentioned, delivers most accurate forecasts of first announcements of GDP growth compared to other options listed above. More importantly, it also delivers more accurate forecasts than a simple autoregressive model. The largest gains in forecast accuracy are observed in the period around the Great Recession.

Our paper is structured as follows. Section 2 summarises the related literature. In section 3 we present the data. In the next section our empirical results are discussed. The final section concludes.

2 Literature overview

The literature about using media data for forecasting purposes significantly expanded in recent years; see, e.g., Ammann et al. (2011) for a good overview over the latest studies focusing on forecasting of financial variables. Ammann et al. (2011) summarise the content of newspaper articles by means of word-count indices and use them to explain future stock returns. They conclude that the constructed word-count indices show predicting power for future DAX (DAX, Deutscher Aktien Index, the German stock index) returns both in and out of sample. Engelberg and Parsons (2011) show that press coverage significantly affects a daily trading volume of retail investors, especially on a local level. Older studies, e.g. Tetlock (2007) and Doms and Morin (2004), find that news coverage is strongly associated with response by the financial markets. Tetlock (2007) measures the interactions between the media and the stock market using the popular Wall Street Journal column “Abreast of the Market” as a source. The daily column reports what happened the day before on stock exchanges, particularly with the closed watched indices like the Dow Jones Industrial Average and the S&P 500.

Although the above mentioned studies provide a solid argument that media data are helpful for forecasting financial variables, there is much more controversy regarding their usefulness for forecasting the real economy. One of the most prominent media-based indicators used for this purpose is the R-word index initiated by *The Economist*. However, the tracking record of the R-word index or its variants for forecasting macroeconomic variables is mixed. As *The Economist* (2011a) admits itself, the R-word index is not foolproof, but boasts a decent record in pinpointing the start of US recessions in 1990 and 2007. The R-word index had its all time peak during the winter months 2008/2009, clearly indicating the economic bust after the collapse of the investment

bank Lehman Brothers. However, we are aware of no study that formally investigates the extent to which accounting for the dynamics of the R-word index helps in predicting recessions in the US. On a more positive note, Uhl (2011) finds that a more broadly defined indicator aggregated from TV news broadcasts brings about a significant boost in forecast accuracy of private consumption in the US compared with the well-known University of Michigan Index of Consumer Sentiment.

Across the Atlantic, in April 2001, the German *Hypo Vereinsbank* started a regular release of a German version of the R-word index counting the occurrence of the word “recession” in the leading German business newspaper *Handelsblatt*, providing a time series of this indicator since the first quarter of 1986. The usefulness of the R-word index for forecasting aggregate economic activity in Germany was investigated in Breitung and Jagodzinski (2001), Bandholz and Funke (2003), and Kholodilin and Siliverstovs (2006). These studies uniformly concluded that the R-word index cannot be regarded as a trustworthy indicator of the business cycle dynamics in Germany. Particularly, in a comprehensive comparative study of various economic indicators Kholodilin and Siliverstovs (2006) conclude that the model augmented with the R-word index did not produce any better forecast accuracy of GDP growth than a benchmark model based on the in-sample mean.³ Perhaps the negative conclusions of these three studies regarding the usefulness of the R-word index for tracking economic conditions in Germany contributed somehow to its eventual dismissal, some time before the occurrence of the Great Recession.

In a more recent study Grossarth-Maticek and Mayr (2008) argue that the poor forecasting performance of the R-word index recorded in Breitung and Jagodzinski (2001) and Kholodilin and Siliverstovs (2006) can be explained by the fact that the R-word index by construction is better suited for timely detecting recessions rather than general tracking of the business cycle dynamics. Therefore its forecasting properties should be evaluated using its ability to correctly date the start and possibly end of recessions. To this end, Grossarth-Maticek and Mayr (2008) evaluate the performance of the logit model augmented with the R-word index, where the dependent variable is a dummy that takes values of one in recession periods and zero otherwise. They record a favourable performance of such a model both in- and out of sample compared to the benchmark model based on the interest-rate spread.⁴

Grossarth-Maticek and Mayr (2008) evaluate also the forecasting performance of another media-based indicator produced by Media Tenor. This indicator is constructed on the basis of newspaper articles read by professionally trained readers who classify every article into those containing neg-

³However, we have to concede that the same conclusion holds for most of the indicators considered in Kholodilin and Siliverstovs (2006), where the evaluation sample from 1998Q1 until 2004Q4 was used.

