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# Business cycle dating and forecasting with real-time Swiss GDP data\*

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## Abstract

We develop a small-scale dynamic factor model for the Swiss economy based on an appropriately selected set of indicators. The resulting business cycle factor is in striking accordance with historical Swiss business cycle fluctuations. Our proposed model demonstrates a remarkable performance in short-term and medium-term forecasting. Using real-time GDP data since 2004, the model successfully anticipated the downturn of 2008-09 and responded in a timely manner to the recent sudden drop following the removal of the Swiss Franc lower bound. In a Markov-switching extension, we propose that our model could be used for Swiss recession dating. Our model does not indicate a regime-switch following the removal of the Swiss Franc lower bound.

**JEL class:** C32, C53, E37

**Keywords:** Dynamic Factor Model, Nowcasting, Real-Time Data, Markov-Switching.

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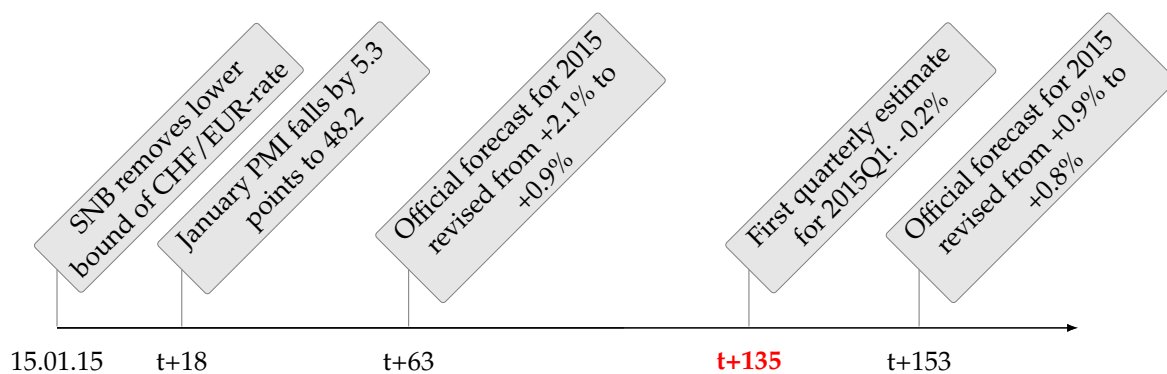
# 1 Introduction

To the surprise of markets and institutions, on January 15, 2015, the Swiss National Bank (SNB) decided to abolish the lower bound for the Euro of Swiss Francs (CHF) 1.20, which had been introduced on September 6, 2011. As Figure 1 shows, it was not until 135 days later, in mid-June, when the official Gross Domestic Product (GDP) estimate for the first quarter of 2015 was released. Until then, economic agents had to rely on indicators which are available throughout the quarter – for instance the Purchasing Managers Index (PMI) – to get a real-time picture of the current state of the economy. In absence of a formal and timely assessment of business cycle developments it is evident that the large delay between a policy change and the release of official growth measures poses a challenge for economic policy making.

Publication delays not only force policy institutions to set their policies without having a clear picture of the current macroeconomic state, they also imply that institutional forecasts often explicitly or implicitly rely heavily on the judgment of experts. As GDP is considered to be the most relevant business cycle indicator for policymakers and economic agents, its forecast is of particular interest.<sup>1</sup>

In this context, we propose a small-scale dynamic factor model (DFM) for the Swiss economy in order to have a timely evaluation of the current economic stance against the background of the delay of official data publication. Furthermore, we provide a transparent business cycle indicator which allows for now- and forecasting of Swiss GDP growth in real-time as well as to assess the economy's current position in the business cycle.

Figure 1: Chronology of events (time in days)



Stock and Watson (1992) pioneered the literature on DFMs by computing a monthly coincident index of economic activity for the US. Mariano and Murasawa (2003) extended their work by including quarterly to monthly indicators, handling ragged edges and missing observations. Using these insights, Camacho and Perez-Quiros (2010) proposed a business cycle indicator from a small-scale DFM for the euro area. Their model has been one of the most successful in computing accurate and timely assessments of short-term GDP developments.<sup>2</sup> What concerns

<sup>1</sup>Judgmental forecast revisions, as the one of March 2015, are difficult if not impossible to replicate and interpret. The federal group of experts which is responsible for the official GDP forecast decided on March 19, 63 days after the monetary policy intervention, to revise its GDP forecast for 2015 from 2.1% to 0.9%. In February 2015, the Economist Poll of Forecasters still expected a growth rate of Swiss GDP for 2015 of 1.8%, which was revised downward to 1% in March.

<sup>2</sup>Further developments of their work have been applied to countries as for instance Argentina Canada, the Czech

the nowcasting performance of DFMs, [Giannone, Reichlin, and Small \(2008\)](#) show that this class of models outperforms standard univariate forecasting methods like random-walk models, autoregressive models or bridge equations as well as institutional forecasts based on expert judgment. Relying largely on developments of quarterly GDP, such naive models also lack the ability to timely assess effects of policy changes on GDP growth. For the case of Switzerland, [Galli, Hepenstrick, and Scheufele \(2017\)](#) perform a horse-race of forecasting models, including a small-scale DFM. They find that a combination of forecasting methods renders the most-reliable nowcast for the Swiss economy.

In this paper, we propose a small-scale dynamic factor model to compute short-term forecasts of Swiss quarterly real GDP growth in real-time. We particularly focus on a model specification that makes use of a small data set. As a consequence of asymptotic theory of DFM, it has been common practice to develop models featuring large data sets. According to [Bai and Ng \(2008\)](#), [Bańbura, Giannone, and Reichlin \(2010\)](#) and [Camacho and Perez-Quiros \(2010\)](#) small-scale DFMs can be well suited for forecasting exercises when the indicators used in the model are selected appropriately. We construct the model to deal with the typical problems affecting real-time economic releases. It deals with ragged edges in order to take into account that available data is released in a non-synchronous way. Further, it incorporates data with mixed frequencies so it can handle both monthly and quarterly indicator series. In contrast to [Galli, Hepenstrick, and Scheufele \(2017\)](#), we show that revisions to GDP growth should not be neglected to perform an accurate forecasting exercise and model them as noise. Our model is dynamically complete and follows a simple algorithm. It accounts for the dynamics of all the indicators used in the analysis and allows the predictive power of any variable to change over time. Finally, our approach adds to the existing literature by investigating if dynamic factor models are able to assess in real-time business cycle developments after an exogenous policy shock as the one of January 2015.

One of our main results is the common factor from the dynamic factor model itself. In the first part of the empirical analysis we provide evidence that the factor can be considered as a trustworthy indicator of Swiss economic developments over the last three decades. The business cycle indicator from our small-scale model is in striking accordance with professional consensus and the history of the Swiss business cycle. Our resulting coincident indicator is able to explain 77% of the variations of Swiss GDP growth in real-time and 72% of final GDP figures. We extract a common factor from quarterly real GDP growth (first and final estimates) and ten – out of a set of totally 32 possible – monthly indicator series. Importantly, it is not necessarily the case that adding more indicators to our model improves the information content of the factor explaining variations in GDP. Both soft indicators from surveys such as the PMI as well as hard indicators like imports or the term spread play an important role for the model-based nowcasts.

The model also proves its effectiveness in real-time forecasting. We study the out-of-sample properties of the model in the second part of the empirical analysis. We make use of the real-time dataset from [Indergand and Leist \(2014\)](#) to construct two data vintages per month starting

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Republic, Canada, etc. ([Chernis and Sekkel, 2017](#); [Camacho and Perez-Quiros, 2010, 2011](#); [Camacho, Dal Bianco, and Martinez-Martin, 2015](#); [Rusnák, 2016](#); [Marcellino, Porqueddu, and Venditti, 2016](#)).

in January 2004. The resulting 312 vintages accurately account for the lag of synchronicity in data publication that characterizes the real-time data flow. We show that our model was particularly well-suited in determining turning points of the Swiss business cycle. During the outbreak of the international financial crisis of 2008-09, the model predicted a negative GDP growth rate for the fourth quarter 2008 already in August of 2008. Importantly, the model also captured in a timely manner the exogenous monetary policy shock of January 2015. The removal of the Swiss Franc lower bound to the Euro resulted in a negative first quarter of 2015, which the model correctly anticipated by the end of the first half of February. Finally, our results suggest that the now- and forecasting performance of our model is more accurate than forecasts from naive models.

In a final exercise, we use the model for business cycle dating. We extend the dynamic factor model by means of a two-state Markov-Chain. The two states capture expansionary and contractionary episodes and allow a probabilistic evaluation of the Swiss economy's position in the business cycle. We show that the Markov-Switching-dynamic-factor model (MS-DFM) provides valuable real-time information for business cycle dating. In particular, the model captures commonly known recessionary periods of the Swiss economy fairly well; this applies to both an in-sample estimation as well as on a real-time basis.

Section 2 outlines the dynamic factor model, how we mix frequencies and take care of revisions to GDP. The empirical analysis is presented in Section 3. In a first part of this section we describe the selection of indicators. Then we discuss in-sample properties of our model and finally we perform a real-time out-of-sample exercise. Section 7 concludes.

## 2 Dynamic Factor Model

In this section we describe the details of the econometric model. The main challenge hereby consists of finding an appropriate statistical framework which allows to (1) analyze jointly data of different sampling frequencies (i.e. monthly business cycle indicators and quarterly National Account figures), (2) to deal with missing observations at various instances of the time-series used, and (3) to take explicit account of data revisions.

The problem of mixed frequencies could be solved in a straightforward fashion by aggregating all monthly series to quarterly ones. This would allow standard techniques, though this approach is associated with a considerable loss of information as the dynamics within a quarter are left un-modeled. Furthermore, it does not solve the problem of how the latest available information from monthly business cycle indicators could be used if observations are available only until the first or second month within a quarter. Hence the method should allow for a quick update of any forecast to incorporate new monthly information.

New information can also be in the form of data revisions. As this can at times be useful, it could also lead to significant changes in the forecast trajectory rendering the projections too sensitive to data revisions; this constitutes a key drawback of auto-regressive models in forecasting time series as their forecasts are highly sensitive to data revisions. Against this background, we finally require that the model is able to produce forecasts which are as far as possible invariant to data revisions.

In this context the dynamic factor model proposed by [Stock and Watson \(1992\)](#) and extended by [Camacho and Perez-Quiros \(2010\)](#) comprises a promising econometric approach. The basic idea of this class of models is that the information of an observable vector of time series under investigation can be explained by a vector of unobserved components with the requirement that the vector of unobserved components has a lower dimension than the vector of time series under investigation. By this dynamic factor models capture the most important co-movements of the variables in the vector of observed time series.

## 2.1 Mixing Quarterly and Monthly Observations

The modeling technique rests on the idea of obtaining quarterly GDP forecasts by exploiting the information of monthly business cycle indicators. However, combining monthly observations with quarterly data requires to express the quarterly data as a function of monthly figures. In this context [Mariano and Murasawa \(2003\)](#) show how mixed frequencies in the form of monthly and quarterly data can be combined. The basic idea is that the level of a quarterly flow variable can be decomposed into the sum of its contemporaneous and lagged latent monthly values. In particular, [Mariano and Murasawa \(2003\)](#) showed that if the sample mean of the three within quarter monthly observations can be well approximated by the geometric mean, then the quarterly growth rates can be decomposed as weighted averages of monthly growth rates.<sup>3</sup>

Let  $y_t^q$  be the quarter-on-quarter growth rate of an observed quarterly indicator and  $y_t^m$  its latent month-on-month growth rate. Then,  $y_t^q$ , can be expressed as the averaged sum of month-on-month growth rates as follows:

$$y_t^q = \frac{1}{3}y_t^m + \frac{2}{3}y_{t-1}^m + y_{t-2}^m + \frac{2}{3}y_{t-3}^m + \frac{1}{3}y_{t-4}^m \quad (2.1)$$

## 2.2 Accounting for GDP-Revisions

A feature of the present model is that it directly takes into account revisions to GDP. The idea is not new. [Camacho and Perez-Quiros \(2010\)](#) use flash, first and second GDP estimates for the Euroarea. Preliminary announcements of Euroarea GDP are biased and positively correlated with revisions, which implies that these are predictable. Hence, revisions to the GDP flash estimate can be modeled as noise. Switzerland does not provide flash, first and second estimates. However, [Indergand and Leist \(2014\)](#) provide real-time vintages starting in 2002Q3, and we consider the last available vintage as the final GDP. In Switzerland, two distinct authorities are responsible for quarterly and yearly GDP estimates. Based on the yearly GDP measures from the Federal Statics Office (FSO), the State Secretariat of Economic Affairs (SECO) uses temporal disaggregation methods to estimate quarterly GDP figures, which are published periodically about 65 days after the end of a quarter. Revisions to the real-time measure from SECO can stem from different sources: (1) revisions to quarterly indicators; (2) revisions to annual base

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<sup>3</sup>Since the evolution of macroeconomic series is smooth enough, such an approximation is appropriate. For instance, [Proietti and Moauro \(2006\)](#) avoid this approximation at the cost of moving to a complicated non-linear state-space model.

data; (3) changes in the methodology of national accounts (benchmark revisions); (4) minor changes in the quarterly estimation methods; (5) technical reasons like changes in seasonal adjustment.<sup>4</sup> We denote the quarterly real-time GDP growth estimates from SECO by  $y_t^{1st}$  and the final vintage of GDP growth rates including all above mentioned revisions by  $y_t^f$ .

We follow the recommendations of [Aruoba \(2008\)](#) to test whether revisions to Swiss quarterly GDP growth should enter the model as *news* or as *noise*. In the former case, the initial announcement is an efficient forecast for the final GDP figure reflecting all available information, revisions then only incorporate new information. In the latter, the initial estimate is an observation of the final series, measured with error. To this end, we define the first available estimates as  $y_t^{1st}$  and the ultimately available vintage as  $y_t^f$ .<sup>5</sup>

First, we find that the mean of revisions is not significantly different from zero, i.e. first estimates are unbiased estimates of the final values. Second, revisions are positively correlated with final estimates, but uncorrelated with initial estimates. Third, the noise-to-signal ratio has an average of 0.15 over all vintages, which is similar to the estimates found in [Aruoba \(2008\)](#) for the US and in [Camacho and Perez-Quiros \(2010\)](#) for the Euroarea. Finally, we perform a forecast efficiency test on the regression  $y_t^{1st} = \alpha_0 + \alpha_1 y_t^f + \epsilon_t$ . We reject the joint null hypothesis that  $\alpha_0 = 0$  and  $\alpha_1 = 1$  with a  $p$ -value of 0.001, which indicates that revisions are news, rather than noise.<sup>6</sup>

Given this evidence, we follow [Mankiw and Shapiro \(1986\)](#) and consider that initial estimates are efficient forecasts of the final figures and revisions in Switzerland should be seen as news. This motivates the following equation linking first estimates to final values of GDP growth rates:

$$y_t^f = y_t^{1st} + \epsilon_t, \quad \epsilon_t \sim NID(0, \sigma_\epsilon^2) \quad (2.2)$$

### 2.3 The dynamic factor model

The premise of dynamic factors models is that a vector of observed time series  $\mathbf{X}_t$  of dimension  $n_X$  can be decomposed into two orthogonal components: common components, also called latent factors, denoted by  $f_t$ , which capture the co-movements among the observed variables in  $\mathbf{X}_t$  and an idiosyncratic component  $u_{t,i}$ ,  $\forall i = 1, \dots, n$ . These idiosyncratic disturbances arise from measurement error and from special features that are specific to an individual series. The latent factors follow a stochastic process which we assume to be of an auto-regressive nature. In what follows we proceed by considering a one-factor structure only implying that  $f_t$  is a scalar.

The vector of time series  $\mathbf{X}_t$  consists of various different business cycle indicators. A key feature of these time series is that they describe the economic conditions prevailing at time  $t_0$  in relation to some point in time in the recent past. In most cases this is either the previous month ( $t_0 - 1$ ) or at times it can be the same month of the last year ( $t_0 - 11$ ). Hence monthly business cycle variables either describe month-to-month patterns or on the other hand, year-to-year pat-

<sup>4</sup>For a detailed description of revisions consider [Indergand and Leist \(2014\)](#).

<sup>5</sup>First estimates corresponds to the diagonal elements in the real-time dataset of [Indergand and Leist \(2014\)](#).

<sup>6</sup>We start the revision analysis for the vintage 2004Q1 up to the final vintage 2016Q4. Our results are qualitatively robust for using different vintages of  $y_t^f$ .



terns on a monthly frequency. The econometric specification for the construction of the latent factor  $f_t$  has to take these peculiarities into account. In order to simplify the exposition, assume that all variables in  $\mathbf{X}_t$  are observed at a monthly frequency. We construct the latent factor such that monthly growth rates of quarterly series and monthly growth rates of indicators of real economic activity (*hard*) exhibit a direct relation with the common factor  $f_t$ . The corresponding factor loadings measure the sensitivity of each hard indicator to movements in the latent factor directly.

In contrast to hard indicators, the relation between the common factor and survey indicators (*soft*) might be treated differently. [Camacho and Perez-Quiros \(2010\)](#) acknowledge, among others, that each confidence indicator is calculated as the simple arithmetic average of the balances of answers to specific questions chosen from the full set of questions in each individual survey. The selection of questions is guided by the aim of achieving an as high as possible coincident correlation of the confidence indicator with the reference series, such as year-on-year growth in GDP. This implies that the business cycle conditions prevailing at time  $t_0$  are compared to the ones of the same month of the previous year. In order to account for this, we relate the level of soft indicators where necessary with the year-on-year common growth rate which can be written as the sum of current values of the common factor and its last eleven lagged values.

For this reason we decompose the variables in  $\mathbf{X}_t$  into a set of  $n_h$  hard indicators  $\mathbf{x}_t^h$  and  $n_s$  soft indicators in  $\mathbf{x}_t^s$ . Additionally, the vector of observed time series includes first and final estimates of the quarterly GDP growth rate:  $\mathbf{X}_t = [(\mathbf{x}_t^h)', (\mathbf{x}_t^s)', y_t^{1st}, y_t^f]'$ . We standardize the observed time series in  $\mathbf{X}_t$  prior to using them in the dynamic factor model. Let  $u_{t,i}^h, \forall i = 1, \dots, n_h$  be the idiosyncratic (dynamic) error term for the hard indicators,  $u_{t,i}^s, \forall i = 1, \dots, n_s$  the equivalent for the soft indicators, and  $u_{t,q}$  the idiosyncratic error term for the two measures of GDP growth.

