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KOF Working Papers

Are GDP Revisions Predictable?
Evidence for Switzerland

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Are GDP Revisions Predictable?

Evidence for Switzerland[§]

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Abstract

This study presents a model that delivers more accurate forecasts of the revised rather initial estimates of the quarterly GDP growth rate in Switzerland during the period of the recent financial crisis. The key explanation to our findings is that our model, capitalizing on the information contained in the Business Tendency Surveys, is able to predict future revisions of the initial estimates. Our findings imply that there seems to be a scope for improvement of how preliminary estimates of the quarterly GDP growth rate are produced in Switzerland.

Keywords: GDP revisions, forecasting, mixed-frequency data, factor model

JEL code: C53, E37.

[§]I am grateful to Jan-Egbert Sturm as well as to the participants at the KOF Brown Bag seminar (Zurich, Switzerland) for useful comments. I also would like to thank Maximo Camacho for sharing the code. Computations were performed in Ox 6.00 and PcGive 13.0 (Doornik, 2007; Doornik and Hendry, 2009). Some functions from the SsfPack Basic were used as well (Koopman et al., 1999). The usual disclaimer applies.

1 Introduction

First releases of GDP figures are routinely followed by all interested parties. These numbers summarise the most recent official view on the current economic conditions and hence are rightfully regarded as the most important single indicator of economic activity. However, it is also a well-known fact that the subsequent GDP releases often (quite substantially) modify the previously published figures (see Cuche-Curti et al., 2008, for an earlier analysis of GDP revisions in Switzerland). For example, in June 2010 the first release of quarter-on-quarter growth rate of real GDP in Switzerland for the first quarter of 2010 was 0.41. Three months later in the next GDP release this figure was modified to 1.03.

Under such conditions the first GDP releases are to be taken rather cautiously and the excessive reliance on them for decision making may not be warranted. Assuming that the subsequent revisions bring us closer to the true but unobserved final figures, one may be interested in discovering ways on whether future revisions can be predicted using either information from past revisions or from a set of some alternative economically relevant indicators. In this paper we resort to the latter approach and investigate whether the information contained in the business tendency surveys help us predicting future GDP revisions in Switzerland.

Our study has the following distinctive features. First, following Jacobs and van Norden (2011) we treat the true unobserved GDP figures as a latent variable which values can be inferred by means of unobserved components models (Harvey, 1989). This class of models links unobserved and observed variables in a state-space representation and the unknown parameters are estimated by the Kalman filter algorithm. Secondly, in order to account for the fact that the GDP variable is observed each quarter and the surveys are monthly variables we follow Mariano and Murasawa (2003) in combining variables observed at different frequencies into a small-scale mixed frequency factor model. This latent factor, commonly shared by all modelled variables, has a natural interpretation of representing true but unobserved stance of the economy. For modelling of the interrelationships between the quarterly GDP growth rate and the surveys we adopted the framework proposed in Camacho and Perez-Quiros (2010a,b), reflecting the fact that surveys tend to be closely related to annual rather than quarterly growth rates of the reference time series. Thirdly, we utilize the complete set of sequentially released historical GDP vintages in our exercise. This allows us to distinguish between first-published and revised estimates of the GDP growth rate. Unfortunately, a similar real-time database of survey indicators does not exist. However, since survey time series undergo rather minor revisions, we take them as they are available now. Then for each GDP vintage we truncate them according to the known stable pattern of publication lags. As a result of this pseudo-real-time simulation, we imitate the information flow as it was available to a forecaster in the past. Fourthly, our forecast evaluation sample starts in 2006Q4 and ends in 2010Q2. Such a choice of the evaluation sample allows us to focus specifically on the period of the recent financial crisis when the precise up-to-date information on the current developments in the economy is especially in high demand.

The main finding of our study is that the future revisions of the GDP growth rate in Switzerland are highly predictable, at least during the period in question. This implies that the first GDP releases do not utilise all the timely available information, and hence there is a scope for improvement of how preliminary

estimates of the GDP growth rate are produced.

The rest of the paper is structured as follows. Section 2 outlines GDP estimation and revision process in Switzerland. The modelling framework and the obtained results are presented in Sections 4 and 5, respectively. The final section concludes.

2 Data description

There are two federal agencies the Swiss Federal Statistical Office (SFSO) and the State Secretariat of Economic Affairs (SECO) that are involved in publishing GDP estimates in Switzerland. The SFSO releases annual GDP estimates for a year y in the following three steps. The first and second provisional estimates are released in the following years $y + 1$ and $y + 2$. The third final estimate of GDP is released in year $y + 3$, i.e. three years later. All the releases typically take place at the beginning of September of respective years.

The system of quarterly national accounts is maintained by the SECO. The SECO publishes GDP estimates for a quarter q with a lag of about two months after the end of that quarter. In production of the quarterly national accounts the SECO relies on the information provided by the SFSO and a set of high-frequency indicators¹ that are used for temporal disaggregation of annual figures.

In our paper we focus on the following GDP releases: the first release of the quarterly growth rate for a quarter q by the SECO and the estimated quarterly growth rate for the same quarter released when the first provisional annual GDP estimate, calculated by the SFSO, becomes known. Consequently here a GDP revision is defined as the difference between the latter and the former estimates of the GDP growth rate. Table 1 presents a sequence of the first releases of GDP growth rate for each quarter of the year 2009 (and the first two quarters of the year 2010) and the corresponding revised estimates. Given this release schedule it implies that the first estimate of GDP growth rate for the first quarter of year y is revised in five quarters, for the second quarter—in four quarters, for the third and fourth quarters—in three and two quarters, respectively.

The main purpose pursued in this paper is to determine whether a sign and a magnitude of such revisions are predictable based on the information contained in the business tendency surveys. To this end we use the following monthly survey indicators: the Purchasing Managers Index (PMI) released by the Credit Suisse, and the set of indicators from the KOF manufacturing industry survey collected at the KOF Swiss Economic Institute at the ETH Zurich. The latter group includes the following time-series: business situation (gg), the change in the order backlog compared to the previous month ($f2a$) and the expected purchase of intermediate goods in the next three months ($f8c$).² The choice of the survey indicators is based on their popularity—the PMI is an internationally renowned indicator of economic activity—and the long tradition of using surveys at KOF for monitoring economic situation in Switzerland. For example the indicator summarising business situation is one of the oldest indicators published by KOF. Similarly, the indicators $f2a$ and $f8c$ were

¹The list of indicators can be found at <http://www.seco.admin.ch/themen/00374/00456/00458/index.html?lang=de>.