⁴Grossarth-Maticek and Mayr (2008) used the out-of-sample forecast evaluation sample was from 2001Q1 through 2007Q2, ending it shortly before the outbreak of the Great Recession.

ative, neutral, and positive economic news. Then the index is calculated as the difference between shares of articles with positive and negative news. Contrary to the encouraging results reported above, Grossarth-Maticek and Mayr (2008) conclude that this version of media-based indicator fails to Granger cause GDP growth in Germany resulting in an inferior forecasting performance than that of a univariate autoregressive model and a model augmented with the Ifo Business Climate index.

All in all, the empirical evidence on the usefulness of information extracted from public media for tracking the current course of the economy still remains inconclusive. In a pioneering attempt, our study provides an additional input to the current debate by constructing the R-word index for Switzerland and evaluating its real-time forecasting properties.

3 Data

We construct several versions of the R-word index depending on the newspaper coverage and keyword search. The *Neue Zürcher Zeitung* (NZZ) is the newspaper of our primary choice. The NZZ has an officially approved circulation of around 133'000 copies and is widely seen as the most important newspaper in Switzerland. The first version of the R-word index is based on counting a number of articles where the keywords “recession” and “Switzerland” jointly occur. We label this version of the R-word index as **NZZ-CH-R**. In constructing the second version of the R-word index we acknowledge that Switzerland is a small open economy. Naturally, its economic performance is affected by the economic situation in its main trading countries. Therefore, we relax the search criteria by retaining only one keyword “recession” which allows us to broaden the coverage of relevant articles in the NZZ. The second version of the R-word index is labelled as **NZZ-R**. Our third and fourth version of the R-word index is based on counting the joint occurrence of the keywords “recession” and “Switzerland” and solely the keyword “recession” in all German-speaking newspapers available in the Swiss Media Database “Schweizerischer Mediendienst (SMD)”, respectively. We label these versions of the R-word index as **SMD-CH-R** and **SMD-R**. We construct the versions of the R-word index for the period from 1998Q1 through 2011Q4.

The various versions of the R-word index are presented in Figure 1. Unsurprisingly, they all show very strong co-movement. We also display recessionary periods in Switzerland using the definition of a classical business cycle (Siliverstovs, 2011b). Siliverstovs (2011b) identified recessions using the GDP vintage that contains data through the fourth quarter of 2010 (2010Q4). In the figure these recessionary periods are shown in a yellow colour. All R-word indices very strongly overshoot during the Great Recession indicating significant public concern about the course of the economy in

that time and shortly afterwards. The small peak in the first quarter of 2008 is to be traced to the collapse of Bear Stearns—the first strong signal of the emanating crisis. The collapse of Lehman Brothers in September 2008 that triggered disastrous consequences for the world economy are well documented in the press, that is well reflected in our R-word indices reaching all-time heights in the fourth quarter of 2008. Then the R-word indices gradually decline until the second half of 2011, when they start to peak up again as a reflection of the escalating Euro debt crisis and losing confidence in the sustainability of economic recovery.

It is also worthwhile noting that surges in the values of the R-word indices observed in the end of 1998 and during the year 2001 are not supported by the business cycle chronology of Siliverstovs (2011b), that is based on the most recent GDP vintage that was available in Spring 2011.⁵ As shown in Siliverstovs (2011b, Figure 6) this can be well explained by the fact that GDP data underwent revisions that changed business cycle pattern in Switzerland.⁶ There was much stronger evidence of these two recessionary periods in earlier GDP vintages as in those released later. This fact clearly emphasizes the importance of paying a very careful attention to real-time aspects of business cycle dating.

The historical vintages of GDP data come from the KOF internal database. In this database the historical GDP vintages released by the Swiss State Secretariat for Economic Affairs (SECO) are stored. The SECO typically releases GDP data in the beginning of the third month in the next quarter resulting in the publication lag of about two months. On contrary, our values of the recession index are readily available as soon as the quarter ends. In the empirical analysis below we investigate whether such advantage in time can be successfully exploited for out-of-sample prediction of GDP growth in Switzerland.