The dynamic factor model can be specified  $\forall t = 1, \dots, T$  as follows:

### System of static equations

$$\begin{pmatrix} \mathbf{x}_t^s \\ \mathbf{x}_t^h \end{pmatrix} = \begin{pmatrix} \gamma_s \cdot \sum_{j=0}^{11} f_{t-j} \\ \gamma_h \cdot f_t \end{pmatrix} + \begin{pmatrix} \mathbf{u}_t^s \\ \mathbf{u}_t^h \end{pmatrix} \quad (2.3)$$

$$\begin{pmatrix} y_t^{1st} \\ y_t^f \end{pmatrix} = \begin{pmatrix} \omega \\ \omega \end{pmatrix} \cdot [\gamma_q f_t + u_{t,q}] + \begin{pmatrix} 0 \\ \epsilon_t \end{pmatrix} \quad (2.4)$$

where  $\mathbf{u}_t^h = (u_{t,1}^h, \dots, u_{t,n_h}^h)'$ ,  $\mathbf{u}_t^s = (u_{t,1}^s, \dots, u_{t,n_s}^s)'$  with  $n = n_h + n_s$ ,  $n_{\mathbf{X}} = n + 2$ , and  $\omega := \frac{1}{3} + \frac{2}{3} \cdot L + L^2 + \frac{2}{3} \cdot L^3 + \frac{1}{3} \cdot L^4$ , where  $L$  is the lag operator. The stochastic properties of  $\epsilon_t$  are defined in equation (2.2). The vector of factor loadings  $\gamma = (\gamma_q, \gamma_h', \gamma_s')$  captures the relation between the latent factor  $f_t$  and the observed variables  $\mathbf{X}_t$  modified by the scalar  $\omega$  which takes into account that  $y_t^{1st}$  and  $y_t^f$  are not observed on a monthly basis and hence proxied by the relation given in equation (2.1) instead.

## System of dynamic equations

$$\phi_q(L) \cdot u_{t,q} = v_t^q \quad \text{with} \quad v_t^q \sim NID(0, \sigma_q^2) \quad (2.5)$$

$$\phi_f(L) \cdot f_t = v_t^f \quad (2.6)$$

$$\Phi_u(L) \begin{pmatrix} \mathbf{u}_t^s \\ \mathbf{u}_t^h \end{pmatrix} = \boldsymbol{\nu}_t \quad (2.7)$$

$$\begin{pmatrix} v_t^f \\ \boldsymbol{\nu}_t \end{pmatrix} \sim NID\left(\mathbf{0}, \begin{bmatrix} \sigma_f^2 & \mathbf{0} \\ \mathbf{0} & \Sigma_v \end{bmatrix}\right) \quad (2.8)$$

where  $\phi_f(L)$ ,  $\phi_q(L)$  and  $\Phi_u(L)$  are in each case second-order polynomials. We assume that  $\Phi_u(L)$  and  $\Sigma_v$  are diagonal, implying that all covariances are zero by construction. For identification reasons we impose that  $\sigma_f^2$  is unity.

Equation (2.6) assumes that the common factor  $f_t$  follows an autoregressive process of order two. This specification is essential for the determination of the dynamics of the model; the AR(2) assumption can be considered as a parsimonious specification in this context as on the one hand it only requires the estimation of two parameters; on the other hand this specification allows a rather rich dynamic pattern since the roots of  $\Phi_u(L)$  can be complex. We discuss the appropriateness of this assumption in Section 6.3 in more detail. This specification, though rich in its dynamics, still features the assumption of linearity, which at times can be too restrictive. We relax the assumption of linearity in Section 5 where we extend equation (2.6) by a Markov-Switching element.

The system of measurement equations shows that once relating the latent factor  $f_t$  to observed business cycle indicators, one can then interpret the latent factor as representing the overall business cycle dynamics which is common to all variables in  $\mathbf{X}_t$ . The advantage of this approach is that on the one hand the effect of each single observed business cycle indicator can be stated explicitly. On the other hand the latent factor has a straight forward interpretation.

In what follows we will consider the above model dynamics within the structure of a state space model where the measurement equation and the transition equation read as follows:

$$\mathbf{y}_t = H\mathbf{s}_t + \mathbf{w}_t, \quad \mathbf{w}_t \sim NID(\mathbf{0}, R) \quad (2.9)$$

$$\mathbf{s}_t = F\mathbf{s}_{t-1} + \mathbf{v}_t, \quad \mathbf{v}_t \sim NID(\mathbf{0}, Q) \quad (2.10)$$

Appendix A.1 has a detailed description of the matrices  $H$ ,  $F$ ,  $R$ ,  $Q$ , the vectors  $\mathbf{y}_t$ ,  $\mathbf{s}_t$ ,  $\mathbf{w}_t$  and  $\mathbf{v}_t$  and their relation to the equation system (2.3)-(2.8).

## 2.4 Estimation

If all series in the model were observable at a monthly frequency and the data panel was balanced, then the estimation of the dynamic factor model could be implemented using standard maximum likelihood methods in conjunction with the Kalman filter. This assumption is, however, rather unrealistic, since in our empirical application we have to deal with mixing quarterly and monthly frequencies and with time series which are published at different time lags and which start at different points in time. Moreover, our context requires additional projections of some unreliable data, which can be considered as missing data from a certain date as well.

According to [Mariano and Murasawa \(2003\)](#), with the subtle transformation of replacing missing observations by random draws  $r_t \sim i.i.d.\mathcal{N}(0, \sigma_r^2)$ , the system of equations remains valid.<sup>7</sup> Importantly, if the distribution of  $r_t$  does not depend on the parameter space that characterizes the Kalman filter, then the matrices in the state-space representation are conformable and do not have an impact on the model estimation since the missing observations just add a constant term in the likelihood function to be estimated.

Let  $y_{i,t}$  be the  $i$ th element of vector  $\mathbf{y}_t$  and let  $R_{ii}$  be its variance. Let  $H_{i,t}$  be the  $i$ th row of matrix  $H_t$ , which has  $z$  columns. The measurement equation can then be replaced by the following expressions

$$y_{i,t}^* = \begin{cases} y_{i,t} & \text{if } y_{i,t} \text{ is observable} \\ r_t & \text{otherwise,} \end{cases} \quad (2.11)$$

$$H_{i,t}^* = \begin{cases} H_i & \text{if } y_{i,t} \text{ is observable} \\ 0_{1 \times z} & \text{otherwise,} \end{cases} \quad (2.12)$$

$$w_{i,t}^* = \begin{cases} 0 & \text{if } y_{i,t} \text{ is observable} \\ r_t & \text{otherwise,} \end{cases} \quad (2.13)$$

$$R_{ii,t}^* = \begin{cases} 0 & \text{if } y_{i,t} \text{ is observable} \\ \sigma_r^2 & \text{otherwise.} \end{cases} \quad (2.14)$$

With this transformation the time-varying state-space model can be treated as having no missing observations and the Kalman filter can be directly applied to  $\mathbf{y}_t^*$ ,  $H_t^*$ ,  $\mathbf{w}_t^*$  and  $R_t^*$ . The implementation of this algorithm corresponds to expanding  $\mathbf{y}_t$ ,  $H$ ,  $\mathbf{w}_t$  and  $R$  in equation (2.9) by means of an indicator function which takes into account if  $y_{i,t} \in \mathbf{y}_t$  is observed or not.

The estimation of the model's parameters can be developed by maximizing the log-likelihood of  $\{\mathbf{y}_t^*\}_{t=1}^{t=T}$  numerically with respect to the unknown parameters in matrices. Let  $\hat{s}_{t|t-1}$  be the estimate of  $s_t$  based on information up to period  $t-1$ . Let  $P_{t|t-1}$  be its covariance matrix. The prediction equations are:

$$\hat{s}_{t|t-1} = F\hat{s}_{t-1|t-1}, \quad (2.15)$$

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q. \quad (2.16)$$

The predicted value of  $\mathbf{y}_t$  with information up to  $t-1$ , denoted  $\hat{\mathbf{y}}_{t|t-1}$  is  $\hat{\mathbf{y}}_{t|t-1} = H_t^*\hat{s}_{t|t-1}$ , such that the prediction error is  $\eta_{t|t-1} = \mathbf{y}_t^* - \hat{\mathbf{y}}_{t|t-1} = \mathbf{y}_t^* - H_t^*\hat{s}_{t|t-1}$  with covariance matrix  $\zeta_{t|t-1} = H_t^*P_{t|t-1}H_t^* + R_t^*$ . In each iteration, the log-likelihood can therefore be computed as

$$\log L_{t|t-1} = -\frac{1}{2} \ln (2\pi |\zeta_{t|t-1}|) - \frac{1}{2} \eta_{t|t-1}' (\zeta_{t|t-1})^{-1} \eta_{t|t-1}. \quad (2.17)$$

The updating equations are:

$$\hat{s}_{t|t} = \hat{s}_{t|t-1} + K_t^* \eta_{t|t-1} \quad (2.18)$$

$$P_{t|t} = P_{t|t-1} - K_t^* H_t^* P_{t|t-1} \quad (2.19)$$

in which  $K_t^*$  is the Kalman gain defined as  $K_t^* = P_{t|t-1}H_t^* (\zeta_{t|t-1})^{-1}$ . The initial values:  $s_{0|0} = 0$  and  $P_{0|0} = I$  used to start the filter are a vector of zeros and the identity matrix, respectively.

<sup>7</sup>Means, medians or zeros are valid alternatives.

Computing short-term forecasts in real-time from this model is straightforward. The future values of the time series can be regarded as missing observations at the end of the sample periods. The Kalman filter accounts for the missing data which are replaced by forecasts. Particularly, the  $k$ -period ahead forecasts are

$$\hat{y}_{t+k|t} = H_t^* \hat{s}_{t+k|t}, \quad (2.20)$$

with  $\hat{s}_{t+k|t} = F^k \hat{s}_{t|t}$ .

As documented by [Banbura and Rünstler \(2011\)](#), the Kalman filter allows to compute the weights or cumulative impacts of each indicator to the forecast of GDP growth. The state vector  $s_t$  can be expressed as the weighted sum of available observations in the past.<sup>8</sup> Given a large enough  $t$  such that the Kalman filter has approached its steady state it holds that  $h$ -period ahead forecasts of GDP growth are approximately

$$y_{t+h} = \sum_{j=0}^{\infty} W_j' y_t, \quad (2.21)$$

in which  $W_j$  is a vector of weights to compute the cumulative weights of series  $i$  in forecasting GDP growth as  $\sum_{j=0}^{\infty} W_j(i)$ , where  $W_j(i)$  is the  $i$ th element of  $W_j$ .

### 3 In-Sample Properties

This section elaborates on the indicator selection process and describes the final data set used in the small-scale DFM for Switzerland. We then proceed by presenting the coincident business cycle indicator for the Swiss economy and discuss its in-sample properties.

#### 3.1 Selection of Indicators

Optimally, the starting point for selecting indicators entering the DFM was based on the model suggested by [Stock and Watson \(1992\)](#). In that case, we would build our model on data for production, expenditure and income side of GDP and have a monthly indicator on employment developments. On this basis, we would then add selected indicators which improved the model fit. Unfortunately however, data availability is rather scarce in Switzerland, which forces us to take a different approach. In a first step, we collect as many monthly indicators as possible. A key criteria to keep a variable in our sample is timely publication. For instance, industrial production does not fulfill this criteria. Although the series have a monthly frequency, they get published together with the quarterly series and have a publication lag of about 60 days to the end of the previous quarter. We end up with a set 31 variables (aggregates), covering a wide range of economic data.<sup>9</sup> To these monthly variables we add the two quarterly series for GDP.

<sup>8</sup>See [Stock and Watson \(1992\)](#) and [Camacho and Perez-Quiros \(2010\)](#) for a detailed description and further details.

<sup>9</sup>Imports, exports, overnight stays, retail sales, new car registrations, energy consumption, term spread, Swiss market index (SMI), Swiss performance index (SPI), oil price, real and nominal effective exchange rate, bank assets, loans, KOF industrial orders, PMI, UBS consumer survey, KOF industry and construction surveys, vacancy postings, unemployment rate, social security contributions, CPI, EPI, IFO survey, ZEW survey

The second step consists of an algorithm to select an appropriate subset out of the 31 monthly indicators. We proceed as follows:

1. Identification of a common factor based on different combinations of variables within the dynamic factor model. With this combinatorial algorithm, the number of variables included is pre-determined. In particular, let  $k$  be the number of variables being included in the dynamic factor model and  $n > k$  be the number of variables in the sample, then we obtain a total of  $b_{n,k} := k! / (k! \cdot (n - k)!)$  different combinations. For each combination we compute the share of the variance of the GDP growth rate explained by the common factor.
2. Exclusion of all variable combinations whose  $R^2$  is lower than some threshold value  $\tilde{\epsilon}$ . This leaves us with a smaller subset of variable combinations relative to the original  $b_{n,k}$  combinations.
3. Use of economic theory to restrict the subset of variable combinations of the second step to only one final combination of variables. The selection pays attention in particular to economic phenomena related to financial market developments and aggregate demand.

We apply this algorithm twice: First, we want to identify a *Core*-model with  $k = 4$ .<sup>10</sup> Second, we follow [Camacho and Perez-Quiros \(2010\)](#) to extend the *Core*-model with further indicators. Within this exercise, the number of variables  $k$  in the dynamic factor model remains unchanged and only the composition of the  $k$  variables changes within each step of the iterations. It is worth highlighting that within this algorithm, it is not necessarily the case that adding more variables leads to a higher correlation of the factor with GDP. As has been shown in previous studies, e.g., [Boivin and Ng \(2006\)](#), when the additional variables are correlated with the idiosyncratic part of some other variables, the estimation of the factor is biased towards this subgroup, making the variance of GDP explained by the factor decrease. In [Section 6.2](#) we show in how far the inclusion of further variables changes the fit of our Benchmark-Model.

The *Core*-model consists of four monthly indicators (total imports, total retail sales, the term spread and bank assets) and two quarterly GDP series. Remarkably, with this specification we achieve a significant positive correlation of 0.79 of the factor with the first release of GDP (0.74 with the final vintage). It has to be kept in mind that several indicator combinations lead to a similar result. However, we intend to stay as close as possible to the original specification of [Stock and Watson \(1992\)](#) and restrict therefor the selection process for the *Core*-model to *hard* indicators only. Imports are an indicator for internal demand, and in the case of Switzerland as a small open economy, also for external demand since the import share in exports is extraordinarily high. Total retail sales cover a broad range of private consumption on the expenditure side. The term spread is well known as a leading business cycle indicator capturing both expectations as well as the monetary policy stance of the economy (see for instance [Camacho and Garcia-Serrador \(2014\)](#)). It enters the model in first-differences. Finally, bank assets

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<sup>10</sup>In principle we could also choose  $k = 3$  or  $k = 5$ . We chose  $k = 4$  keeping in mind that the DFM of [Stock and Watson \(1992\)](#) was built on the same number of indicators.

Table 1: Indicators selected for Swiss DFM

Name	Definition	First obs.	R.	F.	S.A.	T.	D.	M.	S.
GDP 1 <sup>st</sup>	Quarterly real GDP (real time)	2002Q3	Y	Q	1	1	5	2	SECO
GDP final	Quarterly real GDP (final estimates)	1980Q1	Y	Q	1	1	5	2	SECO
Imports	Total imports of goods	1980M1	Y	M	1	1	20	1	FCA
Sales	Total retail sales	1980M1	Y	M	1	1	5	2	FSO
Spread	10y-govt bond yield minus 3-month rate	1980M1	N	M	0	0	1	1	SNB
REER	Swiss Franc real effective exchange rate (broad)	1980M1	N	M	0	1	15	1	BIS
Orders	KOF industrial orders (to previous month)	1980M1	Y	M	1	0	5	1	KOF
Loans	Loans of private households (without mortgages)	1980M1	Y	M	0	1	20	2	SNB
Assets	Total assets of commercial banks	1987M12	Y	M	0	1	20	2	SNB
VSMI	Swiss equity market volatility index	1999M1	N	M	0	0	1	1	SIX
PMI	Total purchasing managers index	1995M1	N	M	1	0	1	1	Markit
UBSc	UBS consumer sentiment indicator	1996M2	Y	M	1	0	30	1	UBS

*Note:* From left to right: *Name* reports the acronym for the variable; *Definition* describes the respective indicator series; *First obs.* specifies since when data are available (the format is either year-quarter or year-month); *R.* indicates whether the series are permanently subject to revisions; *F.* determines the frequency of the series (M: monthly; Q: quarterly); *S.A.* specifies whether the variable is seasonally adjusted; *T.* specifies whether a variable has been transformed to growth rates; *D.* reports the approximate day of release of each variable; *M.* indicates how many months after the end of the reference period the data are released; and finally *S.*: SECO - State Secretariat for Economic Affairs; FCA - Federal Customs Administration; UBS - United Bank of Switzerland; KOF - Swiss Economic Institute; FSO - Swiss Federal Statistical Office; SNB - Swiss National Bank; BIS - Bank of International Settlements; SIX - Swiss Stock Exchange.

contain information on the liquidity of the financial sector, which amounts to around 10% of Swiss GDP.

The final model consists of a total of 10 monthly indicator variables. Details are summarized in Table 1. The correlation of the factor with GDP for this model is 0.88 for the first release (0.85 for the final series). The variance of GDP explained by this set of indicators is 77% for the first release and 72% for the final GDP series. This enlarged model features two soft variables, the PMI and UBS consumer sentiment index. The former asks managers about their economic sentiment with respect to the previous month. The latter contains information on private consumption trends, in particular it is based on credit card transactions made via the bank UBS. To omit the problem of over-differencing, we leave these variables in its level specification.<sup>11</sup> Both indicators exhibit higher correlation with the year-on-year GDP growth rate than with quarter-on-quarter rate, which is why they load with 11 lags on the common factor. Further, the model contains the trade-weighted (broad) real exchange rate, the stock of orders compared to the previous month out of the KOF industry survey (in levels), loans of private households without mortgages and the Swiss stock market volatility index VSMI.

Out of the initial 31 variables the selected combination of ten monthly indicators was the one which performed best and is economically meaningful. The final set proved to be robust to enlargements of the model in various directions. We tested our model using disaggregated versions of the variables already included in the model. For instance, we used retail sales without oil related products instead of total retail sales. In most of the cases, we failed at improving our model. However, in the case of the KOF industry survey, the variable stock of orders compared to previous months lead to a higher correlation than the aggregate KOF industry business trend indicator. Further we tested whether exchanging specific variables could lead to equal or simi-

<sup>11</sup>The model outcome does not change qualitatively when the PMI is specified as hard indicator, loading contemporaneously on the factor.



