Forecasting data revisions of GDP – a mixed frequency approach

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Abstract

Releases of GDP data undergo a process of revisions over time. These revisions have an impact on the results of macroeconometric models as the growing literature with real time data applications document. Revisions of US GDP data can be explained and are partly predictable. This analysis proposes the inclusion of mixed frequency data for forecasting GDP revisions. Thereby, the information set publicly available around the first data vintage can be better exploited than by using pure quarterly data. In-sample and out-of-sample results yield that forecasts of revisions of GDP can be improved by using mixed frequency data.

JEL classification: C33, C53, C83

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1 Introduction

For the analysis of macroeconomic hypothesis as well as for forecasting issues the quality of data available plays a crucial role. In real-time however there exist many problems concerning the frequency, the currency and the validity of the data. Several macroeconomic variables are only available on quarterly basis like the GDP. On the other hand interest rates or stock prices exist at higher frequency. Furthermore, the vintages for macroeconomic variables differ. In the US, the corporate profits are reported with about two quarters delay, for the GDP there is one quarter delay and the first release for figures of the industrial production has only one month delay. Next to differing frequencies and currencies of the vintages there is the problem of the validity of the early released data. These releases underly revisions due to measurement errors and sometimes to changes of definitions and methodologies. Naturally, even with revised data their is uncertainty whether it is the "true" data. This analysis sticks to the definition that final data is the last released data and assumes this data to be the most reliable.

Data revisions can have a significant impact on the empirical results of macroeconomic models as argued by Croushore and Stark (2003). The impact of data revisions led to widespread literature applying real time data for modeling and forecasting, see e.g. Bernanke and Boivin (2003) or Breitung and Schumacher (2006).

It is of particular interest whether the process of data vintages is rational in the sense of Muth (1961), which implies that their is no possibility to predict data revisions. The detection of data irrationality might lead to better data revision methods. Several authors find evidence against the hypothesis of this kind of data rationality, see Swanson et al. (1999), Swanson and van Dijk (2006), Jacobs and Sturm (2004), all concerned with the series of industrial production, or Faust et al. (2005), Golinelli and Parigi (2005) and Fixler and Grimm (2006) analyzing data revisions for the GDP.

This analysis is concerned with data revisions of the US GDP growth. Earlier analysis that deal with revisions of GDP are Golinelli and Parigi (2005) for Italy, Faust et al. (2005) for the G7 and Fixler and Grimm (2006) for the US. Fixler and Grimm (2006) find evidence that the level of the growth rates given in the first data vintage and current GDP forecasts have both explanatory power for the final revisions of GDP growth with opposite signs. To some degree the misjudgement of the state of the business cycle by the early data releases might be detected by regarding other measures e.g. the judgement of the state of the business cycle from other institutions or economic agents that are reflected in surveys, interest rates, prices and GDP forecasts. This idea is advocated by Golinelli and Parigi (2005) who propose to model the actual GDP growth as a linear combination of the first release and the current one step ahead forecast.

In this paper the approach to explain and forecast data revisions of GDP is extended by the consideration of a wider range of variables which are (partly) sampled at a higher frequency data than just quarterly. This analysis aims to explain and forecast revisions to GDP with the information set that is available at the vintage or shortly after the vintage. Thus information available between the date of interest and the vintage is included which might give some insights about the state of the business cycle at the time of interest. Two aspects might lead to improvements when regarding monthly data: 1. more current information (that has already been revised) on the state of the business cycle can be taken into account and 2. the short run dynamics of the business cycle might allow for backcasting the current state of the business cycle with information beyond the date that is of interest.

To get measures for the current state of the business cycle monthly coincident and also leading indicators are considered as explanatory variables and furthermore, based on the recent literature of now- and backcasting GDP growth an approach which uses an approximate factor model taking a larger number of variables into account. This might give a more accurate judgement of the current state of the economy and thereby a better regressor for explaining data revisions than (noisy) single variables. Compared to the approach of Golinelli and Parigi (2005) forecasts are replaced by now- or backcasts.

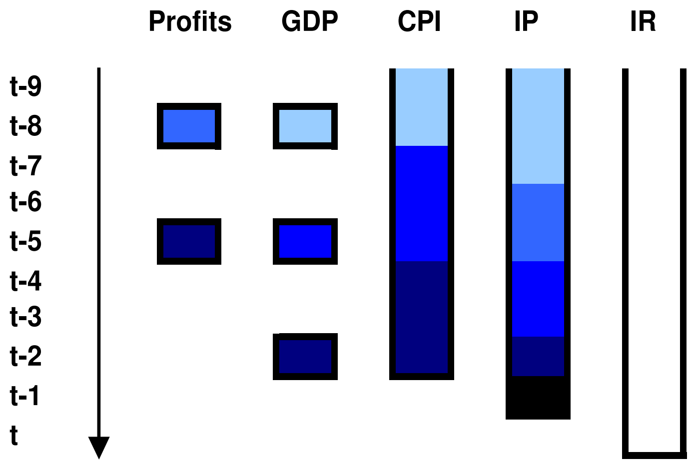
The paper is organized as follows. Section 2 highlights the problems arising with real-time data and data rationality. Section 3 gives a short overview of models dealing with mixed frequency data. Section 4 presents the Dynamic Factor model. In section 5 the results of the analysis are reported. Section 6 concludes.

2 Real time data

2.1 Characteristics of real time data

The problems of real time data at the current edge are manifold. Macroeconomic variables are sampled at different frequencies. While the GDP is available in quarterly form several macroeconomic variables are reported monthly and variables like interest rates, exchange rates or stock prices are available at nearly any frequency. These kinds of variables have furthermore the advantage that they are (almost totally) without measurement errors and that they are available immediately which means without reporting delay.

Summarizing, the following aspects of macroeconomic data at the current edge matter: differing frequencies of sampling, measurement errors (revisions) and lagged vintages. An example for this situation is depicted in Figure (1). The time index is monthly and the depicted point in time t refers to month of a vintage of GDP data. The vintage for profits of enterprizes ("Profits") has an even bigger lag, while the monthly consumer price index ("CPI") is reported together with the GDP. The industrial production ("IP") is sampled monthly and more current than GDP. Finally, interest rates ("IR") can be observed immediately.



The different colors in the figure are chosen to give an impression for the uncertainty of the vintage. A dark color represents high uncertainty on the opposite white represents no uncertainty at all. The example in this figure is for US data. This might highlight the idea of regarding mixed frequency data when dealing with data revisions of GDP. Survey data, interest rates and stock prices are available at a high quality for the point in time of interest and even between it and the vintage. Furthermore, other monthly macroeconomic variables are sampled and partly revised within the time before the vintage of GDP.

The real time data in this analysis stems from the Federal Reserve of Philadelphia. Instead of GDP real output is reported. Before 1991 the series refer to GNP and afterwards to GDP as a measure of real output. The analysis is done for growth rates and therefore the effect of the mixture of GNP and GDP hopefully is less severe. In the following we will refer to GDP as real output in this sense. Interest rates, stock and oil prices as well as survey data are taken from the OECD data source and from FRED. The sample which is analyzed ranges between 1985 and 2003. Earlier periods are neglected to avoid problems concerning the structural break that took place in the US economy around 1984. The release of GDP in 2006:III deals as final data.

2.2 Data rationality

The research concerning the rationality of early data releases is based on the contribution of Mankiw and Shapiro (1986). Data rationality claims that the early release is an unbiased estimator of the final data and that revisions of the data cannot be explained by the information set available at the release date.

