A Monthly Time Series of Swiss GDP: Business Cycle Indicator and Research Tool*†

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Abstract

Gross Domestic Product (GDP) is a key indicator to measure the economic power of a country despite its undisputed weaknesses. This business cycle indicator is a widespread basis for information and planning of strategic decisions. Economic research has always taken this use into account, placing GDP in the center of numerous economic models.

Modern estimation methods in quantitative research require large samples in order to yield reliable results. The GDP series defined according to the current standard (ESA78) includes approximately 70 quarterly estimations, which is insufficient for many models. An interpolated time series covering a shorter observation interval would supply more data and open the way to monthly models.

To avoid the disadvantage of quarterly or longer frequencies, the use of a monthly variable that correlates with GDP is available as an alternative to the GDP interpolation. In foreign studies for example, industrial production is often used as a proxy variable. But generally, industrial production leads the business cycle by a few months. Furthermore, this series does not exist for Switzerland. A disaggregation of GDP into monthly data points thus becomes a logical choice.

The literature describes two different ways of interpolation of data series. Within the first, the missing observations are found by a geometric

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curve function that is optimized by the available GDP data series only. The disadvantage of this disaggregation method is that the interpolated series do not contain additional information compared to the original data. Consequently, it cannot improve the estimation of economic relationships in empirical models. For this reason, an alternative procedure that filters out information from available monthly series - the so-called related series - is clearly preferred. These related series must be correlated with GDP and give the dynamic impulses in order to realistically disaggregate the quarterly data. So, monthly GDP estimations are calculated based on economic and statistical criteria.

The best method to estimate a series in higher frequencies is with a Kalman filter. This versatile algorithm was developed in the field of physics and is used in many practical applications, e.g. in navigation systems of airplanes. Approximately 15 years ago it entered the economic literature, too. The Kalman filter is a dynamically-iterative method to make forecasts that can be continuously improved by consideration of previous realized forecast errors. In our study, a forecast value for the unobserved GDP is computed every month which is based on the assumed development of economic growth and information from predetermined related series. Additionally, the algorithm automatically corrects with an adjusting mechanism the monthly estimations at the end of every quarter to ensure that the sum of three months corresponds to the published quarterly value.

The selection of related series and assumptions for the dynamic development of economic growth are quite difficult since no true reference is available. Only through a combination of statistical and economic selection criteria can an optimal interpolation be achieved.

Using the Kalman filter, we calculate a monthly data series of real GDP that includes 204 observations from 1981 to 1997. The related series are taken from the expenditure side of GDP. While net exports are raised monthly we use retail sales as a monthly approximate value for private consumption. Construction and equipment investments are not available monthly and are therefore replaced by 'not utilized construction loans' that react in the opposite direction. We exclude government spending because of atypical business cycle behavior. A set of alternative related series that rely on the international economic cycle turned out to be insufficiently informative due to large divergences between the Swiss and the foreign economic cycles in the middle of the 1990's.

The resulting monthly series turns out to be statistically more volatile than expected at quarterly frequency. However, the series does not contain any seasonal effects. It provides an adequate possibility to describe the Swiss business cycle in detail and promises to be very useful in future empirical research.

1 Introduction

Gross Domestic Product (GDP) is a key indicator to measure the economic power of a country despite its undisputed weaknesses. This business cycle indicator is a widespread basis for information and planning of strategic decisions. Economic research has always taken this use into account, placing GDP in the center of numerous economic models.

However, for economic studies using quarterly data, a low number of observations can cause serious flaws in the quality of quantitative analysis. Using relatively short time series in vector autoregressions (VAR) for example, many degrees of freedom are used up in the estimates, reducing drastically the power of the estimation. Moreover, monthly frequency is sometimes implied by the assumptions of the model being estimated, while only quarterly data are released. Estimates of Swiss GDP for every quarter are dating back to 1965[1].

Therefore, economists are sometimes forced to use variables that proxy GDP and that are available at a higher frequency. A common proxy in many countries is industrial production (IP) which is often recorded monthly and which comoves closely with GDP. In Switzerland, it is difficult to find such a monthly indicator for aggregate productive activity. The IP index is a series at a quarterly frequency, and other series like business surveys or filled orders can only be used as very imperfect GDP proxies. Hence, in cases where adequate proxies are not at hand, monthly estimates of GDP by interpolation[2] are an appropriate solution to this problem. The goal of this paper is to provide a monthly deseasonalized[3] real GDP series for practitioners and empirical researchers.

Chow and Lin (1971) were the first to present a coherent and easily applicable econometric approach that handles interpolation problems for stock and flow variables. Assuming a linear relation between the series of interest (series for which observations are missing, i.e. monthly GDP) and other data with more frequent recording (so-called related series), they estimate a univariate regression equation. This multiple regression approach is flexible enough to take into account heteroskedasticity and autocorrelation in the residuals.

More recent approaches use of the Kalman filter (Harvey and Pierse (1984),

[1] The official figures of quarterly GDP estimates are published by the State Secretariat for Economic Affairs (seco). Furthermore, an official annual GDP is raised by the Federal Statistics Office from the national income accounts. The quarterly estimates are then corrected and published again to match the official annual statistics.

[2] We regard interpolation as a process of computing flow or stock series at a higher frequency than the original one. In this terminology we do not distinguish between interpolation and distribution which is often done in studies with both, stock and flow variables. Here, we present models that serve exclusively for interpolation and not for out-of-the-sample predictions.

[3] In our view, deseasonalized time series are of greater interest as they are handy to use in economic models. To estimate a seasonalized series, the seasonality would have to be estimated separately and then added to the deseasonalized series, as done for example by the State Secretariat for Economic Affairs for quarterly GDP estimates.

and Bernanke, Gertler and Watson (1997)). This dynamic framework is much more flexible, since it is capable of nesting various models and is more promising because the first two estimates within a quarter are updated every time new information about GDP arrives.

In this paper, the focus is directed on econometric details such as model assumptions about the treatment of stationarity and on the evaluation of various related series. Competing state-space formulations are analyzed theoretically and then evaluated empirically. More precisely, we evaluate two setups with different assumptions about the stochastic behavior of monthly GDP - a static and a dynamic model - using related series with the aim to get the most appropriate interpolated series. Prior to estimating the model, we evaluate competing related series. The potential related monthly series are based on the expenditure definition of GDP and on statistical properties of the comovement with GDP. However, the dearth of Swiss data at higher frequency limits severely the choice of these variables. Therefore, we consider other related series, for example, foreign aggregate economic activity, as alternatives for interpolation. In fact, all related series that closely and robustly move together with quarterly GDP could be appropriate series helping to extract monthly GDP. Then, we sort out series with low information content for the interpolation. With the remaining related series available, we then estimate monthly GDP for Switzerland for 1980-1998[4] within the two setups.

The paper is organized as follows. It starts in section 2 with a short survey of the interpolation literature. In section 3, we briefly review the Kalman filter methodology and present our two interpolation models. In section 4, various related series are evaluated and described. We comment our results in section 5. We then evaluate the appropriateness of these interpolations. Section 6 concludes.