4 Results

In our out-of-sample forecasting exercise we use the following empirical model:

$$y_t^v = \alpha + \beta_1 y_{t-1}^v + \beta_2 y_{t-2}^v + \gamma R_t^i + \epsilon_t. \quad (1)$$

This autoregressive distributed lag model (henceforth, ARDL(2,0)) includes two lags of dependent variable and contemporaneous value of the R-word index (R_t^i), where the superscript $i =$

⁵The vintage was published in March 2011 and correspondingly contains data until 2010Q4.

⁶For convenience, we replicate the corresponding graphics in Figure 2. The business cycle chronology was obtained by means of the approach of Artis et al. (2004). For each historical GDP vintage the algorithms assigns a probability with which each quarter was labelled as recessionary. The darker is the colour, the larger is the assigned probability. The historical vintages are denoted as GDP.YYQ, where YYQ denotes the last quarter for which data are available in this vintage. For example, the vintage GDP.104 contains the data through the fourth quarter of 2010.

{NZZ-CH-R, NZZ-R, SMD-CH-R, SMD-R} corresponds to the various versions of the index described in the previous section. The dependent variable we aim to forecast is the quarterly year-on-year growth rate of real GDP in Switzerland. The superscript v indicates that we use real-time GDP vintages. For example, $v = 2001Q4$ indicates that the corresponding vintage has the last observation in 2001Q4. Given the publication lag of about two months it also means that this vintage was released in March 2002. The ARDL model specification is fixed⁷ and we use the sliding window of 16 observations for estimation of model parameters and out-of-sample forecasting. We intentionally use a rather short estimation sample in order to limit the influence of the past observations, allowing us to put more weight on information from the more recent observations.

More precisely, the timing of our forecasting exercise is following. The forecast evaluation sample starts in 2002Q1 and ends in 2011Q4. In order to produce forecast for 2002Q1 we use the GDP vintage released in March 2002 that contains data through the fourth quarter of 2001, 2001Q4. As the quarter 2002Q1 elapses, and the value of the R-word index for this quarter becomes available, model parameters are estimated as follows:

$$y_{t-1}^{2001Q4} = \alpha + \beta_1 y_{t-2}^{2001Q4} + \beta_2 y_{t-3}^{2001Q4} + \gamma R_{t-1}^i + \epsilon_{t-1}, \quad (2)$$

where the time index t starts in 1998Q1 and extends until 2002Q1. Then the forecasting equation is given by:

$$\hat{y}_{2002Q1} = \hat{\alpha} + \hat{\beta}_1 y_{2001Q4}^{2001Q4} + \hat{\beta}_2 y_{2001Q3}^{2001Q4} + \hat{\gamma} R_{2002Q1}^i. \quad (3)$$

Next, we shift the estimation sample by one observation forward, such that it starts in 1998Q2 and ends in 2002Q1. Then we use the GDP vintage released in June 2002, that correspondingly has the last observation in 2002Q1, in order to produce a forecast of GDP growth in 2002Q2, and so on.

We compare the forecasting performance of the indicator-augmented model with that of univariate autoregressive (AR) models. Our choice of using univariate AR model as a benchmark model is based on the following arguments. First, simple AR models proved to be a rather robust forecasting device that is often difficult to beat in practice by more sophisticated models. Secondly, the ability of the indicator to contribute to forecast accuracy of a pure autoregressive model can be related to a seminal notion of the Granger causality, verified out of sample. As noted in Ashley et al. (1980, p. 1149): “In our view the out-of-sample forecasting performance ... provide[s] the best information bearing on hypotheses about causation.”

⁷We tried the model selection based on the Schwarz Information Criterion (SIC) allowing for more lags of both dependent and explanatory variables. However, this approach to model selection did not result in a systematic over-performance of the preferred parsimonious ARDL(2,0) model.

The forecasting performance of the models is summarised in Table 1. We assess forecasting accuracy of the models in terms of the Root Mean Squared Forecast Error (RMSFE) with respect to first-released data and latest-available to us GDP vintage, as of time of writing. The latter vintage was released in March 2012 and correspondingly extends until 2011Q4. From the current perspective a much more prominent attention is paid to first releases of GDP growth, which remains the sole most important indicator of the current economic activity backed by official statistics and certainly plays a significant role for forming expectations on the future course of the economy. In order to account for the fact that these initial estimates are revised later as new information arrives, we also check to what extent our model forecasts are able to predict these revised data.