The data rationality can be tested via the following regression:

$$ {}_{t+k}Y_t = \alpha + {}_{t+1}Y_t\beta + X_{t+1}{}'\gamma + e_{t+k}, \quad (1) $$

where ${}_{t+k}Y_t$ represents the growth rate of GDP at time t reported at time $t+k$ and e_{t+k} denotes an error term assumed to be uncorrelated with ${}_{t+k}Y_t$. The null hypothesis consists of the following restriction on the parameters in Equation 1, $\alpha = \gamma = 0$ and $\beta = 1$. The time index underset in front of the variable denotes the release date. X_{t+1} represents variables containing the relevant information at time $t+1$.

One contribution of this analysis is to regard variables within X with a higher frequency than Y. In fact, when quarterly data is considered X contains only information up to t because the first release of GDP is within the following quarter, such that information within the quarter of the release is neglected. Therefore the idea of now- and backcasting GDP is adopted to gain regressors that are available at the time of the first data release or soon after the release containing information about the state of the business cycle at the particular moment of interest.

3 Dealing with mixed frequency data

This section summarizes some possibilities to cope with mixed frequency data. The problem of mixed frequencies can be seen as closely related to the problem of missing data. The interpolation approach and the Kalman Filter approach can be interpreted as treating missing data while an aggregate of the missing values can be observed. The MIDAS (MIxed DAta Sampling) is developed for the context of financial markets with big differences between the observed frequencies and cannot be interpreted in the sense of missing data treatment.

3.1 Interpolation

The issue of coping with mixed frequency macroeconomic data entered the literature in the 60s and 70s. Friedman (1962) and based on that Chow and Lin (1971) bring forward the idea to use higher frequency data to interpolate low frequency data e.g. to give a representation for monthly GDP. Chow and Lin (1971) proposes a best linear unbiased estimator when the dependent is of a lower frequency than the coincident covariates and a corresponding interpolation of the dependent based on the assumption that the error variance is known. Closely related are the contributions of Fernandez (1981) and Litterman (1983).[1].

Given the number of quarters of the sample T and the number of month M ($M = 3 \cdot T$) assume the following model

$$\underset{M\times 1}{Y^m} = \underset{M\times 1}{X}\beta + u, \tag{2}$$

where u gives an vector of errors distributed with the variance covariance matrix V. The dependent Y^m and the regressors X are both at a monthly frequency. However, only an aggregate of the dependent is observable while the type of aggregation is known:

$$\underset{T\times 1}{Y} = \underset{T\times M}{W}{}'Y^m = W'X\beta + W'u. \tag{3}$$

In case of a quarterly observable series Y that is based on a monthly one Y_m the matrix W has the dimension $T \times M$ where T gives the number of quarters. The design of W depends on the kind of aggregation.[2]

Chow and Lin (1971) derive the best linear unbiased estimator for β given that the Covariance matrix V of the error term u is known as:

$$\widehat{\beta} = \left[X'W(W'VW)^{-1}W'X\right]^{-1} X'W(W'VW)^{-1}Y. \tag{4}$$

The interpolation of the monthly series results in:

$$\widehat{Y}_m = X\widehat{\beta} + VW(W'VW)^{-1}[Y - W'X\widehat{\beta}]$$

This approach has recently been applied by Mitchell et al. (2005). The interpolation is applied within the EM algorithm of Stock and Watson (2002) which enables the use of a PC analysis in the presence of mixed frequent data.[3] The application of the EM algorithm combined with a principal components (PC) analysis is widespread, see e.g. Angelini et. (2003), Breitung and Schumacher (2006), Giannone et al. (2005).

[1]Fernandez (1981) gives the conditions under which the approach of Chow and Lin (1971) is also blue without knowing the error variance

[2]See Appendix A for an example of W.

[3]See Appendix A.

3.2 Kalman Filter

As argued by Proietti (2006) the interpolation methods of Chow and Lin (1971) are encompassed by state space models, which can easily cope with further data problems like additional missing data as it is the case at the current edge. The dealing with mixed frequency data by applying state space models dates back to Jones (1980) and Ansley and Kohn (1983). Recent applications are given by Evans (2005) or Mittnik and Zadrozny (2004). The latter implement a VAR model with GDP and several monthly indicators, furthermore, in the context of extracting a coincident indicator representing monthly GDP by a (exact) dynamic factor model see Mariano and Murasawa (2003), Nunes (2005) and Proietti and Moauro (2006).

The model in Equation 3 can be formulated in state space form as follows:

$$\begin{aligned} y_t &= \begin{pmatrix} w_1 & w_2 & w_3 & \ldots \end{pmatrix} \begin{pmatrix} y_t^m \\ y_{t-1/3}^m \\ y_{t-2/3}^m \\ \vdots \end{pmatrix} + e_t \ , \quad e_t \sim N(0, \sigma_2) \\ \begin{pmatrix} y_t^m \\ y_{t-1/3}^m \\ y_{t-2/3}^m \\ \vdots \end{pmatrix} &= \begin{pmatrix} x_t^m \beta \\ 0 \\ 0 \\ \vdots \end{pmatrix} + \begin{pmatrix} 0 & 0 & \ldots & 0 \\ 1 & 0 & \ldots & 0 \\ 0 & 1 & \ldots & 0 \\ \vdots & \vdots & \ddots & 0 \end{pmatrix} \begin{pmatrix} y_{m,t-1/3} \\ y_{m,t-2/3} \\ y_{m,t-1} \\ \vdots \end{pmatrix} . \end{aligned} \tag{5}$$

The weights w_i depend on the type of aggregation. In the case of "monthly" GDP growth $\begin{pmatrix} w_1 & w_2 & w_3 & w_4 & w_5 \end{pmatrix}$ [1/3 2/3 1 2/3 1/3]. The model can be estimated via Maximum Likelihood. The Kalman Filter works at the monthly frequency, however, forecast errors and thereby the entries of the likelihood function are calculated each third step when y_t is available.

3.3 MIDAS

The aim of the MIDAS approach is to forecast a variable by using covariates sampled at a (much) higher frequency. In contrast to the interpolation method which imposes a linear relation in the highest frequency combined with a fixed weighting no such relation is assumed in the MIDAS approach. Instead the weighting itself is parameterized and is subject to estimation. The basic equation is given by:

$$y_t = \beta_0 + \beta_1 G\left(L^{1/h}; \theta\right) x_{t-1}^{(h)} + \varepsilon_t^{(h)}, \tag{6}$$

where $G\left(L^{1/h};\theta\right) = \sum_{j=0}^{J} g(j,\theta)L^{j/h}$, and $L^{j/h}x_{t-1}^{(h)} = x_{t-1-j/h}^{(h)}$. The index t represents the time index of the lower frequency. h denotes the relation between the lower and the higher frequency. If y is sampled quarterly and x monthly $h = 3$. J represents the number of (monthly) lags of x that are considered. Note, $x_{t-1}^{(h)}$ represents a vector of timely connected observations of x with the length of J. The functional $g(j,\theta)$ is a weighting function used to aggregate the higher frequency data. Ghysels et al. (2004) proposes the following form for the weighting function:

$$g(j,\theta) = \frac{\exp(\theta_1 j + \theta_2 j^2)}{\sum_{\tilde{j}=1}^{J} \exp(\theta_1 \tilde{j} + \theta_2 \tilde{j}^2)}$$

The weighting function is steered by the two parameters θ_1 and θ_2.

