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Keeping a Finger on the Pulse of the Economy: Nowcasting Swiss GDP in Real-Time Squared*

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Abstract

This study evaluates forecasting performance of a large-scale factor model developed in Siliverstovs and Kholodilin (2012) in a genuine *ex ante* forecasting exercise. We perform our forecast of GDP growth in Switzerland in real time using real-time data vintages collected at weekly frequency. This allows us to monitor how newly released economic and financial data influence our forecasts and hence capture prevailing tendencies in current course of economic development.

Keywords: Business tendency surveys, Forecasting, Nowcasting, Real-time data, Dynamic factor model

JEL code: C53, E37.

[1]The paper benefited from comments of the participants at the KOF Brown Bag Seminar in Zurich. All computations were performed in Ox version 6.10 (Doornik, 2007), figures—in R-2.9.2.

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1 Introduction

Inferring current state of aggregate economic activity is of a great interest both to policy-makers and practitioners alike. Since it deals with forecasting of the present, it is typically referred to as *nowcasting*. Given publication lags of official statistical releases of GDP data, nowcasting uses the currently available information in order to form a judgment on the current economic conditions. The information set typically consists of economic and financial indicators that are released with shorter publication lags and/or at a higher than quarterly frequency.

In evaluating various approaches to nowcasting or, more generally, forecasting most of published studies rely on pseudo real-time simulations. In such simulations genuine real-time aspects of data are lost and the fact that data often undergo substantial revisions is simply ignored (Croushore and Stark, 2003). Typically, in these studies a last-available data vintage is used, which is truncated in such a way that mimics availability of data in the past. Moreover, since these exercises are carried *ex post*, it may tempt a researcher to engage in data mining by searching over various modelling approaches or indicator choices and subsequently report results that are favourably biased to his or her preferred alternatives. Croushore (2011) provides a thorough discussion on using real-time versus last-available data vintages and summarises recent advances and challenges in dealing with real-time data.

At the same time there is only a handful of studies that specifically address forecasting performance in a genuine real-time environment, where researchers publically announce their out-of-sample forecasts and hence tend to put their reputation at stake, as summarised in Hamilton (2010). In an relevant extension of their research a group of researchers[1] set up an online tool for nowcasting economic developments in the Euro Area and a number of countries, `http://now-casting.com`. For the most part, however, this service is not open to a general public but is available to subscribers only. More important for us is the fact that Switzerland is not covered in this project.

For Switzerland, Müller and Köberl (2012) provide a description of an *ex ante* real-time experiment in forecasting quarterly year-on-year GDP growth. The forecasting exercise of Müller and Köberl (2012) is an ongoing project that was started in the third quarter of 2007. Since then a GDP growth forecast was issued every quarter and the authors committed themselves to released forecasts by making them publically available at the web and by means of electronic communication.[2]

In this paper we describe a forecasting experiment that is similar in spirit to that of Müller and Köberl (2012). Nevertheless, it has a number of distinctive features concerning target variable, timing and frequency of release, and econometric approach. Essentially, this paper is an extension of

[1]The team members are Domenico Giannone, Lucrezia Reichlin, Jasper McMahon, Michele Modugno, and Saverio Simonelli.

[2]Description of the project and its results are available at `http://www.cmueller.ch/8897a3`.

Siliverstovs and Kholodilin (2012), where we investigate forecasting performance of a large-scale factor model in a pseudo real-time framework. Based on this *ex post* forecasting experiment we selected factor model specification that delivered largest forecast accuracy. Here we put the preferred factor model specification to a stress test under genuine real-time conditions. That is, we use actual historical vintages of data as they were available at the time forecasts were made, and we announce our forecasts on the same day data become available.

Our target variable is seasonally adjusted quarterly GDP growth that we forecast on a weekly basis. In order to do so, we save the data every Tuesday at 5 p.m. and use them to make forecasts. For a given quarter we produce initial forecast in the beginning of the third month of the previous quarter, when official GDP estimates for the preceding quarter are released with a publication lag of about two months. We keep making forecasts of GDP growth in the quarter of interest every week until the beginning of the third months of that quarter, when a new vintage of GDP data is officially released. The final forecast or, more precisely, nowcast of GDP growth in the current quarter is fixed at this date. According to the results reported in Siliverstovs and Kholodilin (2012), such timing of a final forecast release delivers most accurate predictions. Parameters of the large-scale factor model are estimated using the approach of Giannone et al. (2008), which proves to be a popular nowcasting method as summarised in the devoted website `http://now-casting.com/research`.