2 Related Literature

As Lanning (1986) illustrates, economists facing missing data have basically two different ways using external information to solve that problem. A first approach is to estimate the missing data simultaneously with the economist's model parameters, thereby considering the missing observations as any other parameters. A second way is a two-step approach where in a first step the missing data, which could be independent from the researcher's model, are interpolated. In a second step, the new augmented series are used to estimate the economist's model. Lan-

[4] We exclusively concentrate our investigation on the period 1980-1998 because these figures are compatible with the new national accounting system in Switzerland, the European System of Integrated Economic Accounts (ESA78). In Switzerland it was introduced in 1996, which the State Secretariat for Economic Affairs used to retropolate quarterly GDP figures back to 1980. See Schwaller and Parnisari (1997) for a very good survey. The structural break is too important between the former and new system for not considering it.

ning found that the simultaneous approach yields estimates of the economist's model parameters that have a greater variance and thus are less reliable than the model parameters estimated with complete data in the second stage. Based on these empirical findings, he suggests the use of the two-step approach. Related literature on the latter procedure can be subdivided in the following three classes[5].

First, the seminal approach for the use of the univariate multiple regression technique with related series was established by Chow and Lin (1971, 1976) who presented a unified framework which allows to treat the interpolation of stocks and flows variables. This approach was able to overcome the problems faced by Friedman (1962) who treated stocks and flows in different ways. Specifically, they could deal with the requirement that if an observed flow value is distributed among the corresponding subintervals, the higher frequency estimates must add up to the observation of the original lower frequency variable. Until now, this static regression approach has been widely used for interpolation due to its easy implementation compared to the state-space approach. This argument seems to more than just outweigh the potential advantages of more sophisticated procedures like the Kalman filter. An annual GDP was for example interpolated for Mexico by DeAlba (1990). Schmidt (1986) gives a good survey of this method interpolating personal income of US regions.

Second, Denton (1971), Fernandez (1981), and Litterman (1983) proposed an approach that minimizes a weighted quadratic loss function of the difference between the series to be estimated and a linear combination of the observed related series. This strategy nests the Chow and Lin regression, but allows for more complicated assumptions about the driving process of the interpolated variable and the use of data in first difference. An illustration with Portuguese data is given in Pinheiro and Coimbra (1993).

Third, Bernanke, Gertler and Watson (1997) have recently used a state-space model to interpolate real GDP in the US. Their approach is to first estimate monthly components of nominal GDP plus the GDP deflator and then to aggregate the individual estimates. The lack of data in Switzerland prevents us from interpolating these components and hence, proceeding as Bernanke, Gertler and Watson. The methodology they followed was suggested by Harvey and Pierse (1984) who provide a general framework - state-space formulation for stock and flow variables, and for stationary and nonstationary series, with and without related series[6] - to estimate missing observations in economic time series. Solving such state-space models requires the use of the Kalman filter. A Kalman filter

[5] The signal extraction literature is very vast and difficult to objectively classify. Here, we only review the interpolation literature, without considering general approaches such as the problem of unobserved components in economic time series or the estimation of irregularly missing data.

[6] This paper does not interpolate without related series. For a broader discussion of this issue see Cuche and Hess (1999).

interpolation was done for Canadian GDP by Guay, Milbourne, Otto and Smith (1990).

3 Models

3.1 Kalman Filter

The multivariate Kalman (1960, 1963) filter is an algorithm for sequentially updating a linear projection on the vector of interest. A general review is given here and a more detailed description in the appendix[7]. In the next section, we present two configurations of the state-space system used for GDP interpolation.

The general state-space representation is given by a system of two vector equations. First, the state or transition equation describes the dynamics of the state vector ($\boldsymbol{\xi}_t$) containing the unobserved variables we want to estimate. The second type of equation represents the observation or measurement equation linking the state vector to the vector containing the observed variables $\left(\mathbf{y}_t^+\right)$. The equations of this system for $t = 1, \ldots, T$ where T is the number of monthly observations are the following:

$$\begin{aligned} \boldsymbol{\xi}_{t+1} &= \mathbf{F}_t \boldsymbol{\xi}_t + \mathbf{C}_t' \mathbf{x}_{t+1} + \mathbf{R}_t \mathbf{u}_{t+1}, & (1) \\ \mathbf{y}_t^+ &= \mathbf{H}_t' \cdot \boldsymbol{\xi}_t + \mathbf{N}_t \mathbf{w}_t. & (2) \end{aligned}$$

In addition to the unobserved and the observed variables of interest, vector equation (1) contains the related series ($\mathbf{x}_t$) as exogenous and explanatory variables. Both equations have error terms $\begin{pmatrix} \mathbf{u}_t & \mathbf{w}_t \end{pmatrix}'$ multinormally distributed $N\left(\begin{pmatrix} \mathbf{0} \\ \mathbf{0} \end{pmatrix}, \begin{pmatrix} \mathbf{Q} & \mathbf{0} \\ \mathbf{0} & \mathbf{G} \end{pmatrix}\right)$. Premultiplied by matrices $\mathbf{R}_t$ and $\mathbf{N}_t$, these orthogonal disturbances transform into non-orthogonal residuals within each vector equation. The coefficients matrices $\mathbf{F}_t$, $\mathbf{C}_t'$, $\mathbf{R}_t$, $\mathbf{H}_t'$, $\mathbf{N}_t$, and the two variance-covariance matrices $\mathbf{Q}$ and $\mathbf{G}$ are estimated by maximizing the log-likelihood function of this system.

3.2 Interpolation Models

3.2.1 Overview

In this section, we adapt the general state-space representation[8] (1) and (2) to our problem in two different ways according to the assumed stochastic processes

[7] Very detailed descriptions of the Kalman filter technique can be found in the Handbook of Econometrics by Hamilton (1994a) and in his textbook (Hamilton, 1994b). Other useful contributions can be found in Aoki and Havenner (1991), Harvey (1989), and Lütkepohl (1993).

[8] The Kalman filter algorithm and the derivation of the log-likelihood function are displayed in Appendix A.

for monthly GDP we can implement in matrix $\mathbf{F}$. The interpolation framework[9] for $t = 1, \ldots, T$ is:

$$\boldsymbol{\xi}_{t+1} = \mathbf{F}\boldsymbol{\xi}_t + \mathbf{C}'\mathbf{x}_{t+1} + \mathbf{R}\mathbf{u}_{t+1}, \quad (3)$$

$$y_t^+ = \mathbf{h}_t' \cdot \boldsymbol{\xi}_t. \quad (4)$$

On one hand, the state vector equation (3) describes the vector dynamics of the unobserved variable, monthly GDP (y_t), stacked in the state vector $\boldsymbol{\xi}_t = \begin{pmatrix} y_t & y_{t-1} & y_{t-2} \end{pmatrix}'$. The $[3 \times 1]$ dimension serves to take the three months within a quarter together in order to satisfy the sum-up constraint. The exact formulation of this vector equation is difficult, because there is no prior knowledge about the true process driving monthly GDP. In order to shed light on this issue, we compare two basic assumptions in the next sections. Throughout this paper we assume time-invariant coefficients for the matrices $\mathbf{F}$, $\mathbf{C}'$ and $\mathbf{R}$.