In fact the interpolation approach is a special case of the model given in Equation 6 whereby the weighting function is fixed. The innovation of the MIDAS model is the introduction of a parameterized weighting function. The MIDAS model can be estimated using nonlinear least squares. Clements and Galvao (2005) apply the MIDAS on forecasting US GDP growth with monthly indicators.

The following represents the MIDAS model in case that $h = 3$ and $J = 12$:

$$\begin{aligned} y_t &= \beta_0 + \beta_1[g(0,\theta)x_{t-1} + g(1,\theta)x_{t-1-1/3} \\ &+ g(2,\theta)x_{t-1-2/3} + \ldots + g(12,\theta)x_{t-5}] + \varepsilon_t^{(h)}. \end{aligned} \tag{7}$$

Both, the interpolation as well as the MIDAS approach will be used to incorporate additional monthly regressors in Equation (1) to get an improved forecasting model for data revisions.

4 Factor based now- and backcasting GDP

The approach to now- and backcast GDP growth has been put forward recently by several authors, see e.g. Mariano and Murasawa (2003), Angelini et al. (2003), Evans (2005), Giannone et al. (2005) or Nunes (2005). Information sampled at a higher frequency and announced with a shorter or no delay is used to estimate the current GDP growth. The information at different frequencies is plugged together into a state space model. Several authors assume an underlying factor structure. Mariano and Murasawa (2003) and Nunes (2005) apply an exact factor model with one factor which can be interpreted as a monthly representation of GDP growth. Regarding a larger number of variables the approaches of Angelini et al. (2003) and Giannone et al. (2005) are based on the approximate factor model proposed by Stock and Watson (2002). In this analysis these approaches are applied to gain regressors in form of monthly GDP growth estimates or factor estimates to explain and forecast data revisions.

4.1 Approximate Factor model

Factor models are widely used for dimensional reduction and in the context of this analysis they shall yield appropriate regressors based on many variables. In the context of macroeconomic time series it seems favorable to account for the dynamic dimension of the data e.g. by a model of the following type:

$$Z_t = \mu_i + \alpha_{i,1} f_t + ... + \alpha_{i,j} f_{t-j+1} + ...\alpha_{i,p} f_{t-p+1} + \zeta_t, \tag{8}$$

where Z_t represents a (large) vector of standardized macroeconomic variables and ζ_t denotes their ideosyncratic components. Stock and Watson (2002) argue that the dynamic model in Equation 8 can be represented in the static form

$$Z_t = \mu + \Lambda F_t + \zeta_t, \tag{9}$$

where F_t can be estimated consistently via PC and the estimate of Λ is gained via an OLS regression, where $\widehat{F}_t$ is plugged in as regressors. This approximate factor model has the advantage that it does not impose any covariance structure on the ideosyncratic errors and that it is rather easy to implement even for big data sets. The problem of missing data caused by late vintages and of mixed frequency is regarded by applying the EM-algorithm.[4] F_t is a $k \times 1$ vector representing k static factors. The number of static factors can be determined by applying the model selection criteria proposed in Bai and Perron (2002), see Appendix B.

4.2 Dynamic Factor model

There are two shortcomings of the approximate factor model concerning the aims of this analysis. The estimated factors shall represent a reliable representation for the state of the business cycle at the point in time of interest. Thereby, ideally the most current information should be used to backcast this state. The static form of the factor model precludes backcasting in the absence of any dynamics. Furthermore, data uncertainty is not taken into account during the estimation of the factors according to the approach of Stock and Watson (2002). Both shortcomings can be eased by the application of a model extension proposed by Giannone et al. (2005) which relates the results

[4]For details see Appendix A.

of the approximate factor model to an exact dynamic factor model. The approach of Giannone et al. (2005) is based on the approximate factor model but assumes an explicit dynamic structure of the factors in form of a VAR model. The dynamic factors are estimated via a state space model whose formulation needs further restricting assumptions compared to the approximate factor model. The whole model is given as follows:

$$
\begin{aligned}
Z_t &= \Lambda F_t + \zeta_t + \chi_t, && (10)\\
F_t &= A(L)F_{t-1} + Bu_t, && (11)\\
u_t &\sim N(0, I_r),\\
\chi_t &\sim N(0, \Sigma_{\chi t}),\\
\zeta_t &\sim N(0, \Sigma_\zeta).
\end{aligned}
$$

The parameters A can be estimated via applying OLS on the factors F gained from the PC analysis of the static factors. The lag length of the A can be determined via the classical model selection criteria like AIC or BIC. Estimation of B is accomplished by a further PC analysis applied to the residuals of the VAR assuming r principal components. The rank r of the $k \times k$ variance-covariance matrix of the residuals might be smaller than k due to the circumstance that some of the factors F are linear combinations of past values of F at least asymptotically.[5]

For determining the number r Breitung and Kretschmer (2004) propose a method exploiting the canonical correlation between the static factors and the lagged static factors and provide a corresponding model selection criterion.[6] The variances of the ideosyncratic components σ_{ζ_i} are estimated based on the estimated residuals of Equation 9. Finally, a second ideosyncratic component χ_{it} is assumed covering the data uncertainty at the current edge. For the corresponding time varying variances the sample variances of the data revisions are plugged in Σ_{χ_t}. Given the estimates for $\{\Lambda, A, B, \Sigma_\zeta, \Sigma_{\chi_t}\}$ the factors F are re-estimated via the Kalman-Filter and Smoother. Within the Kalman-Filter the aspects of mixed frequency and missing data as well as data uncertainty are regarded.[7]

Due to the model assumptions the approach of Giannone et al. (2005) is closely related to the exact dynamic factor model. Doz et al. (2005) stress this connection and argue in favor of exact dynamic

[5]If one assumes that the model given in Equation 8 is the right model and f_t has the dimension q than F_t has the dimension $q \cdot p$. Obviously, F_t and F_{t-1} have $q(p-1)$ entries in common such that the rank of the variance covariance matrix of the corresponding VAR model is q.

[6]For details see Appendix B.

[7]For details see Appendix C.

factor models even if the assumption of the ideosyncratic error variance is violated. However, the two step procedure based on the approximate factor model is computational convenient especially in the light of mixed frequency data. In this real time analysis the factors are estimated for each quarter again such that the model is applied 72 times and computational convenience is of particular interest.

5 Results

5.1 The forecasting model

The aim of this analysis is to gain a model that can explain and forecast data revisions and thereby improve the early data estimates of the data reporting agencies. The core model is based on the reformulation of Equation (1) in terms of revisions:

$$_{t+k}rev_t =_{t+k} Y_t - \ _{t+1}Y_t = \alpha + \ _{t+1}Y_t(\beta - 1) + X_{t+1}{}'\gamma + e_{t+1}. \tag{12}$$

In a first step seasonal dummies and information of the revision history known at time $t+1$ is assumed as X_{t+1} to establish the benchmark model (Model I). In a second benchmark model (Model II) additionally macroeconomic variables sampled at quarterly frequency or sampled at monthly frequency but aggregated before the regression analysis are taken into account. Regressors which are subject to revisions itself are treated as real time variables, too. Such that X_{t+1} includes e.g. $_{t+1}x_t$, $_{t+1}x_{t-1}$, $_{t+1}x_{t-2}$ and X_t includes e.g. $_tx_{t-1}$, $_tx_{t-2}$, $_tx_{t-3}$.

Within the candidate model (III/IV) the benchmark model is enhanced by macroeconomic variables sampled at monthly frequency. The information set is broader than in II because monthly observations between the vintage and the date of interest are regarded. In Setup III the interpolation approach is used to incorporate the monthly data within the forecasting model which has a dependent sampled at a quarterly frequency. In Setup IV this is done via the MIDAS approach.