The paper is structured as follows. Section 2 contains description of data used. In section 3, the modelling approach of Giannone et al. (2008) is presented. Results of our forecasting exercise are presented in section 4. The final section concludes.

2 Data

The data set of monthly indicators is essentially the same as used in Siliverstovs and Kholodilin (2012). The data set of monthly indicators consists of 558 indicators sub-divided into the following 9 blocks[3]: Purchasing Managers Index in manufacturing supplied by Credit Suisse (9 time series, "PMGR"), consumer price indices (28, "CPI"), labor market indicators (6, "LABOUR"), producer price indices (13, "PPI"), business tendency surveys in manufacturing collected at the KOF Swiss Economic Institute (150, "CHINOGA"), exports and imports (249, "TRADE"), stock market indices (80, "STMKT"), interest rates (20, "INT.RATE"), and exchange rates (3, "EXCH.RATE").[4]

Information on the monthly indicators is presented in Table 1. Observe that blocks of macroeconomic data differ both in terms of size and timeliness. The largest block is the block containing

[3] The block with retail trade statistics containing 4 indicators, that was present in Siliverstovs and Kholodilin (2012), was omitted in the current exercise due to data availability issues.

[4] Observe that the selected monthly indicators do not contain any time series of industrial production in Switzerland. In contrast to many industrialized countries the industrial production index is released at a quarterly frequency in Switzerland.

the exports and imports statistics, followed by the KOF surveys. The smallest block is one with the exchange rates, followed by labor-market indicators, and the "PMGR" block where the number of indicators is below 10. In our setup, the timeliest block is the KOF surveys released in the middle of the month with zero publishing lag. Following Giannone et al. (2008), we consider only monthly averages of the financial variables that are incorporated in the model at the end of each month. Observe that these variables are available at the daily frequency and by considering their monthly averages we are likely to downplay importance of these variables for forecasting accuracy, on the one hand. On the other hand, the informational content of the financial variables, e.g., stock market indices, may be impaired by their high volatility when those are recorded at daily frequency. In this case, considering only monthly averages is likely to smooth the noise out, thus positively influencing forecast accuracy. The rest of blocks are released with lag of one month.

Application of a factor model requires that monthly indicators satisfy covariance stationarity. However, macroeconomic variables rarely meet this requirement. Instead they typically display a persistent growth or long-term trends. To deal with such features of our data, we initially apply the first-order differencing procedure to all blocks of data, except business tendency surveys ("PMGR" and "CHINOGA" blocks). That is we express our monthly indicators either in their monthly growth rates or in monthly changes (block of interest rates).[5] Following Giannone et al. (2008) we further transform all but business tendency survey variables in order to ensure that these correspond to quarter-on-quarter growth. This is achieved by the following transformation $(1 - L^3)(1 + L + L^2) = (1 - L)(1 + 2L + 3L^2 + 2L^3 + L^4)$.

The target variable that we forecast is quarter-on-quarter seasonally adjusted growth of the Swiss GDP, for which we also have real-time vintages.

3 Model

Let us denote quarterly GDP growth by y_{t_q}, where t_q is the quarterly time index $t_q = 1, 2, ..., T_q$, and T_q indicates the last quarter for which GDP observations are available. The quarterly variable also can be expressed on the monthly time scale, assuming that it only can be observed in the last month of each quarter, $y_{t_m^*} = y_{t_q}$, where $t_m^* = 3, 6, ..., 3t_q, ..., 3T_q$. We aim at predicting GDP growth for h_q quarters or $h_m = 3h_q$ months ahead relative to the quarter T_q, i.e. $y_{T_q+h_q} = y_{T_m+h_m}$ with $T_m = 3T_q$.

Out-of-sample forecasts are made conditional on an available information set. This information set consists of a panel of monthly economic indicators $X_{t_m|T_{m+\kappa}} = (X_{1t_m|T_{m+\kappa_1}}, ..., X_{nt_m|T_{m+\kappa_n}})'$ with t_m as the monthly time index. These indicators are available κ_i months ahead of GDP data.