²The abbreviation in the brackets reported next to a time-series name corresponds to that used in the FAME database *chinoga.db* that contains the KOF manufacturing industry survey. The survey time-series in question can be identified by the following names *chimt_d_NNN_s01*, where *NNN* should be substituted with the abbreviation in brackets, for example *chimt_d_gg_s01*.

components of the older version of the KOF Economic Barometer published since 1976 until 2006. The latter indicator also enters the new KOF Barometer based on a multi-sectoral design (for more details on construction of the earlier and current versions of the KOF Economic Barometer see Graff, 2010). The KOF manufacturing surveys are released in the middle of a month and they have a zero publication lag. The PMI time-series is released on the first business day of the next month, and formally it has a publication lag of one month.

3 Monthly real-time data vintages

The full sample covers the period from 1995M1 till 2010M9. The starting point was selected on the basis of availability of the PMI time-series for Switzerland as the 1995M1 is the first month when it was reported. The ending point of the sample is determined by the fact that in September 2010 the first annual GDP estimate for the year 2009 was released by the SFSO, allowing us to compute revisions for that year. Given the GDP publication lag, this vintage released by the SECO has the last observation for 2010Q2. The full sample is split into two parts: the initial estimation sample (from 1995M1 until 2006M12) and the forecast evaluation sample determined by the quarterly publication schedule of GDP data. The latter starts in 2006Q4 and ends in 2010Q2.

We estimate the factor model at monthly frequency. This means that for each month in our forecast evaluation sample we specify the corresponding data vintage that mimics the information available to a forecaster in that month. For example, the information set available in December 2006 includes all data vintages released in that month: the GDP vintage (released in the beginning of the month) with the last observation for 2006Q3, the PMI indicator (released in the beginning of the month) with the last observation for November 2006, and the KOF manufacturing surveys (released in the middle of the month) that already have the observation for December 2006. The information set available in January 2007 includes the following data: the GDP vintage with the last observation for 2006Q3 as before, the PMI indicator (released in the beginning of the month) with the last observation for December 2006, and the KOF manufacturing surveys (released in the middle of the month) that already have the observation for January 2007. Similarly, in the next month the information set comprises the GDP vintage as before, the PMI indicator with the last observation for January 2006, and the KOF manufacturing surveys with the last observation for February 2007. In March 2007, the data vintage consists of the new GDP vintage released in this month that has the last observation for 2006Q4, the PMI indicator, and the KOF surveys, released in the beginning and in the middle of March that have the last observation for February and March, respectively. Since the last quarter, for which forecasts are made, is 2010Q2, the relevant monthly data sets reflect the data stand in June, July, and August.

This real-time setup of the monthly data vintages implies that one-step ahead forecasts of the GDP growth rate in a particular quarter q can be made either in the middle of the last month of this quarter (*nowcast*), or in the middle of the first (*backcast* - 1) or second (*backcast* - 2) month of the quarter $q + 1$. For example, for the fourth quarter of 2006 a one-step ahead prediction can be made either in the middle of December,

January, or February. The drawback of the *nowcast* is that not all monthly values of the important coincident indicator (PMI) are incorporated into the information set. Hence, one expects that such a loss of information could result in inferior forecast accuracy compared to backcasts when all monthly values of the PMI indicator are included in the information set. As a result, we are left with backcasts, which, as it will be shown below, produce a very similar prediction accuracy. Since the *backcast* – 1 is more timely than the *backcast* – 2 we report the results of an out-of-sample forecasting exercise for the one-step ahead predictions made in the middle of the first month of the next quarter $q + 1$. Given the two-month publication lag of GDP data it implies that our forecast precedes the first official release by about six weeks and by 7.5 to 16.5 months the quarterly GDP estimates based on the first annual GDP estimate by the SFSO, depending on a quarter under scrutiny.

4 Econometric approach

The setup for modelling of mixed-frequency data is adapted from Mariano and Murasawa (2003). The quarterly variable y_t , which corresponds to the observed quarter-on-quarter growth rate of real GDP in empirical application, has an unobserved monthly counterpart y_t^* . Furthermore, a linear approximative relationship between y_t and y_t^* is assumed

$$y_t = \frac{1}{3}y_t^* + \frac{2}{3}y_{t-1}^* + y_{t-2}^* + \frac{2}{3}y_{t-3}^* + \frac{1}{3}y_{t-4}^*, \quad (1)$$

see Mariano and Murasawa (2003) for more details. We also assume that the dynamics of a monthly GDP growth is governed by two components:

$$y_t^* = \beta f_t + u_t,$$

where f_t is the common factor shared by y_t^* and the selected monthly survey indicators $z_t = (z_t^{PMI}, z_t^{gg}, z_t^{f8c}, z_t^{f2a})'$; u_t is an idiosyncratic component. A similar two-component dynamic structure is also imposed on the indicators.

The measurement equation summarises the relationship between observed variables on the one hand and unobserved variables like the common factor and idiosyncratic components on the other:

$$\begin{pmatrix} y_t \\ z_t^{PMI} \\ z_t^{gg*} \\ z_t^{f8c*} \\ z_t^{f2a} \end{pmatrix} = \begin{pmatrix} \beta(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}) \\ \lambda^{PMI} \sum_{j=0}^{11} f_{t-j} \\ \lambda^{gg} \sum_{j=0}^{11} f_{t-j} \\ \lambda^{f8c} \sum_{j=0}^{11} f_{t-j} \\ \lambda^{f2a} f_t \end{pmatrix} + \begin{pmatrix} \frac{1}{3}u_t + \frac{2}{3}u_{t-1} + u_{t-2} + \frac{2}{3}u_{t-3} + \frac{1}{3}u_{t-4} \\ v_t^{PMI} \\ v_t^{gg} \\ v_t^{f8c} \\ v_t^{f2a} \end{pmatrix}$$

with $z_t^{gg*} \equiv z_{t+3}^{gg}$ and $z_t^{f8c*} \equiv z_{t-3}^{f8c}$. This implies that in the measurement equation some indicators are specified with contemporaneous values like z_t^{PMI}, z_t^{f2a} but the indicator z_t^{gg} is specified with a lead of three months and the remaining indicator z_t^{f8c} enters with a lag of three months relative to the variable y_t . This

is done in order to account for the cross-correlation pattern between the indicators that allows us to extract the latent common factor more efficiently. For example, we found out that cross-correlation between z_t^{PMI} and z_{t+j}^{gg} is maximized for $j = 3$. Hence by stating that the indicator z_t^{gg} enters the model with a lead of three months we can better identify a business cycle component provided that the corresponding loading coefficient β remains significant. Similar considerations are behind our decision to lag the indicator z_t^{f8c} by three-months. In doing so we acknowledge that compared to the PMI-indicator, which is widely regarded as a coincident indicator³, the indicator z_t^{f8c} is a leading one.