The additionally assumed Models V and IV replace the macroeconomic variables by the estimated factors derived via the approach described in Section 4.[8] Again the interpolation approach (V) and the MIDAS approach (VI) are employed.

The models are assessed for two different horizons of revision. Firstly, final or long term revisions are taken into account, such that k is decreasing in t. "Long term" revisions denote the difference

[8]Attempts to take the macroeconomic variables and the factors jointly into account show up no improvement of the fit of the model.

between the last available release of GDP growth and the firstly (or early) available release. Secondly, the horizon k is fix and equal to 8 quarters (two years). Following Faust et al. (2005) these revisions will be denoted "short term" revisions. Furthermore, different information sets depending on the time are assumed. Set A considers information publicly available at the first vintage date. Set B considers the additional information that is available two month after the first vintage and in Set C the second vintage is available. This set is taken into account to check whether the information of the additional regressors is incorporated into the data by the first revision. An overview of all model specifications considered is presented at the beginning of Appendix E.

5.2 In-sample results

Explaining "long term" revisions

Estimates of Model I show a strong rejection of the hypothesis of data rationality. The results are given in Table 1. A finding in line with Faust et al. (2005) and Fixler and Grimm (2006). A constant, seasonal dummies, the current revision of the growth rate 3 quarters before and the growth rate of GDP itself are taken in according to the adjusted R^2. In Model II this setup is enhanced by three at the quarterly level aggregated macroeconomic variables, namely the consumer sentiment, the yield spread and employment figures. According to the adjusted R^2 these variables improve the in-sample fit. However, the single regressors are only slightly significant with exception of the employment. A better result is obtained when the monthly represents of these variables are taken into account. Both models III and IV show up with remarkable improvements of the adjusted R^2 while the MIDAS yields a slightly better fit than the interpolation approach. Interestingly, the announced growth rate ${}_{t+1}y_t$ turns strongly significant in the models III and IV while the macroeconomic variables that shall represent the current state of the business cycle have a positive impact.

The variable ${}_{t+1}y_t$ stays strongly significant when instead of single variables the estimated factor ${}_{t+1}\widehat{F}$ is in place of the regressors. However, models V and IV are only slightly better than the benchmark model I when only information up to the date of the vintage is considered (Set A).

Regarding the information that can be collected in the two following month the in-sample fit of the models III through VI is enhanced, see Table 2. Regarding the MIDAS models the intake of the additional information does not alter the point estimates substantial but reduces their variance.

Explaining "short term" revisions

Next to the "long term revisions" the models are assessed for "short term revisions". This is done to control for stability of the results over the revision history and to check whether the systematic information provided by the regressors in the long term setup is already included after two years of revisions.

The relations between the models concerning their in-sample fit are almost the same as before. However, the in-sample fit concerning the "short term" revisions is worse for all models independent on the set of information, A or B.[9] The system of the (measurement) errors of the early vintages that can be detected by the models does not seem to be fully incorporated after two years of revising the data.[10] By and large, the signs of the regression results of the significant regressors are the same as within the regressions explaining the "long term" revisions. Additionally, the first revision of y_{t-1} is taken in as a regressor corresponding to the model selection via the adjusted R^2. A further exception is given for the factor based approach (Model V) given Set B and using the interpolation method. The regressor ${}_{t+1+2/3}\widehat{F}_{t+1}$ is insignificant and gets a negative sign.

The finding in Faust et al. (2005) that "short term" revisions are less explainable by current information can be reproduced in this analysis. However, due to the use of a somewhat different data set the in-sample fit concerning the "short term" revisions is higher for all models.[11]

Explaining "long term revisions" based on the second vintage

Finally, a further dependent variable is assessed. The "long term" revisions based on the second vintage date. This is done to check whether the collection of information by regarding currently released macroeconomic variables after the first vintage is superfluous if one waits for the next data release of GDP (about one month later compared to Set B). The in-sample results given in Table 5 correspond to the results for Set B. The models II through VI outperform the benchmark model I and again the inclusion of monthly regressors yields some improvement of the in-sample fit. Monthly releases of other macroeconomic variables between the vintages of GDP supply additional information concerning future revisions beyond the first revision.

Summary

In line with the foregoing literature the data rationality of the GDP growth is rejected and at least "long term" revisions can be explained by additional macroeconomic variables. The consideration of monthly indicators and the intake of information at the current edge improve the in-sample

[9]See Table 3 and 4.

[10]If one applies the Models I through VI on the dependent ${}_{t+k^*}y_t - {}_{t+8}y_t$ the null of data rationality is still rejected.

[11]Faust et al. (2005) assess the releases of the OECD data source and consider a sample between 1965 to 1997.

fit. Furthermore, two years of data revisions are not enough to ensure data rationality and the information contained in the different models corresponds partly to revisions which occur after more than two years.

Concerning the different forecasting models the inclusion of three monthly regressors, namely Model III and IV, yields the best results and outperforms the factor based approach as well as the inclusion of the same but beforehand aggregated variables. Comparing the lead and lag structure of the three variables consumer sentiment, yield spread and employment relative to GDP with a single coincident factor which is included in the Models V and VI it seems that the single factor model is to parsimonious.

5.3 Out-of-sample results

The in-sample fit advises the use of forecasting models to gain more reliable GDP growth data at the current edge. The additional information in form of other macroeconomic variables collected around the first vintage date and between the first and the second vintage date might improve these early data releases.

This is assessed in an out-of-sample experiment which mimics the situation at the current edge such that for the last 20 observations of the sample forecasts are gained based on the correspondingly reduced information set starting in 1999:I. The different models are estimated with an expanding sample size. Thereby the real time character of the data is taken into account. Any of the 20 parameter estimates is accomplished with a different "final" data set which represents the most current information at that particular moment. For the same reason that this analysis as a whole is constraint to data up to 2003 the estimation sample ends eight quarters before the point in time which revision shall be forecasted. The forecast of the "long term" revision is the expected value of Equation 12.

As a naive benchmark it is assumed that the first release of the data is the best forecast for the final data and the forecasted revision is equal to zero ("data rationality"). This benchmark is compared to a simple model, namely the mean of the former revisions, and to the Models I through III and V.[12] The mean squared error (MSE) for the different models is given in Table 6. According to this criterion Model III given Set B is the best forecasting model followed by a version of Model

[12]The MIDAS models are no considered at this point. Their out-of-sample performance is rather poor. MIDAS is a non-linear approach and therefore maybe more data demanding. During the out-of-sample experiment sample sizes below 50 are considered.

V given Set B that assumes five factors to capture the state of the business cycle. Although it is highly parameterized it yields a quite good out-of-sample fit. Model III given Set A and Model V given Set B with one factor as regressor show up with slightly better MSE than Model I. Model V given Set A has almost the same MSE as Model I. Both are better than the naive model. However, the mean as well as Model II which includes additional quarterly regressors perform worse.

Next to the MSE empirical significance levels (p values) of the Diebold Mariano Test and the Encompassing Test of Harvey et al. (1998) are reported. Both tests compare the prediction accuracy of two models with the null hypothesis that both models predict equally well. The results are given in Table 7. A p value lower than 0.5 indicates that the model of the column is better than the model of the row and vice versa, e.g. the value 0.940 can be interpreted, that zero is a better prediction than the mean instead. p values lower than 0.1 and higher than 0.9 are bold to mark significant differences of the performance of the models.