[5] See Appendix in Siliverstovs and Kholodilin (2010) for description of indicators and their transformations.

Depending on publication lag of a particular indicator X_i and its release timing within a given month κ_i may vary across indicators. This typically results in unbalanced panel at the end of the sample or the "ragged-edge" problem. We make h_q-quarter ahead forecasts conditional on information set containing monthly indicators up to $T_{m+\kappa}$, $\Omega_{T_{m+\kappa}}$. This information set is updated every week if a new data block is released.[6]

Giannone et al. (2008) suggest a following approximate dynamic factor model with monthly indicators are assumed to be driven by r unobserved common factors $F_t = (f_{1t_m}, ..., f_{rt_m})'$ with $r \ll n$ and individual-specific idiosyncratic components $\xi_{t_m|T_{m+\kappa}} = (\xi_{1t_m|T_{m+\kappa}}, ..., \xi_{nt_m|T_{m+\kappa}})'$. In matrix notation the model reads

$$X_{t_m|T_{m+\kappa}} = \mu + \Lambda F_{t_m} + \xi_{t_m|T_{m+\kappa}}, \tag{1}$$

where $\mu = (\mu_1, ..., \mu_n)'$ is a vector of individual specific intercepts and Λ is a $(n \times r)$ matrix of factor loading coefficients. Additional assumptions include a white-noise process for idiosyncratic shocks $\xi_{t_m|T_{m+\kappa}}$ in equation (1), i.e., $E(\xi_{t_m|T_{m+\kappa}}\xi'_{t_m-s|T_{m+\kappa}}) = 0$ with $s > 0$ for all j and v, zero cross-correlation, i.e., $E(\xi_{t_m|T_{m+\kappa}}\xi'_{t_m|T_{m+\kappa}}) = \Psi_{t_m|T_{m+\kappa}} = diag(\psi_{1t_m|T_{m+\kappa}}, ..., \psi_{nt_m|T_{m+\kappa}})$, as well as the assumption of Gaussian error terms.

The common factors are assumed to follow a vector autoregressive process

$$F_{t_m} = AF_{t_m-1} + Bu_{t_m}, \quad u_{t_m} \sim WN(0, I_q), \tag{2}$$

where A is a $r \times r$ parameter matrix satisfying a stationarity restriction such that all roots of $\det(I_r - Az)$ lie outside the unit circle, B is a $r \times q$ matrix of full rank q, and u_t is a $q-$dimensional white-noise process, representing shocks to the common factors.

Equations (1) and (2) represent a so-called state-space form which parameters need to be estimated. The parameter estimates are obtained using the following procedure:

1. All monthly indicators $X_{t_m|T_{m+\kappa}}$ are standardised to have zero mean and unit variance in order to remove scale effects. Then the panel containing monthly indicators is balanced by deleting observations at the end of the sample in order to remove the "ragged edge". The principal component analysis applied to the balanced panel delivers estimates of the common factors $\widehat{F}_{t_m|T_{m+\kappa}}$.

2. The matrix of factor loadings $\widehat{\Lambda}$ is obtained by means of the OLS regression of $X_{t_m|T_{m+\kappa}}$ on $\widehat{F}_{t_m|T_{m+\kappa}}$. This OLS regression also delivers an estimate of the covariance matrix of

[6]Strictly speaking, since our data vintages are collected on a weekly basis, an addition subscript allowing to differentiate between different vintages within a month is needed. For the sake of notational simplicity we do not introduce it here.

idiosyncratic disturbances $\xi_{t_m|T_{m+\kappa}}$, denoted by $\widehat{\Sigma}_\xi$. The off-diagonal entries of this covariance matrix are set to zero.

3. Use $\widehat{F}_{t_m|T_{m+\kappa}}$ in order to estimate VAR model parameters $\widehat{A}$ and the residual covariance matrix, denoted by $\widehat{\Sigma}$.

4. Apply an eigenvalue decomposition to $\widehat{\Sigma} = MPM$, where M is a $(r \times q)$ matrix of eigenvectors corresponding to the q largest eigenvalues, and P is a $(q \times q)$ matrix with the largest eigenvalues on the main diagonal and zero otherwise. Then an estimate of B is given by $\widehat{B} = MP^{1/2}$.