On the other hand, equation (4) relates the state vector to the observed quarterly GDP (y_t^+). Following Harvey and Pierse (1984), this observation equation represents the constraint that the sum of three monthly observations within a quarter must equal the quarterly observed GDP. Hence, this equality constraint implies that the error term ($\mathbf{N}_t\mathbf{w}_t$) disappears from the observation equation. The sum-up constraint is only introduced by the coefficients vector $\mathbf{h}_t'$.

Both specifications of the state-space model described hereafter correspond to different assumptions about the stochastic process of monthly GDP and influence therefore the representation of the state equation. First, we assume monthly GDP not to follow any stochastic process (static model) by simply setting $\mathbf{F} = \mathbf{0}$. This implies that we do not specifically correct our model for the GDP nonstationarity. The Kalman filter takes this feature into account. Alternatively, we assume that the growth rate of monthly GDP follows a first-order autoregressive process (dynamic model). We thus impose a correction for stationarity on the state-space model. Both selected assumptions are also guided by simplicity and technical considerations concerning the construction of the Kalman filter.

A class of models we do not consider here, but which could be used for interpolation is designed without related series. They extract information from the quarterly series, its autocovariance function, and from assumed economic growth profiles of monthly GDP. However, such interpolated series are purely econometric products and do not yield additional economic information as compared to the quarterly series. There exist even more 'naive' models that do not exhibit a stochastic growth pattern. One of these models calculates three monthly GDP values following a quarterly linear trend centered around the quarterly mean[10]. We take this model as a benchmark for our evaluation procedure.

[9] In all the models, quarterly GDP $\left(y_t^+\right)$ is given each month, $y_1^+ = 0$, $y_2^+ = 0$, $y_3^+ =$ first quarterly value, $y_4^+ = 0$, $y_5^+ = 0$, $y_6^+ =$ second quarterly value, $y_7^+ = 0, \ldots$, etc. Note that with T months to interpolate we observe $\frac{T}{3}$ quarterly values.

[10] Monthly observations are interpolated linearly within a quarter, where we assume that we can split each quarter (except the first one) into an initial value y_{t-3} which is the last month

3.2.2 Static Model

In the static setup, we assume that only related series can explain monthly GDP. So, monthly GDP does not follow a specific growth pattern. The autoregressive part is dropped from the state equation and the related series[11] are exerting influence via the $[3 \times w]$ matrix $\mathbf{C}'$. The observation equation is simply incorporating the sum-up constraint. This implies that $\mathbf{h}_t'$ takes on two different values depending on the month. Using this Kalman filter model, we do not have to assume a driving process for them. We estimate the c coefficients by numerically maximizing the log-likelihood function. The state-space form and the values for $\mathbf{h}_t'$ are given below:

$$\begin{pmatrix} y_{t+1} \\ y_t \\ y_{t-1} \end{pmatrix} = \begin{pmatrix} c_1 & \dots & c_w \\ 0 & \dots & 0 \\ 0 & \dots & 0 \end{pmatrix} \begin{pmatrix} x_{t+1}^1 \\ \vdots \\ x_{t+1}^w \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} u_{t+1} \\ u_t \\ u_{t-1} \end{pmatrix}, \quad (5)$$

$$y_t^+ = \mathbf{h}_t' \cdot \boldsymbol{\xi}_t, \quad (6)$$

where $\mathbf{h}_t'$ takes on the value $\begin{pmatrix} 0 & 0 & 0 \end{pmatrix}$ for $t = 1, 2, 4, 5, 7, \dots, T-1$, and $\begin{pmatrix} 1 & 1 & 1 \end{pmatrix}$ for $t = 3, 6, 9, \dots, T$. We assume that the elements of $\mathbf{u}_{t+1}$ are normally distributed.

3.2.3 Dynamic Model

In this model, we assume that the first difference of monthly GDP follows a stationary AR(1) process: $\Delta y_t = \phi \Delta y_{t-1} + u_t$. Δy_t is the first difference of monthly GDP, ϕ is a coefficient constrained to lie inside the unit circle. In the treatment of the nonstationarity, we rewrite this AR(1) as an AR(2) of the series in level:

$$y_t = (1 + \phi)\, y_{t-1} - \phi y_{t-2} + u_t. \quad (7)$$

This equation written in companion form yields the new state equation (8) for $t = 1, \dots, T$,

$$\begin{pmatrix} y_{t+1} \\ y_t \\ y_{t-1} \end{pmatrix} = \begin{pmatrix} 1+\phi & -\phi & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} y_t \\ y_{t-1} \\ y_{t-2} \end{pmatrix}$$

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of the previous quarter and a step d_t for $t = 4, 5, \dots, T$ according to the following equation:

$$(\varphi y_{t-3} + d_t) + (\varphi y_{t-3} + 2d_t) + (\varphi y_{t-3} + 3d_t) = y_t^+$$

As the quarterly GDP (y_t^+), the step d_t is given each month, $d_4 = 0$, $d_5 = 0$, and $d_6 =$ second quarter step, etc. φ is a scalar that takes on 1 for $t = 6, 9, \dots, T$ and 0 for $t = 4, 5, 7, \dots, T-1$.

[11]Note that a formulation without related series simply sets $\mathbf{C}' = \mathbf{0}$ in equation (3).

$$+\begin{pmatrix} c_1 & \dots & c_w \\ 0 & \dots & 0 \\ 0 & \dots & 0 \end{pmatrix} \begin{pmatrix} x^1_{t+1} \\ \vdots \\ x^w_{t+1} \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} u_{t+1} \\ u_t \\ u_{t-1} \end{pmatrix}. \qquad (8)$$

Equation (6) remains unchanged. Introducing an AR structure, we hope to get valuable new information for describing monthly GDP besides correcting for the GDP nonstationarity.

4 Data

4.1 Signal Extraction from Related Series

A key factor in the present interpolation problem is the signal extraction from related series. Besides the assumption about the dynamics of GDP in the dynamic framework, related series data represent the main information source for both types of interpolation. These related series must fulfill two requirements.

First, they need to be correlated with the series to interpolate. The higher the systematic comovements with GDP are, the stronger is the signal that can be exploited to fill the gaps. On the other hand, if there is only a modest information content, related series come at the cost of a lot of noise that is introduced in the interpolated series. The choice of the related series is therefore crucial in order to successfully estimate a series at higher frequency.

Second, the related series need to be available in the desired higher frequency of the interpolated GDP. The fact that there are not many macroeconomic series available at monthly frequency imposes a strong restriction in Switzerland. This leads us to use other than Swiss variables that we assume to be highly correlated with the desired related series.

The choice of the correct related series requires a thorough investigation along these two points. Amemiya (1980) suggests a joint strategy based on economic-theoretic considerations and on statistical evidence. Economic intuition can often indicate which related series to choose and what functional form they should have. Moreover, it is convenient to have a single statistical measure to choose related series that produce the 'best' result. These two aspects, intuitive approach and choice metrics, should be viewed as forming a single choice package rather than being in competition with each other. They allow to make a final choice of the series which we use in our models. Both elements of the selection process will be presented in detail in the following section.

4.2 Choice of Related Series

4.2.1 Economic Intuition

The most natural way to approach the series selection problem is to split up GDP into its expenditure components, private consumption (C), private domestic investments (I), government expenses (G) and net exports ($X - M$):

$$Y = C + I + G + X - M. \quad (9)$$

With the exception of exports and imports, none of these series is available at the higher frequency. Therefore, it is necessary to identify related data series that proxy for the desired components.