Regarding the Diebold-Mariano Test it appears that only the Model III given Set B is a significantly better forecasting model for the GDP growth rate releases than the first release of the reporting agency itself. Concerning the Encompassing Test this result is confirmed with the addition that Model V with five factors given Set B exhibits a similar low p value. Model I exhibits p values of 0.197 and 0.101, respectively. The mean as a forecasting model is rejected against almost any alternative for both tests.

Model III given Set$B$ prevails as the best forecasting model. It exhibits the lowest MSE. The p values are all in the "right" direction with the only exception of the comparison to Model V within the Encompassing Test.

6 Conclusion

This paper proposes a forecasting model for "long term" data revisions of GDP growth which is applied on US data for real output provided by the Philadelphia FED. A key feature of the forecasting model is the inclusion of data sampled at a higher frequency than the GDP. Therefore the interpolation as well as the MIDAS approach are considered.

In a first step data rationality of the early releases of GDP is tested and rejected which is in line with the results of Fixler and Grimm (2006) and Faust et al. (2005). Based on this result and the foregoing literature the hypothesis is formulated that other indicators, like the perception of economic agents, of the state of the business cycle may lead to an improved forecasting model for “long term” data revisions. This hypothesis is checked by considering several macroeconomic variables, partly sampled at a monthly frequency, as regressors. A further enhancement is done by replacing the single regressors with estimated factors. The factors are considered for dimensional reduction.

The parameters of the factor model are estimated based on a principal components analysis. The parameter estimates itself are plugged in a state space model to estimate the factors again via the Kalman-Smoother. This second step allows to account for data uncertainty and other irregularities at the current edge.

The in-sample results of the different specifications of the forecasting model favor the inclusion of mixed frequency data. A model that incorporates single regressors, namely consumer sentiment, yield spread and employment, instead of factors performs best. This holds true for an out-of-sample experiment. It can be shown that the proposed model can be applied in real time to gain improved data releases. The forecasts based on the mixed frequency data perform significantly better than the early releases of GDP growth itself and a simpler forecasting model which only depends on univariate information.

Summarizing, “long term” revisions of US GDP can be predicted with information publicly available few month after the first vintage. This additional information is not comprised in the early revisions of the GDP. The consideration of mixed frequency data is preferred. Based on the used real time data set a model selection strategy leads to better results than a factor based approach.

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A Treatment of Mixed Frequency within the PC analysis

Stock and Watson (2002) propose the use of the EM algorithm within the PC analysis. For missing data this is accomplished by plugging in the expected value of the missing data. Generally, a balanced panel $\widehat{y}_{it}$ is build by setting $\widehat{y}_{it} = y_{it}$ if y_{it} is observed else $\widehat{y}_{it}$ is set to its expected value $\widehat{y}_{it} = \widehat{\lambda}_i \widehat{F}_t$. After (re-)estimation of λ_i and F_t the expected values are calculated again. This procedure is continued until convergence. In practice, convergence is assumed to be reached when the estimates of two consecutive replications are sufficient close to each other.

Mixed frequency is treated as a special case of the missing data problem. The estimation of λ_i and F_t is not affected, however, the expectation step is somewhat different due to the fact that the corresponding time series are observable at a lower frequency. Given the quarterly observable values $y_{Qi,t}$, which are growth rates of a $I(0)$ flow variable, the expected monthly values are:

$$\widehat{y}_{it} = \widehat{\lambda}_i \widehat{F}_t + W_i'(W_i W_i')^{-1}(y_{Qi,t} - W_i \widehat{\lambda}_i \widehat{F}_t),$$

whereby the design matrix W_i of dimension $\frac{T}{3} \times T$ is given by

$$W_i = \begin{pmatrix} \ddots & & & & & & & & & & & & \\ & \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 & 0 & \\ & 0 & 0 & 0 & \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & 0 & 0 & 0 & \\ & 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & \\ & & & & & & & & & & & & \ddots \end{pmatrix}.$$

This particular form can be explained by the relation between the monthly growth rates and the quarterly growth rates when the original variable is a $I(0)$ flow variable, like GDP. In this case the relation between quarterly and monthly differences is given as follows:

$$Y_{t_q} - Y_{t_q-1} = \frac{1}{3}\Delta Y_{t_q,3} + \frac{2}{3}\Delta Y_{t_q,2} + \Delta Y_{t_q,1} + \frac{2}{3}\Delta Y_{t_q-1,3} + \frac{1}{3}\Delta Y_{t_q-1,2}$$

t_q denotes the time index of the quarters while $t_q, 1$ represents the first month in quarter t_q. Δ are the first differences to the month before.

B Model Selection in the context of approximate factor models

Bai and Ng (2002) propose different model selection criteria to determine the number of (static) factors in an approximate factor model. Given the following factor model

$$z_{it} = \mu_i + \lambda_i^k F_t^k + \zeta_{it}$$

with a fixed number of factors k it can be shown that the PC analysis and the corresponding OLS estimate for Λ^k solves the following minimization problem:

$$V(k) = \min_{\Lambda^k, F^k} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (z_{it} - \lambda_i^k F_t^k)^2.$$

The following three criteria are proposed:

$$\begin{aligned} IC_{p1}(k) &= \ln(V(k, \widehat{F}^k)) + k \left(\frac{N+T}{NT} \right) \ln \left(\frac{NT}{N+T} \right), \\ IC_{p2}(k) &= \ln(V(k, \widehat{F}^k)) + k \left(\frac{N+T}{NT} \right) \ln C_{NT}^2, \\ IC_{p3}(k) &= \ln(V(k, \widehat{F}^k)) + k \left(\frac{\ln C_{NT}^2}{C_{NT}^2} \right), \end{aligned}$$

where $C_{NT}^2 = \min\{N, T\}$. The number of factors that exhibits the minimum value of the criteria is chosen.

Due to the time series character of the data and its lead and lag structure the number of static factors does not have to correspond to the number of dynamic factors. It is possible, as Equation 8 suggests, that some of the k^* static factors are linear combinations of the past of the factors. This instance leads to a reduced rank of the variance covariance matrix of the errors within the VAR model below $(r < k^*)$.

$$F_t = A(L)F_{t-1} + Bu_t \ , \quad u_t \sim N(0, I_r)$$

To determine the rank Breitung and Kretschmer (2004) propose the following procedure. They apply the canonical correlation between the estimated factors $\widehat{F}$. Let

$$S_{ij} = T^{-1} \sum_{t=2}^{T} \widehat{F}_{t-i} \widehat{F}'_{t-j}, \quad i, j \in \{0, 1\}$$

and assume the corresponding eigenvalue problem

$$|\lambda S_{11} - S_{10}(S_{00})^{-1} S_{01}| = 0.$$

The likelihood dependents on the eigenvalues and the LR statistic between a model assuming the number of dynamic factors equal to the number of static factors k and a model assuming only r dynamic factors $(r < k)$ is based on the $v = k - r$ smallest eigenvalues μ_i:

$$LR = - \sum_{i=k-v+1}^{k} \ln(1 - \mu_i).$$

Breitung and Kretschmer use the LR statistic to construct a model selection criterion:

$$IC(\widehat{v},k) = \min_{v^*}\left\{\left(-\sum_{i=k-v^*+1}^{k}\ln(1-\mu_i)\right) + \frac{(k^2-kv^*)c(T)}{T}\right\},$$

where $c(T)$ denotes a penalty function. The following represents are considered $c(T) = 2$ (AIC) and $c(T) = \ln(T)$ (BIC).

