Mixed-frequency models for tracking short-term economic developments in Switzerland*

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PRELIMINARY VERSION
February 15, 2016

Abstract
We compare several methods to monitor short-term economic developments in Switzerland. Based on a large mixed-frequency dataset the following approaches are presented and discussed: a large scale dynamic factor model, a version using the three-pass regression filter and a model combination approach resting on MIDAS regression models. In an out of sample GDP forecasting exercise, we show that the three approaches clearly beat the relevant benchmarks that work with one or a small number of indicators. This suggests that a large dataset is an important ingredient to successful real-time monitoring of the Swiss economy. This particularly helps during and after the crisis. Comparing the three approaches we find that the dynamic factor model outperforms slightly. We conclude by discussing the three approaches relative merits and giving some guidance to the applied economist.

JEL classification: C32, C53, E37

Keywords: Mixed frequency, GDP nowcasting, forecasting, Switzerland

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*The views expressed here are those of the authors and do not necessarily reflect the views of the Swiss National Bank. In particular, the models described in the paper are not part of the suite of models used for Swiss National Bank's inflation forecast, published on a quarterly basis in its Quarterly Bulletin.

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1 Introduction

Policy institutions such as central banks depend on a timely assessment of past, current and future economic conditions. However, many official statistics on economic development are released at low frequency and come in with a substantial time delay. GDP, for example, is released about two months after the end of a quarter. This means that between different data releases it is very hard to track short-term economic developments.

For Switzerland, the problem of imperfect and incomplete information for recent short-term developments is even more pronounced. Compared to larger countries such as the US, Germany or the UK, it has no official monthly available coincident indicators (e.g., industrial production, turnover or new orders). However, despite the shortage of early and frequent official data, other sources of information can be used to assess the current state of the economy, namely financial indicators or surveys. Moreover, data on foreign and domestic trade are important data sources which are available monthly and prior to the release of GDP data.

In this paper, we assess several methods to extract information for judging current economic conditions in Switzerland in a timely and efficient manner. This study relates to similar techniques applied for other countries. Evans (2005), Banbura, Giannone, and Reichlin (2011), Banbura and Rünstler (2011) and Kuzin, Marcellino, and Schumacher (2011) are some prominent examples. This study focuses on several factor models and model combination techniques to be used for tracking short-term economic developments in Switzerland. A common feature of these models are that they are able to handle indicators available at different frequency and therefore can be characterised as mixed-frequency methods.

The forecasting methods under consideration can be grouped into three categories: information combination, model combination and model selection. Information combination by dynamic factor models. Those models assume that a small number of latent variables can be used to describe the fluctuations in the given data set and that those factors are highly correlated with the business cycle and GDP (see e.g. Stock and Watson 2002b, 2006). Four different factor procedures are compared. First, a standard dynamic factor (DFM) based on a two-step estimation technique and using the Kalman filter. Second, a small scale factor model that is based on a pre-selected variable set. Third, a factor model based on the Three Pass Regression Filter is used as an additional alternative. Finally, we employ a very simple expectation-maximization algorithm to the unbalanced data set and extract static factors by means of principle component analysis. The alternative to combining information is to combine forecasts form different models. In this case, single indicator models are used to explain GDP within a linear regression framework. For higher frequent variables (weekly and monthly indicators) MIxed DAta Sampling (MIDAS) methods are used to take into account the temporal aggregation issue.

To compare the models under investigation we conduct a pseudo out-of-sample forecast exercise. Using a very large data set of more than 600 variables on weekly, monthly and quarterly frequency and taking into account two different states of information, we generate forecasts for the different models for the period 2005-2014. With all our forecasting procedures, we take into account the problem of missing observations at the end of the sample (ragged-edge problem).

Our results show that all of our considered models clearly beat relevant benchmarks such as univariate time series models and indicator models that rely on a very small data set. Factor models based on the large data set are better than the small scale model and notably more robust after the crises. Model combination techniques do also well, but did not capture the crises period as well as factor models. After the crisis the most promising model combination does similarly well than the best factor models, in particular for the two step ahead forecast. Overall we can show that a combination of our models under consideration produce even better results than the best single model procedure.

2 Forecasting approaches

2.1 Information combination

Information combination is done by specifying dynamic factor models. This approach assumes that a small number of latent variables can be used to describe the fluctuations in the given data set and that those factors are highly correlated with the business cycle and GDP (see e.g. Stock and Watson 2002b, 2006). Three different factor procedures are compared. First, a standard dynamic factor (DFM) based on a two-step estimation technique. Second, a small scale factor model that is based on a pre-selected variable set. Finally, a factor model based on the Three Pass Regression Filter is used as an additional alternative.

All approaches assume the following monthly relationship given by

$$z_t = c_t + u_t = \Lambda f_t + u_t, \tag{1}$$

where a large panel of time series z_t can be decomposed into a common component c_t and an idiosyncratic error term u_t. The common component consists of a small number of factors f_t which are linked to the observed time series by the loading coefficients Λ, with $\mathrm{Var}(u_t) = \Sigma_u = \mathrm{diag}(\sigma_1, ..., \sigma_N)$.

The factors are assumed to follow a VAR(p)-process

$$f_t = \Phi_1 f_{t-1} + ... + \Phi_p f_{t-p} + v_t, \tag{2}$$

with $\mathrm{Var}(v_t) = \Sigma_v$. From these two equations (eqs 1 and 2) we can make iterative forecast for all variables included in x_t. Therefore, one has to estimate the latent factors f_t as well as the model parameters, namely the loadings Λ the VAR coefficients $\Phi_1, ..., \Phi_p$ and the two covariance matrices Σ_u and Σ_v.

Time aggregation

We define our data vector at a monthly frequency as

$$z_t = \begin{bmatrix} y_t \\ x_t \end{bmatrix}, \tag{3}$$

where y_t denotes real gdp growth and x_t denotes our vector of indicator variables. x_t contains both variables measured at a monthly frequency and variables measured at a quarterly frequency. For non-stationary indicators, we use growth rates or first differences. The corresponding data vector at a quarterly frequency is defined as

$$z_t^Q = \begin{bmatrix} y_t^Q \\ x_t^Q \end{bmatrix}. \tag{4}$$

The monthly correspondence for an observation in the quarterly period t, x_t^Q, is the observations in the monthly period t, x_t. This means that, e.g., the observation for the first quarter of a given year corresponds to the month of March.

