# Permanent Components in Swiss Macroeconomic Variables

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## 1. INTRODUCTION

Since the beginning of the 80ies the traditional modelling of the trend in macroeconomic series as a linear trend has been given up. This was motivated by the work of NELSON and PLOSSER (1982), who found considerable evidence for stochastic trends in most economic time series. This means that shocks have not only a transitory, but also a permanent effect on the level of macroeconomic variables. These findings supported the view of the «New Classicals», who argued that fluctuations in variables are due to permanent shocks and can be interpreted as a transition to the new steady state growth path[1].

In subsequent research, econometric analysis tried to establish the importance of permanent components, and several methods to estimate stochastic trend components were presented. The work of BEVERIDGE and NELSON (1981), WATSON (1986), CLARK (1987), COCHRANE (1988) and CAMPBELL and MANKIW (1988, 1987a) have to be mentioned here. But univariate decompositions do not bring new economic insights, as the existence and the estimation of a stochastic trend say nothing about its source. However, multivariate analyses permit a greater variety of economic interpretation, and using the concept of cointegration, the long-run equilibrium relationships between variables that are postulated by economic theory can be included in the estimation. Several methods to estimate structural components in time series were presented by BLANCHARD and QUAH (1989), SHAPIRO and WATSON (1988), KING, PLOSSER, STOCK and WATSON (1991) and GONZALO and GRANGER (1991). BONJOUR and KUGLER (1993) and KUGLER (1992) applied the two first mentioned methods to Swiss data and found evidence for the importance of supply shocks in the long and in the short run. However, in their analyses, demand shocks also explain a substantial part of the short run fluctuations in the observed time series.

This paper estimates the influence of permanent real and nominal shocks to quarterly Swiss data by applying the method of KING et al. (1991) and compares the estimate of the trend component of GDP with those estimated by applying the methods of GONZALO and GRANGER (1991) and BEVERIDGE and NELSON (1989). Moreover, the evidence

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1. See e.g. models of KYDLAND and PRESCOTT (1982), LONG and PLOSSER (1983).

obtained using quarterly data adjusted only for deterministic seasonality will briefly be compared to that obtained using a set of quarterly series adjusted by the commonly used Census X-11 method. The next section motivates the analysis by describing a simple economic model. Section 3 sketches the econometric methodologies. The results are found in section 4. A brief summary is then given in section 5.

## 2. AN ECONOMIC MODEL

To motivate the analysis we start with a simple neoclassical model as advocated by KING, PLOSSER and REBELO (1988) and also used in KING et al. (1991). *Output*, $Y_t$, is produced via a Cobb-Douglas production function:

$$Y_t = \lambda_t K_t^{1-\theta} N_t^{\theta},$$

where $K_t$ is the capital stock and $N_t$ is labor input. Total factor productivity follows a logarithmic random walk:

$$\log(\lambda_t) = \mu_\lambda + \log(\lambda_{t-1}) + \xi_t .$$

The innovations $\xi_t$ are i.i.d. normally distributed with mean 0 and variance $\sigma^2$. $\mu_\lambda$ is the average growth rate of productivity and the $\xi_t$'s are the deviations of actual growth rate from the average.

In the neoclassical model with deterministic trend[2] log per capita output, consumption and investment all grow at the same rate $\mu_\lambda/\theta$ (SOLOW [1988]). In other words, the great ratios $C_t/Y_t$ and $I_t/Y_t$ are constant. In the model with a stochastic trend, the innovations $\xi_t$ change the future rate of productivity growth permanently. The common stochastic trend of production, consumption and investment is then $\log(\lambda_t)/\theta$ with growth rate $(\mu_\lambda + \xi_t)/\theta$. So the great ratios become stationary processes. In terms of cointegration, this means that in a three-variables system with real per capita production, real per capita consumption and real per capita investment, $(y_t, c_t, i_t)$, all variables taken in logs are, according to the common stochastic trend, $I(1)$-variables but the linear combinations $c_t - y_t$ and $i_t - y_t$ are $I(0)$ or stationary. The dynamic responses to a permanent innovation shock $\xi_t$ then depend on specifications on preferences and propagation mechanisms. In general, the innovation shock sets off transitional dynamics, so that work effort and the great ratios may change temporarily until a new steady state growth path is reached.