C Kalman Filter and Smoother

We define the following two 1×5 vectors:

$$C = [1 \;\; 0 \;\; 0 \;\; 0 \;\; 0] \quad \text{and} \quad D = \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} \end{bmatrix}.$$

Furthermore, the monthly time index t is introduced as follows:

$$\begin{aligned} t_q = 1 \quad &\Rightarrow \quad t_q, 1 \Leftrightarrow t = 1 \\ t_q = 1 \quad &\Rightarrow \quad t_q, 2 \Leftrightarrow t = 2 \\ t_q = v \quad &\Rightarrow \quad t_q, 1 \Leftrightarrow t = 3 \cdot v - 2 \\ t_q = v \quad &\Rightarrow \quad t_q, 3 \Leftrightarrow t = 3 \cdot v \end{aligned}$$

The quarterly growth rates y_{Qi,t_q} are transformed in a monthly variable $y^*_{Qi,t}$ and the matrix D^* is build as follows:

$$y^*_{Qi,t} = \begin{cases} y_{Qi,t_q} & \text{if } \; t/3 \in IN \\ 0 & \text{otherwise,} \end{cases} \qquad D^* = \begin{cases} D & \text{if } \; t/3 \in IN \\ 0 & \text{otherwise.} \end{cases}$$

The state space model in the case that $p \leq 4$:

$$\underbrace{\begin{pmatrix} y_{M1,t} \\ \cdots \\ y_{MN,t} \\ y^*_{Q1,t} \\ \cdots \\ y^*_{QN,t} \end{pmatrix}}_{y_t} = \underbrace{\begin{pmatrix} \lambda_{M1} \otimes C \\ \cdots \\ \lambda_{MN,t} \otimes C \\ \lambda_{Q1} \otimes D^* \\ \cdots \\ \lambda_{QN} \otimes D^* \end{pmatrix}}_{\Lambda^*} \underbrace{\begin{pmatrix} F_t \\ F_{t-1} \\ F_{t-2} \\ F_{t-3} \\ F_{t-4} \end{pmatrix}}_{F^*} + \begin{pmatrix} \zeta_{M1,t} \\ \cdots \\ \zeta_{MN,t} \\ \zeta_{Q1,t} \\ \cdots \\ \zeta_{QN,t} \end{pmatrix}$$

$$
\begin{pmatrix} F_t \\ F_{t-1} \\ F_{t-2} \\ F_{t-3} \\ F_{t-4} \end{pmatrix} = \begin{pmatrix} \mu \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} + \underbrace{\begin{pmatrix} A_1 & A_2 & \cdots & A_4 & 0 \\ I & 0 & 0 & 0 & 0 \\ 0 & I & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 \\ 0 & 0 & 0 & I & 0 \end{pmatrix}}_{A^*} \begin{pmatrix} F_{t-1} \\ F_{t-2} \\ F_{t-3} \\ F_{t-4} \\ F_{t-5} \end{pmatrix} + \begin{pmatrix} Bu_t \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}
$$

The latent variable of the state space model can be estimated via the Kalman Filter:

$$F^*_{t|t-1} = \mu + A^* F^*_{t-1|t-1}$$

$$P_{t|t-1} = A^* P_{t-1|t-1} A^* + B^* B^{*\prime}$$

$$\Downarrow$$

$$y_{t|t-1} = \Lambda^* F^*_{t|t-1}$$

$$\Sigma_{t|t-1} = \Lambda^* P_{t|t-1} \Lambda^{*\prime} + \Sigma_\zeta$$

$$\Downarrow$$

$$F^*_{t|t} = F^*_{t|t-1} + P_{t|t-1} F^{*\prime} \Sigma^{-1}_{t|t-1} (y_t - y_{t|t-1})$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1} \Lambda^{*\prime} \Sigma^{-1}_{t|t-1} \Lambda^* P_{t|t-1}$$

Kalman Smoother:

$$F^*_{t|T} = F^*_{t|t} + P_{t|t} A^{*\prime} P^{-1}_{t+1|t} (F^*_{t+1|T} - \mu - A^* F^*_{t|t})$$

$$P_{t|T} = P_{t|t} + P_{t|t} A^{*\prime} P^{-1}_{t+1|t} (P_{t+1|T} - P_{t+1|t}) P^{-1}_{t+1|t}{}' A^* P_{t|t}$$

D Data description

Quarterly data - real time
real output (GNP and GDP)
output-price index
real personal consumption - services
real personal consumption - durables
real personal consumption - nondurables
real investment business
real investment residential
real investment change in inventories
real exports
real imports
price index for imports
nominal corporate profits after tax

Source: Philadelphia FED

Monthly data - real time (monthly vintage)
index of industrial production, total
index of industrial production, manufacturing
employees on non-farm payrolls
capacity utilization, total
capacity utilization, manufacturing
new privately owned housings units started
weekly hours worked, total
weekly hours worked, goods-producing sector
weekly hours worked, service-producing sector

Source: Philadelphia FED

Monthly data - real time (quarterly vintage)
monetary base
M1
M2
unemployment rate

Source: Philadelphia FED

Monthly data - non revised
oil price
stock prices (Dow Jones)
new orders
consumer sentiment
business climate
exchange rate Dollar/DM
terms of trade
yield spread (10 years/ 3 months)
yield spread (6 months/ 3 months)
yield spread (1 month/ 3 months)
yield spread (prime rate/ 3 months)
yield spread (AAA/ 3 months)
yield spread (BAA/ 3 months)
yield spread (6 months CD/ 3 months)
yield spread (1 month CD/ 3 months)

Sources: OECD data bank and FRED

All data given here is employed within the factor analysis. The revisions of the real output are the dependent of the forecasting model. As singular regressors the following list of variables has been considered: industrial production, capacity utilization, employment, housings started, new orders, consumer sentiment, business climate, yield spreads. After the in-sample model selection procedure yield spread (10 years/ 3 months), consumer sentiment and employment remained as regressors of the forecasting model.

E Tables

The following tables report the in-sample and out-of-sample fit of the models considered. The different models are abbreviated by roman numbers:

I	"univariate" model (quarterly regressors like seasonal dummies)
II	extension of model I by quarterly regressors, macroeconomic variables
III	extension of model I by monthly regressors, macroeconomic variables (interpolation)
IV	extension of model I by monthly regressors, macroeconomic variables (MIDAS)
V	extension of model I by monthly factors (interpolation)
VI	extension of model I by monthly factors (MIDAS)

Furthermore, the results differ in the information sets that are denoted by capital letters A through C, where A denotes the scenario with the lowest degree of information, namely the inclusion of information available at the first vintage of y_{t+1}. Set C includes the information available at the first vintage of y_{t+2} and thereby the revision of y_{t+1}. Set B is timely between both vintages.