This procedure fully specifies the state-space form of the model, which allows to apply the Kalman smoother in order to get estimates of common factors also for a sample period when some or all observations are missing.

Let us denote the expected value of the common factors by

$$\widehat{F}_{t_m|T_{m+\kappa}} = E(F_{t_m}|\Omega_{T_{m+\kappa}})$$

and the associated factor estimation uncertainty

$$\widehat{V}_{T_{m+\kappa}} = E[(F_{t_m} - \widehat{F}_{t_m|T_{m+\kappa}})(F_{t_m} - \widehat{F}_{t_m|T_{m+\kappa}})')].$$

Both these quantities of interest are available as a standard output of the Kalman smoother.

Giannone et al. (2008) suggest to compute GDP forecasts by projecting the quarterly GDP growth rate on the estimated monthly factors that have been converted to quarterly frequency by keeping only their values in the last month of the quarter, $F_{3t_q|T_{m+\kappa}}$ with $t_q = 1, ..., T_q$, where T_q is the last month in the quarter for which GDP is available:

$$\widehat{y}_{3t_q|T_{m+\kappa}} = \widehat{\gamma}_0 + \widehat{\gamma}'\widehat{F}_{3|T_{m+\kappa}}. \tag{3}$$

The parameters of the forecasting equation are estimated for the following values of the quarterly time index $t_q = 1, ..., T_q$, and out-of-sample forecasts are made for $t_q = T_{q+1}, ..., T_{q+h_q}$. The associated forecast uncertainty is computed as

$$V_{y_{3t_q|T_{m+\kappa}}} = \widehat{\gamma}'\widehat{V}_{T_{m+\kappa}}\widehat{\gamma} + Var(\widehat{e}_{3t_q|T_{m+\kappa}}),$$

where $\widehat{e}_{3t_q|T_{m+\kappa}} = y_{3t_q|T_{m+\kappa}} - \widehat{y}_{3t_q|T_{m+\kappa}}$ are the estimated residuals in the forecasting model (3).

4 Results

Siliverstovs and Kholodilin (2012) investigate *ex post* forecasting performance of a large-scale factor model using the period from 2005Q1 until 2009Q2. In this paper we extend their study by reporting *ex ante* real-time forecasting performance of model specification that yielded most accurate out-of-sample forecasts. As shown in Siliverstovs and Kholodilin (2012), most accurate current-quarter forecasts of GDP growth are made in the beginning of the third month of that quarter, when official GDP data are released. Moreover, it turns out that a single-factor model should be preferred to specifications allowing for multiple factors. Our, admittedly, a rather short sample, for which real-time data vintages are available, starts in 2010Q1 and ends in 2011Q4. This implies that we have only 8 quarterly observations for comparison with actual GDP growth. During this period we collected 112 out-of-sample forecasts recorded at the weekly frequency. This weekly forecasts were mostly made on Tuesdays. In those cases when GDP data were released on Thursdays, we produced forecasts twice per week.

Figures 1 and 2 display sequences of real-time forecasts for the years 2010 and 2011, respectively. In each of these figures a sequence of weekly forecasts is shown. Changes in forecasts are attributable to updates in information set due to new data releases. The whole exercise was started on the 26th of January, 2010, when we began saving real-time data vintages on a regular basis. We kept producing forecasts for the first quarter of the year 2010 until the 2nd of March of 2010, when we fixed the forecast, or, more precisely, nowcast value for that quarter. Similarly, for the second quarter of 2010 the sequence of forecasts starts on the same day (02.03.2010) and ends on 02.06.2010, when a final nowcast is made for this quarter. We perform the same procedure for each of the remaining quarters in our evaluation sample.