For quarterly flow variables, time aggregation of monthly observations (growth rates) to quarterly values is given by

$$z_{i,t}^Q = (\frac{1}{3} + \frac{2}{3}L + L^2 + \frac{2}{3}L^3 + \frac{1}{3}L^4)z_{i,t} = G^f(L)z_{i,t}. \tag{5}$$

For quarterly stock variables, time aggregation of the monthly observations to quarterly values is given by

$$z_{i,t}^Q = (\frac{1}{3} + \frac{1}{3}L + \frac{1}{3}L^2)z_{i,t} = G^s(L)z_{i,t}. \tag{6}$$

If the first block of variables in z corresponds to quarterly flow variables, the second to quarterly stock variables and the third to monthly variables, the generalized link between z_t^Q and z_t is then given by

$$z_t^Q = (G_0 + G_1L + G_2L^2 + G_3L^3 + G_4L^4)z_t \tag{7}$$

with

$$G_0 = \begin{bmatrix} \frac{1}{3}I_{n^{Qf}} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \frac{1}{3}I_{n^{Qs}} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & I_{n^M} \end{bmatrix}, G_1 = \begin{bmatrix} \frac{2}{3}I_{n^{Qf}} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \frac{1}{3}I_{n^{Qs}} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \mathbf{O} \end{bmatrix}, G_2 = \begin{bmatrix} \frac{3}{3}I_{n^{Qf}} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \frac{1}{3}I_{n^{Qs}} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \mathbf{O} \end{bmatrix},$$

$$G_3 = \begin{bmatrix} \frac{2}{3}I_{n^{Qf}} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \mathbf{O} \end{bmatrix} \text{ and } G_4 = \begin{bmatrix} \frac{1}{3}I_{n^{Qf}} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \mathbf{O} \end{bmatrix},$$

where n^{Qf} denotes the number of quarterly flow variables, n^{Qs} the number of quarterly stock variables and n^M the number of monthly variables.

Combining the dynamic factor model and the time aggregation equations, we get the following relationship between the observed variables z_t, the monthly factors f_t and the monthly errors u_t:

$$z_t^Q = \mathbf{G}_t(L)z_t = \mathbf{G}_t(L)(\Lambda f_t + u_t) = \mathbf{G}_t(L)\Lambda f_t + \mathbf{G}_t(L)u_t, \tag{8}$$

where $\mathbf{G}_t(L) = (G_0 + G_1L + G_2L^2 + G_3L^3 + G_4L^4)$.

Dynamic factor model I: large scale case

In this setup, we apply the standard dynamic factor approach to a large scale dataset for Switzerland (see section 3.1). To select the number of factors (r), we regress quarterly GDP on the quarterly aggregation of the factors obtained from a principal component analysis over a balanced sample of the monthly variables and chose the model with the lowest BIC,

$$BIC(r) = ln(\hat{\sigma}_\epsilon^2) + \frac{ln(T)}{T}r. \tag{9}$$

Given the number of factors r, we choose the number of lags p based on the VAR(p) of the factors which is associated with the lowest BIC,

$$BIC(p) = -2l(r,p) + rpln(T), \tag{10}$$

where $\ell(r,p) = -\frac{Tr}{2}log(2\pi) - \frac{T}{2}log|\Omega| - \frac{1}{2}\sum_1^T e_t'\Omega^{-1}e_t$.

Alternatively, one could follow Lütkepohl (2005), pp. 150 and 140, and write the BIC as

$$BIC(p) = ln|\hat{\Sigma}_e(p)| + \frac{lnT}{T}pr^2, \tag{11}$$

where $\hat{\Sigma}_e(p) = \frac{1}{T}(f_t - \hat{\Phi}_1 f_{t-1} ... - \hat{\Phi}_p f_{t-p})(f_t - \hat{\Phi}_1 f_{t-1} - ... - \Phi_p f_{t-p})'$.

We estimate the model using a two step approach. In the first step, we estimate the parameters of the model via principal components and linear regressions using the procedure described in the appendix. In the second step, we estimate the factors $\hat{f}_t$ using the Kalman filter and smoother. Our monthly fitted values are then given by $\hat{z}_t = \hat{\Lambda}\hat{f}_t$ and the monthly interpolated values for quarterly variables are given by $\hat{z}_t^* = \hat{\Lambda}\hat{f}_t + \hat{u}_t$.

The forecast for quarterly GDP in period t is then given by

$$\hat{y}_t^Q = G^f(L)\hat{y}_t. \tag{12}$$

Dynamic factor model II: small scale case

As a second setup, we apply the standard dynamic factor model to a small hand-selected set of indicators; put differently indicators are pre-selected from the large database using expert-judgement. The 9 indicator series are the Swiss PMI, real Swiss export and import growth, the percentage change in the number of unemployed, production expectation in the manufacturing sector according to the KOF survey, real retail sales growth, Euro area industrial production growth, the German ifo survey, and Swiss GDP growth. Following Mariano and Murasawa (2003) we assume that these indicators follow one common factor f_t, so that for the monthly indicators (all but GDP growth) we have

$$x_{i,t} = \lambda_i f_{i,t} + e_{i,t}$$

and for GDP growth we have

$$y_t = \lambda_y \left(f_t + 2f_{t-1} + 3f_{t-2} + 2f_{t-3} + f_{t-4}\right) + e_{y,t}.$$

For the state dynamics it is assumed that the idiosyncratic errors can follows an AR process

$$e_t = \sum_{j=1}^{J} \theta_j e_{t-j} + \varepsilon_t$$

as does the common factor

$$f_t = \sum_{i=1}^{I} \phi_i e_{t-i} + v_i,$$

with $\varepsilon_{i,t}$ and v_t being i.i.d. We choose $J = 2$ and $I = 1$ and rewrite the model as a state space system that is estimated using Maximum Likelihood (for details we refer to Mariano and Murasawa (2003) and Camacho and Perez-Quiros (2010)). Using on the estimated state space system one can then filter the data and form forecasts for the factor as well as for the individual indicators. In our application we will focus on the resulting real GDP growth forecasts.

Dynamic factor model III: Three pass regression filter

The Three Pass Regression Filter (3PRF) as described in Kelly and Pruitt (2013) and Kelly and Pruitt (2015) and extended to a mixed-frequency environment by Hepenstrick and Marcellino (2016). Besides the frequency-mixing, the latter discuss a number of issues that arise in the application of the filter, in particular the presence of indicators with differing publication lags and various approaches to generate the GDP forecast. In the present paper we use one specification of the 3PRF that performs particularly well for Switzerland and that is very easy to implement. For results on alternative specifications we refer to Hepenstrick and Marcellino (2016).[1]

The algorithm can be represented in four steps. Step 0 deals with the ragged edge arising for differing publication lags, steps 1 and 2 ("Pass 1" and "Pass 2" of the 3PRF) extract a factor from the indicator set, and step 3 ("Pass 3") translate the factor into a GDP forecast:

0. Vertical realignement as suggested by Altissimo, Cristadoro, Forni, Lippi, and Veronese (2010): Define T as the last month for which data is observed. For each indicator series generate a new series of its lags such that the last observation is in T as well. We denote the standardised realigned series as $x_{i,t}$.
1. Pass 1 of 3PRF: run for each indicator $i = 1, ..., N$ a time series regression of the indicator aggregated to the quarterly frequency, $x^q_{i,t}$, on GDP growth, y_t

   $$x^q_{i,t} = \phi_i y_t + \epsilon_{i,t}.$$

   Drop all indicators with a p-value of the F-test that is higher than 10%. For the other indicators retain the slope estimates, $\hat{\phi}_i$.
2. Pass 2 of 3PRF: run for each month $t = 1, ..., T$ a cross section regression of the remaining indicators $x_{i,t}$ on the slope estimates

   $$x_{i,t} = \alpha_t + f_t \hat{\phi}_i + \varepsilon_{i,t}.$$

[1]Specific results for Switzerland are available upon request.

The time series of the resulting slopes $\hat{f}_t$ is the 3PRF factor.