When nominal variables are included in the analysis, the impact of nominal shocks on short run fluctuations in real variables can be estimated. In this case additional cointegrating relations may arise. Here we include the money demand equation:

2. That is when $\lambda_t = e^{\mu_\lambda t}$.

$$m_t - p_t = \beta_y y_t - \beta_R R_t + v_t \,.$$

$m_t$ - $p_t$ is the logarithm of per capita real balances, $R_t$ is the nominal interest rate and $v_t$ is the money-demand disturbance. Additionally we take the Fisher relation:

$$R_t = r_t + E_t \Delta p_{t+1} \,,$$

where $r_t$ is the *ex ante* real interest rate, $p_t$ is the logarithm of the price level and $E_t \Delta p_{t+1}$ is the expected inflation rate between $t$ and $t + 1$. If real balances, output and the nominal interest rate are integrated but the process of $v_t$ is stationary, then the three variables must be cointegrated. Likewise, if the real interest rate is $I(0)$ but inflation is $I(1)$, then nominal interest rate and inflation are cointegrated. So the three permanent components driving the data of this model in the long run can be associated with a productivity shock, an inflation shock and a real interest rate shock. Moreover, according to the theory of cointegration, when three common trends appear in a six-variables system, there are three cointegrating vectors that transform the integrated variables to stationary linear combinations.

Using the estimate of a vector error correction model (VECM) for the six-variables ($y_t$, $c_t$, $i_t$, $m_t - p_t$, $R_t$, $\Delta p_t$) the subsequent analysis will try to answer following questions. First, is there evidence for cointegrating vectors in the data and if there is, are they consistent with those postulated by theory. Second, after identifying structural components, how much variation in the data is explained by permanent components, and third, what part of the forecast error variance is attributable to permanent innovations of nominal variables. Evidence will be presented for data adjusted only for deterministic seasonality and for data adjusted with Census X-11.

## 3. THE ECONOMETRIC METHODOLOGY

### *3.1 Estimating common trends*

The first step consists in estimating a VECM for the variables included in the analysis:

$$\Delta X_t = \rho + \sum_{i=1}^{p-1} B_i \Delta X_{t-i} - \Pi X_{t-p} + \varepsilon_t \qquad (1)$$

where $X_t$ has dimension $n{\times}1$ and

$$\varepsilon_t \sim i.i.d.N_n(0, \Sigma_\varepsilon) \,.$$

We assume that there is evidence for $r$ cointegrating vectors, so $\Pi$ can be written as

$$\Pi = \underset{(n\times r)(r\times n)}{\alpha\beta'} \tag{2}$$

where the cointegrating vectors form the $r$ columns of $\beta$ and the adjustment coefficients of the error correction form are found in $\alpha$. We know that in this case there must be $k = n - r$ common trends driving the data. Now, inverting (1) gives the reduced form of the system

$$\Delta X_t = \mu + C(L)\varepsilon_t \tag{3}$$

$$\text{with } C_0 = I_n.$$

From the reduced form we want to estimate the structural form of $\Delta X_t$:

$$\Delta X_t = \mu + \Gamma(L)\eta_t \tag{4}$$

$$\eta_t \sim i.i.d.N_n(0, \Sigma_\eta),$$

in which the elements of $\eta_t$ can be given a specific economic interpretation. The structural form (4) has the reduced form (3) if $\varepsilon_t = \Gamma_0\eta_t$ and $C(L) = \Gamma(L)\Gamma_0^{-1}$. So if we know the matrix $\Gamma_0$, the structural components and the coefficients of $\Gamma(L)$ can be recovered from (3). Two sets of restrictions will help identify $\Gamma_0$. First, due to the fact that $k$ common trends are present in the data, $k$ elements of $\eta_t$ have a permanent effect on $X_t$. The matrix of long-run multipliers $\Gamma(1)$ can then be partitioned in a $n\times k$ matrix A, in which we have the long-run effects of the permanent components of $\eta_t$ on $X_t$ and a $n\times r$ matrix of zeroes reflecting the fact that the remaining $r$ transitory components have no long-run effect on $X_t$,

$$\Gamma(1) = [A\ 0].$$

With these restrictions the structural permanent components can be identified. Second, with the additional assumption that the permanent and the transitory components are uncorrelated (in other words, that $\Sigma_\eta$ is block-diagonal), the coefficients of the impulse responses can be identified.[3]

Moreover, if we solve (4) for $X_t$ we get

3. See Appendix of KING et al. (1991) or MELLANDER et al. (1992) for a detailed discussion of the identifying restrictions.

$$X_t = X_0 + t\mu + \Gamma(1)\sum_{i=1}^{t}\eta_t + \Gamma^*(L)\eta_t \tag{5}$$

$$\text{where } \Gamma_j^* = \sum_{i=j+1}^{\infty}\Gamma_i.$$

This corresponds to the common trends representation of $X_t$ as developed by STOCK and WATSON (1988) and also to a decomposition of $X_t$ into a trend and a transitory component,

$$X_t = X_t^P + X_t^S, \tag{6}$$

where, if $X_0 = 0$, then $X_t^P = t\mu + \Gamma(1)\Sigma_{i=1}^t\eta_t$. In the univariate case this representation reduces to the BEVERIDGE and NELSON (1981) decomposition of a time series in a permanent and a transitory component.