As a result of sequential updates of information set we are able to monitor how different data releases contribute to changes in our forecasts. For example, in the beginning of 2010, when Swiss economy recovered from the world-wide Great Recession, the new data releases pushed our forecasts consistently in one upward direction. At that time, it reflected growing confidence in the strength of economic recovery, resulting in a continuous stream of news that were predominantly positive. The peak was reached in May and for the remaining quarters of 2010 our forecasts fluctuated at a relatively high level, as shown in Figure 1. In the year 2011, our forecasts continued to stay approximately at the same level as before until the beginning of May. This period is marked by Portugal's admission of financial problems that it is not able to solve on its own. In May 2011, the bail-out package of 78bn Euro for Portugal was agreed.[7] Since than our forecasts were mainly driven by negative news, reflecting escalating European debt crisis and growing fears of entering

[7]For a time line of crisis see `http://www.bbc.co.uk/news/business-13856580`.

into a new recession. In Switzerland, rapid appreciation of the Swiss Franc in Summer 2011 also created substantial concerns regarding the performance of the domestic economy. Reacting to such development in the currency exchange markets, the Swiss National Bank (SNB) set a minimum exhange rate at 1.20 Franc per Euro on the 6th September, 2011. In an interesting coincidence, our nowcast for the third quarter made precisely on this day indicates a zero growth in GDP, i.e. the lowest nowcast made until this date in our evaluation sample. Nevertheless, the stream of negative news also continued in the fourth quarter of 2011, pushing our forecasts further down, below the zero line. The ultimate nowcast made on 01.12.2011 is -0.15% GDP growth in 2011Q4.

In Figures 1 and 2 official GDP growth releases of the Swiss State Secretariate for Economic Affairs (SECO) are shown. These are denoted by straight lines (a bold line corresponds to the first release for that particular quarter). Revision to GDP growth can indeed be substantial. For example, the first estimate of non-annualised quarterly GDP growth for 2010Q1 released on 01.06.2010 was 0.41. Three months later in the next data release on 02.09.2010 it was revised up to 1.03. Presence of such large revisions, known only *ex post*, illustrate challenges a forecaster faces when making predictions in real time. It also implies that much less worth should be put in first releases of GDP growth as these will be most likely revised and often substantially.

The ultimate nowcasts collected over all evaluation sample are presented in Table 2 along with corresponding values of official estimates of GDP growth. The table contains also information on first-available values of GDP growth, GDP growth reported in the most recent vintage released on the 1st of March, 2012, and median values across all vintages. For information on the revision magnitude, we also report minimal and maximal values of officially released GDP growth.

The summary of nowcast accuracy of the factor model in terms of the Root Squared Mean Forecast Error (RMSFE) is presented in Table 3. We compare our nowcasts with those based on a naive benchmark model, based on a historical mean. This historical mean was calculated using latest available GDP vintages for the sample period starting from 1992Q1 until the most recent quarter for which observations are available. We compute the RMSFEs with respect to first-available, last-available, and median values of GDP growth, denoted by (First), (Last), and (Median) in the table, respectively. In doing so, we acknowledge that GDP revisions in Switzerland tend to be rather large and volatile (Cuche-Curti et al., 2008) and hedge us against excessive outcome sensitivity with respect to a particular data vintage used for forecast accuracy evaluation. In a related research, Siliverstovs (2011) analyses implications of such revision pattern for business cycle dating in Switzerland.

The factor model produces more accurate out-of-sample nowcasts as the naive model, as the reported RMSFEs ratios are below one. The largest gain in forecast accuracy of about 18% reduction in the RMSFE is obtained when one compares our nowcasts with median GDP growth computed across available vintages.

5 Conclusion

In this paper we put a large-scale factor model developed in Siliverstovs and Kholodilin (2012) to a forecasting exercise in real-time squared. That is, we strictly use only the information that was available to us at a time of making forecasts and we announce our forecasts at the same time we made those. The fact that we produce forecasts of quarterly GDP growth at the weekly frequency allows us to continuously monitor the state of the economy and trace the influence of newly released patches of economic data on our forecasts. On basis of this, we were able to capture a phase of economic recovery after the Great Recession, a phase of relatively high growth during the year 2010, and a phase of declining confidence caused by escalating European debt crisis and growing fears of entering a new recession during the evaluation period from 2010Q1 until 2011Q4. According to our results, the latter phase started in May 2011 and continued until November 2011, when pessimistic sentiments dominated economic outlook.