3. Pass 3 of 3PRF: Translate the factor estimates $\hat{f}_t$ into a GDP forecast using the U-MIDAS approach of Foroni, Marcellino, and Schumacher (2015). For this K quarterly series, $\hat{f}_t^1, ..., \hat{f}_t^K$, are generated from the monthly factor, $\hat{f}_t$. The first series consists of the factor values of the month within the running quarter with the last observation. The second series contains the values of the month before, etc.[2] Next, the new quarterly series, $\hat{f}_t^1, ..., \hat{f}_t^K$, are used as explanatory variables in the forecast for GDP growth in $t + h$

$$y_{t+j} = \beta_{0,j} + \sum_{k=0}^{K} \beta_{1,j,K} \hat{f}_t^k + \eta_{j,t}.$$

We chose $K = 5$.

Dynamic factor model IV: Approximate dynamic factor model based on static factors

This subsection discusses an alternative factor estimator based solely on principle components and simple linear regressions. Based on the theoretical work of Stock and Watson (2002a) and Bai (2003), Stock and Watson (2002b) as well as Schumacher and Breitung (2008) successfully applied principle component based factor analysis to macroeconomic forecasting situations. Those studies apply a simple expectation-maximization EM algorithm to deal with missing observations. There are three reasons missing observations in our panel. First, there is a large fraction of indicators that are only available at quarterly frequency. Second, due to infrequent publication dates there is the ragged edge problem. The third reason is that many of our time series have missing observations at the beginning of the sample. So the EM algorithms provides a balanced data set on which principle component analysis can be employed.

This approach basically consists of two steps:

1. Extract one factor from the entire data set by use of principle components. The

[2] As an example assume that we have estimates of the monthly factor up to February 2016. The first new quarterly series therefore contains values of February 2016, November 2015, August 2015, etc.. The second series contains the values of January 2016, October 2015, etc. and the third series contains the values of December 2015, September 2015, etc. The fourth (fifth/sixth) series is the one quarter lag of the first (second/third) series, and so on.

EM-algorithm is used to deal missing observations (see Stock and Watson 2002b, appendix).

2. Quarterly GDP is regressed on the monthly factors by a U-MIDAS approach (Foroni, Marcellino, and Schumacher 2015)

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2.2 Model combination

In the following we present an alternative to combining information into one or a few variables (or factors) used to explain current and future GDP developments. This procedure is based on simple dynamic linear regression models that relate GDP to leading indicators. We concentrate on single indicator models where GDP is regressed on one leading indicator with its potential lags and lags of the endogenous variables. Therefore we basically follow the work of Kitchen and Monaco (2003) or Stock and Watson (2003) using so-called bridge models. Since leading indicators may be available on higher frequency than the quarterly target variable we do apply MIxed DAta Sampling (MIDAS) methods to take into account the temporal aggregation issue in an efficient way (as proposed by Ghysels, Santa-Clara, and Valkanov 2004, Andreou, Ghysels, and Kourtellos 2011). At the end we present methods that combine the information of the different indicators and methods to arrive at a pooled indicator based forecast.

Specification of single indicator models using MIDAS

To take into account the complete weekly information flow, we employ the framework proposed by Ghysels, Santa-Clara, and Valkanov (2004), Ghysels, Sinko, and Valkanov (2007) and Andreou, Ghysels, and Kourtellos (2011) which has been applied successfully by Clements and Galvão (2009) and Marcellino and Schumacher (2010) to macroeconomic forecasting. We follow their MIxed DAta Sampling (henceforth MIDAS) regression models procedure, which circumvents problems of quarterly conversion of the higher frequency indicator. MIDAS models are closely related to distributed lag models (see, Judge, Griffiths, Hill, Lütkepohl, and Lee 1985) and use parsimonious polynomials to reflect the dynamic response of a target variable to changes in the explanatory variables. This specification is particularly useful for time series that do not change much from one month to another (which may imply that explanatory variables are nearly linearly dependent). Thus one does not need to estimate an unrestricted model using all observed monthly data points which would result in a highly parameterized dynamic model. The main advantage is that only a small number of parameters has to be estimated for the distributed lag specification although long lags can be captured.

Generally, all our specified models fall into the category of autoregressive distributed lag (ARDL) models. For the models using monthly or weekly indicators they are MIDAS models. Similar to Andreou, Ghysels, and Kourtellos (2013), we estimate the following regression model:

$$y_{t+h}^{Q} = \mu + \sum_{j=0}^{p_y^i} \alpha_{j+1} y_{t-j}^{Q} + \sum_{k=0}^{p_x^i} \omega_k^i(\theta) x_{t+h,N_i-J_i-k}^{i} + u_{t+h} \tag{13}$$

while i denotes the frequency of the indicator variable x. This can be quarterly, monthly or weekly. p_y^i and p_x^i reflect the lags of the variables.[3] N_i is the number of observations (months or weeks) per quarter and J_i denotes the number of missing observations relative to the reference quarter $t+h$. In the case of quarterly indicators, eq. 13 simplifies to a standard ARDL model (see e.g. Stock and Watson 2003), $N_i = 0$ and $\omega(\theta)$ is linear with coefficients θ_k for each lag.

In the case of higher frequent indicators (monthly or weekly available indicators), this paper employs a Almon-Distributed Lag model in order to link indicators to the low frequent target variable (as applied by Drechsel and Scheufele 2012a). In this case $\omega_k^i(\theta)$ is specified as

$$\omega_k^i(\theta) = \omega_k^i(\theta_0, \theta_1, ...\theta_q) = \theta_0 + \theta_1 k + \theta_2 k^2 + ... + \theta_q k^q, \tag{14}$$

where q is the polynomial degree which can be substantially lower than p_x^i. Even with very small q many flexible forms can be approximated. The great advantage of using a simple Almon-Distributed Lag model instead of using a more complex functional form, is that it can by easily estimated by restricted least squares (and no non-linear optimization is required). Subscript k is specified in terms of subperiods (weeks or months) and counts

[3]Note that p_y^i and p_x^i are selected by the Schwartz criterion. For quarterly variables the maximum lag of the lagged endogenous variable is four. In the case of monthly and weekly variables the maximum is one.

back for quarter $t+h$ into the past. Note that J_i (missing observations for the nowcast) depends on the variable, the horizon and the forecasting round. Within each recursive estimation window we re-optimize the optimal lag-length and polynomial degree of the models.

Pooling techniques

While some single indicator models may already provide good forecast accuracy, it is generally undesirable to rely on such a limited set of information. Throwing away the majority of information by employing only one single best (in-sample) fitting model is inefficient in most cases. One way to employ the full set of available information is to pool the results of several indicator models. The literature has shown that the combination of forecasts often results in an improvement of forecast accuracy compared to univariate benchmark models or to a specific selected model (see Granger and Newbold 1977, Clemen 1989, Stock and Watson 2004, Timmermann 2006). An additional advantage of model averaging is that it guards against instabilities (Hendry and Clements 2004) and often results in a more stable and reliable forecasting performance (see Drechsel and Scheufele 2012b, before and during the financial crisis). In our application we take into account a large set of pooling techniques that combine the forecasts based on MIDAS models (for weekly and monthly available indicators) with those based on standard ARDL models (for quarterly indicator variables).