In order to clarify the treatment of indicators we present the dataset in Table 2 as it was available in September 2010. The upper panel reflects the availability of the indicators and GDP data in real time with corresponding publication lags. The same dataset is presented in the lower panel after taking a three-month lag and lead of the indicators z_t^{gg} and z_t^{f8c} , respectively. The latter dataset is used for parameter estimation and predictions.

In specifying the relationship between the latent factor and the survey indicators we followed Camacho and Perez-Quiros (2010a,b) by stating that the levels of surveys are related to the sum of the contemporaneous and eleven lagged values of the common factor. This modelling approach reflects the fact that surveys tend to be closely related to annual rather than quarterly growth rates of the reference time series. Observe that for one survey indicator z_t^{f2a} we made an exception and directly related it to the monthly factor. The reason is that the corresponding question asks respondents to evaluate the change in the order backlog compared to the *previous* month.

Then dynamics of the factor and the idiosyncratic components is specified as the first-order autoregressions

$$\begin{aligned} f_{t+1} &= \psi f_t + \epsilon_t, \\ u_{t+1} &= \theta u_t + \zeta_t, \\ v_{t+1}^{PMI} &= \theta_{PMI} v_t^{PMI} + \zeta_t^{PMI}, \\ v_{t+1}^{gg} &= \theta_{gg} v_t^{gg} + \zeta_t^{gg}, \\ v_{t+1}^{f8c} &= \theta_{f8c} v_t^{f8c} + \zeta_t^{f8c}, \\ v_{t+1}^{f2a} &= \theta_{f2a} v_t^{f2a} + \zeta_t^{f2a}, \end{aligned}$$

where $\epsilon_t \sim iidN(0, \sigma_f^2)$, $\zeta_t \sim iidN(0, \sigma^2)$, $\zeta_t^{PMI} \sim iidN(0, \sigma_{PMI}^2)$, $\zeta_t^{gg} \sim iidN(0, \sigma_{gg}^2)$, $\zeta_t^{f8c} \sim iidN(0, \sigma_{f8c}^2)$ and $\zeta_t^{f2a} \sim iidN(0, \sigma_{f2a}^2)$, so that all the common factor and unit-specific components are orthogonal. We also impose the following identifying restriction $\sigma_f^2 = 1$.

The corresponding state space representation has to account for relation (1) as well as for eleven lags of the factor f_t present in the measurement equation. The state vector is

$$s_t = (f_t, f_{t-1}, f_{t-2}, \dots, f_{t-10}, f_{t-11}, u_t, u_{t-1}, \dots, u_{t-4}, v_t^{PMI}, v_t^{gg}, v_t^{f8c}, v_t^{f2a})'.$$

³For example, according to the Deutsche Bank research newsletter from March 2003: "In terms of coincidental indicators, the euro zone PMI is hard to beat".

Then the transition equation summarising the dynamics of the latent factor as well as the idiosyncratic components can be compactly stated in the matrix form as follows:

$$s_{t+1} = F s_t + B \varsigma_t,$$

where $\varsigma_t = (\epsilon_t, \zeta_t, \zeta_t^{PMI}, \zeta_t^{gg}, \zeta_t^{f8c}, \zeta_t^{f2a})'$ and $B_{(21 \times 6)}$ is a matrix with zeros and six unit values loading the corresponding elements of the innovation vector into the transition equation. Similarly, the measurement equation can be compactly written as

$$\begin{pmatrix} y_t \\ z_t^* \end{pmatrix} = H s_t,$$

where $z_t^* = (z_t^{PMI}, z_t^{gg*}, z_t^{f8c*}, z_t^{f2a})'$. In Appendix we provide an extensive description of the system matrices F and H used in the empirical model.

Once the model is cast into the state-space form its parameters can be estimated by the Kalman filter⁴, which also handles the missing observations present in the dataset, see Table 2.

5 Results

In this section we first report the model estimation results obtained for the full sample. Then we describe model forecasting performance out of sample.

5.1 Estimation results for the full sample

Table 3 reports the values of the factor loading coefficients to each of the indicator time series for the factor model estimated for the full sample. They are all positive and statistically significant at the 1% level. This signals that our model successfully accounts for common dynamics shared not only among the survey time-series but, more importantly, also by the quarterly GDP growth rate. The positive sign of the loading coefficient indicates that these indicators are pro-cyclical, as expected. As shown in Figure 1 this conclusion not only holds for the full sample but also generalises to the estimation results obtained for sub-samples. In the figure the recursively estimated factor loading coefficients are presented. The first point estimates are obtained using the initial estimation window from 1995M1 until 2006M12. Then the estimation sample is extended to include information available in 2007M1 and the model parameters are reestimated. The estimation results obtained for the final estimation window (1995M1 until 2010M9) are reported in Table 3, as stated above.

The model in-sample fit can be assessed from Figure 2. The solid line indicates monthly estimates of the quarterly GDP growth rate. The solid circles—their actual realisations as reported in vintage released in September 2010. According to the model assumptions these actual values are observed in the third month of every quarter included in the estimation sample. Note that due to the Kalman filter methodology the actual and estimated values coincide whenever the former are observed.

⁴For model estimation some of the functions in the SsfPack Basic software were used (Koopman et al., 1999).