### *3.2 Estimating common factors*

The second method used in this paper is the one presented by GONZALO and GRANGER (1991) who estimate the common $I(1)$ factors of variables without economic restrictions. They set up a factor model for the multivariate system

$$X_t = A_1 f_t + A_2\tilde{z}_t \tag{7}$$

and identify it with two restrictions. First, the $k$ $I(1)$ common factors of $f_t$ are linear combinations of the variables in $X_t$ and second, the transitory component $\tilde{z}_t$ has no permanent effect on $X_t$. Transforming the VECM in (1) by setting

$$f_t = \alpha'_\perp X_t,$$

where $\alpha'_\perp$ is the orthogonal complement of $\alpha$ in (1), we get

$$\Delta f_t = \alpha'_\perp \rho + \sum_{i=1}^{p-1}\alpha'_\perp B_i A_1 \Delta f_{t-i} + \sum_{i=1}^{p-1}\alpha'_\perp B_i A_2 \Delta\tilde{z}_{t-1} + \alpha'_\perp \varepsilon_t. \tag{8}$$

Under the assumption of cointegration the level of the error correction term $\beta' X_{t-p}$ cancels out of the equation and we see that the transitory component $\tilde{z}_t$ may have only a transitory impact on $\Delta f_t$ and thus a transitory effect on $f_t$ and on $X_t$. Remember that the linear combinations $\beta' X_t$ are stationary, so that the transitory component can be set to $\tilde{z}_t = \beta' X_t$. System (7) can then be rewritten as

$$X_t = A_1 \alpha'_\perp X_t + A_2 \beta' X_t \tag{9}$$

and as the matrix $[\alpha_\perp\ \beta]'$ has full rank[4], the factor model (7) exists.

## 4. RESULTS

### *4.1 The data and their seasonal adjustment*

In this section the methods outlined above are applied to quarterly, seasonally unadjusted Swiss data[5] covering the period 65:1 to 90:2. Real GDP (XS), real consumption (CS), real gross investment (INV), real balances (MP), a short term interest rate (INTSEU, 3-months Euromarket interest rate) and the GDP deflator as a measure for the price level (PX) are included in the analysis. The data for the money supply were completed from 89:2 to 90:2 with observations published by the Swiss National Bank. Real balances is measured by the money supply (M1) deflated with the price level. All variables but the interest rate are taken in logs.

4. See GONZALO and GRANGER (1991), proposition 3.
5. Data source: BAK (Basler Konjunkturforschung), Basel.

**Table A.1: Unit root tests of HYLLEBERG, ENGLE, GRANGER und YOO, (regression sample: 66:4 to 90:2)**

$$\Delta_4 x_t = \beta_1 t + \sum_{i=0}^{3} \delta_i D_{it} + \pi_1 y_{1t-1} + \pi_2 y_{2t-1} + \pi_3 y_{3t-2} + \pi_4 y_{3t-1} + \sum_{j=1}^{p} \Phi_j \Delta_4 x_{t-j} + \varepsilon_t$$

$$y_{1t} = (1 + L + L^2 + L^3)\, x_t$$
$$y_{2t} = -(1 - L + L^2 - L^3)\, x_t$$
$$y_{3t} = -(1 - L^2)\, x_t$$

| | $p$ | $\pi_1$ | $\pi_2$ | $\pi_3$ | $\pi_4$ | F–value of $\pi_3 = \pi_4 = 0$ |
|---|---|---|---|---|---|---|
| XS | 0 | -0.206E-01 | -0.405 | -0.587 | -0.380 | |
| | | (-1.98) | (-5.09)*** | (-6.48) | (-4.22) | 41.71*** |
| CS | 2 | -0.235E-01 | -0.269 | -0.781E-01 | -0.264E-01 | |
| | | (-2.66) | (-3.77)*** | (-1.43) | (-0.48) | 1.15 |
| INV | 0 | -0.190E-01 | -0.479 | -0.381 | -0.206 | |
| | | (-1.17) | (-5.50)*** | (-4.95) | (-2.68) | 18.02*** |
| MP | 0 | -0.303E-01 | -0.537 | -0.562 | -0.504 | |
| | | (-2.63) | (-5.62)*** | (-5.87) | (-5.30) | 49.56*** |
| INTSEU[1] | 0 | -0.549E-01 | -0.544 | -0.540 | -0.558 | |
| | | (-3.78)** | (-5.82)*** | (-5.88) | (-6.12) | 60.43*** |
| PX | 1 | -0.145E-01 | -0.170 | -0.466 | -0.112 | |
| | | (-2.45) | (-2.22) | (-4.90) | (-1.06) | 12.58*** |