As shown in the upper part of the table, the autoregressive model of order two, AR(2), provides much better forecasting accuracy than the first-order autoregressive model, AR(1). Therefore the AR(2) model is chosen as a benchmark for univariate models, and it also explains the use of the second-order autoregressive dynamics in Equation (1). The forecasts of both autoregressive models were done in the same fashion as described above for Equation (1), only the indicator, R_t^i , was omitted.

Comparison of forecast accuracy reveals that both the AR and ARDL models are much better in forecasting first releases of GDP growth rather than revised figures. The reason for this is that during most of the period in question—starting from 2004 until the second quarter of 2008—estimates of GDP growth were systematically revised upwards, indicating that first estimates were too pessimistic. On the contrary, in the period of the Great Recession the first estimates were mostly revised downwards, indicating too optimistic initial estimates. Altogether, if we use the first GDP estimate as a predictor of the revised GDP data then the resulting RMSFE is 0.75, as reported in Table 1 in line GDP(FA). This indicates a rather large discrepancy between these two estimates of GDP growth which apparently was rather difficult to foresee given information available to forecasters in the past.⁸

In the middle panel of Table 1 we report RMSFEs for all versions of the R-word index, which are uniformly lower than the RMSFE corresponding to the benchmark autoregressive model. We also report the results of the pooling of the indicator-augmented models. Using equal weights for forecast pooling produces the second best result in terms of RMSFE both for first and final GDP releases. It is interesting to note that the best forecasting model is based on counting of the number of articles that mention both the keywords “recession” and “Switzerland” in the NZZ newspaper. The statistical significance of differences in forecast accuracy was verified by the test of

⁸Siliverstovs (2011a) argues that the information contained in business tendency surveys can be successfully used to forecast GDP revisions in Switzerland.

Clark and West (2007), specifically designed for comparison of nested models. As reported in Table 1 we can reject the null hypothesis of equal forecast accuracy in favour of the indicator-augmented models at the usual significance levels.

Figure 4 provides more insight in comparative performance of the models in questions. In the upper panel of the figure the actual (first-released) values of GDP growth are shown together with the forecasts from competing models: the benchmark AR(2) and the best performing ARDL(2,0) model that is augmented with the R-word index labelled **NZZ-CH-R**. In the lower panel of the figure the corresponding absolute forecast errors are shown. We observe that the largest gain of the indicator-augmented model occurs in the fourth quarter of 2008; i.e. in the quarter when negative quarterly GDP growth on the year-on-year basis was first recorded since 2003. This example illustrates that the indicator augmented model performs best exactly when it is expected to perform so. At the same time the fact that there are also a number of quarters when the ARDL models delivers lower forecast errors indicates that the recession index captures business cycle dynamics in other than recessionary times.

Summarising, on the basis of statistical tests we are able to define a version of the R-word index that delivers most accurate forecasts of GDP growth out of sample. That is, the R-word index based on counting articles that simultaneously mention the keywords “recession” and “Switzerland” in the leading Swiss newspaper *Neue Zürcher Zeitung* delivers the best results. As reported in Table 1, the econometric model that incorporates information from this index delivers more accurate forecasts of first GDP growth announcements than those from a univariate autoregressive model. It is also encouraging that on the basis of statistical tests we are able to reject the null hypothesis of equal forecast accuracy with the benchmark model.

5 Conclusion

In this paper a pioneering attempt to construct the R-word index for Switzerland is presented. We constructed the index starting from the first quarter of 1998 using the electronic Swiss Media Database ‘Schweizerischer Mediendienst’. We used a simple keyword search like “recession” as well as “recession” AND “Switzerland” in Switzerland’s most influential newspaper, the *Neue Zürcher Zeitung*, as well as in all German-speaking newspapers in the archive. On the basis of these searches, the corresponding four versions of the R-word index were created by counting the number of articles where the respective keywords were used.

We evaluated the predictive content of the R-word indices for quarterly GDP growth in an out-of-sample forecasting exercise. To this end, we used real-time GDP vintages in order to simulate

the information set that was available to forecasters in the past. The forecast evaluation sample is from 2002Q1 until 2011Q4. Due to the publication lag of GDP data, our forecasts precede first official estimates of GDP growth by about two months. We compared forecasting accuracy of the model augmented with the R-word index against a simple autoregressive model, which is widely regarded as a simple and, in the same time, robust forecasting device in practice.