Table 2: Dataset available on Friday 12/05/17

Date	$GDP1^{st}$	$GDP^f$	PMI	UBSc	Imports	Sales	Spread	REER	Loans	Orders	Assets	VSMI
2016.7	n.a.	n.a.	51.47	1.24	7.42	0.12	-0.06	0.10	-0.37	0.02	-0.64	16.07
2016.8	n.a.	n.a.	51.56	1.24	-4.63	-0.17	0.07	-0.12	-0.38	-23.22	0.61	15.80
2016.9	0.05	n.a.	54.39	1.28	-2.93	0.24	-0.05	-0.53	1.19	-16.86	-0.35	15.10
2016.10	n.a.	n.a.	55.20	1.22	6.47	1.20	0.14	0.12	0.62	-4.05	-0.12	15.31
2016.11	n.a.	n.a.	55.92	1.22	-4.61	0.61	0.25	0.71	1.46	-17.94	2.75	17.51
2016.12	0.08	n.a.	56.20	1.26	2.11	-2.24	-0.03	-0.78	-1.27	-5.73	-1.68	14.10
2017.1	n.a.	n.a.	54.60	1.38	-8.13	0.95	0.07	1.00	-0.72	-14.60	0.35	13.59
2017.2	n.a.	n.a.	57.84	1.45	4.34	0.83	-0.14	0.34	0.18	0.36	1.10	12.72
2017.3	n.a.	n.a.	58.62	1.50	1.59	0.69	0.11	-0.59	n.a.	4.38	n.a.	11.56
2017.4	n.a.	n.a.	57.42	n.a.	n.a.	n.a.	0.00	n.a.	n.a.	11.13	n.a.	14.46
2017.5	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2017.6	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2017.7	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2017.8	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
2017.9	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

Note: See Table 1 for acronyms, data transformation and a description of these indicators.

lar results. In that case, we included vacancies as labor market indicator or exports as indicator for external demand. However, the loading of vacancies turned out non-significant, although the correlation would have been comparably high. For exports, the correlation decreased substantially. As a final test we simulated the model including the complete set of 32 variables. The resulting correlation for this large sample factor model decreased to as low as 0.15.

The monthly in-sample data available on May 12 2017 includes data from 1980.01 to 2017.04.<sup>12</sup> Table 2 shows the particular publication pattern of these series. The key series to be forecasted are the first and final estimates of quarterly GDP. The first real-time vintage is available for 2002Q3, final GDP figures start in 1980Q1. The first two months of each quarter are treated as missing data. We add as many months of missing data as are needed to forecast the following year. In this case it would be until 2018.12. As can be seen in Table 2, months 2017.1-2017.3 refer to the backcast of 2017Q1; months 2017.4-2017.6 refer to the nowcast of 2017Q2; and 2017.7-2017.9 refer to the forecast of 2017Q3. The Kalman filter routine fills in these missing observations by computing dynamic forecasts. Once a new quarterly GDP figure is released, we shift the forecasting window one quarter forward.

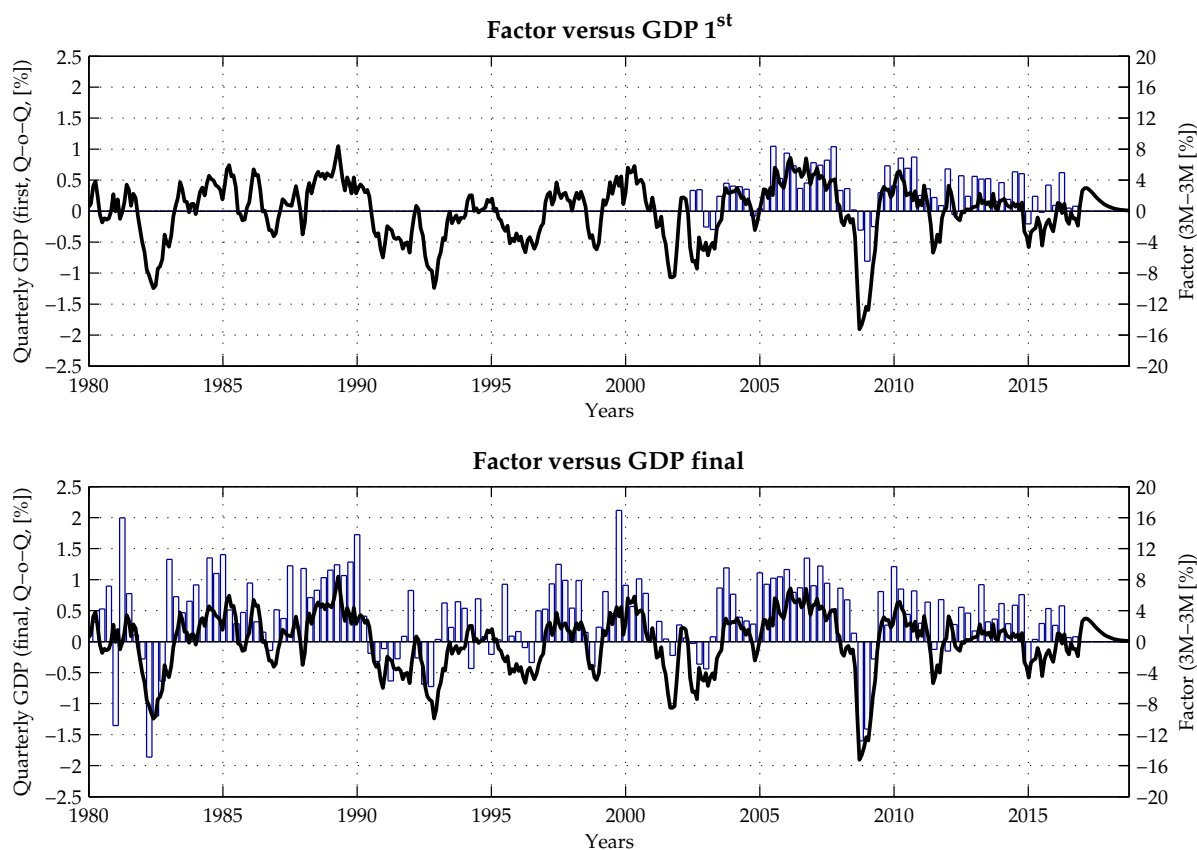
Some words regarding the publication schedule of the chosen indicators are in order. Typically, survey data has very short publication lags. For instance, the PMI index is released every first day of the month with a number for the preceding month. The UBS consumer sentiment index contains some hard data and has therefore a publication lag of 30 days. Timely variables are also the term spread, VSMI and stock of orders. Imports are published around every 20<sup>th</sup> of the following month, while sales have a delay of about 35 days to be published. The numbers from the SNB banking statistics are released with a lag of slightly more than one and a half months.

### 3.2 A coincident index for the Swiss business cycle

One of the main goals of this paper is to develop a business cycle indicator for the Swiss economy using the small-scale DFM outlined above. The model is based on the notion that co-

<sup>12</sup>Figure 11 in the Appendix depicts the development of each individual series.

Figure 2: Estimated factor and quarterly GDP growth



Note: The factor is estimated from the dynamic factor model with data from 80.01 to 16.12 by using all the information available on 12/05/17. The last vintage for real Swiss GDP contains data until 2016Q4.

Table 3: Factor loadings

Model	Indicators											$R^2$	
	GDP	Imports	Sales	Spread	Assets	REER	Loans	Orders	VSMI	PMI	UBSc	$GDP^{1st}$	$GDP^f$
Core	0.374 (0.12)	0.113 (0.09)	0.086 (0.02)	-0.261 (0.10)	0.161 (0.08)							0.62	0.55
Final	0.062 (0.02)	0.023 (0.01)	0.017 (0.01)	-0.055 (0.02)	0.023 (0.01)	-0.017 (0.01)	0.032 (0.02)	0.144 (0.05)	-0.154 (0.07)	0.271 (0.11)	0.227 (0.12)	0.77	0.72

Note: The first row shows the estimated loading factors and (in brackets) their standard errors. See Table 1 for a description of these indicators.

movements among the macroeconomic variables have a common element represented by the estimated factor,  $f_t$ . Figure 2 shows the resulting series (black line) together with the real-time GDP growth (top figure) and the *final* GDP vintage (bottom row). Evidently, the business cycle factor captures surprisingly well the turning points and fluctuations over time. Moreover, in periods of downturn, the indicator appears to have a slight leading characteristic (consider for instance the downturn of 1990 when the Swiss housing bubble imploded). The indicator also captured well the periods of strong growth between 1995 and 2000. Interestingly, the factor drops contemporaneously with the removal of the Swiss Franc lower-bound with respect to the Euro in January 2015. Using information up to March 2017, the factor clearly shows positive signals of a recovery.



Table 4: Cumulative weights (in%)

Month	$GDP1^{st}$	$GDP^f$	PMI	UBSc	Imports	Sales	Spread	REER	Loans	Orders	Assets	VSMI
2016.06	100	0	0	0	0	0	0	0	0	0	0	0
2016.07	0	0	7.6	7.0	18.7	10.2	12.4	2.5	11.6	14.5	5.2	10.3
2016.08	0	0	8.0	7.4	19.4	10.6	12.5	2.5	11.9	13.3	5.2	9.2
2016.09	100	0	0	0	0	0	0	0	0	0	0	0
2016.10	0	0	7.6	7.0	18.7	10.2	12.4	2.5	11.6	14.5	5.2	10.3
2016.11	0	0	8.0	7.4	19.4	10.6	12.5	2.5	11.9	13.3	5.2	9.2
2016.12	100	0	0	0	0	0	0	0	0	0	0	0
2017.01	0	0	7.6	7.0	18.7	10.2	12.4	2.5	11.6	14.5	5.2	10.3
2017.02	0	0	8.0	7.4	19.4	10.6	12.5	2.5	11.9	13.3	5.2	9.2
2017.03	0	0	9.9	9.2	23.6	12.9	15.1	3.0	0	15.6	0	10.7
2017.04	0	0	19.5	0	0	0	29.2	0	0	30.3	0	21.0

Note: See Table 1 for acronyms, data transformation and a description of these indicators.

We present the estimated factor loadings in Table 3; with standard errors in parenthesis. The complete list of estimated parameters can be found in Table 10 in Appendix A.5. The estimates reflect the degree to which variations in each observed variable are correlated with the latent factor. All variables in the model show statistically significant loading factors. In the first row, we report the factor loadings for our core model which consists just of four monthly indicators plus the quarterly GDP. For this specification, bank assets have the largest loading factor apart from GDP, the term spread the lowest. In our final small-scale DFM, the economic indicators with largest loading factors in absolute terms are stock of orders, loans and the term spread. Notably, the term spread and real effective exchange rate carry a negative sign, which indicates countercyclicality of these two series. This is in line with what one would expect a priori about the contemporaneous correlations with the business cycle.

The weights or cumulative impact of each indicator to the dynamics of GDP growth provide another output from the dynamic factor model. Table 4 reports the evolution of forecast weights (standardized to sum up to one) over the latest months. According to the model characteristics, whenever the GDP figures are published (March, June, September and December), the cumulative forecast weights of all other indicators on the GDP forecast are zero. The series only have weights different from zero during the periods in which they are available and the corresponding number for the GDP growth rate is not. As can be seen in the table, the weights change according to the information set available in each period of time. In the first half of the month, the term spread (29.2%) and orders (30.3%) carry the largest weights. With more data made available, other indicators become important. Imports have a weight of 18.7% once all data for a month is available (see for instance 2017.2). The weight of the PMI is substantially reduced (8.0%), also the term spread loses importance (12.5%). Although the real exchange rate and assets carry relatively low weights, they still incorporate non-negligible information about the stance of the Swiss business cycle and are important for the performance of the model.

## 4 Out-of-sample analysis using real-time GDP data

Apart from providing a coincident index for the Swiss business cycle, the DFM allows for computing forecasts of GDP on a real-time basis, which makes the model particularly attractive for

a recurrent application.<sup>13</sup> In this section we perform a real-time simulation to study the out-of-sample forecasting performance of our model. We evaluate the performance of our model for predicting quarterly (short-term) and annual (medium-term) GDP growth. Finally, we show the usefulness of our model to detect turning points in the Swiss business cycle.

#### 4.1 The real-time exercise

The starting point of the out-of-sample exercise is the construction of a real-time data set. To do so, we follow the principle of putting the data available at a specific point in time into its corresponding cell within the so-called real-time data set. Hence, we make sure that at each point in time when a forecast is made, only the information available at that specific day is used. The benefit of constructing such a data set is a better judgment of the model's workings when forecasting. An evaluation of forecast errors by using the ex-post data for a specific point in time is questionable since measures of forecast errors – as root-mean-squared error (RMSE) – can be deceptively lower when using ex-post data rather than real-time data (Stark and Croushore, 2002).

We base our real-time data set on bi-monthly vintages. For each month within the period 2004-2016 we collect the whole set of time series available at the following two vintages: h1/mm/yy and h2/mm/yy; where h1 refers to the end of the first half of a month and h2 to the end of the same month. These vintages are kept fixed until the point in time when a new series was updated. Our analysis is truly real-time in the sense that we use the genuine real-time GDP series from Indergand and Leist (2014). With respect to the monthly indicators the exercise is pseudo real-time, i.e., we use the latest available data vintage.<sup>14</sup> This data set allows us to closely mimic the forecasting procedure a practitioner would have performed at any time during the last few years when computing model forecasts. Table 1 shows which of the model's time series got updated in which of the two vintages (h1 or h2). The first vintage for which we collect data for all indicators was vint-h1/01/04, thus we start the real-time analysis with the forecast of GDP growth in January 2004. We end up with 312 different vintages for the period h1/01/04 to h2/12/16.

#### 4.2 Short-run forecasting

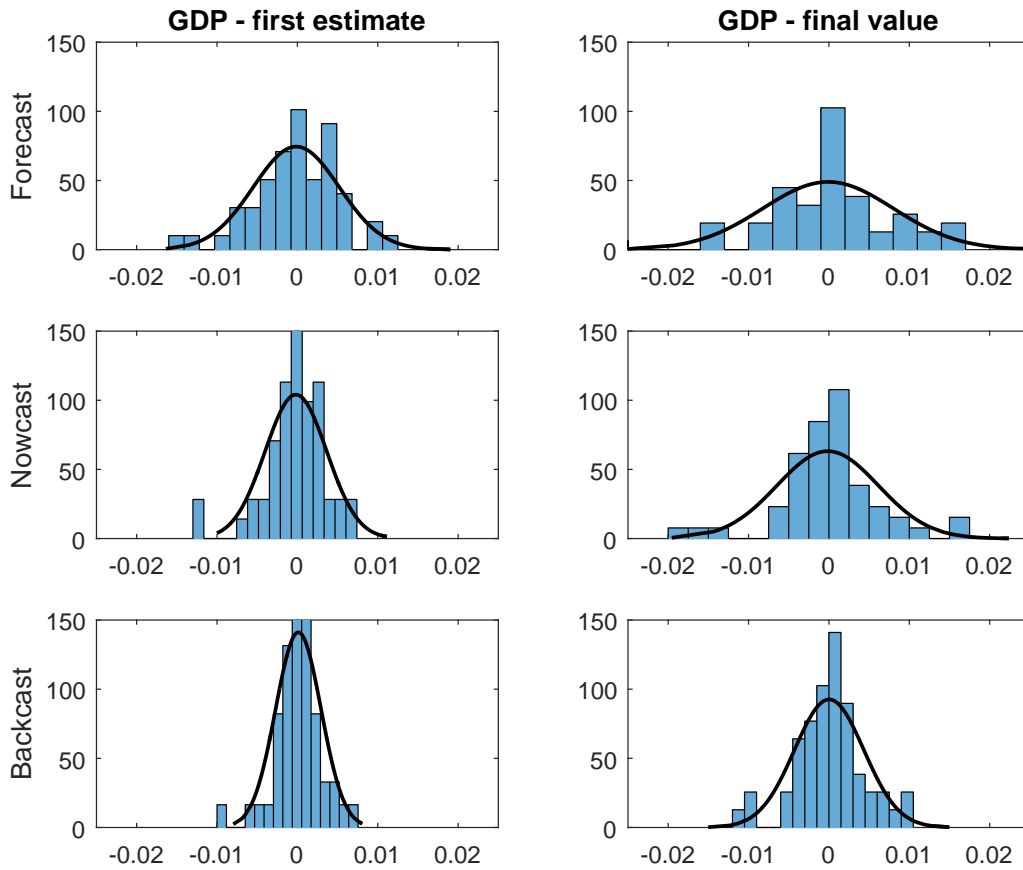
Our real-time data set allows to assess the gain in prediction precision of the DFM once further prompt observations are added. To do so we calculate prediction errors resulting for a (i) forecast, (ii) nowcast, and a (iii) backcast of quarterly Swiss real GDP growth. For the nowcast of quarter  $t_q$ , we use all information up to and including the middle of quarter  $t_q$ , i.e., the middle of the second month of quarter  $t_q$ . Similarly, we compute errors for the backcast based on information up to and including one month after quarter  $t_q$  ended. We do so for all quarters from Q1:2004 until Q4:2016. The forecast errors are defined as the model's prediction minus

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<sup>13</sup>In principle, because of its dynamic specification forecasts are also available for all monthly indicators. This information can be useful for understanding how the next values of these indicators affect the GDP forecast.

<sup>14</sup>To the best of our knowledge, there is no real-time data of monthly Swiss economic indicators publicly available. Of the ten monthly indicators, only imports and sales might have undergone substantial revisions. Financial variables are not revised, and revisions to survey data are seldom and at most marginal.

Figure 3: Prediction errors - temporal consideration



*Note:* The figure plots the histogram of the prediction errors for (i) forecasts (one month ahead of quarter  $t_q$ ), (ii) nowcasts (in the middle of quarter  $t_q$ , and (iii) backcasts (one month after quarter  $t_q$ ), for both the first estimate of GDP growth rate and its final value.

the first official GDP growth estimate. We carry out the same exercise for the final value of the GDP growth rate. The corresponding histograms for the prediction errors are shown in Figure 3. To ease comparison, Figure 3 also features the path of the probability density function of a normal distribution based on the moments of each of the prediction errors.

Several highlights emerge. In each case, the histograms of the prediction errors are centered around zero. This implies that the DFM is not plagued by any systematic over- or under-prediction of the GDP growth rates. Further, the predictions of the DFM tend to have a higher precision for the first estimate of the GDP growth rate. Across all three temporal predictions (forecast, nowcast and backcast) the histograms of the prediction errors for the first estimate of the GDP growth rate are narrower throughout. Finally, there is clear evidence that more prompt information used adds substantially to the prediction precision: the predictions errors of the backcast are in general smaller than those of the nowcast, which in turn are smaller than those of the forecast. This pattern applies to both the first and final estimate of the GDP growth rate and does not come as a big surprise, though, it highlights the workings behind the computation of the predictions within the DFM.