An alternative to breaking GDP into its expenditure components is to benefit from the characteristics of Switzerland as a small open economy and the important comovement between domestic and foreign business cycles. Taking into consideration monthly foreign main economic indicators allows us to choose the related series from a broader data set as Switzerland's closest trade partners have traditionally large statistical databases[12].

4.2.2 Statistical Evaluation

We discuss here the search for individual proxy variables in economic models[13]. Let there be a set of related data series $\mathbf{x}$ out of which variable x_k is unobservable. Furthermore, the variable y which is being interpolated depends linearly on $\mathbf{x}$, according to equation (10).

$$y_t = \alpha_0 + \alpha_1 x_{1,t} + \alpha_2 x_{2,t} + \ldots + \alpha_k x_{k,t} + \ldots + u_t \quad (10)$$

The goal is to choose the best observable proxy for x_k. In cases like this, an informal method often applied is replacing x_k with the variable z_k which yields the highest R^2 of all possible variables z in equation (10). Leamer (1983) shows that if the proxy variables z are assumed to depend linearly on x_k and the error terms being Niid, the best proxy is the one that produces the highest R^2. In the univariate regression $z_{i,t} = \delta_i x_{k,t} + \varepsilon_{i,t}$, the particular z_i which yields the smallest variance $\sigma^2_{\varepsilon_i}$ could be defined as the best proxy. Leamer (1983) uses a likelihood ratio test to show the unambiguously negative relationship between the variance of the error term and the R^2.

Another popular method which can be applied to a wider range of competing models than the one R^2 criterion above is the method of penalized likelihood. The

[12] From the limited degrees of freedom in applying economic theories due to data availability restrictions follows that the statistical evaluation must take a more important place than it usually would according to Amemiya (1980).

[13] At this stage of the text, we describe the data selection within one group of related series as described in section 4.2.1. Choosing the best set of related series is also independent of the different models presented in section 3.

best known examples in this class of criteria which has grown a lot in the last twenty years are the Akaike (1974) Information Criterion (AIC) and the Schwarz (1978) Information Criterion (SIC). In this class of criteria, a term that acts to punish additional coefficients is added to the likelihood function.

4.3 Data Description

For a long time, Switzerland has stayed far behind other European countries in the development of economic statistical data. In 1996, as part of a reform program, national accounting was adapted to ESA78[14]. Thereafter, GDP was calculated differently. The Federal Statistics Office dated the series back to 1980 such that there is now a data sample of more than 18 years or 73 quarterly observations. The figures to be interpolated are deflated and deseasonalized[15].

The related series[16] in the national accounting approach have been identified as retail sales (rs) to proxy for private consumption and as the level of not utilized construction loans to inversely proxy for investment (nl). These monthly available proxies have been selected based on the three criteria described in the previous section. Furthermore, we include exports (X) and imports (M). All series are entered in levels[17]. Government expenditure was dropped in the national accounting approach due to its low covariance with the business cycle. This would have introduced too much noise and moreover, there is no sensible proxy at monthly frequency for it.

As foreign series in our alternative set of related series, we use a composite IP index (*comip*)[18], British IP (*ukip*), and German IP (*brdip*). IP are the foreign monthly available series that move closest with the Swiss business cycle (*gdp*) of all the related foreign series considered (results not reported).

Prior to estimation, we have discarded several potential series based on economic arguments or on the statistical evaluation of the previous section. French IP, Italian IP, survey data by the KOF[19], labor market figures, exchange rates and commodity prices were eliminated statistically. We have neither included variables that have proved to have predicting power for GDP such as the term spread because of unrealistic assumptions on the lead-lag relationship that would have been necessary. Figure 1 and table 1 give an overlook over the series used

[14] Up to and including 1996, Swiss GDP was recorded following the OECD standard 58. According to the Federal Statistics Office, it is planned to adopt the ESA95 standard within a few years.

[15] Deseasonalization was executed using the X12/ARIMA method of the US Bureau of Census.

[16] All the series, with the exception of real GDP given by the State Secretariat for Economic Affairs, are provided by Datastream.

[17] The models transform the level vectors into the desired form. as described in section 3.2.

[18] IP of five countries (major trade partners of Switzerland) are weighted according to the share of Swiss exports to the respective countries in 1996.

[19] Institute for Business Cycle Research of the Swiss Federal Institute of Technology, Zürich.

in this paper.

Fig. 1 and Table 1 here

During the 18 years of observations, the state of the Swiss economy can be roughly divided in two parts. Figure 1 clearly shows the phases of economic growth and prosperity in the 1980's and of stagnation in the 1990's. During its recession, Switzerland exhibited the lowest real GDP growth of all European countries[20].

Table 1 reports basic summary statistics of the quarterly and monthly series that will be used for interpolation. From augmented Dickey-Fuller (ADF) tests, we find that the level of all the series is nonstationary. Hence, we report the figures for growth rates. The ADF tests and the AR(1) regressions on the growth rates confirm that the level of the series is not stationary. The different values of the contemporary cross-correlations also confirm the requirement of the comovements of the related series with quarterly GDP. Finally, these cross-correlations also show why we only consider contemporary relationships between the related series and the quarterly GDP. It is actually very difficult to find robust leads and lags between GDP and our related variables.

5 Results

5.1 Overview

The descriptive statistics of the interpolation results are displayed in table 2. It contains for each model statistical information about the estimated series for the period 1981-1997[21], the related series, the information criterion, the log-likelihood, and key indicators for the annualized growth rate of the monthly interpolated GDP. A mean square error (MSE) with our linear benchmark without related series for the evaluation of the models is given. Table 2 provides the results of competing models - static (#1-3) and dynamic (#4-6) - to identify the most appropriate related series and stochastic assumptions about monthly GDP. For both cases, they represent our best estimations using alternatively *comip*, *nl* or together rs, nl, X, and M.

Table 2 here

[20] To keep things simple and for further research, we decided not to take into account this structural break that would mean to combine our interpolations models with time-varying parameters generally dealt within the Kalman filter framework or with the use of dummy variables.

[21] Due to initial oscillations we discard twelve months of observations which otherwise would have heavily influenced the results.

5.2 Static vs Dynamic Model

Dynamic models systematically produce a regular pattern within a quarter[22] as shown in figure 2. Results show that related series cannot break this pattern because of their low influence on monthly GDP. Compared to the static model where related series introduce a lot of variance through the coefficient matrix $\mathbf{C}'$, dynamically interpolated series are very smooth indicating that the influence of related series remains weak and cannot break the systematic regularity caused by the autoregressive structure.

Fig. 2 here

Figure 2 shows the plot of series #6 and the published quarterly GDP estimates[23]. The cyclical pattern within the quarter is illustrated as an average difference for the three months within the quarter between series #6 and the benchmark for growth and decline periods, respectively. The deviations are significant for the first and the last observation within the quarter and lead us to reject the dynamic models for economic reasons. The shape of the pattern depends on the sign of GDP growth. The only way to eliminate the pattern is to remove its source, the autoregressive structure, and to use models assuming no autocorrelation, our static setup. In these models we can see the related series implementing their movements in the interpolated GDP leading to the desired oscillations and the Kalman filter taking into account the nonstationarity problem[24].