Pooling the individual indicator forecasts $\widehat{y}_{i,t}$ we obtain the total forecast $\tilde{y}_t$ by:

$$\tilde{y}_t = \sum_{i=1}^{n} \omega_{i,t} \widehat{y}_{i,t} \quad \text{with } \sum_{i=1}^{n} w_{i,t} = 1 \tag{15}$$

where $\omega_{i,t}$ is the weight assigned to each indicator forecast that results from the fit of the i^{th} individual equation. Note that due to the subscript t we allow for time-varying weights. n_t is the total number of models retained at time period t.[4]

We take into account several model averaging strategies, namely:

1. Equal weighting scheme (which is just the average of all candidate models): $w = 1/n$

[4]According to the recursive model selection scheme of each indicator model, only those models survive for the model averaging scheme that obtain a smaller SIC than the AR-model (which exclusively consists of a constant and its own lags). The time varying nature is mostly taken into account by a recursive estimation scheme which implies that in- and out-of-sample criteria get updated at each point in time.

2. Approximate bayesian weighting scheme which depends on the model's Bayesian (or Schwarz) information criterion. Accordingly, this scheme implies $w_i^{SIC} = \frac{\exp\left(-0.5 \cdot \Delta_i^{SIC}\right)}{\sum_{i=1}^{n} \exp\left(-0.5 \cdot \Delta_i^{SIC}\right)}$ with $\Delta_i^{SIC} = SIC_i - SIC_{\min}$.
3. As a third model averaging scheme employing the full in-sample covariance information, we consider Mallows Model Averaging (MMA) criterion proposed by Hansen (2007) and Hansen (2008). This measure is based on Mallows' criterion for model selection. The goal of this measure is to minimize the MSE over a set of feasible forecast combinations. This implies minimizing the function $C = (y - Fw)'(y - Fw) + w'Ks^2$, where K is a vector including the number of coefficients of each model and $s^2 = \frac{\hat{e}(M)'\hat{e}(M)}{T-k(M)}$ is an estimate σ^2 from the model with the smallest estimated error variance. We apply the constraints $0 \leq w \leq 1$ and $\sum_{i=1}^{n} \omega_i = 1$. Note that MMA explicitly takes into account the number of estimated parameters of the model.
4. Weights that are inversely proportional to the models' past mean square forecast errors (mse). Weights based on mean square forecast errors (MSFEs) for a specific training sample of size p. This combination scheme have been applied quite successfully by Stock and Watson (2004) and Drechsel and Scheufele (2012b) for output predictions based on leading indicators. This implies that S_{it} is the recursively computed mean square forecast error of model i over a training sample of size p which is computed as $S_{it} = \sum_{s=t-h-p}^{t-h} (\hat{e}_{i,s})^2$. The mean square forecast error weights are based on
$$w_{i,t} = \frac{S_{it}^{-1}}{\sum_{j=1}^{n} S_{jt}^{-1}} \tag{16}$$
5. Another weighting scheme based on the models past forecast performance is based on ranks of the specific models (Aiolfi and Timmermann 2006, Drechsel and Scheufele 2012a). It is thus closely related to the previous combination scheme, but the weights are assigned according to the model ranks instead of the number of MSFEs (and thus also depend on S_{it}). For each model, i, the rank for a h-step ahead forecast up to time t is then assessed by $\mathcal{R}_{t,t-h,i} = f(S_{1t}, ..., S_{nt})$. The model with the best MSFE forecasting performance, gets a rank of 1, the second best a rank of 2 and so on. The individual weights are then calculated as

$$w_{i,t} = \frac{\mathcal{R}_{i,t-h}^{-1}}{\sum_{j=1}^{N} \mathcal{R}_{j,t-h}^{-1}}. \tag{17}$$

One advantage of ranks compared to direct MSFE-weights is that they are less sensitive to outliers and thus should be more robust. In practice, the weighting scheme based on ranks puts very high weight on the group of best models and nearly zero weight to models with less accurate past performance.

2.3 Model selection using Autometrics

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3 Model and forecast evaluation

In order to evaluate the models, we have produced one and two quarter ahead forecast using a recursive pseudo real-time setup. The different models are compared in terms of root mean squared error (RMSE). The target variable is annualized quarter on quarter growth of Swiss GDP (real, calendar and seasonally adjusted).

In terms of timing of the forecast production, two specific dates are selected. The first, "early-quarter" information set is given by indicator information available at 11th March/June/September/December. At this date, surveys are usually available for one month of the quarter, hard data for none or one month, and financial data for two months. For this information set, we use an underlying data vintage available at 11th September 2015.

The second, "late-quarter" information set is given by data available at the 6th May/August/November/February. At this date, surveys are usually available for all three month of the quarter, hard data for two or three months, and financial data for all three months. Theoretically, this additional information should improve the forecasts. For this information set, we use an underlying data vintage available at 6th November 2015.

The evaluation is conducted over the period 2005Q1-2014Q4. It is based on GDP data that came with SECO's GDP release for the second quarter of 2015. Following the forecast literature, we use autoregressive models as the main benchmark.

3.1 Data

We work with two data sets. For the large scale dynamic factor model, the three pass regression filter approach, and the MIDAS model, we use a large data set which consists of 637 variables (351 monthly, 286 quarterly), covering the following areas:

- Gross domestic product (quarterly: 27, monthly: 0): Total GDP, demand components, value added of sectors.
- Labour market (quarterly: 61, monthly: 43): OASI statistics, unemployment statistic, job statistics, employment statistics, surveys, hours worked, wage index.
- Consumption (quarterly: 13, monthly: 10): Overnight stays of domestic visitors, retail sales, import of fuel, electricity consumption, new car registrations, consumer sentiment.
- Investment (quarterly: 12, monthly: 3): SwissMEM survey, imports of investment goods, industrial production of investment goods.
- Foreign trade (quarterly: 2, monthly: 19): Trade statistics, overnight stays of foreign visitors.
- International activity (quarterly: 21, monthly: 62): Several indicators covering Germany, euro area, United States, Japan, emerging asia and the CESifo world economic survey.
- Financial markets (quarterly: 0, monthly: 64): Stock market indices, exchange rates, commodity indices, monetary aggregates, monetary conditions, interest rates, spreads.
- Prices (quarterly: 3, monthly: 12): Consumer prices, real estate prices, import prices, production prices, construction prices.
- Construction sector (quarterly: 24, monthly: 17): Surveys, production, order books, cement delivieries.
- Retail trade sector (quarterly: 5, monthly: 5): Surveys.
- Wholesale trade sector (quarterly: 9, monthly: 0): Surveys.
- Accomodation sector (quarterly: 7, monthly: 1): Overnight stays, surveys.
- Manufacturing sector (quarterly: 40, monthly: 52): Industrial production, surveys, PMI, electricity production, number of working days.

- Project engineering sector (quarterly: 7, monthly: 6): Surveys.
- Banking sector (quarterly: 21, monthly: 34): Credit statistics, surveys, balance sheet statistics, illiquidity index.
- Insurance sector (quarterly: 14, monthly: 16): Surveys.

For the small scale dynamic factor model and the Autometrics approach, we use a smaller data set which consists of quarterly GDP and the following monthly variables: Manufacturing PMI, export of goods, imports of goods, retail sales, number of unemployed, inflows into unemployment, industrial production of the euro area, ifo climate index for Germany.