Our results suggest that the version of the R-word index, that is based on the number of articles in the *Neue Zürcher Zeitung* newspaper, where both the keywords “recession” AND “Switzerland” are mentioned, provides the most accurate forecasts. We also find that the models with the R-word index are much more accurate in predicting first releases of GDP growth rather than revised GDP growth figures. This allows us to conclude that revisions to GDP are not predictable on the basis of information contained in the R-word index.

Interestingly, the R-word index solely computed with the keyword search within the NZZ does better than an overall R-word index, drawing information from all Swiss German newspapers. We only can speculate why this is the case. One reason might lie in the NZZ itself which is credited with being non-out-crying regarding to economic trends, which prevents it from overreacting. This observation leads us to a point, famously been made by Akerlof and Shiller (2009, p. 54) in their book *Animal Spirits*: “The news media are, after all, in the business of creating stories that people would like to hear.” These stories have a tendency towards over-interpretation and are mainly filled with theories from pundits after pundits. However, Akerlof and Shiller (2009) continue, what is, if the news itself are the news? The stories no longer merely explain the facts; they are the facts. The self-fulfilling prophecy theory is not at the core of our study. However, in a next step it might be of interest to analyse the self-fulfilling prophecy for Switzerland. One hypothesis might be that the competition in the news business has become harsher, overstating the actual economic situation. It would, therefore, be interesting to compute the R-word index for a longer time period, and, possibly, for each newspaper in the database. This might show a shifting reporting among Swiss newspapers.

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Table 1: Assessment of forecast accuracy (2002Q1—2011Q4)

| | First-available GDP | | | Last-available GDP (2011Q4) | | |
|----------------------------|---------------------------------|-------------|--------------------|-----------------------------|-------------|-----------|
| | RMSFE | Ratio | [p-value] | RMSFE | Ratio | [p-value] |
| AR(1) | 0.982 | 1.22 | | 1.215 | 1.06 | |
| AR(2)^a | 0.805 | 1.00 | | 1.151 | 1.00 | |
| | ARDL(2,0) ^b vs AR(2) | | | | | |
| NZZ-CH-R | 0.613 | 0.76 | 0.026 ^c | 1.022 | 0.89 | 0.013 |
| NZZ-R | 0.666 | 0.83 | 0.044 | 1.051 | 0.91 | 0.024 |
| SMD-CH-R | 0.698 | 0.87 | 0.062 | 1.065 | 0.93 | 0.033 |
| SMD-R | 0.712 | 0.88 | 0.052 | 1.069 | 0.93 | 0.023 |
| Model average ^d | 0.654 | 0.81 | 0.045 | 1.040 | 0.90 | 0.022 |
| GDP(FA) ^e | | | | 0.748 | | |

^a The benchmark model is autoregressive model of order two, shown in bold font.

^b The models with the R-word index are autoregressive distributed lag (ARDL(2,0)) models that include two lags of dependent variable and contemporaneous value of the recession indicator. All RMSFE ratios of competing models in this panel are computed against the AR(2) model.

^c Reported p-values are obtained using the Clark and West (2007) test for equal forecast accuracy between nested models. One-sided p-values are reported.

^d Forecast accuracy is evaluated for pooling combination of the ARDL models using equal weights.

^e Forecast accuracy is evaluated of first GDP releases against the last-available GDP vintage.