In order to assess the in-sample fit of the factor model it is also instructive to examine the dynamics of the two components in the measurement equation for the GDP growth rate. The components on the right side can be labelled as the signal $(\beta(1/3f_t + 2/3f_{t-1} + f_{t-2} + 2/3f_{t-3} + 1/3f_{t-4}))$ and the noise $(1/3u_t + 2/3u_{t-1} + u_{t-2} + 2/3u_{t-3} + 1/3u_{t-4})$ components. The former describes the signal from the factor that is loaded into the variable of interest and the latter describes the residual. Both components are depicted in Figure 3, where only time-series values for the third month in each quarter are retained. The signal component quite accurately tracks the actual values during the whole sample as well as during the recent crisis. The noise component fluctuates around the zero line and picks up the residual fluctuations in the GDP growth rate. The correlation coefficient between the actual values and the signal component is 0.87, which is much higher than that observed between the actual values and the noise component (0.54). The signal and noise components are almost orthogonal exhibiting correlation of 0.06.

5.2 Out-of-sample forecast evaluation

Next we turn to the out-of-sample assessment of the factor model. We compare its forecasting accuracy with the two benchmark models: a random-walk (RW) model, corresponding to the projection of the historical mean of observed growth rate, and a first-order autoregressive (AR) model. The metric is the Root Mean Squared Forecast Error (RMSFE). The forecast evaluation sample is from 2006Q4 till 2010Q2. Table 4 reports the results. The forecast accuracy is assessed using the two sets of quarterly GDP growth rate. The first-published GDP growth rate which is referred to as “SECO”. The second set includes the quarterly GDP growth rate published whenever the first annual GDP estimate by the SFSO is released. The latter set is referred to as “SECO(SFSO)”. Since for the last two quarters in our forecast evaluation sample (2010Q1 and 2010Q2) we don’t have the observations corresponding to the “SECO(SFSO)” release, we use the corresponding values from the vintage released in September 2010.

On the basis of information in Table 4 several observations can be made. First, the factor model predicts GDP growth rate reported later after the quarterly breakdown of the annual SFSO estimates much better than first-releases. The corresponding RMSFE are 0.20 against 0.27, implying the reduction of about 70%.⁵ Interestingly, the opposite is observed for both the benchmark models: 0.67 vs 0.51 for the RW model and 0.56 vs 0.40 for the AR model. Secondly, the AR model produces more accurate forecasts than the model based on a historical mean. Nevertheless, the factor model still improves upon the performance of the AR model. The respective RMSFE ratios are 0.35 and 0.66 for “SECO(SFSO)” and “SECO” releases. The forecasting performance of the factor model for both the sets of GDP growth rate is presented in Figure 4.

The ability of the factor model to produce more accurate forecasts of revised rather than first-published estimates of the GDP growth rate is a remarkable finding. Hence it is instructive to investigate the sources of such improvement in forecast accuracy. Apparently, the explanation to this finding is related to the ability of the factor model to predict future revisions. However, given the timing of when predictions are made the extent and the magnitude of a future revision can only be assessed once a preliminary estimate of the

⁵For *nowcasts*, the corresponding RMSFE are 0.24 against 0.28. For *backcasts* – 2, the corresponding RMSFE are 0.21 against 0.28. Recall that the results of the out-of-sample forecasting results are reported for *backcasts* – 1 in Table 4; see Section 3 for definition of timing possibilities when one-step ahead predictions could be made.

growth rate is released by the SECO: thus, only in six weeks after predictions are made. At this point our model delivers a judgment of how likely that the initial estimate will be revised in future and by how much. For example, if the prediction error with respect to the initial estimate is small, than we conclude that it is very likely that the initial estimate will be only slightly revised. On the contrary, in case if the prediction error is relatively large, than it is very likely that a substantial revision will take place.

The hypothesis that we going to test is that if the factor model predicts higher (lower) quarterly growth rate than the first-released GDP data than it implies that growth rate will be adjusted upwards (downwards) in the subsequent revision.⁶ A sequence of (negative) prediction errors based on the first-released GDP data (denoted as “FM-SECO”) and the revisions (“SECO(SFSO)-SECO”) is plotted in Figure 5.

In order to formally assess whether revisions are predictable we use the following two approaches. First, we conduct the Pesaran-Timmermann test of directional accuracy. Here we test the hypothesis whether a sign of a prediction error with respect to the first-released GDP data is informative about the sign of a future revision. To set up the necessary notation, let Y_t be an indicator variable that takes value of one whenever a revision “SECO(SFSO)-SECO” $_t > 0$ and zero otherwise. An indicator variable X_t is similarly defined for “FM-SECO” $_t > 0$. The final indicator variable Z_t takes value of one when the following condition fulfilled $\text{sign}(\text{“SECO(SFSO)-SECO”}_t) = \text{sign}(\text{“FM-SECO”}_t)$ and zero otherwise. Then the corresponding shares are

$$\hat{P}_Y = \frac{1}{T} \sum_{t=1}^T Y_t \quad \hat{P}_X = \frac{1}{T} \sum_{t=1}^T X_t \quad \hat{P} = \frac{1}{T} \sum_{t=1}^T Z_t,$$

where \hat{P} is share of correctly predicted revision directions. The Pesaran and Timmermann (1992) test is based on the following test statistic

$$S_T = \frac{\hat{P} - \hat{P}_\star}{[\hat{V}(\hat{P}) - \hat{V}(\hat{P}_\star)]^{0.5}}, \quad (2)$$

where $\hat{P}_\star = \hat{P}_Y \hat{P}_X + (1 - \hat{P}_Y)(1 - \hat{P}_X)$. The variances of \hat{P} and \hat{P}_\star are

$$\begin{aligned} \hat{V}(\hat{P}) &= T^{-1} \hat{P}_\star (1 - \hat{P}_\star), \\ \hat{V}(\hat{P}_\star) &= T^{-1} (2\hat{P}_Y - 1)^2 \hat{P}_X (1 - \hat{P}_X) + T^{-1} (2\hat{P}_X - 1)^2 \hat{P}_Y (1 - \hat{P}_Y) + 4T^{-2} \hat{P}_Y \hat{P}_X (1 - \hat{P}_Y)(1 - \hat{P}_X). \end{aligned}$$

Under the null hypothesis of independence the test statistic has an asymptotic standard normal distribution.

The results of the Pesaran-Timmermann test are reported in Table 5. The share of correctly predicted revision directions is $11/14 = 0.786$. The corresponding test statistic is significant at the 5% level. It implies that the factor model is useful for predicting directions of future revisions in the period under scrutiny.