Table 5 shows in the first row the mean-squared errors (MSE) associated with the DFM for

Table 5: Predictive accuracy

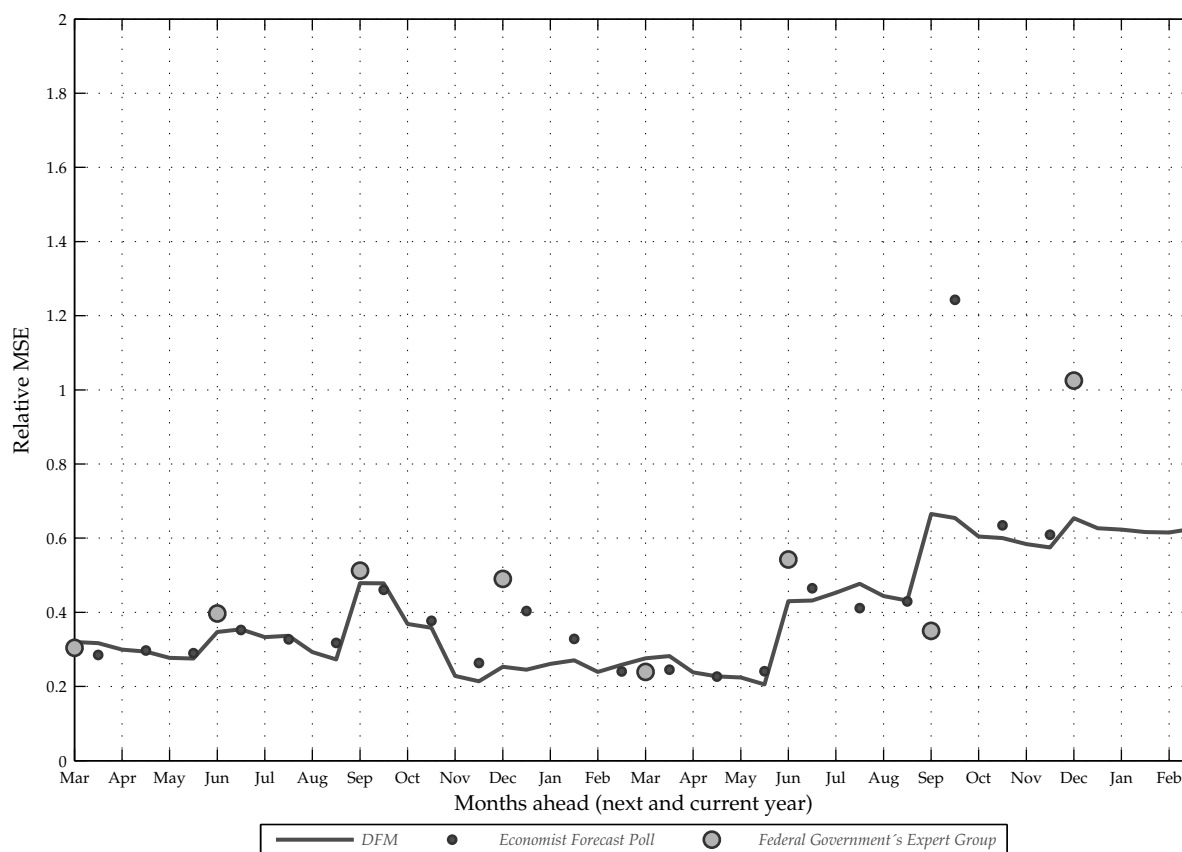
	$GDP^{1st}$			$GDP^f$		
	Backcasts	Nowcasts	Forecasts	Backcasts	Nowcasts	Forecasts
<i>Mean squared errors</i>						
DFM	0.054	0.053	0.085	0.104	0.111	0.210
RW	0.153	0.176	0.281	0.728	0.721	0.722
AR	0.114	0.132	0.153	0.426	0.365	0.337
Consensus	0.070	0.101	0.096	0.100	0.148	0.155
<i>Relative performance of DFM to</i>						
RW	0.355	0.303	0.304	0.142	0.154	0.291
AR	0.474	0.405	0.556	0.243	0.305	0.623
Consensus	0.777	0.529	0.888	1.037	0.752	1.355
<i>Equal predictive accuracy tests (p-values)</i>						
RW	0.000	0.024	0.033	0.001	0.038	0.073
AR	0.002	0.083	0.154	0.006	0.122	0.200
Consensus	0.041	0.336	0.576	0.694	0.386	0.828

Note: Totally 53 quarters in the period 2004Q1-2016Q4 are evaluated. Consensus refers to the Bloomberg surveys (2014Q4-2016Q4). Entries in rows 1-4 are mean squared errors (MSE) of the presented dynamic factor model (DFM), a random walk (RW) and an autoregressive process of order two (AR). The last three rows display the  $p$ -values of the *modified* Diebold-Mariano test of equal forecast accuracy according to [Harvey, Leybourne, and Newbold \(1997\)](#). Backcasts refer to two months backwards, nowcasts are performed at the end of the quarter (three months forwards) and forecasts refer to six months forwards.

backcasts, nowcasts and forecasts. We consider two benchmark models to compare the performance of the DFM. The former is a random walk (RW) and the latter is an autoregressive model of order two (AR). Both benchmark models are estimated in real time, producing iterative forecasts. In addition, we evaluate the DFM against a consensus forecast from the Bloomberg surveys (available only for the period 2014Q4-2016Q4). Calculating the MSE leads to a ranking of the competing models according to their forecasting performance. [Diebold and Mariano \(1995\)](#) provide a pairwise test to analyze whether the empirical loss differences between two or more competing models are statistically significant. As there is potentially a short-sample problem, we apply the modified version of the Diebold-Mariano test according to [Harvey, Leybourne, and Newbold \(1997\)](#). The last three rows display the  $p$ -values resulting from a test of the DFM forecasts against one of the benchmark models or the consensus forecasts.

In line with the results presented in [Figure 3](#), the gains in using the DFM in forecasting GDP depend on the forecasting horizon. With respect to the first release of GDP, the MSE of the DFM is lowest for all three forecast horizons. In the backcasting exercise, the relative MSE of the DFM versus RW and AR are 0.355 to 0.474, and according to the  $p$ -values of the DM-test, the differences are highly statistically significant. The same holds with respect to nowcasts. However, when it comes to forecasts, the DFM only performs significantly better relative to the random walk (RW). Concerning the consensus forecasts, the DFM performs significantly better in the very short-term but not so for nowcasts and forecasts. The results are similar considering the final GDP estimates. For backcasts, the reductions in MSE are significant compared to RW and AR. Although the relative MSE compared to the two benchmark models are also large for nowcasts and forecasts, they are only significant regarding the RW. Compared to the consensus forecast, the forecasting performance of the DFM is not significantly better.

Figure 4: Relative MSE



Note: The horizontal axis reports the months in which forecasts of the current and following year are made. For instance, in March (on the very left) the forecasting horizon is 24 months or 8 quarters. The horizontal line at 1 corresponds to the mean squared error (MSE) of the random walk model. Relative mean squared errors (MSE) are computed for the DFM predictions, for the Economist Poll of Forecasters and for the Federal Government's Expert Group.

### 4.3 Medium-run forecasting

The DFM not only allows to predict the very short-term of GDP, it can also be used to forecast annual GDP growth rates.<sup>15</sup> Knowledge about medium-run GDP growth is of interest as it enables both policymakers and the public to form expectations about the state of the economy in the near future. In this section, we show that our proposed model is at least as well suited for predicting annual GDP growth as other available institutional forecasts.

Every quarter, the Federal Government's Expert Group publishes the official forecast for annual Swiss GDP growth. This *judgmental* forecast is the outcome of a discussion among several federal agencies.<sup>16</sup> Generally, this forecast is published about 10 days after the release of the quarterly estimate of Swiss GDP. While the judgment of experts might be helpful in increasing the precision of forecasts, the disadvantage of such judgment based forecasts is that they might be blurred by individual excess optimism or pessimism. The forecasting process is therefore rather a subjective exercise instead of an objective quantitative measurable analysis.

<sup>15</sup>For instance, in Switzerland the forecasts of annual GDP are used by the Federal Department of Finance for budgetary purposes and to estimate the debt brake rule.

<sup>16</sup>Participants of the meeting are State Secretariat for Economic Affairs (SECO), Federal Customs Administration (FCA), Swiss Federal Statistical Office (FSO), Swiss National Bank (SNB) and Federal Finance Administration (FFA).

For our analysis, we collect forecasts from the Federal Government’s Expert Group starting in 2002Q4 up to 2016Q4. The forecast horizon varies from 8 to 1 quarters.

Apart from the official forecast, a variety of institutions provide forecasts of Swiss GDP growth.<sup>17</sup> A combination of such forecasts might also provide a more accurate prediction of GDP growth as if only one institution is considered. For a series of countries, the Economist Poll of Forecasters provides GDP forecast by averaging the predictions of several major banks. This procedure is similar to a *consensus* forecast. The forecasts are available on a monthly basis. We collect these data starting in March 2003. The first year to be predicted is therefore 2004 and the forecast horizon is between 1 and 24 months.

The forecasting exercise spans over the years 2004-2016. We compare the judgmental and consensus forecast with the predictions from our proposed model. We use our real-time analysis and make forecasts of  $GDP^{1st}$  for as many quarters as necessary to complete the current and the following year. The Expert Group’s and Consensus forecasts are based on the vintage of GDP available at the time of the forecast, i.e., they include revisions to GDP. To make the exercise comparable, we therefore appended our model forecasts to the corresponding GDP vintage and calculate annual growth rates.<sup>18</sup>

Figure 4 displays mean squared errors (MSE) from the DFM, the consensus and federal forecasts relative to the random walk benchmark. Random walk forecasts are made every quarter using the latest available GDP vintage at the time of the forecast. Forecast horizons are 1 to 8 quarters, or 1 to 24 months respectively. Several results emerge: (i) the DFM outperforms the random walk at all horizons. (ii) Predicting growth of the following year, the judgmental forecast beats the DFM only at 24 months. (iii) Judgmental and consensus forecasts have no predictability of Swiss GDP growth with only one quarter ahead. (iv) With six or less months to predict the current year, the performance of the DFM worsens slightly relative to the benchmark.

Following the methodology of Harvey, Leybourne, and Newbold (1997), we report results from equal predictive accuracy tests in Table 6. Notably, at the 5% significance level the DFM outperforms the RW benchmark at horizons 2, 3, and 4 quarters ahead. Compared to consensus forecasts, the performance of the DFM is not significantly better at any horizon. In comparison to the Expert Group’s predictions, the DFM has better predictive power for the short horizon of 1 and 2 quarters. This is in line with the results presented in Section 4.2 and confirms the fact that the DFM is particularly well suited for short-run forecasting.

#### 4.4 Detecting turning points

Besides investigating the model’s forecasting performance over the entire sample, of particular interest is to study how the model performs during specific historic episodes. Our real-time data allows for such an assessment and we simulate the sequential information set which was available as history unfolded. We focus our analysis on two distinct episodes: (1) the global financial crisis of 2008/2009; (2) the first quarter of 2015 when the Swiss economy was exposed

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<sup>17</sup>For instance major banks or economic research institutes among others.

<sup>18</sup>See Appendix A.4 for the technical details on the calculation of annual GDP growth rates.



Table 6: Predictive accuracy for annual growth rates

Horizon [quarters]	8	7	6	5	4	3	2	1
<i>Mean squared errors</i>								
DFM	1.710	1.511	0.950	0.359	0.332	0.269	0.110	0.014
RW	5.792	4.722	2.795	1.469	1.420	0.610	0.180	0.023
AR	1.571	1.620	1.572	1.152	0.793	0.359	0.147	0.026
Consensus	1.673	1.561	1.005	0.460	0.315	0.250	0.130	0.076
Exp.Group	1.763	1.874	1.433	0.720	0.340	0.331	0.063	0.023
<i>Relative performance of DFM to</i>								
RW	0.295	0.320	0.340	0.244	0.234	0.440	0.610	0.625
AR	1.088	0.933	0.604	0.312	0.419	0.748	0.749	0.552
Consensus	1.022	0.968	0.945	0.780	1.055	1.075	0.848	0.187
Exp.Group	0.970	0.806	0.663	0.499	0.979	0.812	1.743	0.610
<i>Equal predictive accuracy tests (p-values)</i>								
RW	0.232	0.265	0.272	0.132	0.037	0.028	0.021	0.176
AR	0.548	0.690	0.376	0.305	0.028	0.064	0.059	0.258
Consensus	0.835	0.596	0.589	0.306	0.879	0.874	0.460	0.273
Exp.Group	0.680	0.344	0.330	0.161	0.962	0.702	0.100	0.026

*Note:* Totally 13 years in the period 2004-2016 are evaluated. Consensus refers to the Economist Poll of Forecasters. Entries in rows 1-4 are mean squared errors (MSE) of the presented dynamic factor model (DFM), a random walk (RW) and an autoregressive process of order two (AR). The last three rows display the *p*-values of the *modified* Diebold-Mariano test of equal forecast accuracy according to Harvey, Leybourne, and Newbold (1997).

to a significant monetary policy shock. We start with the global financial crisis period.

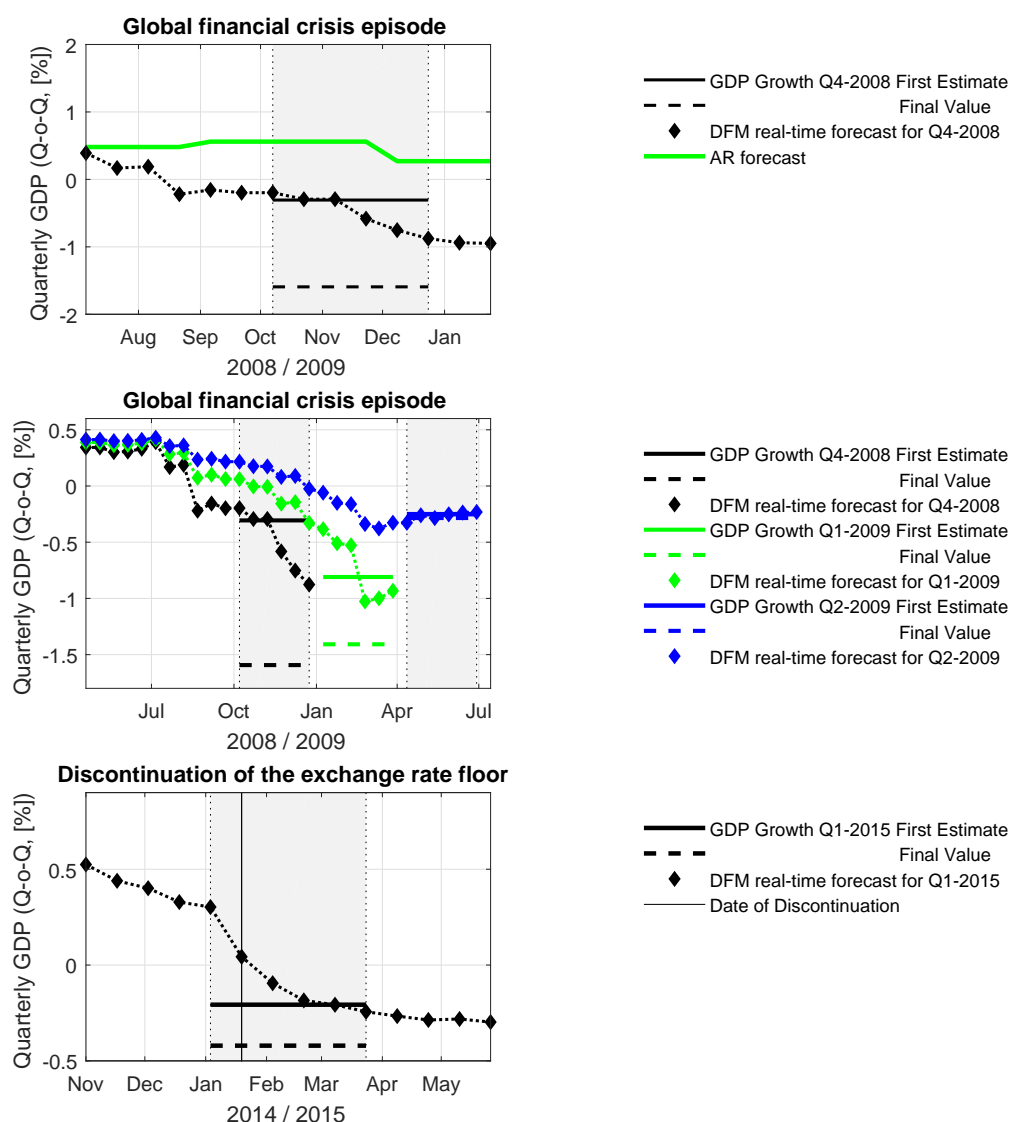
#### 4.4.1 The global financial crisis

The upper subplot in Figure 5 shows the forecast trajectory of the model for the fourth quarter 2008 which were made at different points in time.<sup>19</sup> This plot is useful in order to address one important question: When did the authorities realize that the downturn had started? It is worth recalling that projecting business cycle turning points has always been a difficult task, however, in particular within the global financial crisis episode. The reason for this is twofold: on the one hand, the upcoming financial turbulence had increased the forecast uncertainty to elevated levels. On the other hand, despite many financial variables and soft indicators having given correct signals for a near downturn, the signals from real economic activity pointed in part even in the opposite direction. On top of that, the negative growth rate in the fourth quarter 2008 was the first negative quarterly GDP growth rate in Switzerland in eight years. Despite the difficulties associated to the turning point identification, the upper subplot in Figure 5 shows that clear signals of a business cycle turning point started to become more evident only around summer of 2008.

Using the vintage of mid January 2008, *vint-h1/01/08*, we estimate the model and compute GDP forecasts as well as nowcasts and backcasts. To make the idea of the exercise clearer, consider for instance the first point of the black line-dotted path – this point gives the forecast for the fourth quarter of 2008 made at the 15th of July 2008 (*vint-h1/07/08*) with the information available at that point in time. The model is fully estimated with the available information at this point in time and then used to produce a forecast for the fourth quarter 2008. The second point on the black line-dotted path is a forecast again for the fourth quarter 2008, however, with the information available up to and including the end of July 2008 (*vint-h2/07/2008*); again the

<sup>19</sup>We have omitted the confidence bands for better visibility of the point estimates.

Figure 5: Forecasting in real-time - different episodes



*Note:* The figure plots real-time forecasts of the dynamic factor model (DFM) for various episodes. The first subplot shows real-time forecasts for Q4:2008 (black diamonds) jointly with a forecast based on an AR(2)-model (green line) and the GDP growth rate for Q4:2008 (first estimate and final value; black dashed and solid lines). The second subplot shows the real-time forecasts for Q4:2008, Q1:2009 and Q2:2009 jointly with the corresponding GDP growth rates for each quarter. Finally, the third subplot shows real-time forecasts for Q1:2015 and the GDP growth rate for Q1:2015 (first estimate and final value; black dashed and solid lines).

model is fully estimated for producing a forecast.