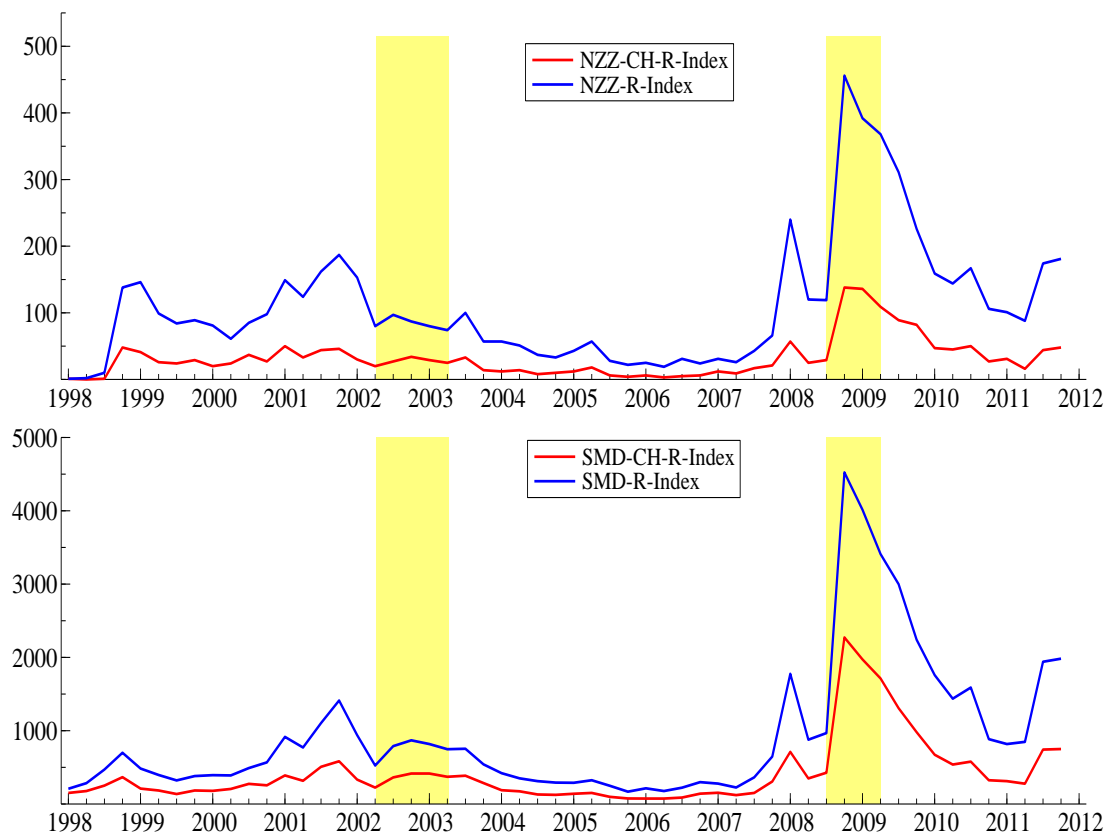


Figure 1: R-word index and recession periods (shown in yellow colour) according to the classical business cycle (Siliverstovs, 2011b, Table 2). The chronology is based on the GDP vintage released in March 2011.