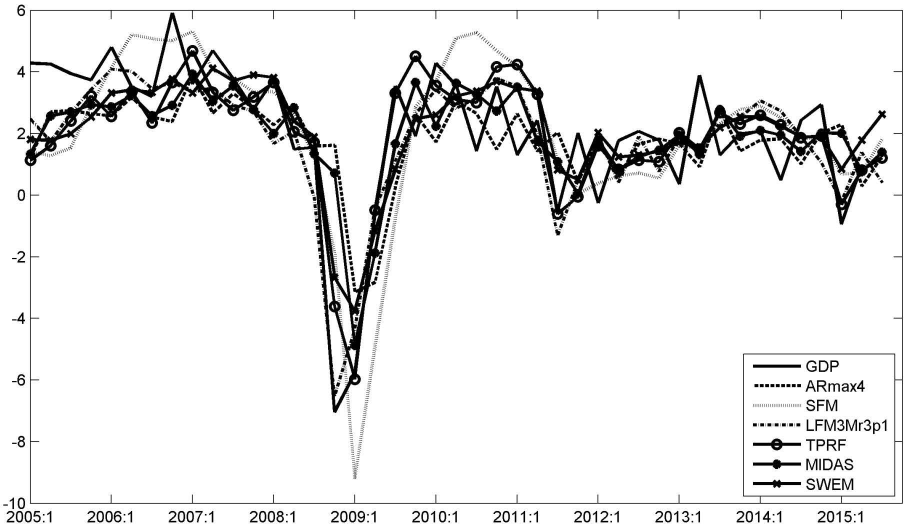
3.2 Evaluation results

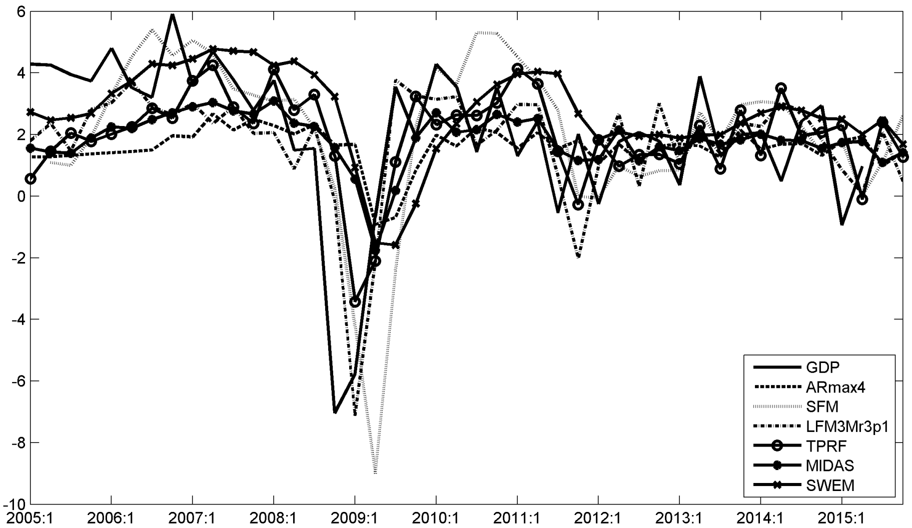
Figure 1 plots the forecasts of the different models over time. Generally, the general tendency of the forecasts are very similar, but for some quarters the models can differ quite substantially from each other. Most notably, the predicted through of the financial crisis differs across models. Based on the early-quarter information set, only the large DFM is in line with current GDP figures which display the largest drop in the fourth quarter of 2008. All other models saw the crisis trough in the first quarter of 2009. When incorporating more information (late-quarter information set), these outcomes change somewhat: 3PRF is now in favor of the 2009Q4, while the large DFM shifts to 2009Q1. The small DFM even sees the bottom in 2009Q2.

Looking at the forecasts for two quarters ahead, the results suggest that it was rather difficult for most models to accurately foresee the financial crisis in terms of both magnitude and timing. Based on the early-quarter information set, only the large DFM and the SFM anticipated the crisis in terms of magnitude, but were one (large DFM) and two (small DFM) quarters lagging in terms of timing. 3PRF was also able to catch the dynamics comparatively well. With more information (late-quarter information set), also the 3PRF adjusted its forecast to the downside. The AR benchmark as well as the MIDAS model are still not or only to a limited extent able to capture the crisis dynamics. This is clearly due to the backward looking components of these models.

Table 1 reports the root mean squared errors of the models and benchmarks. Looking at panel I, the results for one step ahead forecast based on the early-quarter information

Figure 1 — Out of sample forecasts (1 and 2 quarters ahead)





set and evaluated over the full sample show that all models perform clearly better than the autoregressive benchmark for the full sample, with largest gains in terms of RMSE for the large DFM (36%) and the 3PRF (30%). The worst performer is the small DFM. When looking in more detail at different evaluation periods the results indicate that these gains are to a major extent driven by the crisis periods. For the pre-crisis period, the gain of the best model (still the large DFM) shrinks to 22%. In the post-crisis period, the gains are even smaller (4 to 7%) and the worst model (small DFM) is even worse as the autoregressive benchmark. This may be associated to the fact that Swiss GDP, seen in an

Table 1 — Root mean squared errors of forecasts

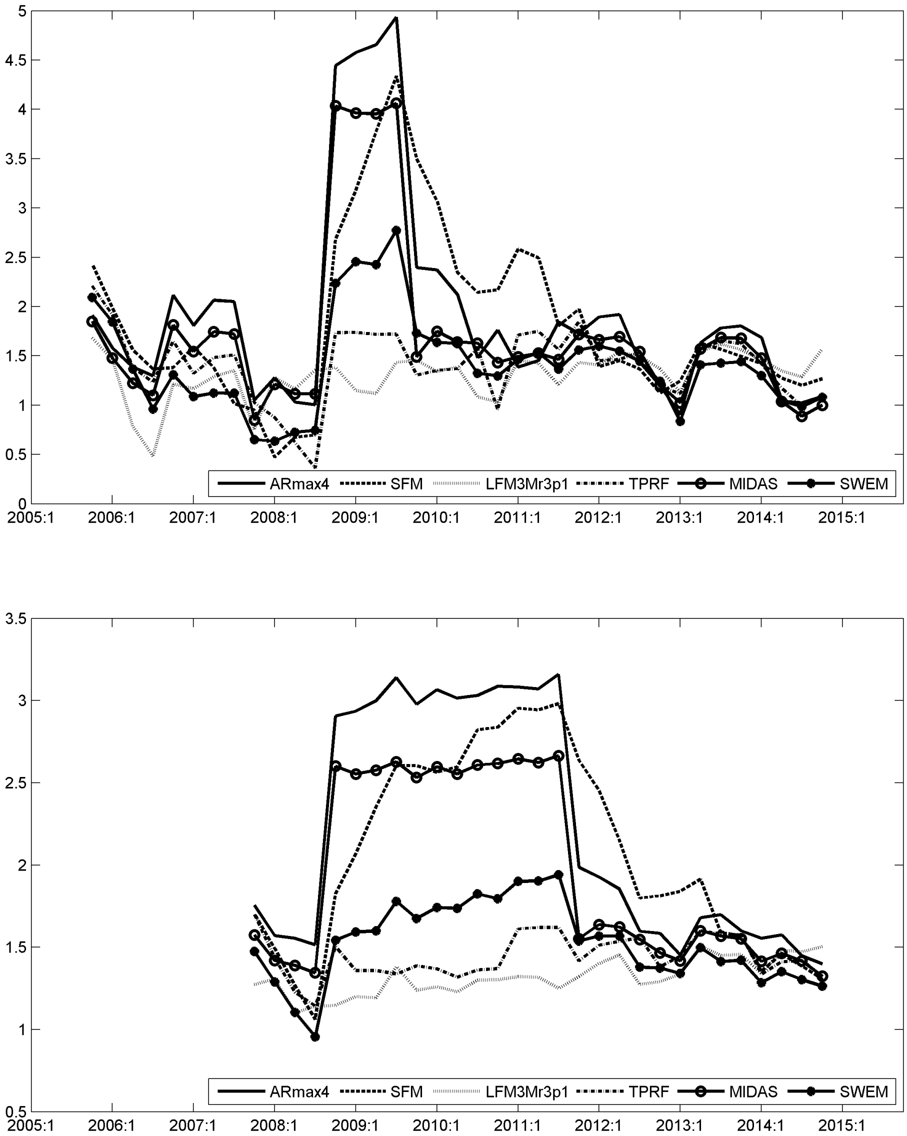
	h=1			h=2		
Model	full	pre-crisis	post-crisis	full	pre-crisis	post-crisis
I. EARLY-QUARTER INFORMATION SET						
Small DFM	2.05	1.61	1.66	2.58	1.70	1.75
Large DFM	1.37	1.31	1.41	1.85	1.71	1.46
3PRF	1.51	1.58	1.38	2.16	1.95	1.50
SWEM	1.53	1.39	1.33	2.63	1.43	1.73
MIDAS	1.90	1.57	1.43	2.25	1.89	1.11
II. LATE-QUARTER INFORMATION SET						
Small DFM	2.44	1.58	1.74	2.59	1.52	1.76
Large DFM	1.42	1.31	1.38	1.47	1.57	1.36
3PRF	1.45	1.34	1.39	1.71	1.75	1.20
SWEM	1.36	1.42	1.29	2.05	1.43	1.44
MIDAS	1.73	1.53	1.32	2.15	1.89	1.12
III. BENCHMARKS						
AR1 (iterative)	2.15	1.68	1.48	2.44	2.03	1.21
ARmax4 (direct)	2.16	1.71	1.55	2.54	2.34	1.24
Long-run average	2.52	2.29	1.29	2.53	2.31	1.29