The subplot shows that the model's forecasts for GDP growth for the fourth quarter 2008 (black line-dotted path) were in the range of 0.4% and 0.6% for a long time, however, in mid-July they dropped markedly. At the beginning of July the projection of Q4:2008 GDP growth was still at an elevated level of 0.45%, however, at the end of August this forecast dropped down to a value of -0.23%. In fact, the model predicted a negative growth rate for Q4:2008 the first time at the end of August 2008 (vint-h2/08/08). There are two variables at work which drive the significant drop in the projection; these are on the one hand the PMI - it dropped



from 48.5 (July) down to 41.4 (August) - as well as the UBS consumer sentiment indicator - it dropped from 2.0 (June) down to 1.78 (July). The model's forecast for GDP growth for the fourth quarter made at the end of August is already very close to the first estimate for the GDP growth rate in this quarter (black horizontal solid line) which in turn was published at the beginning of March 2009. Hence the model gave a rather precise projection for the first estimate of the Q4:2008 GDP growth rate already seven months ahead of the first official GDP release for that specific quarter.

The remaining variables in the model contribute to the steady drop in the projection of the Q4:2008 GDP growth rate especially within the fourth quarter. This explains why the forecast continues dropping from around -0.3% in October 2008 down to around -1.0% at the end of the fourth quarter 2008 where it finally remains.

We compare the projections of the DFM to those of a simple AR(2)-model. Notably, the DFM forecast reacts to news quicker and more frequently than the AR-model. In particular, the DFM's forecasts change whenever one of the indicators is updated. In contrast to that, the predictions of the AR-model occur only with the release of a new quarterly GDP estimate. While the DFM projected GDP to grow at around 0.5 percent in July 2008 and indicated a contraction as of August onwards, the AR-model predicted positive GDP growth rates for Q4:2008 over all horizons considered. Moreover, with the release of Q2:2008 in September 2008, the forecast of Q4:2008 even indicated stronger GDP growth. If a policymaker had taken the AR-model for granted, this would have led to severe policy and communication mistakes.

The second subplot of Figure 5 displays the forecasts for the quarters surrounding the global financial crisis. The episode was marked by substantial financial turbulence and Switzerland recorded the first recession in several years (see also Figure 2). We produce forecasts for the quarters Q4:2008 - Q2:2009. Next to each quarter's projections, the figure also displays the first estimate (solid horizontal line) and the final value (dashed horizontal line) of the growth rate of GDP for the aforementioned quarters.

The black dotted line in the subplot is the forecast for Q4:2008 at different points in time which is the same as in the upper subplot. The projections for Q1:2009 and Q2:2009 follow a similar trajectory as the one for Q4:2008. The predictions for the growth rate of GDP drop markedly in mid summer 2008 and remain at depressed levels throughout. For each quarter depicted in the subplot, the model's projections match the first estimate of the GDP growth rate quite well even up to two months ahead of the quarter. Overall, the DFM proves its ability to capture severe downturns in economic development. It also gives an early indication of how GDP growth will evolve in the next quarters and provides policymakers a more solid footing than when using traditional models.

#### **4.4.2 Severe monetary policy interventions**

The aftermath of the global financial crisis has been characterized in Switzerland by, among others, a significant appreciation of its currency (Swiss Franc - CHF) in nominal effective terms. Between 2008 and 2011, the CHF appreciated sharply against the Euro (EUR) and against the US-Dollar (USD). This appreciation made the Swiss National Bank (SNB) believe that it posed

"an acute threat to the Swiss economy" and carried "the risk of a deflationary development". Thus, on September 6, 2011, the SNB said in its press release that it would "no longer tolerate a EUR/CHF exchange rate below the minimum rate of CHF 1.20", and thus it would "enforce this minimum rate with the utmost determination" and would "buy foreign currency in unlimited quantities" (SNB, 2011). The exchange rate floor announced in 2011 was a revisit of the 1978's strategy<sup>20</sup>. To the surprise of markets and institutions, on 15th January 2015, the Swiss National Bank (SNB) removed the exchange rate floor of CHF 1.20 per Euro. Within one day, the CHF appreciated more than 10% to 1.05 EUR/CHF. This sudden severe monetary policy intervention had strong real effects in the very short-term and led to negative GDP growth in Q1:2015.

In what follows we analyze the extent to which the DFM was able to capture the effect of the monetary policy shock in January 2015. The empirical model allows for two transmission channels of the monetary policy intervention: (1) the news channel and (2) the financial market channel. Severe policy changes are usually associated with a change in economic agents' perception of the future economic outlook. In our DFM, news are considered as changes in economic sentiment which in turn are captured by soft indicators. The DFM contains two such indicators (PMI, UBScons). They allow for an immediate effect, as they are likely to be affected already at the time of the announcement of the new policies. The latter channel is captured by means of the real effective exchange rate, the term structure and the implicit stock market volatility index. They are promptly available and characterize the effect of the monetary policy interventions that operates by means of financial markets.

In the bottom subplot of Figure 5 we show the model's projections for the first quarter of 2015. The monetary policy shock triggered some immediate contractionary effects for real economic activity with the result of a negative GDP growth rate in Q1:2015. The first official release of GDP data for this quarter was in June 2015, that is more than five months after the monetary policy shock. We use the DFM to figure out if the model's prediction for GDP growth in Q1:2015 would have pointed towards a negative growth rate earlier than the first official GDP releases of June. We report the growth projections for Q1:2015 made at different points in time. Up to and including the information until mid January 2015, the growth projections remained between 0.3% and 0.5%. However, at the end of January (vint-h2/01/15) growth projections drop significantly owing to a strong drop in the PMI, though growth projections remained positive. In mid February, once next to the PMI figure also the most recent values for the real effective exchange rate and the implicit stock market volatility for January are added to the information set, the nowcast drops negative, down to a value which already compares well to the first official GDP growth estimate released in June.<sup>21</sup> At the end of February, the model's predictions are basically indistinguishable from the first official GDP estimate, though

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<sup>20</sup>The announcement of the exchange rate floor of DEM/CHF (number of Swiss Franc per Deutsche Mark) in 1978 was considered as a significant event after Switzerland adopted a flexible exchange rate in 1973. The adoption of the floor successfully brought up the DEM/CHF exchange rate. However, during the four-year period after the adoption of the floor, Switzerland experienced high inflation, which reached 7.4% in 1981.

<sup>21</sup>In this episode the DFM growth projections were characterized particularly by the real effective exchange rate (REER) and the Swiss stock market volatility index VSMI. Variation in each of them has a non-negligible impact on the model's GDP growth predictions. We show the sensitivity of these two variables on the GDP projections in more detail in Appendix A.2.

they continue to decline with the forthcoming vintages. In summary, the performance of the DFM following the removal of the currency floor was surprisingly well. At the time, policy-makers outside the SNB could have derived important information about the state of the Swiss business cycle using our proposed model.

## 5 Towards Swiss recession dating: A Markov-switching extension

The DFM presented in Section 2 rests on the notion that co-movements among a set of macroeconomic variables have a common element which is summarized in a factor. This factor is supposed to give an accurate picture of the business cycle dynamics for the Swiss economy. However, a short-coming of the linear coincident indicator approach taken above is that it does not provide information about the regime the economy stands in. As mentioned in Section 4.4, the Swiss economy has experienced business-cycle shifts which could have strongly impacted the dynamics of Swiss GDP. To account for this possibility, we extend our DFM by introducing a Markov-switching specification following the methodology advocated by Hamilton (1989). This non-linear specification of our DFM allows us to computed inferences about the regime of the Swiss business cycle. As of today, no official recession dating for Switzerland exists. Our model could ultimately serve as a tool for dating recessions of the Swiss economy.

### 5.1 The MS-DFM model

The framework we propose extends the single-index DFM of Section 2 by assuming that the dynamic behavior of the business cycle factor is governed by an unobserved regime-switching state variable. More formally, let the common factor at time  $t$ ,  $f_t$ , be controlled by an unobservable state variable,  $\zeta_t$ , that is allowed to follow a first-order Markov-chain, where  $\zeta_t = 0$  and  $\zeta_t = 1$  label states of expansion and recession at time  $t$ . In this context it is standard to assume that the state variable evolves according to a two-state Markov-Chain whose transition probabilities are given by:

$$p(\zeta_t = i | \zeta_{t-1} = j, \zeta_{t-2} = h, \dots) = p(\zeta_t = i | \zeta_{t-1} = j) = p_{ij}. \quad (5.1)$$

The state variable is assumed to interact with the common factor as follows:

$$f_t = \mu(\zeta_t) + v_t^f. \quad (5.2)$$

Equation (5.2) states that the common factor is governed by a regime-switching mean plus some noise,  $v_t^f$ , which is a white noise process with the same properties as depicted in equation (2.8). This specification assumes that knowledge of  $\zeta_t$  characterizes the population parameter  $\mu(\zeta_t)$ , though it still leaves some uncertainty about the common factor that comes from the common shock  $v_t^f$ <sup>22</sup>. We use equation (5.2) in order to substitute equation (2.6) from the DFM outlined above. By this, we introduce a Markov-switching element in to the DFM as discussed

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<sup>22</sup>Equation (5.1) ignores the autoregressive terms as included in Equation (2.6). This is primarily due to the fact that numerical problems related with the non-linear estimation approach render the model intractable. In particular, the final estimates tend to depend too strongly on the starting values which weighs on the robustness of the estimates. Moreover, these numerical problems would impede an effective recurrent application of the model.

Table 7: MS-DFM - Estimates

Parameters	$\mu(\zeta_t = 0)$	$\mu^*(\zeta_t = 0)$	$\mu(\zeta_t = 1)$	$\mu^*(\zeta_t = 1)$	$p_{00}$	$p_{11}$
Estimates	0.28 (0.06)	0.61%	-3.10 (0.48)	-1.54%	0.98 (0.17)	0.86 (0.20)

Note:  $\mu^*(\zeta_t = 0)$  and  $\mu^*(\zeta_t = 1)$  refer to the de-standardized values of  $\mu(\zeta_t = 0)$  and  $\mu(\zeta_t = 1)$ , respectively. They refer to the conditional mean q-o-q growth rate of final GDP in either state. The values in parentheses are p-values for the Null-Hypothesis that the corresponding point estimate is zero.

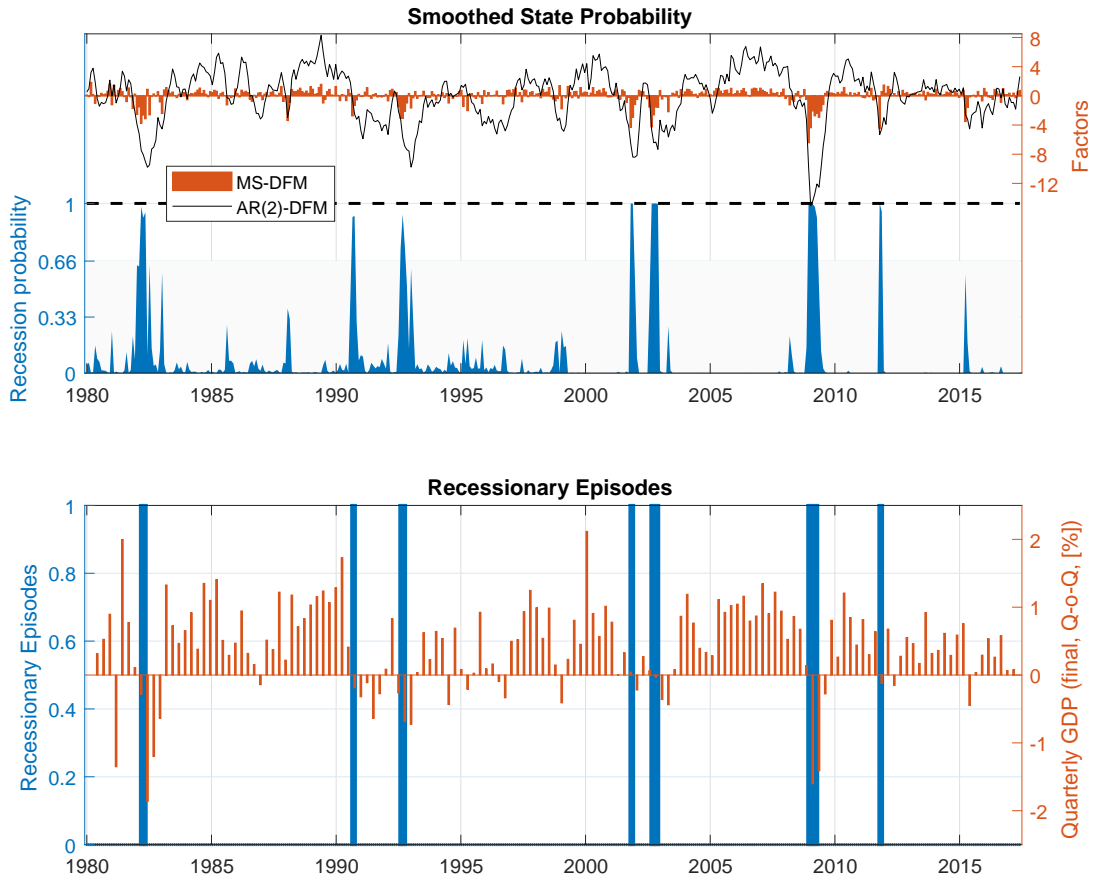
in depth in [Camacho, Perez-Quiros, and Poncela \(2012\)](#). The density function of any variable in  $X_t$  in the measurement equation (2.9) does not depend explicitly on the lags of the state variable  $\zeta_t$ . The specification of equation (5.2) implies that the dynamic behavior of the model comes from the common switch in the state variable  $\zeta_t$ , whereas in the original specification the dynamics of the model was determined by the characteristic roots of the AR(2) specification as given by equation (2.6). The non-linearity of the observed time series is captured by  $\mu(\zeta_t)$ , which is allowed to change across the two distinct states  $\zeta_t = 1$  and  $\zeta_t = 0$ .

We follow [Camacho, Perez-Quiros, and Poncela \(2012\)](#) as regards the estimation of the Markov-switching dynamic factor model (MS-DFM): as in the linear Kalman filter, the algorithm calculates recursively one-step-ahead prediction and updating equations of the dynamic factor and the mean squared error matrices, given the parameters of the model and starting values for the state vector, the mean squared error and, additionally, the probabilities of the Markov states. The updating equations are computed as averages weighted by the probabilities of the Markov states. The filter evaluates this likelihood function, which is then maximized with respect to the model parameters using a non-linear optimization algorithm. The maximum likelihood estimators and the sample data are then used in a final application of the filter to draw inferences about the dynamic factor and probabilities. [Appendix A.3](#) gives details concerning the overview of the MS-DFM model and its state space representation; additionally we discuss some key aspects within the estimation.

The maximum likelihood estimates of this monthly model are given in [Table 7](#), where we only show the parameter estimates related to the Markov-switching extension. The complete list of estimated parameters of the MS-DFM can be found in [Table 10](#) in [Appendix A.5](#). The maximum likelihood estimates imply that, as concerns the regime represented by  $\zeta_t = 0$ , the intercept is positive and statistically significant; while the regime represented by  $\zeta_t = 1$ , has a statistically significant negative intercept. Hence, we can associate the first regime with economic expansions and the second regime with recessions. [Table 7](#) also shows the mean values for the two states once they have been de-standardized ( $\mu^*(\zeta_t = 0)$  and  $\mu^*(\zeta_t = 1)$ ); these values imply that the average q-o-q growth rate of GDP in the expansionary regime is around 0.6%, and -1.5% in the recessionary regime.

Our estimates for the transition probabilities are 0.98 for  $p_{00}$  and 0.86 for  $p_{11}$ , respectively. These estimates are in line with the well-known fact that expansions are longer than contractions, on average. In this context,  $p_{00}$  describes the probability that an expansion is followed by an expansion, and  $p_{11}$  captures the probability that a recession follows a recession. These estimates imply that the expected duration of an expansion is around 50 months ( $= 1/(1 - p_{00})$ )

Figure 6: Recessary Episodes - in sample estimates of state probability



Note: The upper subplot of the figure compares the DFM of Section 2 to the MS-DFM extension, together with the smoothed state probability based on in-sample estimation. The lower subplot shows the quarterly growth rate of final GDP and the recessary episodes based on values of the smoothed state probability above 0.66.

and that of a recession around 7 months ( $= 1/(1 - p_{11})$ ).

Based on these estimates, the upper subplot in Figure 6 shows the factor based on the Markov switching specification (5.2) (orange bars) and the factor based on the AR(2) specification (2.6) (black solid line). The two factors co-move strongly and have a high correlation with each other (around 0.82). The factor based on the AR(2) specification follows the typical smooth and persistent pattern of an autoregressive process. In contrast to that, the factor based on the Markov switching extension shows a high degree of non-linearity; the non-linearities appear to be particularly pronounced during recessary episodes, to which we turn next.

## 5.2 Identifying recessary episodes

The upper subplot in Figure 6 shows the probability that the coincident indicator (orange bars) is in the recessary regime based on an estimation of the regime probability involving the whole sample; in particular, the regime probability shown refers to  $prob(\zeta_t = 1 | I_T; \vartheta)$  where  $I_t = (\mathbf{X}_1, \dots, \mathbf{X}_t)$  is the information set up to and including period  $t$ , and  $t = 1, \dots, T$  where  $T$  is the sample length and  $\vartheta$  is the vector comprising all estimated parameters of the MS-DFM.

Figure 7: Business Cycle Dating - Comparison



Note: The figure shows two different measures for Swiss business cycle dating. In the upper figure, the grey area refers to a technical recession measure (Definition: two consecutive negative quarters of negative GDP growth rate are considered as a recession). In the lower figure, the black stem-plot refers to a OECD measure for business cycle dating: values of 1 are associated with a peak and values of -1 are referred to as a trough - in each case the reference point is the path of potential GDP. Additionally, each subplot shows our measure for the state probability for recessionary episodes and the quarterly final GDP growth rate.

The regime probability  $prob(\zeta_t = 1 | I_T; \vartheta)$  allows to make inference about what regime was more likely to have been responsible for producing the date  $t$  observation of  $X_t$ . The regime probability gives clear advice concerning several recessionary episodes. There are, however, also a few episodes where the regime probability is at a value around 0.5 and hence the evidence concerning the prevailing state is uncertain. Following [Nierhaus and Abberger \(2015\)](#), we associate only those values of the regime probability with a recession which are above 0.66. This leaves us with seven recessionary episodes which are depicted in the lower subplot in [Figure 6](#). These recessions are characterized by differences concerning the duration of the economic downswing as well as the deepness of the recession. Interestingly, the removal of the Swiss franc lower bound in January 2015 did not induce a regime shift. However, the period of strong appreciation of the currency in 2012 did cause a regime switch. This provides an explanation why the SNB at the time decided to introduce the currency floor in the first place. Other recessions can be attributed to the housing crisis in the early 1990s, the DotCom-bubble of 2003 and the financial crisis of 2008.