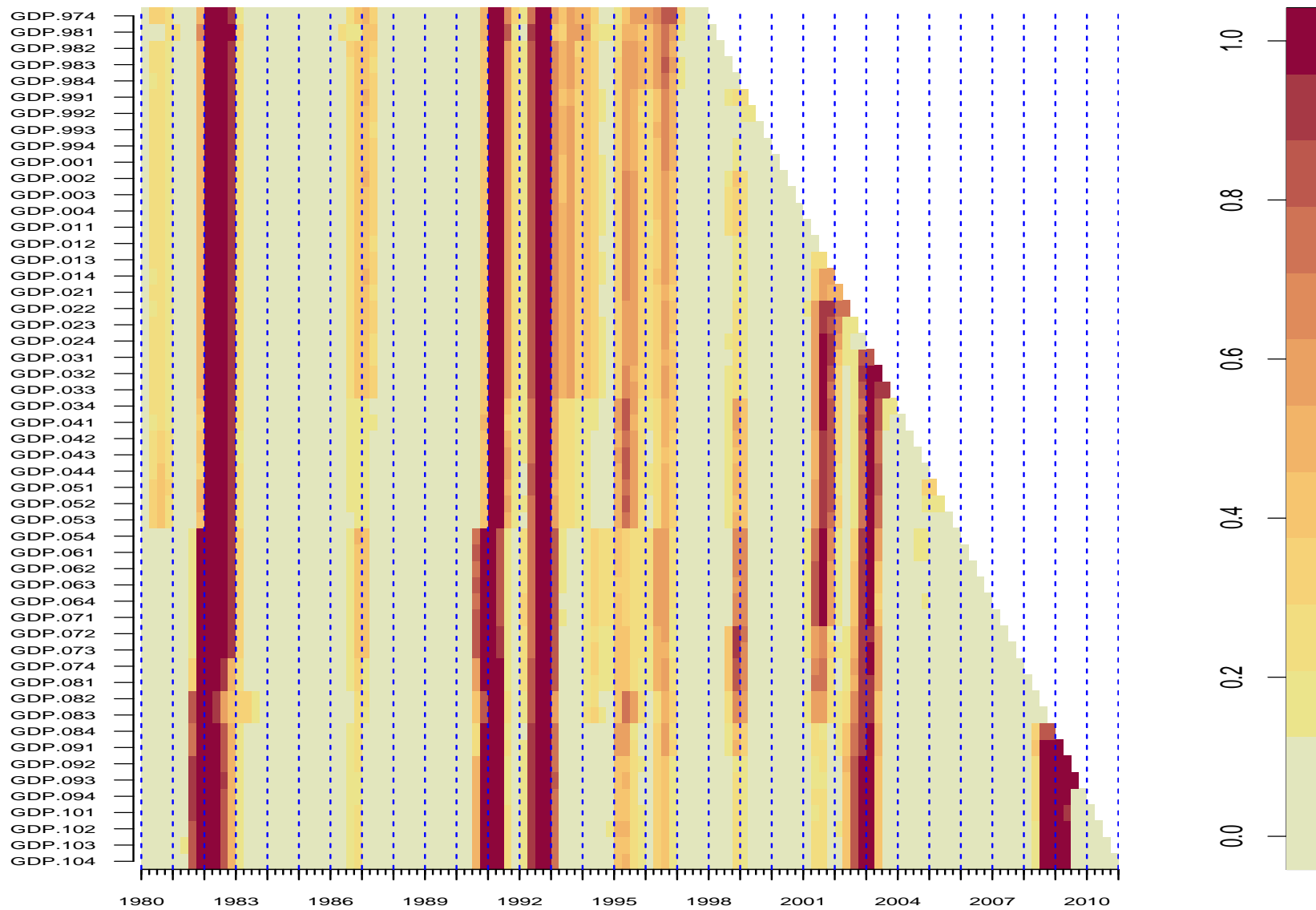


Figure 2: Vintage-specific relative frequency of recession: the first vintage ends in 1997Q4, the last vintage ends in 2010Q4; replicated from Siliverstovs (2011b, Figure 6).