In our case, numerous monthly series display too much noise in order to make an economic sense[25]. The standard deviation of the growth rates of different interpolated series is a good indicator. Hence, all the models generating too much volatility relative to the annualized standard deviation of the quarterly GDP estimates are not displayed[26] in table 2.

Regarding the two sets of related series, one observes that in general related series based on the open economy assumption introduce less volatility in the gen-

[22]The pattern is systematically convex or concave if the model has an autoregressive structure, depending on growth state of the economy.

[23]The three months of each quarter sum to the value of this quarter. However, the line of the monthly interpolated GDP does not exactly pass through the points of quarterly GDP as the latter is simply scaled by a factor of 1/3. The fact that the dots are not exactly on the line cannot be interpreted as a quality indicator.

[24]In a simple model using a constant term as related series, the Kalman filter corrects this phenomenon in producing monthly values of a third of the quarterly observation each.

[25]Additional related series always come at a cost of introducing noise in the interpolated series.

[26]We restrict ourselves to models that produce series with an annualized standard deviation lower than four times the variability of the growth rate of the official quarterly GDP estimates (13%). Comparisons between monthly and quarterly values of industrial production growth in various countries show that the annualized values of monthly standard deviation are 2 to 4 times higher than quarterly ones which serve as a reference.

erated growth rates than the national accounting variables (not reported). For the reported related series *comip* and *nl* this relation is reversed. However, including additional variables in the national accounting approach increases the volatility considerably. To further investigate the characteristics of the most appropriate related series, note that within each model the log-likelihood values show that the national accounting approach is preferable even if not always significantly.

Another evaluation criterion is the mean squared error (MSE) of a model series with respect to the benchmark. We think ex-post that this criterion is a rather soft one and, as there is no clear-cut evidence that the smallest MSE corresponds to a better model. This benchmark does not seem suitable for model evaluation. Moreover, it is only founded on practical reasons and hence, cannot be regarded as an objective measure for model evaluation.

5.3 A Monthly GDP Estimate

Based on this mixed evidence, we recommend and report the series #3. The resulting monthly series turns out to be statistically more volatile than expected at quarterly frequency. However, the series does not contain any seasonal effects nor does it display any regular pattern due to the absence of autoregressive structure.

The graph is given in figure 3 and the corresponding values in table 3.

Fig.3 and Table 3 here

This series is based on the static approach using related series from the national accounting approach. These related series primarily contain more information because GDP is per definition a composite. Moreover, the weakness of foreign industrial production is the temporal mismatch between Swiss and foreign business cycles. As a consequence, there results a lower information content from foreign industrial production, a fact which is underpinned by the observation that the Swiss industrial production is leading GDP. We exclude all dynamic series for economic reasons. First, as mentioned above, the autoregressive structure reduces the influence of related series considerably and second, the regular pattern cannot be justified economically.

From all these arguments, series #3 provides an adequate possibility to describe the Swiss business cycle in detail and promises to be very useful in future empirical research.

6 Conclusion

Due to unavailable proxy variables for the Swiss business cycle at monthly frequency, interpolating GDP offers an accurate way to provide a great number of observations to empirical researchers and practitioners. Adapting the Kalman filter methodology is probably the best way to proceed because of its flexibility and dynamics. We base our interpolation on information extracted from related monthly series in order to economically justify the variation in monthly GDP.

The resulting series issues from an approach with the four related series exports, imports, retail sales and not utilized construction loans, the latter two of which are proxying for consumption and investment. The choice of the related series is based on several economic as well as statistical selection criteria. Furthermore, we find that the best results are achieved when assuming no autocorrelation in monthly real GDP growth. Given a state-space representation of the model this results in using nonstationary series which the Kalman filter automatically corrects for.

Monthly GDP estimates track well the Swiss business cycle between 1980 and 1997 but display a fairly high volatility. It does not contain any seasonal or other regular pattern and represents an ideal manner to introduce Swiss real activity into any empirical economic research.

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Appendix A: Kalman Filter

We show the iteration steps of the Kalman filter and its log-likelihood. All interpolation models are based on equations (3) and (4), $\boldsymbol{\xi}_{t+1} = \mathbf{F}\boldsymbol{\xi}_t + \mathbf{C}'\mathbf{x}_{t+1} + \mathbf{R}\mathbf{u}_{t+1}$, and $y_t^+ = \mathbf{h}_t' \cdot \boldsymbol{\xi}_t$. The Kalman filter iteration, correction, prediction, and MSE steps at time t, is the following loop. At time t assume that $y_0^+, y_1^+ y_2^+, \ldots, y_{t-1}^+, y_t^+$ are known. The related series $\mathbf{x}$ are known but up to $t+1$. The predictions at time $t-1$ are also known: $\hat{\boldsymbol{\xi}}_{t|t-1}, \hat{y}_{t|t-1}^+$. The MSE are also known: $\mathbf{P}_{t|t-1} = \mathrm{MSE}\left(\hat{\boldsymbol{\xi}}_{t|t-1}\right)$, and $\mathrm{MSE}\left(\hat{y}_{t|t-1}^+\right)$.

Correction or update step:

- $\hat{\boldsymbol{\xi}}_{t|t} = \hat{\boldsymbol{\xi}}_{t|t-1} + \underbrace{\mathbf{P}_{t|t-1}\mathbf{h}_t \left(\mathrm{MSE}\left(\hat{y}_{t|t-1}^+\right)\right)^{-1}}_{Gain} \cdot \left(y_t^+ - \hat{y}_{t|t-1}^+\right)$

- $\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \mathbf{P}_{t|t-1}\mathbf{h}_t \left(\mathrm{MSE}\left(\hat{y}_{t|t-1}^+\right)\right)^{-1} \mathbf{h}_t'\mathbf{P}_{t|t-1}$

Prediction step:

- Prediction step: $\hat{\boldsymbol{\xi}}_{t+1|t} = \mathbf{F}\hat{\boldsymbol{\xi}}_{t|t} + \mathbf{C}' \cdot \mathbf{x}_t$

- Prediction step: $\hat{y}_{t+1|t}^+ = \mathbf{h}_{t+1}' \cdot \hat{\boldsymbol{\xi}}_{t+1|t}$

MSE step:

- $\mathrm{MSE}\left(\hat{\boldsymbol{\xi}}_{t+1|t}\right) = \mathbf{P}_{t+1|t} = \mathbf{F} \cdot \mathbf{P}_{t|t} \cdot \mathbf{F}' + \mathbf{RQR}'$

- $\mathrm{MSE}\left(\hat{y}_{t+1|t}^+\right) = \mathbf{h}_{t+1}'\mathbf{P}_{t+1|t}\mathbf{h}_{t+1}$

Log-likelihood function:

Each observation of the sample y_t^+ is normally distributed:

$$y_t^+ \mid \left(y_0^+, y_1^+, y_2^+, \ldots, y_{t-1}^+, \mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_t\right)$$
$$\sim N\left(\left(\mathbf{h}_t' \cdot \hat{\boldsymbol{\xi}}_{t|t-1}\right), \left(\mathbf{h}_t'\mathbf{P}_{t|t-1}\mathbf{h}_t\right)\right).$$