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Table 1: Chronology of data releases during the month

Block	Published by	Timing (approx.)	Publication lag (in months)	Block size
PMGR-manufacturing	Credit Suisse	1st working day of month	1	9
CPI	Swiss Federal Statistical Office	First week of month	1	28
Labour	State Secretariat for Economic Affairs	Second week of month	1	6
PPI	Swiss Federal Statistical Office	Second week of month	1	13
BTS in manufacturing	KOF Swiss Economic Institute	Middle of month	0	150
Exports/Imports	Swiss Federal Customs Administration	Middle of month	1	249
Stock market indices	Datastream	Last day of month (monthly average)	0	80
Interest rates	Datastream	Last day of month (monthly average)	0	20
Exchange rates	Datastream	Last day of month (monthly average)	0	3

Table 2: GDP growth: nowcasts and actual values

	2010Q1	Released on	2010Q2	Released on	2010Q3	Released on	2010Q4	Released on
Nowcast	0.57	02.03.2010	0.80	02.06.2010	0.63	02.09.2010	0.66	02.12.2010
95% CI	[-0.16, 1.30]		[0.07, 1.53]		[-0.16, 1.42]		[-0.12, 1.44]	
Naive[a]	0.36		0.36		0.37		0.37	
GDP: First[b]	0.41	01.06.2010	0.85	02.09.2010	0.69	02.12.2010	0.87	01.03.2011
GDP: Last	0.77		0.69		0.77		0.58	
GDP: Median	0.81		0.70		0.76		0.61	
GDP: (Min,Max)	(0.41, 1.03)		(0.60, 0.85)		(0.68, 0.87)		(0.42, 0.87)	

	2011Q1	Released on	2011Q2	Released on	2011Q3	Released on	2011Q4	Released on
Nowcast	0.80	01.03.2011	0.61	05.06.2011	0.00	06.09.2011	-0.15	01.12.2011
95% CI	[0.02, 1.57]		[-0.17, 1.39]		[-0.77, 0.77]		[-0.96, 0.66]	
Naive	0.37		0.38		0.38		0.38	
GDP: First	0.25	31.05.2011	0.36	01.09.2011	0.22	01.12.2011	0.09	01.03.2012
GDP: Last	0.35		0.43		0.30		0.09	
GDP: Median	0.37		0.43		0.26		0.09	
GDP: (Min,Max)	(0.25, 0.64)		(0.36, 0.48)		(0.22, 0.30)		(0.09, 0.09)	

[a] Naive nowcast is based on a historical mean of the released vintage from 1992Q1 until the latest period with a non-missing value.

[b] Columns with GDP entries refer to the first release (First), latest release (Last), median value for the corresponding quarter across all releases (Median), and minimum and maximum values recorded over all releases (Max,Min).

Table 3: Nowcast accuracy: RMSFE

	RMSFE		
	First	Last[a]	Median
Factor model	0.259	0.237	0.230
Naive[b]	0.301	0.266	0.282
Ratio	0.861	0.891	0.817

[a] In column *Last* we compare our nowcasts with values of GDP growth reported in the latest vintage released on 01.03.2012. The last GDP observation in this vintage is for 2011Q4.

[b] Naive nowcast is based on a historical mean of released vintages from 1992Q1 until the latest period with a non-missing value.