historical perspective, was comparatively smooth since 2010.

The results for the two step ahead forecast go into a similar direction. For the full sample, all models except the small DFM perform clearly better than the autoregressive benchmark with the largest gains again for the large DFM (24%). As for the one step ahead forecast, the gains are to a major extent driven by the crisis. All models, except the small DFM perform worse in the pre-crisis period than over the full sample. Furthermore, for the post-crisis period, none of the models is able to beat the AR benchmark for the two step ahead forecast.

Looking at panel II, the results for one step ahead forecast based on the late-quarter information set indicate that while the additional information content of the data helps to increase the gains of the SWEM and MIDAS model, this is not or only to a limited extent the case for the two DFMs and the 3PRF model. For the two step ahead forecast, however, the forecasts of all models improve in almost all periods compared to the early-quarter information set.

Figure 2 — Rolling root mean squared errors (1 and 3 year windows)



To do a more detailed comparison of the different models over time, Figure 3 shows the RMSEs over rolling one year (top panel) and three year (bottom panel) windows. It can be seen that the comparative performance of the different models varies somewhat over time. Furthermore, while the one step ahead rolling RMSEs of the large DFM as well as the 3PRF were mostly unaffected by the financial crisis, the latter had a large impact on the AR benchmark, the MIDAS model and also the small DFM.

[...]

3.3 Combination of model forecasts

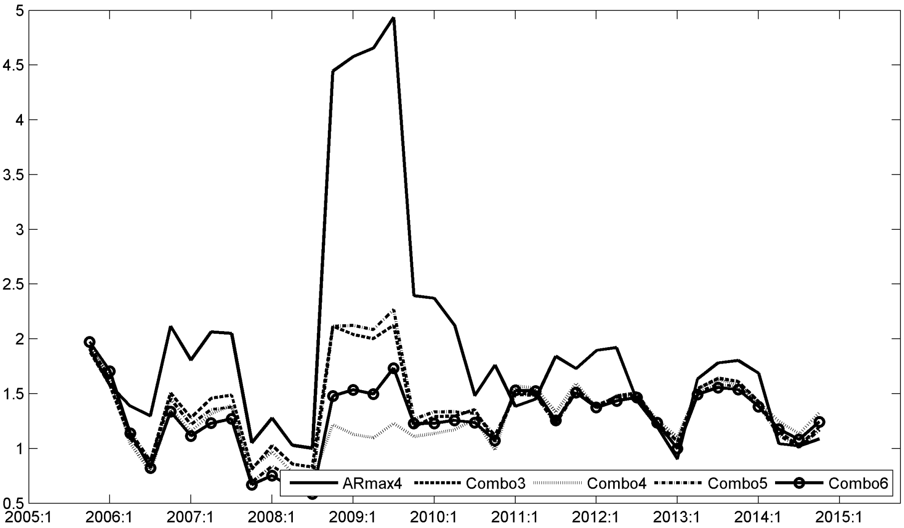
The fact that the models perform different over different time periods indicates possible gains by a combination of the models' forecasts. This point is supported by a correlation analysis of the errors.

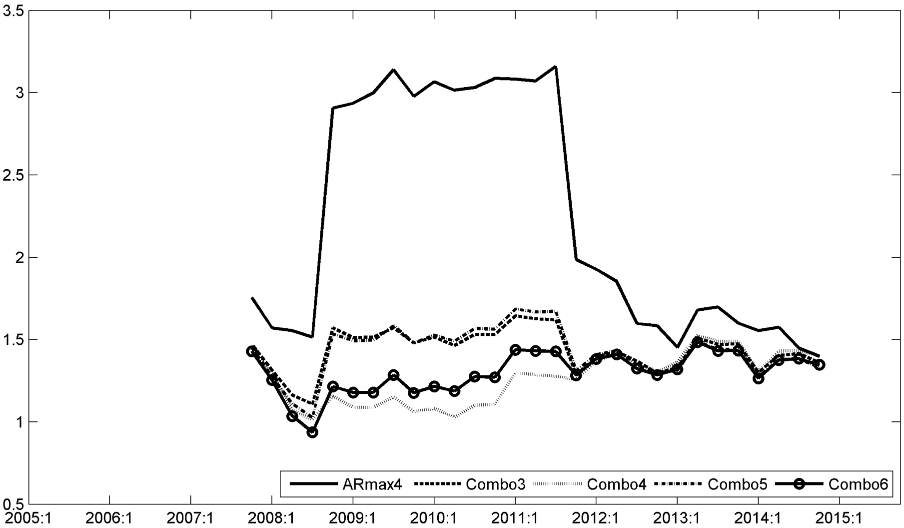
Table 2 reports the root mean squared errors of different combinations of the model forecasts. The results suggest that forecast combination indeed yields gains and especially a more stable performance over time.