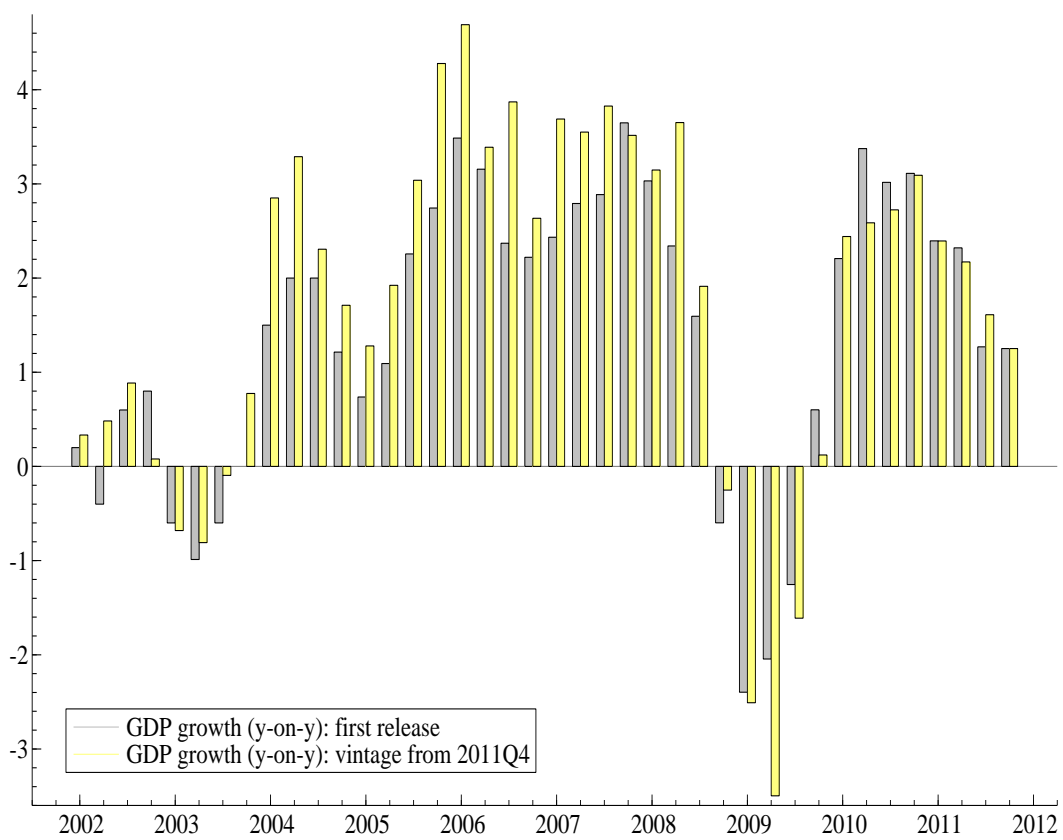


Figure 3: Year-on-year real GDP growth: first-released (in gray) vs. latest-available (in yellow) vintage (until 2011Q4).

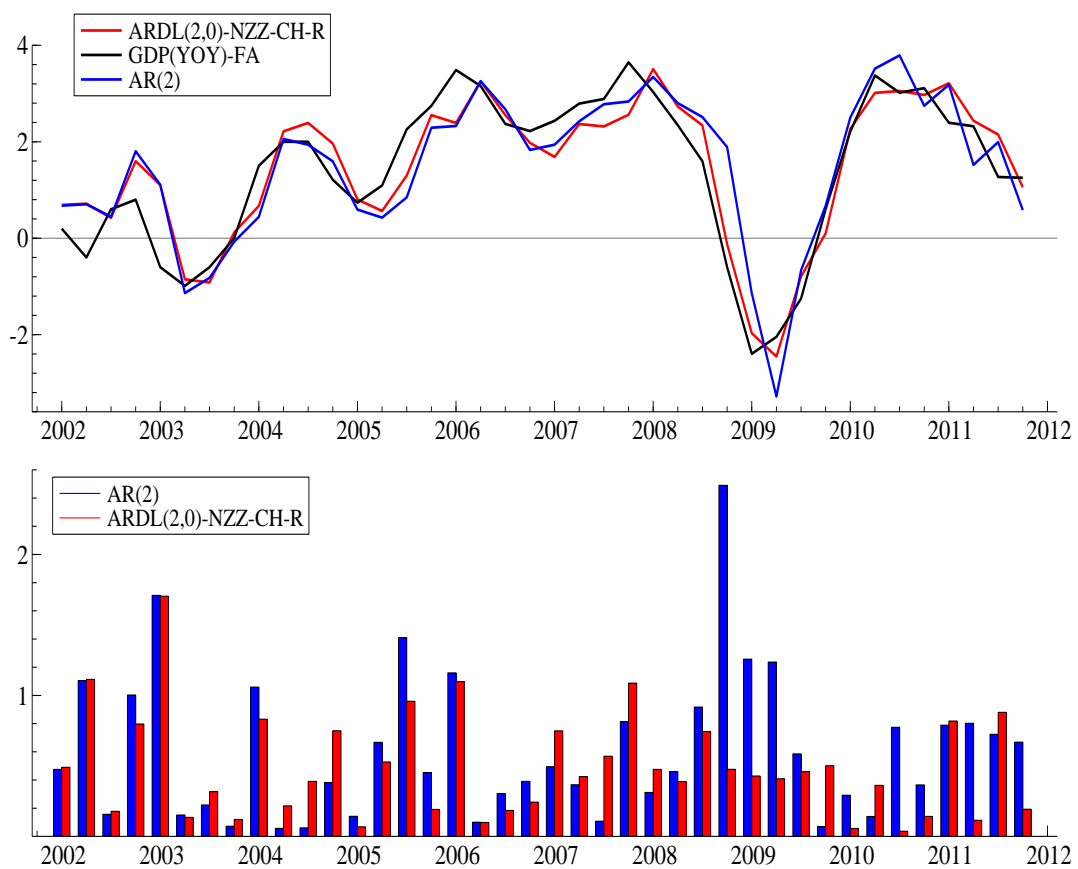


Figure 4: Upper panel: year-on-year real GDP growth (first-released actual values and forecasts from the benchmark AR(2) and the best indicator-augmented ARDL(2,0) model (NZZ-CH-R)); Lower panel: absolute forecast errors for the AR(2) and ARDL(2,0) models.