The log-likelihood function for the whole sample is the following expression:

$$\sum_{t=1}^{T} \ln f\left(y_t^+\right) =$$
$$-\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} \ln\left|\mathbf{h}_t'\mathbf{P}_{t|t-1}\mathbf{h}_t\right|$$
$$-\frac{1}{2}\sum_{t=1}^{T}\left(\left(y_t^+ - \mathbf{h}_t' \cdot \hat{\boldsymbol{\xi}}_{t|t-1}\right)\left(\mathbf{h}_t'\mathbf{P}_{t|t-1}\mathbf{h}_t\right)^{-1}\left(y_t^+ - \mathbf{h}_t' \cdot \hat{\boldsymbol{\xi}}_{t|t-1}\right)'\right),$$

$$\sum_{t=1}^{T} \ln f\left(y_t^+\right) =$$
$$-\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} \ln\left|\mathbf{h}_t'\left(\mathbf{F} \cdot \mathbf{P}_{t-1|t-1} \cdot \mathbf{F}' + \mathbf{RQR}'\right)\mathbf{h}_t\right|$$
$$-\frac{1}{2}\sum_{t=1}^{T}\begin{pmatrix} \left(y_t^+ - \mathbf{h}_t' \cdot \left(\mathbf{F}\hat{\boldsymbol{\xi}}_{t-1|t-1} + \mathbf{C}' \cdot \mathbf{x}_t\right)\right) \cdot \\ \left(\mathbf{h}_t'\left(\mathbf{F} \cdot \mathbf{P}_{t-1|t-1} \cdot \mathbf{F}' + \mathbf{RQR}'\right)\mathbf{h}_t\right)^{-1} \cdot \\ \left(y_t^+ - \mathbf{h}_t' \cdot \left(\mathbf{F}\hat{\boldsymbol{\xi}}_{t-1|t-1} + \mathbf{C}' \cdot \mathbf{x}_t\right)\right)' \end{pmatrix}.$$

Table 1 - Descriptive Statistics of Observed Time Series[1]

	gdp [2,3]	*rs*	*nl*	*X*	*M*	*brdip*	*ukip*	*comip*
mean	1.330	3.198	-0.966	4.087	4.289	1.402	1.310	1.516
st.dev.	2.947	46.289	21.386	49.032	51.113	21.732	13.170	12.163
AR(1)[4]	0.252	-0.653 *	0.249 *	-0.569 *	-0.609 *	-0.428 *	-0.220 *	-0.323 *
JB test	0.050	77.884 *	199.177 *	53.174 *	85.518 *	1370.582 *	6.710 *	68.533 *
ADF	-4.379 *	-11.043 *	-2.981 *	-7.913 *	-8.064 *	-6.261 *	-5.298 *	-5.632 *
***gdp,series* (-4)**[5]		0.086	0.361	-0.082	0.060	0.098	-0.117	0.069
***gdp,series* (-3)**		0.001	0.296	0.103	0.156	0.031	0.030	0.049
***gdp,series* (-2)**		0.124	0.372	0.147	0.175	0.118	0.092	0.176
***gdp,series* (-1)**		-0.006	0.304	0.183	0.202	0.336	0.168	0.409
***gdp,series* (0)**		0.089	0.232	0.261	0.088	0.248	0.050	0.267
***gdp,series* (1)**		0.126	0.235	0.254	0.257	0.352	-0.012	0.302
***gdp,series* (2)**		0.123	0.145	-0.019	-0.053	0.212	-0.088	0.187
***gdp,series* (3)**		0.022	0.164	-0.073	0.035	0.143	-0.172	0.089
***gdp,series* (4)**		0.191	0.027	-0.057	-0.186	-0.076	-0.064	-0.120

Note:

[1]Annualized statistical figures are calculated for quarterly growth rates of *gdp* and for monthly growth rates for all other variables.

[2]*gdp* = Gross domestic product; *rs* = Value of retail sales; *nl* = Level of not utilized construction loans; *X* = Exports volume; *M* = Imports volume; *brdip* = Industrial production in Germany; *ukip* = Industrial productin in UK; *comip* = Composite index of industrial production of four neighboring countries.

[3]All variables except *comip* are seasonally adjusted.

[4] ** = significant at 5 % level; * = significant at 1 % level, for the t-test of a zero coefficient on an AR(1) process, for the Jarque-Bera (JB) test of normal distribution, and for the augmented Dickey-Fuller test of unit root (ADF).

[5]Cross-correlation of leads and lags of quarterly growth rates of related series with quarterly *gdp* growth rate.

Table 2 - Interpolation Results[1,2]

Static Model Related Series	#1 *comip*	#2 *nl*	#3 *rs, nl, X, M*
AIC	11.4703	13.9672	10.9534
log likelihood	-569.7796	-707.0603	-564.4899
mean	1.3820	1.2766	1.3828
standard deviation	9.9682	5.2332	12.1565
AR(1)[3]	-0.3851 *	-0.0188	-0.5220 *
Jarque-Bera test	17.7948 *	216.2845 *	2.5033
ADF test	-5.6695 *	-5.2316 *	-6.2078 *
MSE w. benchmark[4]	19095.04	7152.71	23682.66

Dynamic Model Related Series	#4 *comip*	#5 *nl*	#6 *rs, nl, X, M*
AIC	8.0537	8.0498	8.0407
log likelihood	-562.5552	-562.5514	-562.5456
mean	1.3181	1.2846	1.2839
standard deviation	4.3022	4.3011	4.5758
AR(1)[3]	0.2155 *	0.2235 *	0.1080
Jarque-Bera test	289.2578 *	306.5034 *	156.8350 *
ADF test	-5.4785 *	-5.4467 *	-5.5563 *
MSE w. benchmark[4]	3304.75	3282.52	3701.94

Note: [1]*rs* = Value of retail sales; *nl* = Level of not utilized construction loans;
X = Exports volume; *M* = Imports volume; *brdip* = Industrial production in Germany; *ukip* = Industrial production in UK;
comip = Composite index of IP. All estimations include a constant.

[2]The descriptive statistics are for growth rates of the interpolated GDP for 81-97.

[3] ** = significant at 5 % level; * = significant at 1 % level, for all the tests.

[4]Level MSE with benchmark is for the period 81-97.