Table 2 — Combination of model forecasts

	h=1			h=2		
Combinated models	full	pre-crisis	post-crisis	full	pre-crisis	post-crisis
I. EARLY-QUARTER INFORMATION SET						
Combo3: Large DFM, 3PRF, MIDAS	1.46	1.42	1.35	1.95	1.78	1.26
Combo4: Large DFM, 3PRF	1.35	1.38	1.37	1.91	1.74	1.40
Combo5: Large DFM, 3PRF, SWEM, MIDAS	1.46	1.39	1.33	2.03	1.58	1.30
Combo6: Large DFM, 3PRF, SWEM	1.37	1.35	1.33	1.99	1.49	1.40
II. LATE-QUARTER INFORMATION SET						
Combo3: Large DFM, 3PRF, MIDAS	1.44	1.34	1.31	1.65	1.65	1.12
Combo4: Large DFM, 3PRF	1.38	1.30	1.33	1.50	1.59	1.19
Combo5: Large DFM, 3PRF, SWEM, MIDAS	1.38	1.32	1.27	1.68	1.48	1.15
Combo6: Large DFM, 3PRF, SWEM	1.34	1.30	1.28	1.57	1.40	1.19

Figure 3 — Combination of forecasts: Rolling RMSEs (1 and 3 year windows)





4 Conclusions

Monitoring economic developments in real-time is one of the most important, but also most challenging tasks that the applied Swiss economist faces. In this paper, we set up a large database containing hundreds of potentially relevant variables. We then considered different approaches to condensing the information of dataset into a GDP forecast. The traditional approaches often used in practice select one or a few indicators based on expert knowledge and derive the forecast using OLS regressions or a small scale dynamic factor model. Alternatively, one may use all indicators without an experts pre-selection. We presented three approaches to doing so.

The large scale dynamic factor model extracts a small number of common factors from the database and forecasts the factors using their estimated law of motion. Importantly, the factors are extracted such that they explain as much as possible of the variation in the dataset. There is no ex-ante reason why the factors should be particularly useful for forecasting GDP. Or put differently, this model performs well for any variable that is strongly correlated with the forces that are most manifest in the dataset. GDP is treated as merely another indicator, but it nevertheless turns out that the forecasting performance with respect to GDP is impressive. Another advantage of the model (particularly relevant to a time-constrained practitioner) is that the model automatically generates forecasts for all indicators in dataset. The disadvantage is that setting up the model may prove somewhat tedious and evaluating the model is time consuming since its estimation takes quite some time.

The three pass regression filter extracts one factor from the dataset. The factor is geared towards a particular target (in our case GDP). This avoids the use of irrelevant factors, which can cause problems in a finite sample (see the Monte Carlo in Hepenstrick and Marcellino, 2016). An important advantage of the approach is that it is simply based on a series of OLS regressions, which makes computation very fast. Correspondingly, one can easily run a pseudo out of sample evaluation every time the model is run, which helps to understand what to expect from the model given the current dataset. The disadvantage is that it would require some work to include quarterly indicators.

The third approach estimates MIDAS equations for each indicator and then combines the resulting forecasts to form a final GDP forecast. This makes communicating a particular indicators contribution to the forecast very easy. Also, the variation in the distribution of the forecasts over time can be used as a measure of uncertainty. Moreover, it is quite easy to implement. The disadvantage is that this model performs slightly worse than the two other approaches, particularly so during the crisis.

Compared to models that use only one indicator or a small number of indicators we find that all three large-scale approaches clearly outperform. This advantage is particularly strong following the crisis. Given this finding we strongly recommend to use a large dataset when monitoring the Swiss economy. Which particular approach to use however depends on the forecasters exact task and the resources that she dispose over.

References

Aiolfi, M., and A. Timmermann (2006): "Persistence in forecasting performance and conditional combination strategies," *Journal of Econometrics*, 135(1-2), 31–53.

Altissimo, F., R. Cristadoro, M. Forni, M. Lippi, and G. Veronese (2010): "New Eurocoin: Tracking economic growth in real time," *The Review of Economics and Statistics*, 92(4), 1024–1034.

Andreou, E., E. Ghysels, and A. Kourtellos (2011): "Forecasting with mixed-frequency data," in *Oxford Handbook of Economic Forecasting*, ed. by M. P. Clements, and D. F. Hendry, chap. 8. Oxford University Press.

——— (2013): "Should Macroeconomic Forecasters Use Daily Financial Data and How?," *Journal of Business & Economic Statistics*, 31(2), 240–251.

Bai, J. (2003): "Inferential Theory for Factor Models of Large Dimensions," *Econometrica*, 71, 135–172.

Banbura, M., D. Giannone, and L. Reichlin (2011): "Nowcasting," in *The Oxford Handbook of Economic Forecasting*, ed. by M. P. Clements, and D. F. Hendry, chap. 7, pp. 193–224. Oxford University Press.

Banbura, M., and G. Rünstler (2011): "A look into the factor model black box: Publication lags and the role of hard and soft data in forecasting GDP," *International Journal of Forecasting*, 27(2), 333–346.

Camacho, M., and G. Perez-Quiros (2010): "Introducing the Euro-Sting: Short-term Indicator of Euro Area Growth," *Journal of Applied Econometrics*, 25, 663–694.

Clemen, R. T. (1989): "Combining forecasts: A review and annotated bibliography," *International Journal of Forecasting*, 5(4), 559–583.

Clements, M., and A. Galvão (2009): "Forecasting US output growth using Leading Indicators: An appraisal using MIDAS models," *Journal of Applied Econometrics*, 24(7), 1187–1206.

Drechsel, K., and R. Scheufele (2012a): "Bottom-up or Direct? Forecasting German GDP in a Data-rich Environment," Working Papers 2012-16, Swiss National Bank.

——— (2012b): "The Performance of Short-term Forecasts of the German Economy before and during the 2008/2009 Recession," *International Journal of Forecasting*, 28(2), 428 – 445.

Evans, M. D. D. (2005): "Where Are We Now? Real-Time Estimates of the Macroeconomy," *International Journal of Central Banking*, 1(2).

Foroni, C., M. Marcellino, and C. Schumacher (2015): "U-MIDAS: MIDAS regressions with unrestricted lag polynomials," *Journal of the Royal Statistical Society - Series A*, 178, 57–82.

Ghysels, E., P. Santa-Clara, and R. Valkanov (2004): "The MIDAS touch: Mixed DAta Sampling regression models," mimeo, Chapel Hill, N.C.

Ghysels, E., A. Sinko, and R. Valkanov (2007): "MIDAS Regressions: Further Results and New Directions," *Econometric Reviews*, 26(1), 53–90.

Granger, C. W., and P. Newbold (1977): *Forecasting Economic Time Series*. Academic Press, New York.

Hansen, B. E. (2007): "Least Squares Model Averaging," *Econometrica*, 75(4), 1175–1189.

——— (2008): "Least-squares forecast averaging," *Journal of Econometrics*, 146(2), 342–350.

Hendry, D. F., and M. P. Clements (2004): "Pooling of forecasts," *Econometrics Journal*, 7(1), 1–31.

Hepenstrick, C., and M. Marcellino (2016): "Forecasting with Large Unbalanced Datasets: The Mixed Frequency Three-Pass Regression Filter," *mimeo*.

Judge, G. G., W. E. Griffiths, R. C. Hill, H. Lütkepohl, and T.-C. Lee (1985): *The Theory and Practice of Econometrics*. John Wiley and Sons, 2nd edition edn.

Kelly, B., and S. Pruitt (2013): "Market Expectations in the Cross-Section of Present Values," *The Journal of Finance*, 68(5), 1721–1756.