Second, we verify whether not only direction of revisions but also their magnitude could be predicted. Hence we run a simple regression of revisions “SECO(SFSO)-SECO” on prediction errors “FM-SECO”, see Equation 3. The slope coefficient is positive and highly significant and the regression explains about 56% of variation in the dependent variable. More interestingly, we cannot reject the joint null hypothesis of $\text{incpt} = 0$ and $\text{slope} = 1$ with the $F_{(1,12)}$ -test statistic is equal to 1.404 with the corresponding p-value of

⁶Observe that for 2010Q2 the GDP growth rate is same in both sets, see Table 1. Therefore we evaluate forecastability of revisions only for the period from 2006Q4 till 2010Q1.

0.259.

$$\text{SECO(SFSO)-SECO}_t = - 0.013 + 0.766 \text{ FM-SECO}_t, R^2 = 0.557 \quad (3)$$

(0.056) (0.197)

The regression diagnostic tests are reported in Table 6.⁷ No departures from the OLS regression assumptions can be detected. The cross-plot of revisions against prediction errors along with the regression line is reported in Figure 6.

As a concluding word, we would like to reiterate that our results suggest it is possible to design a model that produces more accurate forecasts of revised rather than initial estimates of the quarterly GDP growth rate. At the same time, it is worthwhile pointing out that the results presented above that were obtained *ex post*. *Ex ante*, it would be rather difficult to design a model that could deliver similar results in a genuine real-time exercise given inherent uncertainty regarding model specification, indicator selection, and, last but not least, a long waiting time before revised estimates are published. In addition, one cannot be sure that the present model will continue delivering similar results in the future. However, our paper contains at least one definitely outstanding message. Namely, the volatility of the revision process, that made our results possible, ought to be reduced and reduced drastically.

6 Conclusions

In this paper we constructed a small-scale mixed-frequency dynamic factor model using data for Switzerland. The factor model combines the quarterly GDP growth rate and the monthly survey indicators. We evaluate the forecasting performance of the model during the period of the recent financial crisis when accurate information on the current stance of the economy is especially in high demand. We demonstrate that this factor model produces more accurate forecasts than the alternative benchmark models such as a random-walk model and a first-order autoregressive model. More importantly, the factor model produces more accurate forecasts of the revised rather than first-published estimates of the GDP growth rate. We demonstrate that this remarkable finding could be explained by the fact that the factor model is useful for predicting not only directions of future GDP revisions but also their magnitude, at least during the period under scrutiny. We conclude that there seems to be a scope for improvement of how estimates of the GDP growth rate are produced in Switzerland: in particular, in the direction of reducing volatility of subsequent revisions.

References

- Camacho, M. and G. Perez-Quiros (2010a). Introducing the EURO-STING: Short term INDicator of Euro Area growth. *Journal of Applied Econometrics* 25(4), 663–694.
- Camacho, M. and G. Perez-Quiros (2010b). Spain-STING: Spain short term INDicator of growth. *The Manchester School*, forthcoming.

⁷The misspecification tests are standard model evaluation tests reported by the PcGive software (Doornik and Hendry, 2009).

- 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.
- Doornik, J. and D. Hendry (2009). *Empirical Econometric Modelling Using PcGive 13*. London: Timberlake Consultants Press and Oxford: www.doornik.com.
- Doornik, J. A. (2007). *Object-Oriented Matrix Programming Using Ox*. London: Timberlake Consultants Press and Oxford: www.doornik.com.
- 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.
- Harvey, A. C. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press.
- Jacobs, J. and S. van Norden (2011). Modeling data revisions: Measurement error and dynamics of "true" values. *Journal of Econometrics* 161(2), 101–109.
- Koopman, S. J., N. Shephard, and J. A. Doornik (1999). Statistical algorithms for models in state space using ssfpack 2.2. *Econometrics Journal* 2(1), 113–166.
- Mariano, R. S. and Y. Murasawa (2003). A new coincident index of business cycles based on monthly and quarterly series. *Journal of Applied Econometrics* 18(4), 427–443.
- Pesaran, M. H. and A. Timmermann (1992). A simple nonparametric test of predictive performance. *Journal of Business & Economic Statistics* 10(4), 561–65.

Appendix

For the model presented in Section 4 the corresponding state-space form can be written as follows. The state vector is

$$s_t = (f_t, f_{t-1}, f_{t-2}, \dots, f_{t-10}, f_{t-11}, u_t, u_{t-1}, \dots, u_{t-4}, v_t^{PMI}, v_t^{gg}, v_t^{f8c}, v_t^{f2a})'.$$

The measurement equation is

$$\begin{pmatrix} y_t \\ z_t^* \end{pmatrix} = H s_t,$$

where $z_t^* = (z_t^{PMI}, z_t^{gg*}, z_t^{f8c*}, z_t^{f2a})'$. Then the state loading matrix H is

$$H_{(5 \times 21)} = \begin{bmatrix} H_1 & 0_{(1 \times 6)} & H_2 & 0 & 0 & 0 & 0 \\ H_{PMI} & H_{PMI} & 0_{(1 \times 5)} & 1 & 0 & 0 & 0 \\ H_{gg} & H_{gg} & 0_{(1 \times 5)} & 0 & 1 & 0 & 0 \\ H_{f8c} & H_{f8c} & 0_{(1 \times 5)} & 0 & 0 & 1 & 0 \\ H_{f2a} & 0_{(1 \times 6)} & 0_{(1 \times 5)} & 0 & 0 & 0 & 1 \end{bmatrix},$$

where

$$\begin{aligned} H_1 &= \left(\frac{1}{3}\beta & \frac{2}{3}\beta & \beta & \frac{2}{3}\beta & \frac{1}{3}\beta & 0 \right) \\ H_2 &= \left(\frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} \right) \\ H_{PMI} &= (\lambda_{PMI} & \lambda_{PMI} & \lambda_{PMI} & \lambda_{PMI} & \lambda_{PMI} & \lambda_{PMI}) \\ H_{gg} &= (\lambda_{gg} & \lambda_{gg} & \lambda_{gg} & \lambda_{gg} & \lambda_{gg} & \lambda_{gg}) \\ H_{f8c} &= (\lambda_{f8c} & \lambda_{f8c} & \lambda_{f8c} & \lambda_{f8c} & \lambda_{f8c} & \lambda_{f8c}) \\ H_{f2a} &= (\lambda_{f2a} & 0 & 0 & 0 & 0 & 0) \end{aligned}$$