In Figure 7 we compare the recession classification of our model with two alternative business cycle dating approaches. The gray bars in the upper subplot of the figure display recessionary episodes based on a technical approach; that is, two consecutive quarters of negative GDP growth are considered as recessions. The figure highlights a high overlap of our recessionary regime probabilities with a technical business cycle dating approach. Strikingly, the MS-DFM recession probabilities tend to spike either at the beginning of a technical recession episode, or even prior to the actual beginning of a technical recession. Against this background, the regime probabilities of the model tend to have a leading character. This applies in particular to the recessions in the years 1991, 2003 and 2008.

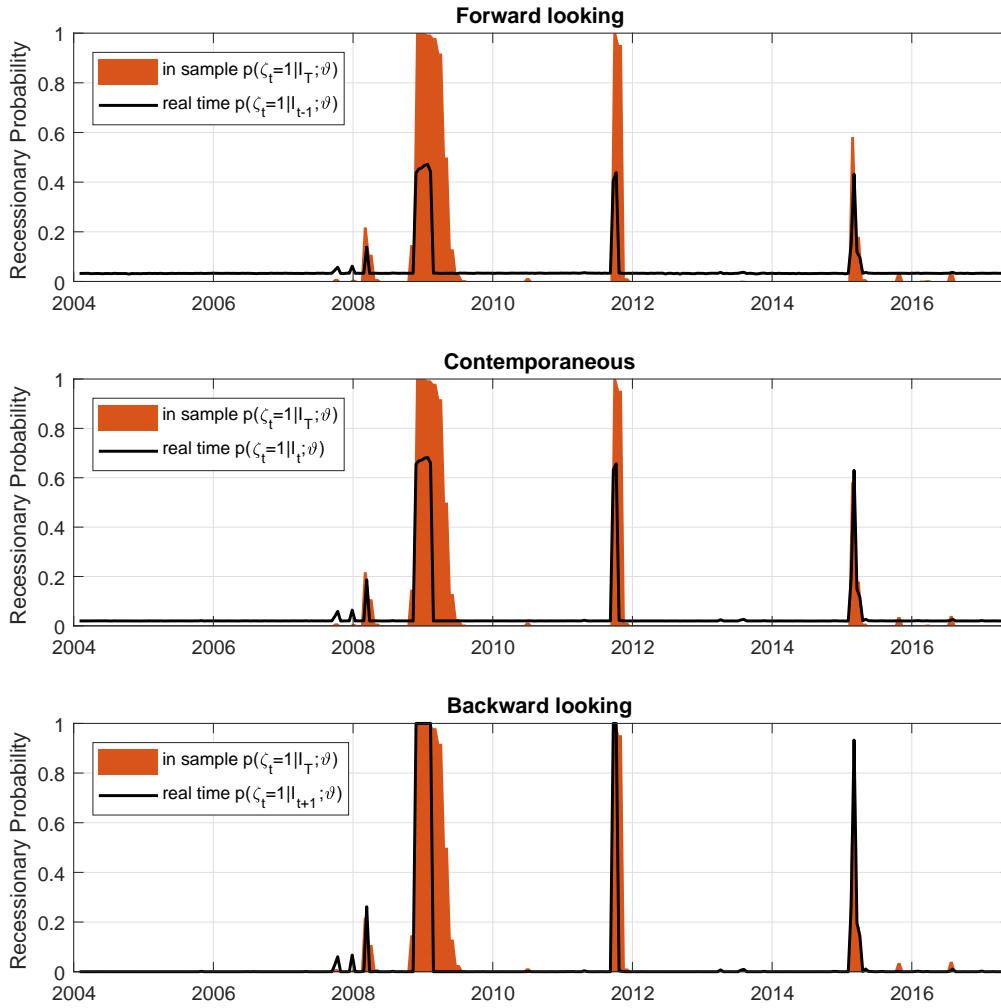
The lower subplot in Figure 7 shows a recession dating from the OECD. The gray bars indicate the time between a peak and a trough. This time is considered as an economic downswing which at times can also involve a recession. This broader classification is based on a trend measure of GDP.<sup>23</sup> The figure highlights that our recessionary regime probability tends to spike in accordance with the gray bars. There are several occasions where the OECD business cycle dating contrasts the regime probabilities of our model. However, this applies especially to episodes where GDP growth was in fact only weak, but not necessarily negative. Hence, the OECD approach classifies also those instances of a negative output gap – induced by below-trend growth rather than negative GDP growth rates – as recessions. This is an aspect that is generally left aside by our model.

### 5.3 Assessing recessionary episodes in real-time

The previous in-sample analysis was computed based on the data set spanning over the whole sample, i.e., the regime probability for recessions was based on:  $prob(\zeta_t = 1 | I_T; \vartheta)$ . However, the real-time data can be deceptively less helpful in monitoring real activity than the in-sample evaluations. This is due to (i) different information sets  $I_t$ , and (ii) data revisions. In our case, the problem of data revisions only applies to a few variables outlined in Table 1. As concerns GDP, the possibility of data revisions has been directly incorporated in the DFM by means of two measures of GDP and a corresponding error term capturing actual data revisions. Regarding monthly indicators, revisions are on average negligibly small and are therefore of minor importance. However, the problem of different information sets still applies. The in-sample analysis does not give us the possibility to evaluate the effect of dealing with the lack of synchronicity between the flow of macroeconomic information on the one hand and the timely assessment of economic developments on the other. Against this background, we perform a more realistic assessment of the actual empirical reliability of the recessionary regime probabilities. We evaluate the performance of our MS-DFM in tracking past Swiss business cycles shifts in real time by means of the same real-time data set established and described in Section 4. We estimate the model by recursively increasing samples of data vintages and evaluating the evidence for each new data point. We compute two real-time inferences for each month - in the middle and at the end of the same month.

<sup>23</sup>Further details can be found in: <http://www.oecd.org/std/leading-indicators/oecdcompositeleadingindicatorsreferenceturningpointsandcomponentseries.htm>

Figure 8: Recessionary Episodes - real-time estimates of state probability



*Note:* The figure shows different estimates for recessionary episodes based on real-time out-of-sample estimations of the state probability at time  $t$  with information up to and including time  $t$ . This applies to the vintages corresponding to the middle of a month (H1), the end of a month (H2), and the two merged together. The subplots compare the real-time estimates of the recessionary episodes with the in-sample estimates for the recessionary probabilities based on the whole sample.

We compute out-of-sample state probabilities of recessionary episodes for different information sets to evaluate in how far new information changes the model's assessment of the current regime. We consider the following three measures for the recessionary regime probability: (i)  $prob(\zeta_t = 1 | I_{t-1}; \vartheta)$ , (ii)  $prob(\zeta_t = 1 | I_t; \vartheta)$ , and (iii)  $prob(\zeta_t = 1 | I_{t+1}; \vartheta)$ . The first case estimates the regime probability at time  $t$  with information up to and including time  $t - 1$ , the estimate for the regime probability at time  $t$  is hence a forecast. The second probability measure captures the contemporaneous scenario; it evaluates the regime probability at time  $t$  considering all information up to and including time  $t$ . Finally, the third probability measure considers the backward looking scenario: it evaluates the regime probability at time  $t$  considering all information up to and including time  $t + 1$ .

Figure 8 shows the corresponding path of the regime probabilities for each scenario (black



solid line). It contrasts the estimates of the real-time regime probabilities with the in-sample estimates (orange bars). In the forward looking scenario, the model gives only a vague hint for each recessionary episode. The estimated regime probabilities for a recession always remain below 0.5. This applies also to the episode surrounding the global financial crisis of 2008/2009. In the contemporaneous scenario, the model's real-time estimates for the recessionary regime probabilities match their in-sample counterpart to a large extent. The probabilities for the 2008/2009 recession and the one in Q3/Q4:2011 are already larger than 2/3 and hence would be classified as recessionary episodes by our classification. Finally, in the backward looking case, the recessionary regime probabilities from the real-time estimation can hardly be distinguished from the in-sample estimates. However, there is still one noteworthy difference: the in-sample estimates for the recessionary regime probabilities point towards a longer recession duration; in other words, the real-time estimates of the recessionary regime probabilities tend to underestimate the duration of the recessionary episodes considered in Figure 8 to some extent.

Overall, extending the linear DFM of Section 2 with a Markov-switching process for the business cycle factor provides valuable real-time information for dating recessions in Switzerland. The model captures well commonly known recessionary periods of the Swiss economy. Furthermore, it indicated that the removal of the Swiss franc lower bound in 2015 did not cause a regime switch.

## 6 Robustness analysis

We check the robustness of the implications from the model presented in Section 2 across various dimensions. First, there is the possibility that the combinatorial selection algorithm is subject to sample-dependency. In this vein, one drawback could be that time variation in the estimated parameters after major economic events might cause time-dependency of the selected variables. Second, the DFM features only a limited number of variables. It could still be the case that introducing at least one further variable could lead to a significant model improvement. Finally, we test our assumption of a lag-length of the factor and the idiosyncratic component of order 2.

### 6.1 Sub-sample instability

The combinatorial algorithm used in Section 3.1 for selecting an appropriate set of variables has been applied to the whole sample. However, structural changes in the underlying economic dynamics could influence the choice of indicators over time or lead to time-variation in the estimated parameters. For instance, it might be possible that the combinatorial algorithm could motivate a different set of indicators once applied to a time span ending before the global financial crisis. Against this background, we analyze the extent to which the fit of our small scale dynamic factor model varies over time. We consider time-variation in the factor loadings  $\gamma_q$ ,  $\gamma_s$  and  $\gamma_h$ , in the variances  $\sigma_q^2$  and  $diag(\Sigma_v)$  and in the model fit measured by the  $R^2$  within a time-span starting in January 2004 and ending in December 2016. In order to introduce time-

variation in the parameters, we apply a rolling regression approach: we estimate the model based on a sample starting in 01:1980 until 01:2004 and recursively extend the window by adding an additional month until we end up in 12:2016; this involves 156 steps. For each step we fully estimate the model and collect the estimates for the factor loadings, the variances and the model fit. Figure 9 displays the time variation by means of boxplots for the factor loadings and the variances (first and second subplot) and the temporal trajectory of the  $R^2$  to capture the overall change in the model fit over time.

The figure highlights on the one hand that time variation is present. On the other, however, it is fairly small for most parameters. The variation of the estimated parameters for the factor loadings is smaller than the estimate of the in-sample standard deviation depicted in Table 3. The same finding also applies to  $\sigma_q^2$  and  $diag(\Sigma_v)$ . All the time-variation of the parameters is still within the one-standard-deviation confidence interval of the full-sample estimates. Hence, the time-variation is of no statistical importance. A similar reasoning applies when considering the temporal trajectory of the model fit - the  $R^2$  between the model and the final value for the q-o-q GDP growth rates varies between 0.70 and 0.75. There appears to be no systematic pattern of time variation in the model fit. The same applies to the case once considering the  $R^2$  between the model and the first estimate for the q-o-q GDP growth rates; the  $R^2$  varies between 0.77 and 0.81. If anything, one could argue that there is some evidence of a slightly decreasing model fit starting in 01:2012. The steady though small decline in the model fit coincides with the finding that the relationship between qualitative survey (*soft*) and quantitative (*hard*) data tends to have changed over time to some extent<sup>24</sup>.

## 6.2 Additional Variables

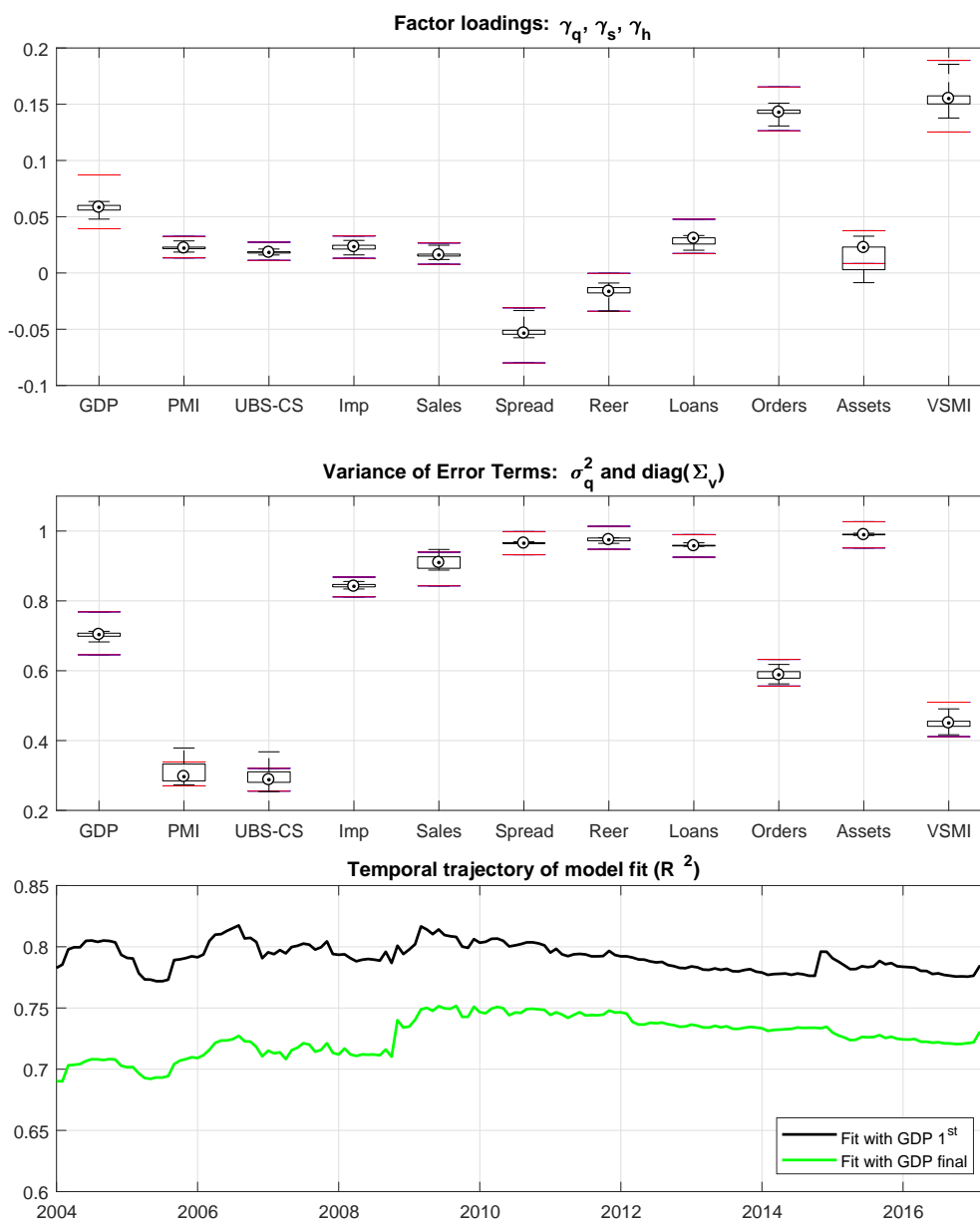
Our proposed small-scale DFM features only ten monthly indicators. This is a rather parsimonious model structure. Although applications of this kind of model for other countries usually have a similar number of variables used to derive the common factor, it might still be possible that further variables might improve the model fit noticeably.<sup>25</sup> We estimate the DFM again including an additional eleventh variable. For each eleventh variable we evaluate the model fit by means of the  $R^2$ . The percentage of the variance of GDP growth (final value) explained by the Benchmark model is 0.77 (see Table 3). In Table 8 we report the corresponding  $R^2$  for every eleventh indicator which is added to the DFM. In most cases, the inclusion of a further variable renders a worse model fit. This applies particularly when we add variables which have a high correlation with those already included. Yet, there are certain variables for which

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<sup>24</sup>The literature on the *New Modesty* argues that the experience of the double-dip recession in the Euro zone in 2008-09 and in 2011-13 and the ensuing slow recovery may have led consumers and business managers to adjust their economic expectations to a more modest *new normal*. Analytically, this would imply a pre/post crisis break in the relationship between qualitative survey (*soft*) and quantitative (*hard*) data, which has traditionally been remarkably stable. Overall, the literature argues that the empirical findings call for caution when translating survey data into actual economic growth rates. There is evidence of shifts of the relationship between hard and soft indicators for the Euro zone as a whole as well as individual countries, sectors, and specific survey questions (see for instance (European Commission, 2016; Bruno, Crosilla, and Margani, 2016; de Largentaye and Roucher, 2015; Ferrara, Guégan, and Rakotomalahy, 2010; Commission, 2011)).

<sup>25</sup>See for instance Camacho and Perez-Quiros (2010); Camacho, Dal Bianco, and Martinez-Martin (2015); Camacho and Perez-Quiros (2011); Rusnák (2016); Barnett, Chauvet, and Leiva-Leon (2014); Luciani and Ricci (2014); Fenz and Spitzer (2006); Galli, Hepenstrick, and Scheufeke (2017).

Figure 9: Sub-sample stability



Note: The figure plots a boxplot for the factor loadings ( $\gamma_q, \gamma_h$  and  $\gamma_s$ ), the variances ( $\sigma_q^2$  and  $\text{diag}(\Sigma_v)$ ) and the  $R^2$  from a regression of the factor on the growth rate of GDP (first estimate and final) including a constant term for various sub-samples.

the  $R^2$  results as high as the one of the Benchmark model. Nevertheless, we could not find a single variable yielding a noticeably higher  $R^2$ . Overall, this exercise reinforces the importance of an appropriate indicator selection process once a small-scale DFM is preferred over a factor model relying on a large data set and several factors.

Table 8: Model fit - adding further variables

<b>Hard Indicators</b>			
Exports	0.73	Labour market tightness (V/U)	0.18
Social security	0.73	Balance Sheet & Flows of MFI Sector, Commercial Banks, Foreign Liabilities, Total, Total, All Banks, CHF	0.41
Retail sales nofuel	0.15	Equity Indices, SIX Swiss Exchange, SMI Index, Price Return, Close, CHF	0.73
Retail sales food	0.13	Monetary Aggregates, M1, Total, CHF	0.73
Unemployment rate	0.73	Monetary Aggregates, M2, Total, CHF	0.74
3 month rate	0.73	Monetary Aggregates, M3, Total, CHF	0.73
3 month Libor	0.45		
10y govt	0.73		
CPI core	0.72	<b>Soft Indicators</b>	
CPI mineral	0.06	KOF index of leading indicators	0.72
CPI domestic	0.15	IFO business climate	0.75
CPI imported	0.69	EU business climate	0.73
SBB kilometers	0.73	Business Surveys, Procure.ch & Credit Suisse, Purchasing Managers Index, Total, SA, Index	0.46
Financial orders	0.03	Business Surveys, KOF, Business Survey, Business Plans, SA	0.55
Oil consumption	0.73	Business Surveys, KOF, Economic Barometer, Total	0.54
New cars	0.74	Business Surveys, KOF, Industry, Total, Stock of Orders, Balance	0.71
Industrial production	0.64	Business Surveys, KOF, Industry, Total, New Orders, Compared to Corresponding Month of Previous Year, Balance	0.68
Vacancies	0.75	Business Surveys, KOF, Industry, Total, Production, Compared to Corresponding Month of Previous Year, Balance	0.69

*Note:* The table presents the  $R^2$  of a regression of the factor on the final value of the q-o-q GDP growth rate (the regression includes a constant term). The factor in turn is based on the final model extended with one further variable mentioned in the table. The corresponding value of the  $R^2$  is listed above for each additional variable that we consider.