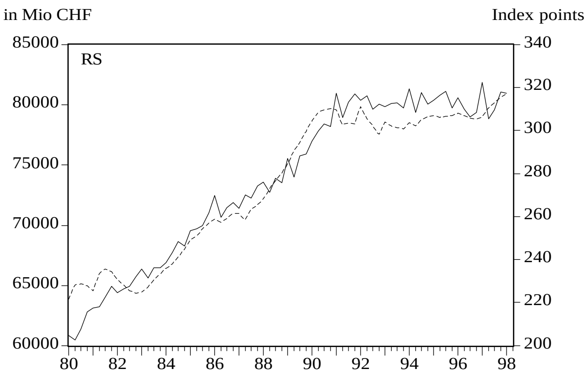
Table 3 - Interpolated GDP[1,2]

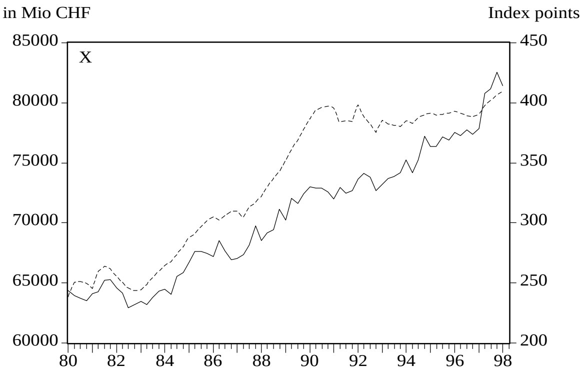
M1 81	21547.19	M1 84	22122.76	M1 87	23741.70	M1 90	25950.00	M1 93	26339.71	M1 96	26518.88
M2 81	21533.94	M2 84	22101.38	M2 87	23803.74	M2 90	26338.53	M2 93	26149.14	M2 96	26319.14
M3 81	21445.75	M3 84	22180.70	M3 87	23399.89	M3 90	26390.93	M3 93	26062.83	M3 96	26454.22
	64526.88		*66404.84*		*70945.33*		*78679.46*		*78551.69*		*79292.24*
M4 81	22019.38	M4 84	22288.97	M4 87	23659.96	M4 90	26353.83	M4 93	26225.01	M4 96	26180.06
M5 81	21924.48	M5 84	22173.38	M5 87	23309.09	M5 90	26370.57	M5 93	26071.01	M5 96	26518.21
M6 81	22034.11	M6 84	22294.04	M6 87	23444.59	M6 90	26636.30	M6 93	25949.31	M6 96	26416.75
	65977.97		*66756.39*		*70413.63*		*79360.69*		*78245.33*		*79115.02*
M7 81	22086.77	M7 84	22293.96	M7 87	23656.61	M7 90	26551.29	M7 93	26208.54	M7 96	26317.14
M8 81	22146.44	M8 84	22646.49	M8 87	24066.38	M8 90	26577.40	M8 93	25932.67	M8 96	26438.84
M9 81	22146.51	M9 84	22427.77	M9 87	23619.80	M9 90	26478.80	M9 93	25968.73	M9 96	26159.72
	66379.72		*67368.22*		*71342.79*		*79607.48*		*78109.94*		*78915.70*
M10 81	22190.22	M10 84	22592.54	M10 87	23942.52	M10 90	26339.18	M10 93	26281.98	M10 96	26123.76
M11 81	21879.02	M11 84	22566.74	M11 87	23608.97	M11 90	26735.52	M11 93	25952.01	M11 96	26452.74
M12 81	22076.78	M12 84	22839.18	M12 87	24130.27	M12 90	26642.29	M12 93	25779.11	M12 96	26234.10
	66146.02		*67998.45*		*71681.76*		*79716.98*		*78013.10*		*78810.60*
M1 82	21847.19	M1 85	22692.26	M1 88	23754.84	M1 91	26570.56	M1 94	26189.55	M1 97	25970.37
M2 82	21828.27	M2 85	22877.37	M2 88	23911.03	M2 91	26354.49	M2 94	25849.91	M2 97	26326.17
M3 82	21836.34	M3 85	23192.12	M3 88	24526.80	M3 91	26655.18	M3 94	26473.88	M3 97	26708.77
	65511.80		*68761.75*		*72192.67*		*79580.23*		*78513.34*		*79005.32*
M4 82	21805.96	M4 85	23141.78	M4 88	24283.51	M4 91	26104.60	M4 94	25860.55	M4 97	26663.08
M5 82	21659.71	M5 85	22895.66	M5 88	24334.66	M5 91	26236.97	M5 94	26172.53	M5 97	26507.56
M6 82	21559.15	M6 85	23053.29	M6 88	24376.48	M6 91	26021.44	M6 94	26226.25	M6 97	26585.48
	65024.82		*69090.73*		*72994.65*		*78363.01*		*78259.34*		*79756.12*
M7 82	21523.04	M7 85	23286.67	M7 88	24443.01	M7 91	26166.88	M7 94	26131.31	M7 97	26782.24
M8 82	21550.88	M8 85	23230.96	M8 88	24622.28	M8 91	26205.93	M8 94	26249.00	M8 97	26895.27
M9 82	21466.62	M9 85	23163.66	M9 88	24644.74	M9 91	26140.26	M9 94	26370.52	M9 97	26514.14
	64540.54		*69681.29*		*73710.03*		*78513.07*		*78750.83*		*80191.65*
M10 82	21575.79	M10 85	23263.82	M10 88	24587.87	M10 91	26184.97	M10 94	26160.96	M10 97	27035.96
M11 82	21351.93	M11 85	23598.24	M11 88	24587.23	M11 91	26350.56	M11 94	26235.31	M11 97	26692.67
M12 82	21411.29	M12 85	23314.73	M12 88	25109.68	M12 91	25896.47	M12 94	26618.72	M12 97	26882.25
	64339.01		*70176.79*		*74284.78*		*78432.01*		*79015.00*		*80610.89*
M1 83	21510.41	M1 86	23465.24	M1 89	24803.75	M1 92	26614.96	M1 95	26334.31		
M2 83	21272.26	M2 86	23281.20	M2 89	24914.50	M2 92	26701.74	M2 95	26438.23		
M3 83	21626.39	M3 86	23743.55	M3 89	25381.97	M3 92	26519.75	M3 95	26354.10		
	64409.06		*70489.99*		*75100.23*		*79836.45*		*79126.64*		
M4 83	21385.29	M4 86	23254.29	M4 89	25386.43	M4 92	26382.97	M4 95	26220.37		
M5 83	21689.72	M5 86	23544.85	M5 89	25186.00	M5 92	26210.13	M5 95	26224.09		
M6 83	21784.81	M6 86	23446.60	M6 89	25533.21	M6 92	26267.09	M6 95	26516.54		
	64859.83		*70245.74*		*76105.64*		*78860.19*		*78961.00*		
M7 83	21713.98	M7 86	23467.64	M7 89	25667.20	M7 92	26001.89	M7 95	26283.06		
M8 83	21681.48	M8 86	23499.52	M8 89	25378.94	M8 92	26293.35	M8 95	26333.46		
M9 83	22044.53	M9 86	23614.40	M9 89	25847.39	M9 92	25957.61	M9 95	26425.39		
	65439.99		*70581.57*		*76893.53*		*78252.86*		*79041.90*		
M10 83	21981.35	M10 86	23652.42	M10 89	25529.57	M10 92	26116.96	M10 95	26088.01		
M11 83	22055.13	M11 86	23764.32	M11 89	25970.32	M11 92	25782.27	M11 95	26460.65		
M12 83	21890.95	M12 86	23549.15	M12 89	26289.12	M12 92	25643.24	M12 95	26582.78		
	65927.43		*70965.89*		*77789.01*		*77542.47*		*79131.45*		

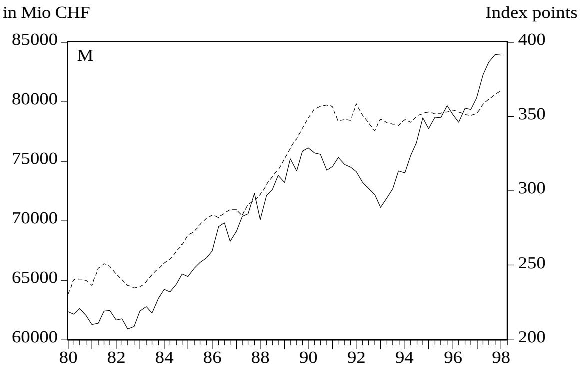
[1] Quarterly values are in italics.