Table 1: Explaining final revisions: ${}_{t+k}y_t - {}_{t+1}y_t$ (Set A)

	I	II	III	IV	V	VI
constant	0.574	0.553	0.614	0.576	0.780	0.826
	4.353	3.444	4.140	4.705	4.619	5.687
$Q2$	−0.704	−0.710	−0.656	−0.674	−0.656	−0.616
	−4.090	−3.960	−3.494	−4.551	−3.816	−3.473
$Q4$	−0.485	−0.439	−0.153	−0.246	−0.422	−0.428
	−2.823	−2.361	−0.809	−1.526	−2.448	−2.511
${}_{t+1}rev_{t-3}$	−0.266	−0.228	−0.297	−0.244	−0.324	−0.344
	−1.004	−0.824	−1.055	−1.081	−1.229	−1.372
${}_{t+1}y_t$	−0.116	−0.202	−0.405	−0.373	−0.281	−0.353
	−1.290	−1.922	−3.728	−4.077	−2.224	−3.181
cs_{t-1}		0.004	0.023			
		0.204	1.594			
cs_t		0.013	0.013			
		0.694	0.978			
$cs_{t+1/3}$			0.351	0.225		
			1.959	3.470		
ysp_{t-1}		0.003	−0.125			
		0.015	−0.692			
ysp_t		0.198	1.093			
		0.990	2.528			
$ysp_{t+1/3}$			−0.678	0.795		
			−1.730	2.377		
${}_{t+1}emp_{t-1}$		−0.328	0.037			
		−0.951	1.970			
${}_{t+1}emp_t$		0.622	0.004			
		1.879	0.012			
${}_{t+1}emp_{t+1/3}$			0.377	1.746		
			0.672	3.597		
${}_{t+1}\widehat{F}_t$					0.095	
					1.254	
${}_{t+1}\widehat{F}_{t+1/3}$					0.135	0.524
					1.107	3.256
σ^2	0.344	0.352	0.290	0.219	0.334	0.289
R^2	0.271	0.322	0.477	0.501	0.313	0.342
adR^2	0.227	0.211	0.349	0.389	0.250	0.270

NOTE: This table shows the point estimates and the corresponding t-values which are underset. Set A implies that public available information at the time of the first vintage is used. The estimates of the parameter θ_1 and θ_2 are not reported.

ABBREVIATIONS: *con*: constant, $Q2$: quarterly dummy (second quarter), $Q4$: quarterly dummy (forth quarter), *cs*: consumer sentiment, *ysp*: yield spread (10 years/3 month), *emp*: employment. The preceding subscripts of the regressors denote their own vintage or information set the estimate is based on.

Table 2: Explaining Final Revisions: ${}_{t+k}y_t - {}_{t+1}y_t$ (Set B)

	III	IV	V	VI
constant	0.592 4.419	0.557 5.283	0.798 5.977	0.729 5.401
$Q2$	−0.617 −3.723	−0.670 −5.011	−0.644 −4.086	−0.668 −4.261
$Q4$	−0.072 −0.418	−0.252 −1.767	−0.416 −2.641	−0.442 −2.811
${}_{t+1}rev_{t-1}$	−0.270 −1.234			
${}_{t+1}rev_{t-3}$	−0.370 −1.525	−0.300 −1.399	−0.302 −1.250	−0.256 −1.058
${}_{t+1}y_t$	−0.432 −4.435	−0.377 −4.726	−0.290 −3.093	−0.227 −2.453
cs_{t-1}	0.042 3.432			
cs_t	0.021 1.620			
cs_{t+1}	0.020 1.605	0.305 4.891		
ysp_{t-1}	−0.070 −0.414			
ysp_t	0.347 2.059			
ysp_{t+1}	−0.169 −1.005	0.801 3.701		
${}_{t+1+2/3}emp_{t-1}$	0.219 0.649			
${}_{t+1+2/3}emp_t$	1.229 2.584			
${}_{t+1+2/3}emp_{t+1}$	−0.828 −2.241	2.046 4.494		
${}_{t+1+2/3}\widehat{F}_{t+1}$			0.202 3.842	0.556 3.971
σ^2	0.242	0.193	0.286	0.255
R^2	0.564	0.560	0.404	0.420
adR^2	0.457	0.462	0.359	0.357

NOTE: This table shows the point estimates and the corresponding t-values which are underset. Set B implies that public available information at the time around two month after the first vintage is used. The estimates of the parameter θ_1 and θ_2 are not reported.

ABBREVIATIONS: *con*: constant, $Q2$: quarterly dummy (second quarter), $Q4$: quarterly dummy (forth quarter), *cs*: consumer sentiment, *ysp*: yield spread (10 years/3 month), *emp*: employment. The preceding subscripts of the regressors denote their own vintage or information set the estimate is based on.

Table 3: Explaining revisions after two years: ${}_{t+8}y_t - {}_{t+1}y_t$ (Set A)

	I	II	III	IV	V	VI
constant	$\underset{1.713}{0.233}$	$\underset{1.858}{0.288}$	$\underset{1.420}{0.224}$	$\underset{1.648}{0.208}$	$\underset{1.955}{0.340}$	$\underset{2.301}{0.324}$
$Q2$	$\underset{-1.617}{-0.286}$	$\underset{-1.554}{-0.281}$	$\underset{-1.699}{-0.339}$	$\underset{-1.642}{-0.280}$	$\underset{-1.415}{-0.254}$	$\underset{-1.562}{-0.259}$
$Q4$	$\underset{-2.655}{-0.465}$	$\underset{-2.423}{-0.446}$	$\underset{-1.642}{-0.330}$	$\underset{-1.643}{-0.276}$	$\underset{-2.295}{-0.410}$	$\underset{-2.398}{-0.413}$
${}_{t+1}rev_{t-1}$	$\underset{-1.475}{-0.356}$	$\underset{-1.298}{-0.326}$	$\underset{-2.071}{-0.513}$	$\underset{-2.207}{-0.471}$	$\underset{-1.813}{-0.450}$	$\underset{-1.925}{-0.446}$
${}_{t+1}y_t$	$\underset{-0.122}{-0.011}$	$\underset{-1.006}{-0.110}$	$\underset{-1.527}{-0.177}$	$\underset{-2.027}{-0.185}$	$\underset{-0.682}{-0.089}$	$\underset{-0.795}{-0.075}$
cs_{t-1}		$\underset{0.195}{0.004}$	$\underset{1.547}{0.023}$			
cs_t		$\underset{1.946}{0.036}$	$\underset{-0.120}{-0.002}$			
$cs_{t+1/3}$			$\underset{0.301}{0.055}$	$\underset{2.066}{0.111}$		
ysp_{t-1}		$\underset{1.235}{0.006}$	$\underset{1.345}{0.259}$			
ysp_t		$\underset{-0.461}{-0.002}$	$\underset{1.305}{0.602}$			
$ysp_{t+1/3}$			$\underset{-0.721}{-0.297}$	$\underset{3.398}{1.247}$		
${}_{t+1}emp_{t-1}$		$\underset{-0.730}{-0.234}$	$\underset{1.723}{0.034}$			
${}_{t+1}emp_t$		$\underset{1.232}{0.401}$	$\underset{0.617}{0.205}$			
${}_{t+1}emp_{t+1/3}$			$\underset{0.835}{0.459}$	$\underset{2.712}{1.570}$		
${}_{t+1}\widehat{F}_t$					$\underset{0.177}{0.014}$	
${}_{t+1}\widehat{F}_{t+1/3}$					$\underset{1.445}{0.183}$	$\underset{1.733}{0.190}$
σ^2	0.356	0.355	0.330	0.240	0.354	0.319
R^2	0.150	0.228	0.317	0.385	0.181	0.180
adR^2	0.099	0.102	0.164	0.247	0.105	0.091

NOTE: This table shows the point estimates and the corresponding t-values which are underset. Set A implies that public available information at the time of the first vintage is used.

ABBREVIATIONS: con: constant, $Q2$: quarterly dummy (second quarter), $Q4$: quarterly dummy (forth quarter), cs: consumer sentiment, ysp: yield spread (10 years/3 month), emp: employment. The preceding subscripts of the regressors denote their own vintage or information set the estimate is based on.