### 6.3 Lag-length of the autoregressive processes

The combinatorial algorithm discussed in Section 2.4 is based on the prior assumption of a lag-order equal to two of the autoregressive processes in the system of dynamic equations (2.5)-(2.7). The lag-length is, of course, a testable assumption and should preferably be checked for each set of variables within the combinatorial algorithm. This is, however, computationally not tractable. Instead, we evaluate the plausibility of our assumption implementing a model selection criterion. We calculate Akaike's information criterion (AIC) and Schwartz's Bayesian

Table 9: Lag-order selection for the dynamic factor model

Lag	AIC	SBIC
0	-3.421	-5.187
1	-0.348	-0.750
2	-0.091	<b>-0.312</b>
3	<b>-0.089</b>	-0.470
4	-0.124	-0.502

information criterion (SBIC). In our application this implies the following:

$$AIC := \frac{1}{T} [\log(L(\hat{\theta})) - (n_{\mathbf{X}} + p + n_{\mathbf{X}}(p + 1))] \quad (6.1)$$

$$SBIC := \frac{1}{T} \left[ \log(L(\hat{\theta})) - \frac{\log(T)}{2} (n_{\mathbf{X}} + p + n_{\mathbf{X}}(p + 1)) \right], \quad (6.2)$$

where  $\hat{\theta}$  is the ML-estimator for the model's coefficients and  $p$  is the lag-length of the autoregressive processes.

Table 9 shows the AIC and SBIC values for various  $p$ . Note that the values for the AIC and SBIC in the table are based on the assumption that all autoregressive processes have the same lag-length  $p$ . AIC selects a lag-order of three and SBIC selects a lag-order of two. Given these results, we consider a lag-order of two as appropriate for at least two reasons: first of all, we prefer simpler models, and secondly, the AIC information criterion is fairly indifferent between a model with two and/or three lags.

## 7 Conclusions

We propose a dynamic factor model for the Swiss economy based on an appropriately selected small set of monthly and quarterly indicators. The resulting coincident business cycle index is in striking accordance with quarterly GDP. Our proposed model can both be useful for short-term as well as for medium-term forecasting. It also demonstrates great performance in capturing turning points of the Swiss business cycle in a timely manner. For instance, the removal of the Swiss franc lower bound in January 2015 lead to a negative growth rate in Q1:2015. While the official GDP figure was released 135 days after the monetary policy intervention – leaving policy makers in the meantime in the dark – our model predicted the negative growth rate as early as 15 days after the policy shock.

Using real-time GDP data, we extend the linear model by means of a Markov-switching process for the business cycle factor. The introduced non-linearity allows to draw inference on the business cycle stance of the economy. In an out-of-sample exercise, we show that our model could be used as a tool for recession dating in Switzerland, which is missing so far. Importantly, the removal of the currency floor did not imply a regime switch, while the introduction of the currency floor can be associated with a business cycle shift.

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## A Appendix

### A.1 State-space representation of the dynamic factor model

This section provides details on how the dynamic factor model spelled out in equations (2.3)-(2.8) can be cast into a state-space representation. To illustrate how the corresponding matrices of the transition and measurement equation look like we use the following:  $0_{(i,j)}$  is a matrix of zeros of dimension  $i \times j$ ,  $I_r$  is an identity matrix of dimension  $r$ . We note that  $\mathbf{x}_t^s$  is a  $n_s$  dimensional vector of soft-indicators,  $\mathbf{x}_t^h$  is a  $n_h$  dimensional vector of hard-indicators. For simplicity, we assume here that the variables are all observed at a monthly frequency and that there are no missing observations. Relaxing this assumption would require to extend  $\mathbf{y}_t$ ,  $\mathbf{w}_t$ ,  $R$  and  $H$  by means of an indicator function as discussed in Section 2.4.

**Transition equation:** This equation relates the observed variables to the factor and can be expressed as:

$$\mathbf{y}_t = H\mathbf{s}_t + \mathbf{w}_t, \quad \mathbf{w}_t \sim NID(\mathbf{0}, R) \quad (\text{A.1})$$

We use the following definition of the vectors  $\mathbf{y}_t$ ,  $\mathbf{s}_t$ ,  $\mathbf{w}_t$  and variance co-variance matrix  $R$ :

$$\mathbf{y}_t = \left[ \mathbf{y}_t^{1st}, \mathbf{y}_t^f, (\mathbf{x}_t^s)^\prime, (\mathbf{x}_t^h)^\prime \right]^\prime \quad (\text{A.2})$$

$$\mathbf{w}_t = 0_{(n_X, 1)} \quad (\text{A.3})$$

$$R = 0_{(n_X, n_X)} \quad (\text{A.4})$$

with  $n = n_h + n_s$ ,  $n_X = n + 2$  and<sup>26</sup>

$$\mathbf{s}_t = \left[ f_t, \dots, f_{t-11}, u_{t,q}, \dots, u_{t-4,q}, \epsilon_t, \dots, u_{t,1}^s, u_{t-1,1}^s, u_{t,2}^s, u_{t-1,2}^s, \dots, u_{t,n_s}^s, u_{t-1,n_s}^s, \dots, u_{t,1}^h, u_{t-1,1}^h, u_{t,2}^h, u_{t-1,2}^h, \dots, u_{t,n_h}^h, u_{t-1,n_h}^h \right]^\prime \quad (\text{A.5})$$

Given these definitions, the matrix  $H$  will be the following:

$$H = \begin{pmatrix} \overbrace{\eta_{11} \quad 0_{(1,6)}}^{f_t, \dots, f_{t-11}} & \overbrace{\eta_{12}}^{u_t, \dots, u_{t-4}} & \overbrace{0}^{\epsilon_t} & \overbrace{0_{(1,2 \cdot n_s)}}^{\tilde{\mathbf{u}}_t^s} & \overbrace{0_{(1,2 \cdot n_h)}}^{\tilde{\mathbf{u}}_t^h} \\ \eta_{11} & \eta_{12} & 1 & 0_{(1,2 \cdot n_s)} & 0_{(1,2 \cdot n_h)} \\ \eta_{31} & \eta_{31} & 0_{(n_s, 5)} & \eta_{32} & 0_{(n_s, 2 \cdot n_h)} \\ \eta_{41} & 0_{(n_h, 6)} & 0_{(n_h, 5)} & 0_{(n_h, 2 \cdot n_s)} & \eta_{42} \end{pmatrix} \quad (\text{A.6})$$

with  $\tilde{\mathbf{u}}_t^s = (u_{t,1}^s, u_{t-1,1}^s, u_{t,2}^s, u_{t-1,2}^s, \dots, u_{t,n_s}^s, u_{t-1,n_s}^s)$ ;  $\tilde{\mathbf{u}}_t^h = (u_{t,1}^h, u_{t-1,1}^h, u_{t,2}^h, u_{t-1,2}^h, \dots, u_{t,n_h}^h, u_{t-1,n_h}^h)$ , and

$$\eta_{11} = \begin{pmatrix} \frac{\gamma_q}{3} & \frac{2\gamma_q}{3} & \gamma_q & \frac{2\gamma_q}{3} & \frac{\gamma_q}{3} & 0 \end{pmatrix} \quad (\text{A.7})$$

$$\eta_{12} = \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} \end{pmatrix} \quad (\text{A.8})$$

$$\eta_{32} = I_{n_s} \otimes (1 \quad 0) \quad (\text{A.9})$$

$$\eta_{42} = I_{n_h} \otimes (1 \quad 0) \quad (\text{A.10})$$

and  $\eta_{31}$  is a  $(n_s \times 6)$  matrix whose columns are  $\gamma_s$  and  $\eta_{41}$  is a  $(n_h \times 6)$  matrix of zeros whose first column is  $\gamma_h$ .

**State equation:** Using the previous definitions of the vectors, the state equation can be expressed as:

$$\mathbf{s}_t = F\mathbf{s}_{t-1} + \mathbf{v}_t, \quad \mathbf{v}_t \sim NID(\mathbf{0}, Q) \quad (\text{A.11})$$

<sup>26</sup>In our particular application,  $n_h = 8$ ,  $n_s = 2$  implying that  $n = 10$  and  $n_X = 12$ .



where  $Q$  is a matrix whose off-diagonal elements are all zero and its diagonal is given by:

$$\text{diag}(Q) = \left[ \sigma_f^2, 0_{(1,11)}, \sigma_q^2, 0_{(1,4)}, \sigma_\epsilon^2, \text{diag}(\Sigma_v)' \otimes (1 \ 0) \right]' \quad (\text{A.12})$$

where  $\text{diag}(\Sigma_v) = (\sigma_{v_s,1}^2, \dots, \sigma_{v_s,n_s}^2, \sigma_{v_h,1}^2, \dots, \sigma_{v_h,n_h}^2)'$ ; and the matrix  $F$  becomes:

$$F = \begin{pmatrix} \overbrace{f_{t,\dots,t-11}} & \overbrace{u_{t,\dots,t-4}} & \overbrace{\epsilon_t} & \overbrace{u_{t,1}^s, u_{t-1,1}^s} & [\dots] & \overbrace{u_{t,n_s}^s, u_{t-1,n_s}^s} & \overbrace{u_{t,1}^h, u_{t-1,1}^h} & [\dots] & \overbrace{u_{t,n_h}^h, u_{t-1,n_h}^h} \\ f_{11} & 0 & 0 & 0_{(1,2)} & \dots & 0_{(1,2)} & 0_{(1,2)} & \dots & 0_{(1,2)} \\ I_{11} & 0 & 0 & 0_{(11,2)} & \dots & 0_{(11,2)} & 0_{(11,2)} & \dots & 0_{(11,2)} \\ 0_{(5,11)} & 0 & f_{\gamma_q} & 0 & 0_{(5,2)} & \dots & 0_{(5,2)} & \dots & 0_{(5,2)} \\ 0_{(1,11)} & 0 & 0_{(1,5)} & 0 & 0_{(1,2)} & \dots & 0_{(1,2)} & \dots & 0_{(1,2)} \\ 0_{(2,11)} & 0 & 0_{(2,5)} & 0 & f_1^s & 0_{(2,\cdot)} & 0_{(2,2)} & \dots & 0_{(2,2)} \\ \vdots & \vdots & \vdots & \ddots & \ddots & \ddots & \vdots & \ddots & \vdots \\ 0_{(2,11)} & 0 & 0_{(2,5)} & 0 & 0_{(2,2)} & \dots & f_{n_s}^s & 0_{(2,2)} & \dots & 0_{(2,2)} \\ 0_{(2,11)} & 0 & 0_{(2,5)} & 0 & 0_{(2,2)} & \dots & 0_{(2,2)} & f_1^h & 0_{(2,\cdot)} & 0_{(2,2)} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \ddots & \ddots & \vdots \\ 0_{(2,11)} & 0 & 0_{(2,5)} & 0 & 0_{(2,2)} & \dots & 0_{(2,2)} & 0_{(2,2)} & \dots & f_{n_h}^h \end{pmatrix} \quad (\text{A.13})$$

$$f_{11} = (\phi_{f,1} \ \phi_{f,2} \ 0_{(1,9)}) \quad (\text{A.14})$$

$$f_{\gamma_q} = \begin{pmatrix} \phi_{q,1} & \phi_{q,2} & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix} \quad (\text{A.15})$$

$$f_1^s = \begin{pmatrix} \phi_{1,1}^s & \phi_{1,2}^s \\ 1 & 0 \end{pmatrix} \quad (\text{A.16})$$

$$f_{n_s}^s = \begin{pmatrix} \phi_{n_s,1}^s & \phi_{n_s,2}^s \\ 1 & 0 \end{pmatrix} \quad (\text{A.17})$$

$$f_1^h = \begin{pmatrix} \phi_{1,1}^h & \phi_{1,2}^h \\ 1 & 0 \end{pmatrix} \quad (\text{A.18})$$

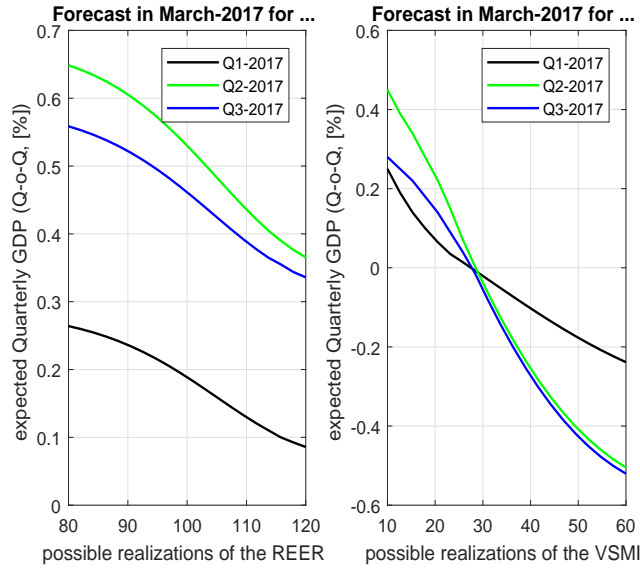
$$f_{n_h}^h = \begin{pmatrix} \phi_{n_h,1}^h & \phi_{n_h,2}^h \\ 1 & 0 \end{pmatrix} \quad (\text{A.19})$$

## A.2 Sensitivity Analysis

Within the dynamic factor model, the transmission of the effects of the discontinuation of the exchange rate floor occurred primarily via the real effective exchange rate and the implicit stock market index. Figure 10 illustrates in general terms how the dynamic factor model can be applied to identify the reaction of GDP projections to different realizations of the REER and the VSMI. The figure plots GDP forecasts made with the information available at the end of March 2017 with simulated values for the March value of the REER and the VSMI. In particular the graphs show how the GDP projections change due to changes in either the REER or the VSMI. The figure considers on the abscissa for both the REER as well as for the VSMI, the minimum and maximum values for each variable observed over the period 1980:2016. The effects of varying the REER and the VSMI on the GDP projections are shown for the first, second and third quarter.

The figures highlight several important aspects. First of all, increases in the REER or the VSMI are associated with lower GDP growth rates. The negative relationship between possible REER and VSMI realizations and expected GDP growth rates captures on the one hand the negative effects of elevated financial market turbulence (VSMI) on GDP growth rates; on

Figure 10: Sensitivity analysis



Note: The figure plots the sensitivity of the GDP forecast in Q1:2017, Q2:2107 and Q3:2017 with respect to potential realizations of the real effective exchange rate (REER) and the implied volatility of the SMI (VSMI).

the other hand real appreciations are considered as contractionary. Secondly, variations in the March value of the REER and the VSMI realization tend to have a larger impact on the expected GDP growth rate in the second and third quarter than in the first one. Thirdly, changes of the REER and the VSMI at extreme values of these indicators tend to have a slightly lower effect on the GDP growth projections than changes when the REER and the VSMI are around around their mean values. This implies that the informational content of these two variables decreases somehow once they approaches *extreme* values.

### A.3 Markov-Switching Dynamic Factor (MS-DF) Model

We consider the following state space representation of the dynamic factor model extended with a Markov-switching element:

$$\mathbf{y}_t = H\mathbf{s}_t + \mathbf{w}_t, \quad (\text{A.20})$$

$$\mathbf{s}_t = \boldsymbol{\mu}(\zeta_t) + F\mathbf{s}_{t-1} + \mathbf{v}_t, \quad (\text{A.21})$$

and

$$\begin{bmatrix} \mathbf{w}_t \\ \mathbf{v}_t \end{bmatrix} \sim i.i.d.N \left( \mathbf{0}, \begin{bmatrix} R & \mathbf{0} \\ \mathbf{0} & Q \end{bmatrix} \right) \quad (\text{A.22})$$

The Markov-switching term  $\boldsymbol{\mu}(\zeta_t)$  in turn is related to  $\mu(\zeta_t)$  as follows:

$$\boldsymbol{\mu}(\zeta_t) := \begin{bmatrix} \mu(\zeta_t) \\ \mathbf{0}_{\zeta-1,1} \end{bmatrix} \quad (\text{A.23})$$

where  $\zeta$  is the length of the state vector  $\mathbf{s}_t$ . The definition of the vectors ( $\mathbf{y}_t$ ,  $\mathbf{s}_t$ ,  $\mathbf{w}_t$  and  $\mathbf{v}_t$ ) and matrices ( $H$ ,  $R$ ,  $F$  and  $Q$ ) is the same as in equations (2.9) and (2.10) with the exception that now expression (A.14), which is part of the matrix  $F$ , changes to the following:

$$f_{11} = ( 0 \quad 0 \quad \mathbf{0}_{(1,9)} ) \quad (\text{A.24})$$

that is, a vector of zeros, since equation (5.2) does not feature any autoregressive terms. Further details can be found in Section A.1 and Section 5. The computational complexity within the estimation of the MS-DF model arises once we maximize the likelihood function, as the combination of the Kalman filter with a Markov-switching element produces a 2-fold increase

in the number of cases to be considered. The problem here can be illustrated as follows:

Assume that we have some initial values for the parameters to be estimated; this gives us an initial value  $s_{0|0}$  and  $P_{0|0}$  which is the unconditional variance of equation (A.21) and (2.10) and captures the uncertainty of  $s_{0|0}$ . The algorithm behind the Kalman filter implies the following forecasting step within the first iteration:

$$\mathbf{s}_{1|0}^{(j)} = \boldsymbol{\mu}(\zeta_0 = j) + F\mathbf{s}_{0|0} \quad (\text{A.25})$$

$$P_{1|0} = FP_{0|0}F' + Q \quad (\text{A.26})$$

$$\boldsymbol{\eta}_{1|0}^{(j)} = \mathbf{y}_1 - \hat{\mathbf{y}}_{1|0}^{(j)} = \mathbf{y}_1 - H\mathbf{s}_{1|0}^{(j)} \quad (\text{A.27})$$

$$\boldsymbol{\Phi}_{1|0} = E \left[ \left( \mathbf{y}_1 - \hat{\mathbf{y}}_{1|0}^{(j)} \right) \left( \mathbf{y}_1 - \hat{\mathbf{y}}_{1|0}^{(j)} \right)' \right] = HP_{1|0}H' + R \quad (\text{A.28})$$

and equivalent expressions for:  $\mathbf{s}_{1|0}^{(i)}$ , and  $\boldsymbol{\eta}_{1|0}^{(i)}$ . Once having obtained expressions for the error terms  $\boldsymbol{\eta}_{1|0}^{(j)}$  and  $\boldsymbol{\eta}_{1|0}^{(i)}$ , we can proceed and compute the log-likelihood functions for each of the two states:  $\zeta_0 = j$  and  $\zeta_0 = i$ :

$$\lambda_1^{(j)} = -\frac{1}{2} \ln \left( 2\pi \left| \boldsymbol{\Phi}_{1|0} \right| \right) - \frac{1}{2} \boldsymbol{\eta}_{1|0}^{(j)} \left( \boldsymbol{\Phi}_{1|0} \right)^{-1} \left( \boldsymbol{\eta}_{1|0}^{(j)} \right)' \quad (\text{A.29})$$

and an equivalent expression for  $\lambda_1^{(i)}$ . The unconditional density of  $\mathbf{y}_1$  can be found by summing  $\lambda_1^{(\zeta_0=\{i,j\})}$  over all values of the states  $\{i, j\}$ :

$$\begin{aligned} f(\mathbf{y}_1) &= \tilde{p} \cdot p(\zeta_0 = j|I_0)e^{\lambda_1^{(j)}} + (1 - \tilde{q}) \cdot p(\zeta_0 = i|I_0)e^{\lambda_1^{(i)}} + \\ &\quad \tilde{q} \cdot p(\zeta_0 = i|I_0)e^{\lambda_1^{(i)}} + (1 - \tilde{p}) \cdot p(\zeta_0 = i|I_0)e^{\lambda_1^{(i)}} \end{aligned} \quad (\text{A.30})$$