The transition equation is defined as follows:

$$s_{t+1} = F s_t + B \varsigma_t,$$

where $\varsigma_t = (\epsilon_t, \zeta_t, \zeta_t^{PMI}, \zeta_t^{gg}, \zeta_t^{f8c}, \zeta_t^{f2a})'$ and $B_{(21 \times 6)}$ is a matrix with zeros and six unit values loading the corresponding elements of the innovation vector into the transition equation. The state transition matrix F has the following structure

$$F_{(21 \times 21)} = \begin{bmatrix} F_1 & O_{(12 \times 5)} & O_{(12 \times 4)} \\ O_{(5 \times 12)} & F_2 & O_{(5 \times 4)} \\ O_{(4 \times 12)} & O_{(4 \times 5)} & F_3 \end{bmatrix},$$

where

$$F_1 = \begin{bmatrix} \psi & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$F_2 = \begin{bmatrix} \theta & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix},$$

$$F_3 = \begin{bmatrix} \theta & 0 & 0 & 0 & 0 \\ 0 & \theta_{PMI} & 0 & 0 & 0 \\ 0 & 0 & \theta_{gg} & 0 & 0 \\ 0 & 0 & 0 & \theta_{f8c} & 0 \\ 0 & 0 & 0 & 0 & \theta_{f2a} \end{bmatrix}.$$

Table 1: GDP vintages (an excerpt)

Target quarter	GDP vintage released on					
	02.06.2009	01.09.2009	01.12.2009	02.03.2010	01.06.2010	02.09.2010 ^a
2009Q1	-0.81	-0.88	-0.92	-1.02	-1.11	-0.98
2009Q2	.	-0.25	-0.28	-0.14	-0.08	-0.56
2009Q3	.	.	0.30	0.49	0.54	0.75
2009Q4	.	.	.	0.73	0.85	0.72
2010Q1	0.41	1.03
2010Q2	0.85

Notes:

^a The GDP vintage that incorporates the first provisional annual SFSO estimate of real GDP for the year 2009.

Table 2: Data vintage available in September 2010

	z_t^{PMI}	z_t^{gg}	z_t^{f8c}	z_t^{f2a}	y_t
2010M3	64.7	-8.6	18.0	8.9	1.03
2010M4	65.1	3.1	17.8	16.1	na
2010M5	65.3	8.7	19.0	16.5	na
2010M6	64.8	10.2	15.2	9.4	0.85
2010M7	66.7	16.3	11.5	9.4	na
2010M8	61.4	11.6	14.8	3.9	na
2010M9	na	13.3	11.4	3.7	na
2010M10	na	na	na	na	na
2010M11	na	na	na	na	na
2010M12	na	na	na	na	na

	z_t^{PMI}	z_t^{gg}	z_t^{f8c}	z_t^{f2a}	y_t
2010M3	64.7	10.2	7.6	8.9	1.03
2010M4	65.1	16.3	8.2	16.1	na
2010M5	65.3	11.6	16.9	16.5	na
2010M6	64.8	13.3	18.0	9.4	0.85
2010M7	66.7	na	17.8	9.4	na
2010M8	61.4	na	19.0	3.9	na
2010M9	na	na	15.2	3.7	na
2010M10	na	na	11.5	na	na
2010M11	na	na	14.8	na	na
2010M12	na	na	11.4	na	na

Notes: The upper panel presents the data vintage as it was available in September 2010. The indicators are released with a publication lag of one month (PMI) and no publication lag for the rest of indicators. The GDP vintage (released on 02.09.2010) contains the latest available data point for 2010Q2. The lower panel presents the data which are used for model parameter estimation.

Table 3: Factor loading coefficients

	β	λ_{PMI}	λ_{gg}	λ_{f8c}	λ_{f2a}
Coef. ^a	0.129	0.043	0.046	0.041	0.197
St. dev.	0.021	0.006	0.006	0.007	0.058
Z-stat.	6.091	6.636	7.397	5.760	3.396
P-value	0.000	0.000	0.000	0.000	0.001

Notes:

^a Row entries denote the factor loading coefficients to each of the survey time series. The estimation time period is from 1995M1 till 2010M9. This sample includes the GDP vintage released on 02.09.2010 containing the first provisional annual SFSO estimate of real GDP for the year 2009.

Table 4: Forecast accuracy evaluation

GDP ^a vintage	FM ^b RMSFE	RW RMSFE	Ratio FM/RW	AR RMSFE	Ratio FM/AR
SECO	0.27	0.51	0.53	0.40	0.66
SECO(SFSO)	0.20	0.67	0.29	0.56	0.35

Notes:

^a The column denotes a GDP vintage used for computation of forecast errors of the alternative models.

^b Columns “FM”, “RW” and “AR” denote RMSFE attained by the factor model, the random-walk model and an autoregressive model of order one. “FM/RW” and “FM/AR” denote the RMSFE ratios for the respective model pairs.

Table 5: Pesaran-Timmermann test

\hat{P}	\hat{P}_Y	\hat{P}_X	\hat{P}_*	S_T	P-value
0.786	0.429	0.500	0.500	2.242	0.012

Table 6: Equation (3): model misspecification tests

	AR(1) F(1,11)	ARCH(1) F(1,12)	Normality $\chi^2(2)$	Hetero F(2,11)	RESET F(1,11)
Test statistic	0.000	0.882	0.825	0.500	0.365
P-value	[0.984]	[0.367]	[0.662]	[0.620]	[0.558]

Notes: The sample period is from 2006Q4 until 2010Q1. The reported misspecification tests are standard model evaluation tests reported by the PcGive software(Doornik and Hendry, 2009).