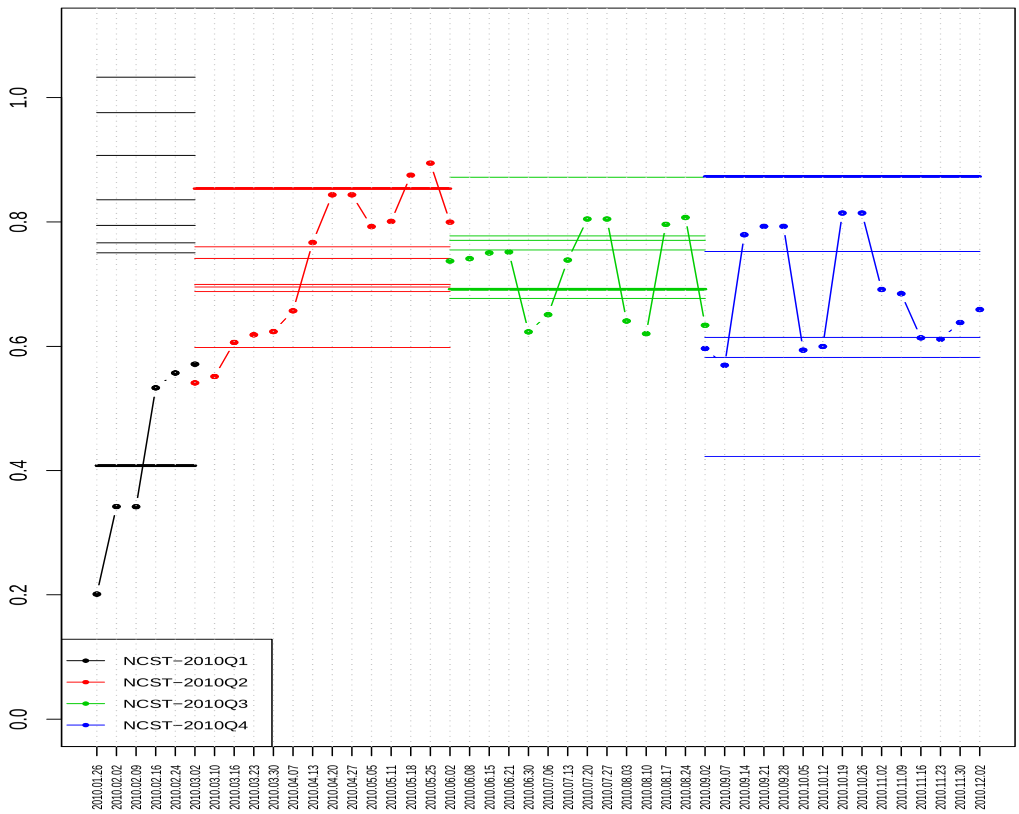

Figure 1: Real-time weekly nowcasts for **2010**; SECO vintages of the quarterly real GDP growth rate [SA, non-annualised] (straigtht lines, a bold line—first release)

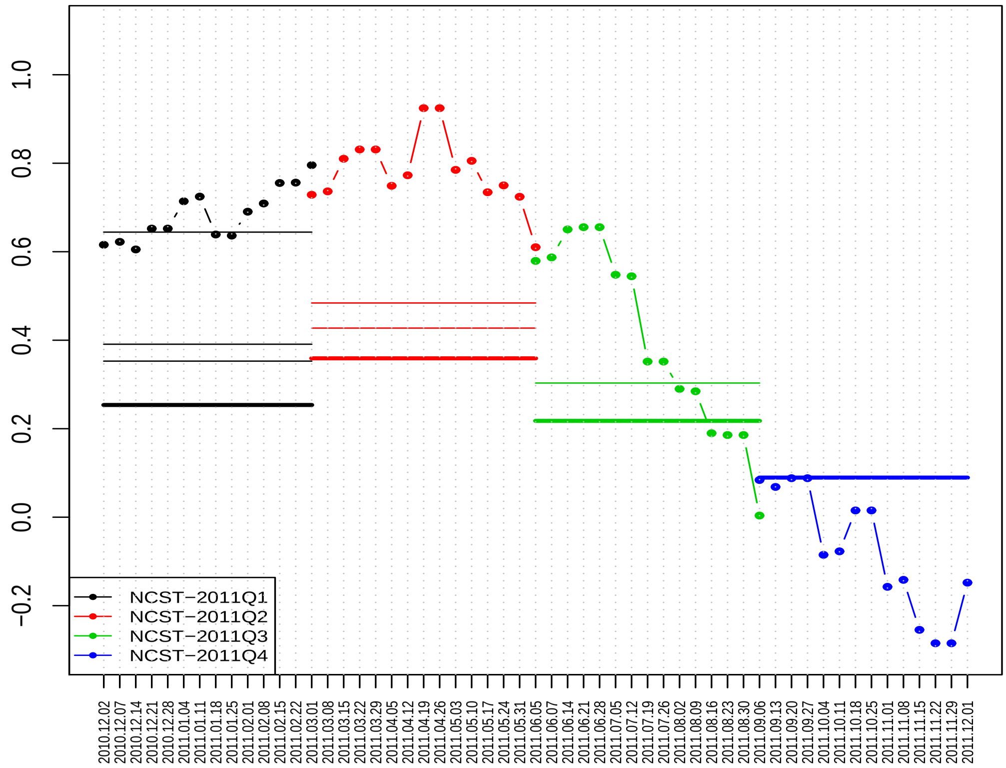

Figure 2: Real-time weekly nowcasts for **2011**; SECO vintages of the quarterly real GDP growth rate [SA, non-annualised] (straight lines, a bold line—first release)