The updating step within the Kalman filter implies:

$$\mathbf{s}_{1|1}^{(j)} = \mathbf{s}_{1|0}^{(j)} + K_{1|0}\boldsymbol{\eta}_{1|0}^{(j)} \quad (\text{A.31})$$

$$P_{1|1} = (\mathbf{I} - K_{1|0}P_{1|0}H) \cdot P_{1|0} \quad (\text{A.32})$$

and an equivalent expression for  $\mathbf{s}_{1|1}^{(i)}$ . The Kalman gain  $K_{1|0}$  is given by:  $K_{1|0} = P_{1|0}H \left( \boldsymbol{\Phi}_{1|0} \right)^{-1}$ . Having obtained values for  $\mathbf{s}_{1|1}^{(j)}$ , and  $\mathbf{s}_{1|1}^{(i)}$ , the first iteration ends and we would move on with the second one; however, this is where the complexity arises: The first iteration yields two expressions for the state vector:  $\mathbf{s}_{1|1}^{(j)}$  and  $\mathbf{s}_{1|1}^{(i)}$ . Considering now the second iteration, equation (A.31) yields *four* expressions for the state vector:  $\mathbf{s}_{1|1}^{(j,j)}$ ,  $\mathbf{s}_{1|1}^{(i,j)}$ ,  $\mathbf{s}_{1|1}^{(j,i)}$  and  $\mathbf{s}_{1|1}^{(i,i)}$ . The third iteration in turn would yield eight expressions, and so on. Hence the iterations would quickly produce too many different state vectors rendering the estimation intractable.

The increase in complexity is not only due to the state vector  $\mathbf{s}_{1|1}^{\{i,j\}}$ ; in fact for the first iteration we have that  $P_{1|0} = P_{1|0}^{(i)} = P_{1|0}^{(j)}$ , however, from the second iteration onwards we also have a Markov-switching state dependency in  $P_{1|0}^{\{i,j\}}$ , which adds an additional degree of complexity to the maximization of the log-likelihood function.

Viewed in more general terms, for each point in time  $t$ , the filter produces a 2-fold increase in the number of cases to be considered, since at each  $t$ , the variable  $\mathbf{s}_t^{\{i,j\}}$  and in turn  $P_t^{\{i,j\}}$ ,  $\boldsymbol{\Phi}_t^{\{i,j\}}$ ,  $K_t^{\{i,j\}}$ , etc. can take two new values and therefore, at each  $t$  we have  $2^t$  possible paths to consider when evaluating the likelihood.

As a solution to this problem, Kim (1994) proposed a modification which results in getting rid of the state dependency of the Markov-switching elements in the state vector; this approach was used in turn by Camacho, Perez-Quiros, and Poncela (2012), Kim and Yoo (1995) and Chauvet (1998). In particular, to collapse the means and variances in order to apply equation

(A.25) and (A.26) in a tractable form within all iterations, Camacho, Perez-Quiros, and Poncela (2012) approximate  $\mathbf{s}_{t|t}^{(j)}$ ,  $\mathbf{s}_{t|t}^{(i)}$  and  $P_{t|t}^{(j)}$ ,  $P_{t|t}^{(i)}$  by a weighted average of the updating equations where the weights are given by the probabilities of the Markov state; this implies for the first iteration:

$$\mathbf{s}_{1|1} = \mathbf{s}_{1|1}^{(j)} \cdot p(\zeta_0 = j|I_1) + \mathbf{s}_{1|1}^{(i)} \cdot p(\zeta_0 = i|I_1) \quad (\text{A.33})$$

$$P_{1|1} = p(\zeta_0 = j|I_1) \left( P_{1|0} + \left( \mathbf{s}_{1|1}^{(j)} - \mathbf{s}_{1|1} \right) \cdot \left( \mathbf{s}_{1|1}^{(j)} - \mathbf{s}_{1|1} \right)' \right) + p(\zeta_0 = i|I_1) \left( P_{1|0} + \left( \mathbf{s}_{1|1}^{(i)} - \mathbf{s}_{1|1} \right) \cdot \left( \mathbf{s}_{1|1}^{(i)} - \mathbf{s}_{1|1} \right)' \right) \quad (\text{A.34})$$

or in more general terms:

$$\mathbf{s}_{t|t}^{(j)} = \frac{\sum_{\zeta_{t-1}=0}^1 p(\zeta_t = j, \zeta_{t-1} = i|I_t) \mathbf{s}_{t|t}^{(i,j)}}{p(\zeta_t = j|I_t)} \quad (\text{A.35})$$

$$P_{t|t}^{(j)} = \frac{\sum_{\zeta_{t-1}=0}^1 p(\zeta_t = j, \zeta_{t-1} = i|I_t) \left( P_{t|t-1}^{(i,j)} + \left( \mathbf{s}_{t|t}^{(j)} - \mathbf{s}_{t|t}^{(i,j)} \right) \cdot \left( \mathbf{s}_{t|t}^{(j)} - \mathbf{s}_{t|t}^{(i,j)} \right)' \right)}{p(\zeta_t = j|I_t)} \quad (\text{A.36})$$

and equivalent expressions for  $\mathbf{s}_{t|t}^{(i)}$  and  $P_{t|t}^{(i)}$ ; and finally

$$\mathbf{s}_{t|t} = \mathbf{s}_{t|t}^{(j)} \cdot p(\zeta_t = j|I_t) + \mathbf{s}_{t|t}^{(i)} \cdot p(\zeta_t = i|I_t) \quad (\text{A.37})$$

$$P_{t|t} = p(\zeta_t = j|I_t) \left( P_{t|t-1}^{(j)} + \left( \mathbf{s}_{t|t}^{(j)} - \mathbf{s}_{t|t} \right) \cdot \left( \mathbf{s}_{t|t}^{(j)} - \mathbf{s}_{t|t} \right)' \right) + p(\zeta_t = i|I_t) \left( P_{t|t-1}^{(i)} + \left( \mathbf{s}_{t|t}^{(i)} - \mathbf{s}_{t|t} \right) \cdot \left( \mathbf{s}_{t|t}^{(i)} - \mathbf{s}_{t|t} \right)' \right) \quad (\text{A.38})$$

This approach eliminates the Markov-switching state dependency in the state vector within the Kalman filter iterations and allows in turn to run the Kalman filter in the standard form. Moreover, this set-up is nested in the dynamic factor model which allows for mixed frequencies and missing observations. It is worth noting that including a missing observation in the data set, the model will automatically replace the missing value by a forecast. Following the same reasoning, forecasts for longer horizons and forecasts for other indicators can be automatically computed.

#### A.4 Calculating annual GDP growth rates

While the forecasts from the Economist Poll of Forecasters and the Federal Government's Expert Group are already reported in *annual* GDP growth rates, the forecasts from the benchmark models and the DFM have to be converted from quarterly to annual rates.

Suppose the quarterly levels of variable  $X_{q,y}$  in year 1 are  $X_{1,1}, \dots, X_{4,1}$  and similarly in year 2  $X_{1,2}, \dots, X_{4,2}$ . Then the annual average growth rate  $g_{X,annual}$  calculated with levels is given by

$$g_{X,annual} = \frac{X_{5,1} + X_{6,1} + X_{7,1} + X_{8,1}}{X_{1,1} + X_{2,1} + X_{3,1} + X_{4,1}} - 1. \quad (\text{A.39})$$

Each quarterly level can be expressed in terms of quarterly growth rates multiplied by the level in the base quarter  $X_{0,0}$ , for instance,  $X_{1,1} = g_1 \times X_{0,0}$  and  $X_{2,1} = g_2 \times g_1 \times X_{0,0}$ . After some algebra, the relationship between quarterly growth rates and annual average growth rates is expressed by

$$g_{X,annual} = \frac{\sum_{j=5}^8 \prod_{i=2}^j g_i}{1 + \sum_{j=1}^4 \prod_{i=1}^j g_i} - 1, \quad (\text{A.40})$$

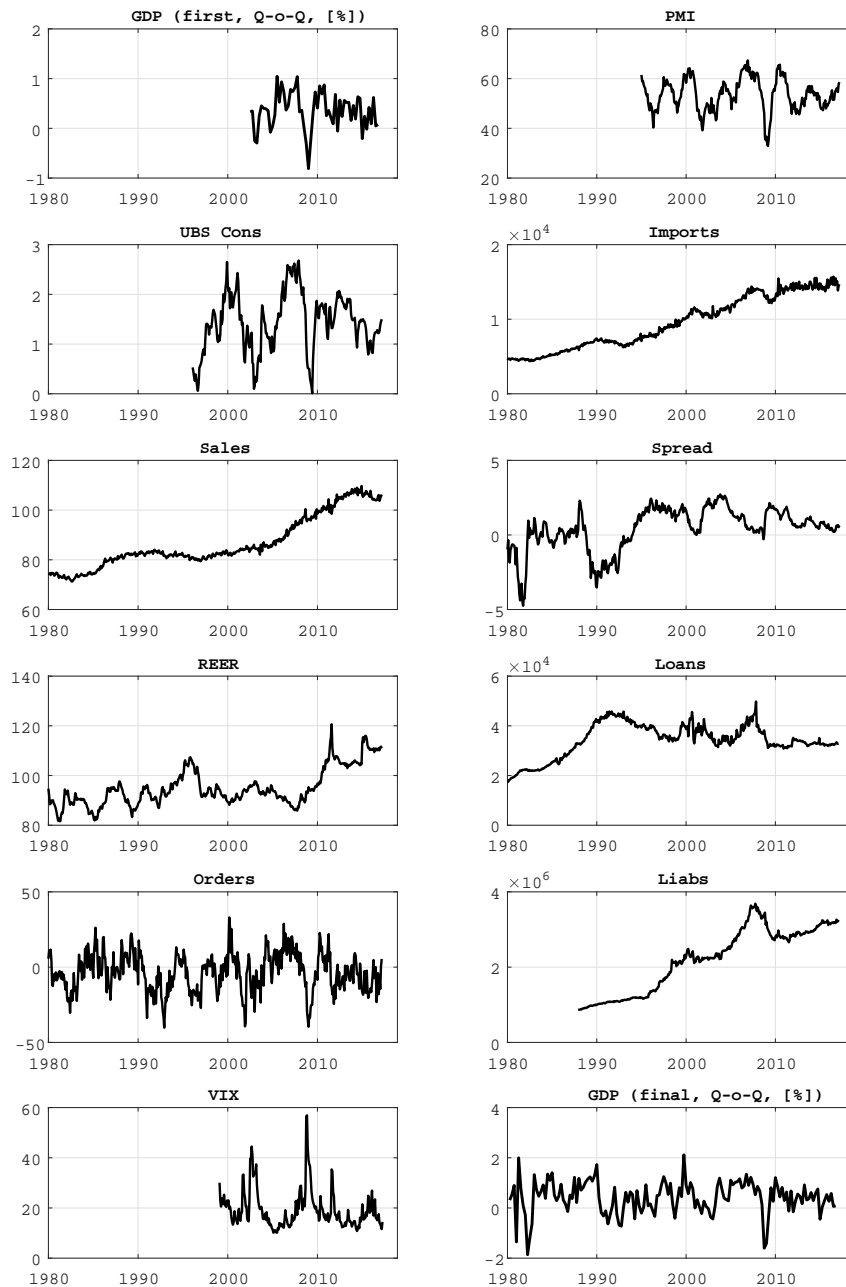
in which the quarterly growth rates of year 1 are referred to with  $g_1, \dots, g_4$  while the four quar-

ters of year 2 are labeled with  $g_5, \dots, g_8$ .

## A.5 Additional figures and tables

The models presented and discussed in Section 2.3 and A.3 feature a series of estimated coefficients of which only a few have been reported in the main text. Table 10 below lists the whole set of estimated parameters for both models including the standard deviation and the ratio of the point estimate and its standard deviation ( $\sim$  t-values) for each parameter.

Figure 11: Monthly indicator series used in the model



Note: See Table 1 for acronyms. Charts refer to data available on Friday 26/01/17.

Table 10: Estimated Parameters

		DFM with $f_t \sim AR(2)$			DFM with $f_t \sim MS$		
		Estimate	Standard Deviation	ratio	Estimate	Standard Deviation	ratio
Factor loadings							
GDP	$(\gamma_q)$	0.06	0.02	2.6	0.11	0.03	3.8
PMI	$(\in \gamma_s)$	0.27	0.11	2.4	0.24	0.06	4.0
UBSc	$(\in \gamma_s)$	0.23	0.12	1.9	0.22	0.09	2.4
Imports	$(\in \gamma_h)$	0.02	0.01	2.3	0.07	0.01	4.9
Sales	$(\in \gamma_h)$	0.02	0.01	1.8	0.07	0.00	15.2
Spread	$(\in \gamma_h)$	-0.06	0.02	-2.3	-0.19	0.05	-3.6
REER	$(\in \gamma_h)$	-0.02	0.01	-1.7	-0.16	0.11	-1.5
Loans	$(\in \gamma_h)$	0.03	0.02	2.1	0.08	0.04	1.9
Orders	$(\in \gamma_h)$	0.14	0.05	3.0	0.02	0.01	2.5
Assets	$(\in \gamma_h)$	0.02	0.01	1.6	0.07	0.02	3.1
VSMI	$(\in \gamma_h)$	-0.15	0.07	-2.2	-0.15	0.02	-7.6
Autoregressive coefficients							
factor ( $f_t$ )	$\phi_{f,1}$	1.49	0.21	7.3	-	-	-
	$\phi_{f,2}$	-0.55	0.19	-3.0	-	-	-
GDP	$\phi_{u_i,1}$	0.54	0.31	1.7	0.50	0.31	1.6
	$\phi_{u_i,2}$	-0.55	0.12	-4.5	-0.40	0.13	-3.2
PMI	$\phi_{u_i,1}$	0.73	0.07	11.0	0.79	0.06	13.3
	$\phi_{u_i,2}$	0.14	0.06	2.2	0.12	0.02	6.6
UBSc	$\phi_{u_i,1}$	1.06	0.06	16.4	1.14	0.11	10.6
	$\phi_{u_i,2}$	-0.21	0.06	-3.3	-0.22	0.05	-4.6
Imports	$\phi_{u_i,1}$	-0.61	0.05	-13.3	-0.61	0.06	-10.4
	$\phi_{u_i,2}$	-0.29	0.05	-6.4	-0.30	0.04	-7.6
Sales	$\phi_{u_i,1}$	-0.49	0.05	-10.5	-0.49	0.11	-4.7
	$\phi_{u_i,2}$	-0.23	0.05	-4.9	-0.22	0.09	-2.3
Spread	$\phi_{u_i,1}$	0.04	0.05	0.7	0.08	0.02	5.0
	$\phi_{u_i,2}$	-0.12	0.05	-2.4	-0.13	0.05	-2.7
REER	$\phi_{u_i,1}$	0.19	0.05	3.9	0.24	0.02	15.4
	$\phi_{u_i,2}$	-0.05	0.05	-1.1	-0.08	0.07	-1.1
Loans	$\phi_{u_i,1}$	-0.24	0.05	-5.1	-0.24	0.03	-9.4
	$\phi_{u_i,2}$	-0.15	0.05	-3.1	-0.13	0.03	-4.0
Orders	$\phi_{u_i,1}$	0.55	0.06	9.4	0.60	0.05	13.0
	$\phi_{u_i,2}$	0.16	0.05	3.2	0.20	0.05	4.3
Assets	$\phi_{u_i,1}$	-0.11	0.05	-2.0	-0.11	0.05	-2.3
	$\phi_{u_i,2}$	0.02	0.05	0.3	0.00	0.00	0.5
VSMI	$\phi_{u_i,1}$	0.97	0.08	12.7	1.02	0.07	14.4
	$\phi_{u_i,2}$	-0.27	0.10	-2.7	-0.35	0.09	-3.9
Variances							
Revision error	$\sigma_\xi^2$	0.34	0.12	2.9	0.35	0.11	3.2
GDP	$\sigma_q^2$	0.71	0.05	13.8	2.04	0.32	6.3
PMI	$(\in \Sigma_v)$	0.30	0.01	21.5	1.36	0.20	6.9
UBSc	$(\in \Sigma_v)$	0.29	0.01	21.7	1.34	0.21	6.5
Imports	$(\in \Sigma_v)$	0.84	0.03	29.7	2.31	0.41	5.6
Sales	$(\in \Sigma_v)$	0.89	0.03	29.8	2.42	0.33	7.3
Spread	$(\in \Sigma_v)$	0.97	0.03	29.2	2.51	0.42	6.0
REER	$(\in \Sigma_v)$	0.98	0.03	29.8	2.54	0.94	2.7
Loans	$(\in \Sigma_v)$	0.96	0.03	29.6	2.61	0.82	3.2
Orders	$(\in \Sigma_v)$	0.59	0.02	26.4	1.89	0.17	11.2
Assets	$(\in \Sigma_v)$	0.99	0.04	26.4	2.67	0.51	5.2
VSMI	$(\in \Sigma_v)$	0.46	0.03	15.4	1.38	0.11	12.8
Markov-Switching coefficients							
factor ( $f_t$ )	$\mu(\zeta_t = 0)$	-	-	-	0.28	0.06	4.5
	$\mu(\zeta_t = 1)$	-	-	-	3.10	0.48	6.5
	$p_{00}$	-	-	-	0.98	0.17	5.8
	$p_{11}$	-	-	-	0.86	0.20	4.3

Note: See Table 1 for acronyms, data transformation and a description of these indicators.