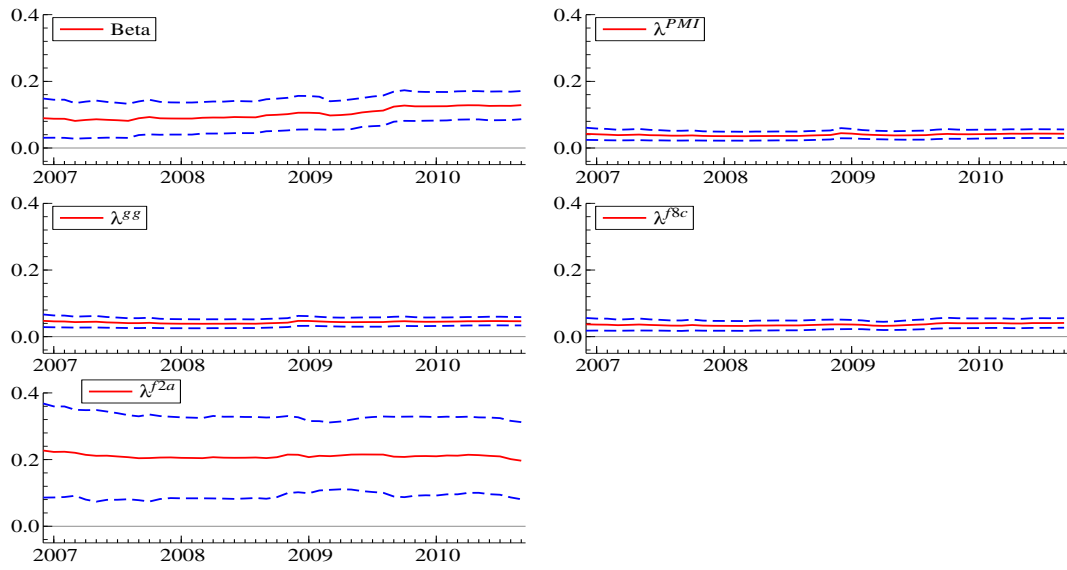


Figure 1: Recursively estimated factor loading coefficients with $\pm 2s.e.$ bands using an expanding estimation window. The initial estimation window is from 1995M1 until 2006M12. The final estimation window is from 1995M1 until 2010M9.

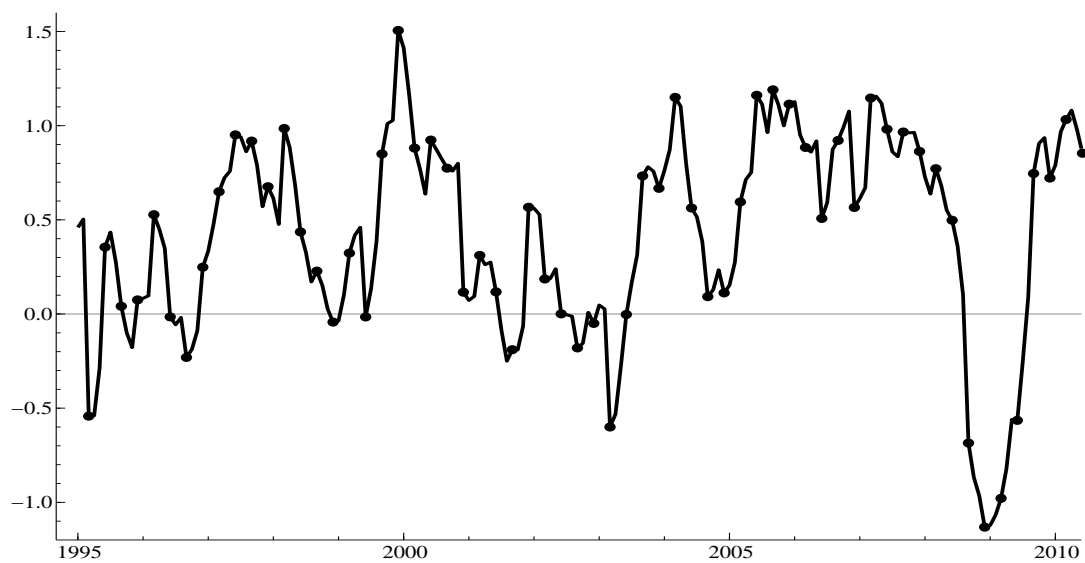


Figure 2: Real GDP growth rate: vintage from 02.09.2010. Dots refer to quarterly GDP growth rate observed every third month in a quarter. The solid line refers to GDP growth rate monthly estimated by the factor model.

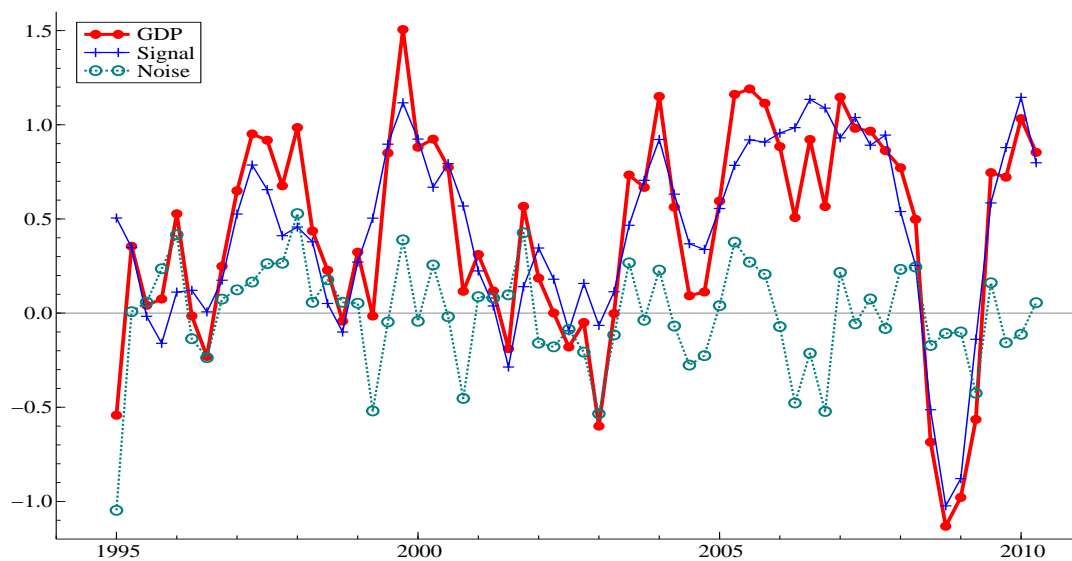


Figure 3: Real GDP growth rate: vintage from 02.09.2010. The thick solid line with dots refer to quarterly GDP growth rate. The solid line with ‘+’ is the signal provided by the latent factor and the dotted line with empty circles—the noise, i.e. the difference between the actual values and the signal.