Table 4: Explaining revisions after two years: ${}_{t+8}y_t - {}_{t+1}y_t$ (Set B)

	III	IV	V	VI
constant	0.205 1.420	0.174 1.470	0.337 2.142	0.352 2.990
$Q2$	-0.278 -1.558	-0.315 -2.145	-0.241 -1.423	-0.220 -1.457
$Q4$	-0.286 -1.546	-0.380 -2.461	-0.416 -2.490	-0.396 -3.334
${}_{t+1}rev_{t-1}$	-0.640 -2.708	-0.482 -2.416	-0.504 -2.167	-0.605 -2.713
${}_{t+1}y_t$	-0.198 -1.884	-0.192 -2.195	-0.081 -0.680	-0.103 -1.267
cs_{t-1}	0.034 2.607			
cs_t	0.016 1.140			
cs_{t+1}	0.001 0.101	0.085 2.787		
ysp_{t-1}	-0.020 -0.108			
ysp_t	0.010 0.054			
ysp_{t+1}	0.272 1.502	1.488 4.236		
${}_{t+1+2/3}emp_{t-1}$	0.622 1.718			
${}_{t+1+2/3}emp_t$	0.378 0.737			
${}_{t+1+2/3}emp_{t+1}$	-0.424 -1.074	2.095 4.471		
${}_{t+1+2/3}\widehat{F}_t$			0.212 3.300	
${}_{t+1+2/3}\widehat{F}_{t+1}$			-0.084 -1.085	0.562 4.617
σ^2	0.282	0.204	0.313	0.260
R^2	0.417	0.476	0.274	0.332
adR^2	0.287	0.358	0.207	0.259

NOTE: This table shows the point estimates and the corresponding t-values which are underset. Set B implies that public available information at the time around two month after the first vintage is used.

ABBREVIATIONS: con: constant, $Q2$: quarterly dummy (second quarter), $Q4$: quarterly dummy (forth quarter), cs: consumer sentiment, ysp: yield spread (10 years/3 month), emp: employment. The preceding subscripts of the regressors denote their own vintage or information set the estimate is based on.

Table 5: Explaining final revisions based on second vintage: ${}_{t+k}y_t - {}_{t+2}y_t$ (Set C)

	I	II	III	IV	V	VI
constant	0.545^{**} 4.261	0.655^{**} 4.764	0.575^{**} 4.703	0.502^{**} 4.526	0.741^{**} 5.537	0.670^{**} 5.053
$Q2$	-0.593^{**} -3.570	-0.604^{**} -3.719	-0.523^{**} -3.391	-0.565^{**} -3.929	-0.565^{**} -3.634	-0.598^{**} -4.089
$Q4$	-0.463^{**} -2.809	-0.410 -2.448	-0.090 -0.564	-0.231 -1.738	-0.412^{**} -2.661	-0.433^{**} -2.819
${}_{t+2}rev_t$	-0.169 -0.697	0.177 0.707	0.250 1.104	0.027 0.134	-0.176 -0.778	-0.289 -1.398
${}_{t+2}y_t$	-0.149 -1.685	-0.406^{**} -3.603	-0.471^{**} -5.070	-0.413^{**} -4.882	-0.290^{**} -3.109	-0.222^{**} -2.517
cs_t		0.011 0.702	0.026^{*} 2.271			
cs_{t+1}		0.000 -0.009	0.020 1.734			
cs_{t+2}		0.012 0.764	0.022 1.877	0.253^{**} 4.282		
ysp_t		0.005 1.046	-0.027 -0.177			
ysp_{t+1}		-0.004 -0.844	0.416^{**} 2.650			
ysp_{t+2}		0.001 0.426	-0.186 -1.167	0.947^{**} 2.831		
${}_{t+2}emp_t$		-0.753^{**} -2.619	0.018 0.059			
${}_{t+2}emp_{t+1}$		0.535 1.525	1.544^{**} 3.493			
${}_{t+2}emp_{t+2}$		0.706^{*} 2.424	-0.957^{**} -2.807	2.182^{**} 4.754		
${}_{t+2}\widehat{F}_t$						
${}_{t+2}\widehat{F}_{t+1}$					0.170^{**} 3.254	0.460^{**} 3.343
σ^2	0.308	0.268	0.203	0.170	0.269	0.243
R^2	0.252	0.438	0.575	0.556	0.357	0.366
adR^2	0.207	0.310	0.478	0.454	0.307	0.295

NOTE: This table shows the point estimates and the corresponding t-values which are underset. Set C implies that public available information at the time of the first vintage of y_{t+1} is used.

ABBREVIATIONS: $Q2$: quarterly dummy (second quarter), $Q4$: quarterly dummy (forth quarter), *cs*: consumer sentiment, *ysp*: yield spread (10 years/3 month), *emp*: employment. The preceding subscripts of the regressors denote their own vintage or information set the estimate is based on.

Table 6: MSE (20 observations)

	MSE rel. to zero	MSE rel. to Model I
zero	1.000	1.125
mean	1.228	1.381
I	0.889	1.000
II_A	1.051	1.182
III_A	0.780	0.877
V_A	0.884	0.994
III_B	0.633	0.712
V_B	0.798	0.898
$V_{B,5}$	0.644	0.724

Table 7: Tests on forecasting performance - p values

Diebold-Mariano (1995) Test

	mean	I	II_A	III_A	V_A	III_B	V_B	$V_{B,5}$
zero	**0.940**	0.197	0.599	0.138	0.256	**0.042**	0.178	0.112
mean	–	**0.052**	0.220	**0.054**	**0.061**	**0.037**	**0.075**	**0.078**
I	–	–	0.781	0.315	0.490	0.121	0.360	0.168
II_A	–	–	–	**0.035**	0.129	**0.031**	0.132	0.105
III_A	–	–	–	–	0.848	0.173	0.558	0.291
V_A	–	–	–	–	–	0.119	0.253	0.197
III_B	–	–	–	–	–	–	0.821	0.525
V_B	–	–	–	–	–	–	–	0.255

Encompassing Test – Harvey et al. (1998)

	mean	I	II_A	III_A	V_A	III_B	V_B	$V_{B,5}$
zero	**0.945**	0.101	0.565	0.275	0.470	**0.043**	0.202	**0.037**
mean	–	**0.061**	**0.096**	**0.046**	**0.049**	**0.035**	**0.045**	**0.037**
I	–	–	0.705	0.435	0.619	**0.084**	0.357	**0.051**
II_A	–	–	–	**0.068**	0.199	**0.052**	**0.079**	**0.067**
III_A	–	–	–	–	0.944	0.153	0.244	0.145
V_A	–	–	–	–	–	**0.090**	**0.084**	0.103
III_B	–	–	–	–	–	–	0.806	**0.094**
V_B	–	–	–	–	–	–	–	0.110

NOTE: Testing out-of sample performance based on 20 observations (one step ahead forecasts).The test statistic of Diebold and Mariano (1995) DM and the test statistic of Harvey et al. (1998) H are given as follows:

$$DM = \frac{\frac{1}{T_f}\sum_t d_t}{\sqrt{\frac{1}{T_f}\sigma_d^2}}\ , \qquad H = \frac{\frac{1}{T_f}\sum_t h_t}{\sqrt{\frac{1}{T_f}\sigma_h^2}},$$

where $d_t = \widehat{e}^2_{row,t} - \widehat{e}^2_{col,t}$ and $h_t = (\widehat{e}^2_{row,t} - \widehat{e}^2_{col,t})(\widehat{e}^2_{row,t})$. Due to the fact that σ_d^2 and σ_h^2 have to be replaced by the sample variances p values refer to the t distribution with 19 degrees of freedom.