——— (2015): "The three-pass regression filter: A new approach to forecasting using many predictors," *Journal of Econometrics*, 186(2), 294 – 316, High Dimensional Problems in Econometrics.

Kitchen, J., and R. Monaco (2003): "Real-Time Forecasting in Practice," *Business Economics*, 38(4), 10–19.

Kuzin, V., M. Marcellino, and C. Schumacher (2011): "MIDAS vs. mixed-frequency VAR: Nowcasting GDP in the Euro Area," *International Journal of Forecasting*, 27(2), 529–542.

Lütkepohl, H. (2005): *New introduction to multiple time series analysis*, vol. 26. Springer.

Marcellino, M., and C. Schumacher (2010): "Factor MIDAS for Nowcasting and Forecasting with Ragged-Edge Data: A Model Comparison for German GDP," *Oxford Bulletin of Economics and Statistics*, 72(4), 518–550.

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, 427–443.

Schumacher, C., and J. Breitung (2008): "Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data," *International Journal of Forecasting*, 24(3), 386–398.

Stock, J. H., and M. W. Watson (2002a): "Forecasting Using Principal Components from a Large Number of Predictors," *Journal of the American Statistical Association*, 97, 1167–1179.

——— (2002b): "Macreconomic forecasting using diffusion indexes," *Journal of Business and Economic Statistics*, 20(2), 147–162.

——— (2003): "Forecasting Output and Inflation: The Role of Asset Prices," *Journal of Economic Literature*, 47(3), 788–829.

——— (2004): "Combination forecasts of output growth in a seven-country data set," *Journal of Forecasting*, 23(6), 405–430.

——— (2006): "Forecasting with many Predictors," in *Handbook of Forecasting*, ed. by G. Elliot, C. W. Granger, and A. Timmermann, vol. 1, chap. 10, pp. 515–554. Elsevier.

Timmermann, A. (2006): "Forecast Combinations," in *Handbook of Forecasting*, ed. by G. Elliot, C. W. Granger, and A. Timmermann, vol. 1, chap. 4, pp. 135–196. Elsevier.

A Two step estimation of the large dynamic factor model

The parameters of the large dynamic factor model are estimated using a two step approach. In the first step, the parameters of the mode are estimated via principal components and OLS using the following procedure:

- Do a principal component analysis with monthly variables only and select r (for example by regressing quarterly GDP on the factors).
- To get the parameters of the measurement equation, the procedure depends on the properties of u_t. If it is not assumed to be autocorrelated, proceed as follows:
  - To get Λ^0, regress all variables on the first r factors using the following regression setup:
    - For quarterly flow variables: $z^Q_{i,t} = \Lambda_i G^f(L) f_t + u^Q_{i,t}$, where $u^Q_{i,t} = G^f(L) u_{i,t}$
    - For quarterly stock variables: $z^Q_{i,t} = \Lambda_i G^s(L) f_t + u^Q_{i,t}$, where $u^Q_{i,t} = G^s(L) u_{i,t}$
    - For monthly variables: $z_{i,t} = \Lambda_i f_t + u_{i,t}$
  - To get Σ^0_{uu}, use the resulting residual from the regressions above in the following way:
    - For quarterly flow variables, we have that $u^Q_{i,t} = G^f(L) u_{i,t}$. Thus, $V[u^Q_{i,t}] = V[G^f(L) u_{i,t}] = \frac{1}{9} V(u_{i,t}) + \frac{4}{9} V(u_{i,t-1}) + \frac{9}{9} V(u_{i,t-2}) + \frac{4}{9} V(u_{i,t-3}) + \frac{1}{9} V(u_{i,t-4}) = \frac{19}{9} V(u_t)$. Therefore, $V(u_{i,t}) = \frac{9}{19} V(u^Q_{i,t})$, which means that the monthly series is less volatile than the quarterly series.
    - For quarterly stock variables, we have that $u^Q_{t,i} = G^s(L) u_{i,t}$, so that $V[u^Q_t] = V[G^s(L) u_t] = \frac{1}{9} V(u_t) + \frac{1}{9} V(u_{t-1}) + \frac{1}{9} V(u_{t-2}) = \frac{3}{9} V(u_t)$ and $V(u_t) = \frac{9}{3} V(u^Q_t)$, which means that the monthly series is more volatile than the quarterly series.
    - For monthly variables, we have that $V(u_t) = V(u_t)$.

  In the case of autocorrelated errors, proceed as follows:
  - First, to account for the autocorrelated errors, the measurement equation has to be combined with the transition equation for the errors as follows: $(1-\theta L) y_t = (1-\theta L)\Lambda f_t + (1-\theta L) u_t$ which yields, rewritten, $y_t = \theta y_{t-1} + \Lambda f_t + \theta \Lambda f_{t-1} + w_t$.
  - To get estimates for Λ^0 and $diag(\Theta_1)$, regress all variables on their lagged values as well as the contemporaneous and lagged values of the first r factors using

the following regression setup:

  * For quarterly flow variables:

    $z_{i,t}^Q = \theta_i z_{i,t-1}^Q + \Lambda_i G^f(L) f_t + \theta_i \Lambda_i G^f(L) f_t + w_{i,t}^Q$, where $w_{i,t}^Q = G^f(L) w_{i,t}$

  * For quarterly stock variables:

    $z_{i,t}^Q = \theta z_{i,t-1}^Q + \Lambda_i G^s(L) f_t + \theta \Lambda_i G^s(L) f_{t-1} + w_{i,t}^Q$, where $w_{i,t}^Q = G^s(L) w_{i,t}$

  * For monthly variables: $z_{i,t} = z_{i,t-1} + \Lambda_i f_t + \theta_i \Lambda_i f_{t-1} + w_{i,t}$

- To get estimates for Σ_{ww}, use the resulting residuals from the regressions above in the following way:

  * For quarterly flow variables, make use of fact that $V[w_t^Q] = V[G^f(L)w_t] = \frac{1}{9}V(w_t) + \frac{4}{9}V(w_{t-1}) + \frac{9}{9}V(w_{t-2}) + \frac{4}{9}V(w_{t-3}) + \frac{1}{9}V(w_{t-4}) = \frac{19}{9}V(w_t)$. Therefore, $V(w_t) = \frac{9}{19}V(w_t^Q)$.

  * For quarterly stock variables, make us of the same fact as for the flow variables, replacing $G^f(L)$ by $G^s(L)$. Therefore, $w_{t,i}^Q = G^f(L)w_{i,t}$, so that $V[w_t^Q] = V[G^s(L)w_t] = \frac{1}{9}V(w_t) + \frac{1}{9}V(w_{t-1}) + \frac{1}{9}V(w_{t-2}) = \frac{3}{9}V(w_t)$ and $V(w_t) = \frac{9}{3}V(w_t^Q)$.

  * For monthly variables, $V(w_t) = V(w_t)$.

- To get Φ^0 and Σ_{vv}^0, estimate a simple VAR(p) of the r factors

In the second step, we estimate the factors $\hat{f}_t$ using the Kalman filter and smoother. Our monthly fitted values are then given by $\hat{z}_t = \hat{\lambda}\hat{f}_t$ and the monthly interpolated values for quarterly variables are given by $\hat{y}_t^* = \hat{f}_t + \hat{u}_t$.