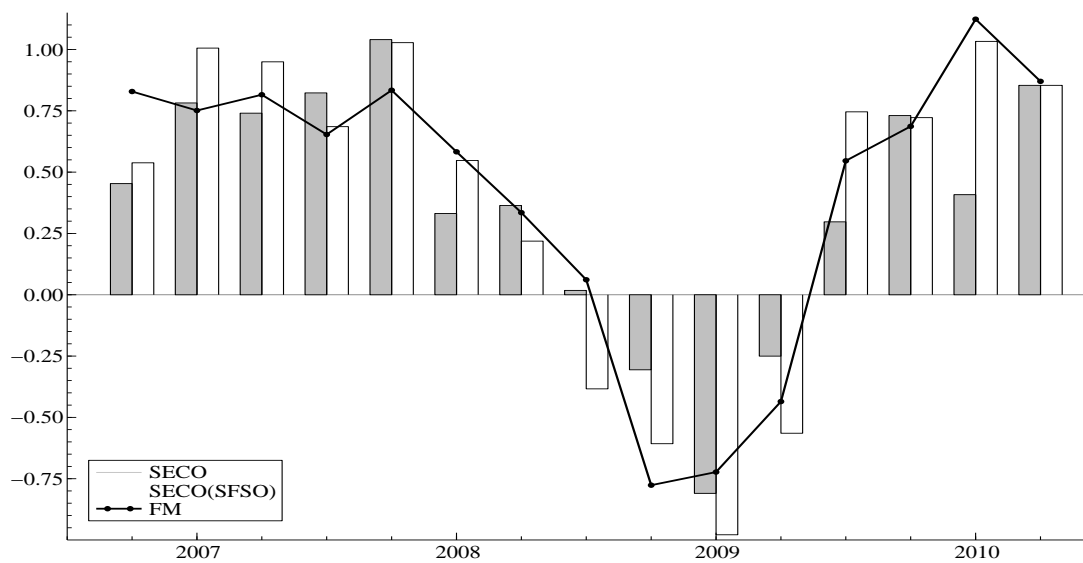


Figure 4: Quarterly real GDP growth rate, 2006Q4—2010Q2: first release (“SECO”); released after the first annual GDP estimation by the SFSO is announced (“SECO(SFSO)”); factor model predictions (FM).

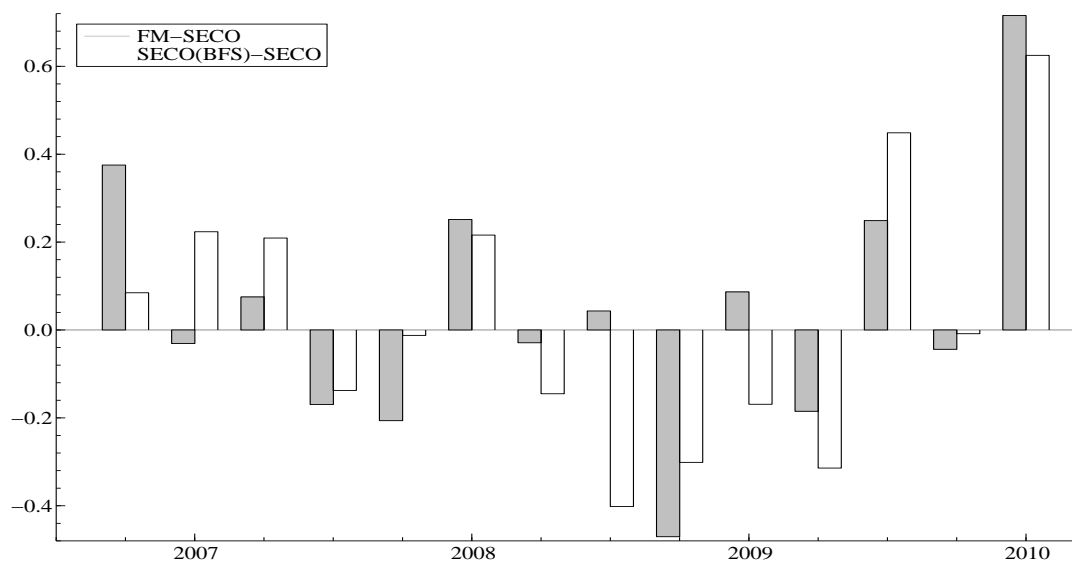


Figure 5: Quarterly real GDP growth rate, 2006Q4—2010Q1: (negative) prediction error (“FM-SECO”); revision (“SECO(SFSO)-SECO”).

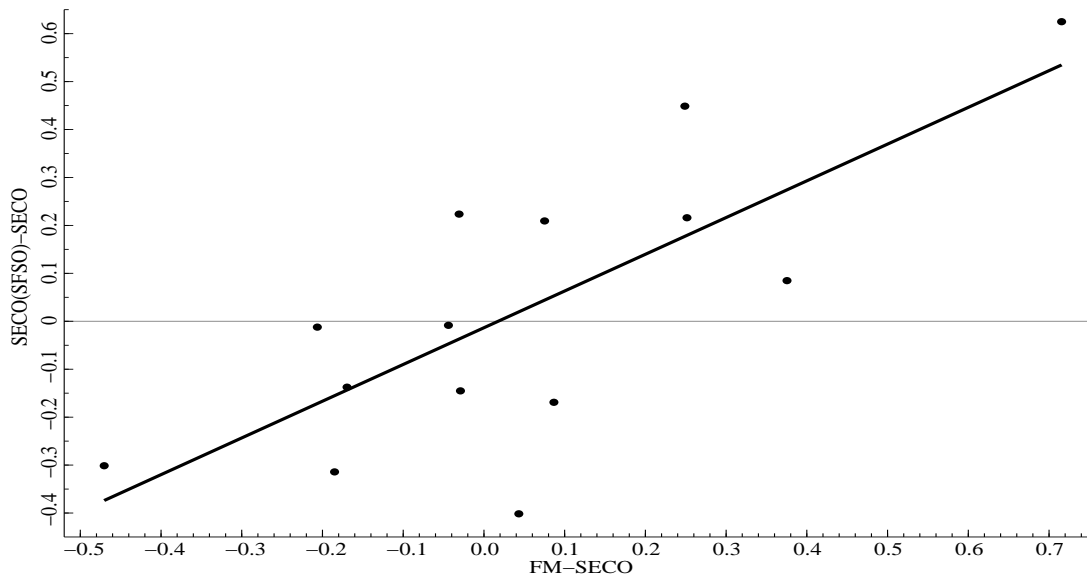


Figure 6: Cross-plot, 2006Q4—2010Q1: revision (“SECO(SFSO)-SECO”) vs (negative) prediction error (“FM-SECO”), the regression line ($R^2 = 0.557$), see Equation (3).