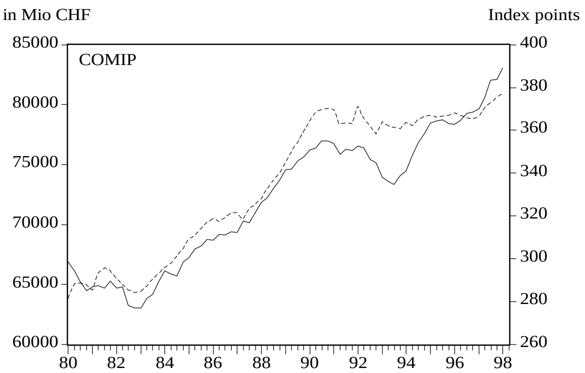
[2] in mio CHF.

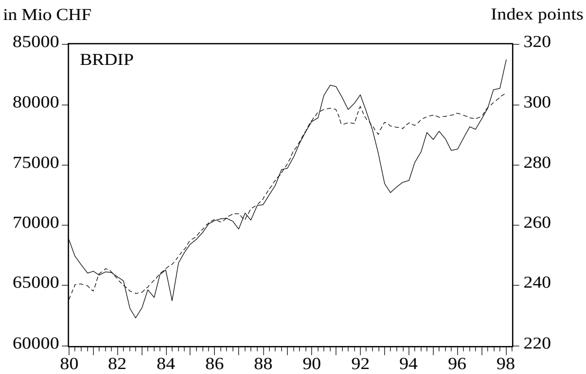
Figure 1 - GDP (-) and Related Series (--)[1,2]

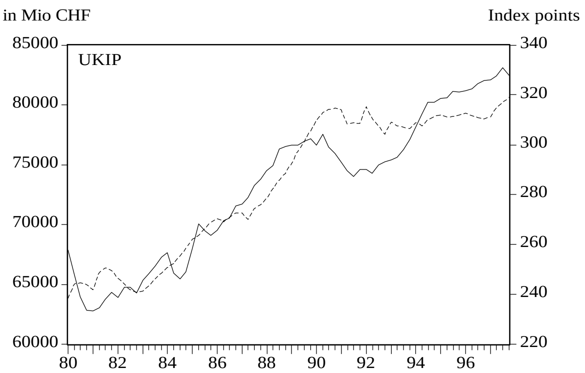












[1] *gdp* = Quarterly Gross Domestic Product; *rs* = Value of retail sales; *nl* = Level of not utilized construction loans; *X* = Exports volume; *M* = Imports volume; *brdip* = Industrial production in Germany; *ukip* = Industrial production in UK; *comip* = Composite index of industrial productions.

[2] Source: Datastream.

Figure 2 - Quarterly GDP and Interpolated Series with Pattern

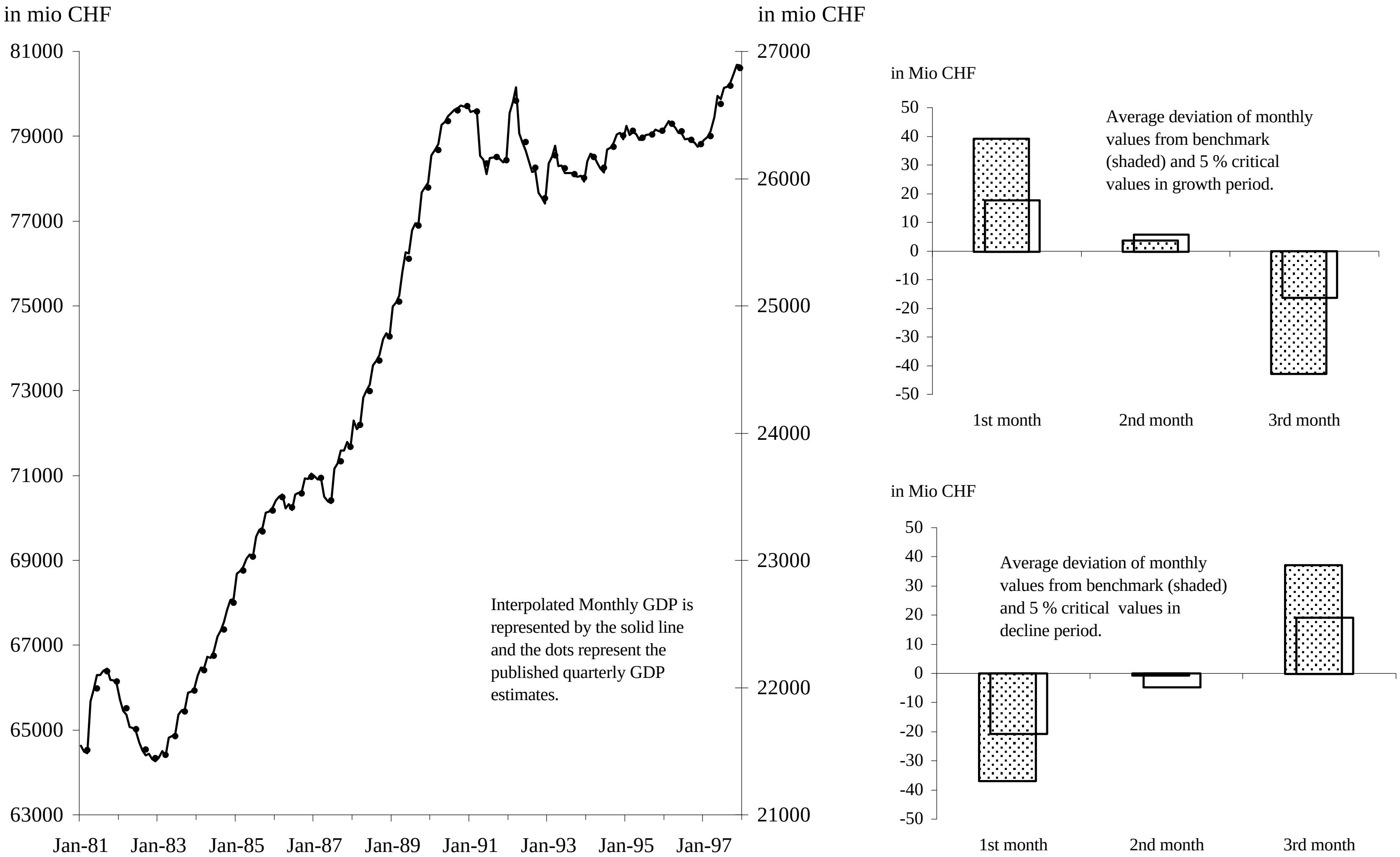


Figure 3 - Monthly GDP 1981-1997