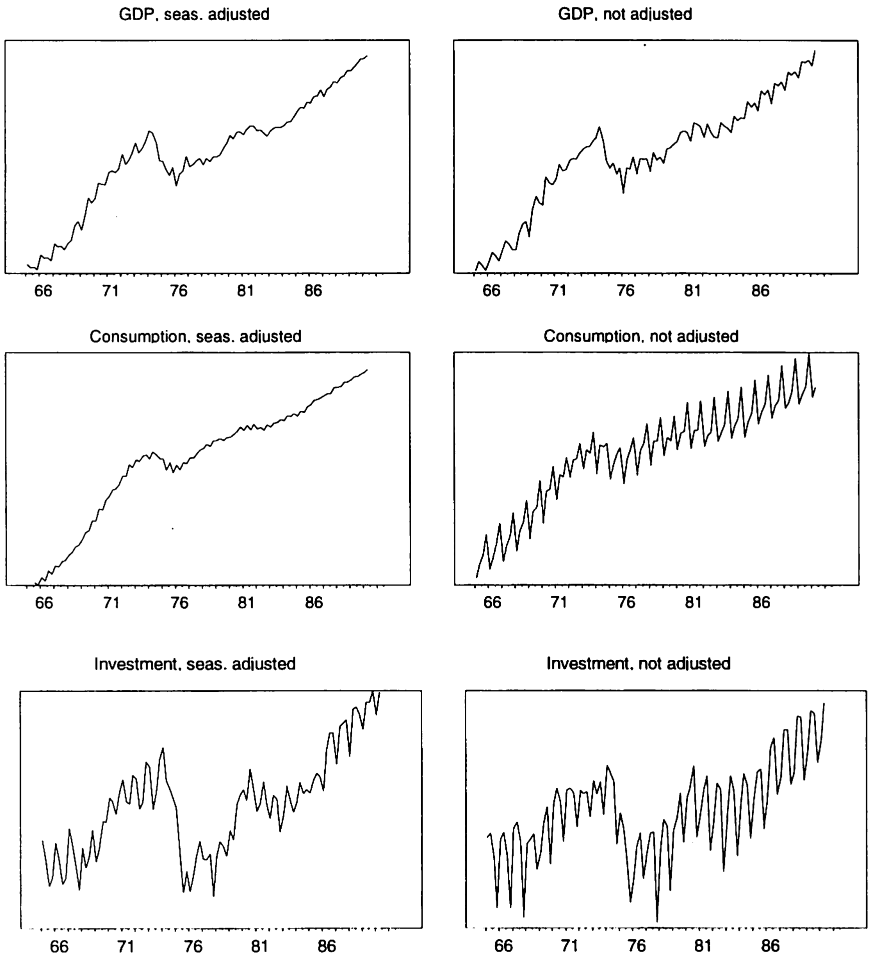
"t"-values are given in parentheses. *, **, *** means significant at the 90%, 95% and 99% significance level, respectively.

[1] Only a constant was included in the regression.

Table A.1 reports unit root tests of HYLLEBERG, ENGLE, GRANGER and YOO (HEGY) (1990) for the seasonally unadjusted data. In this framework testing for a unit root at the zero frequency is done by testing the hypothesis $\pi_1 = 0$. Similarly, testing $\pi_2 = 0$ and $\pi_3 = \pi_4 = 0$ is equivalent with testing for unit roots at seasonal frequencies, namely two cycles and one cycle per year, respectively. The lag length $p$ is augmented until the hypothesis of white noise residuals cannot be rejected by the Ljung-Box Q-statistic. For GDP, investment and real balances the unit root hypotheses cannot be rejected at the zero frequency. As there seem to be no unit roots at seasonal frequencies, these three series are adjusted only for deterministic seasonality by Kalman filtering[6]. The remaining stochastic seasonal component is left in the series. For consumption and the price level

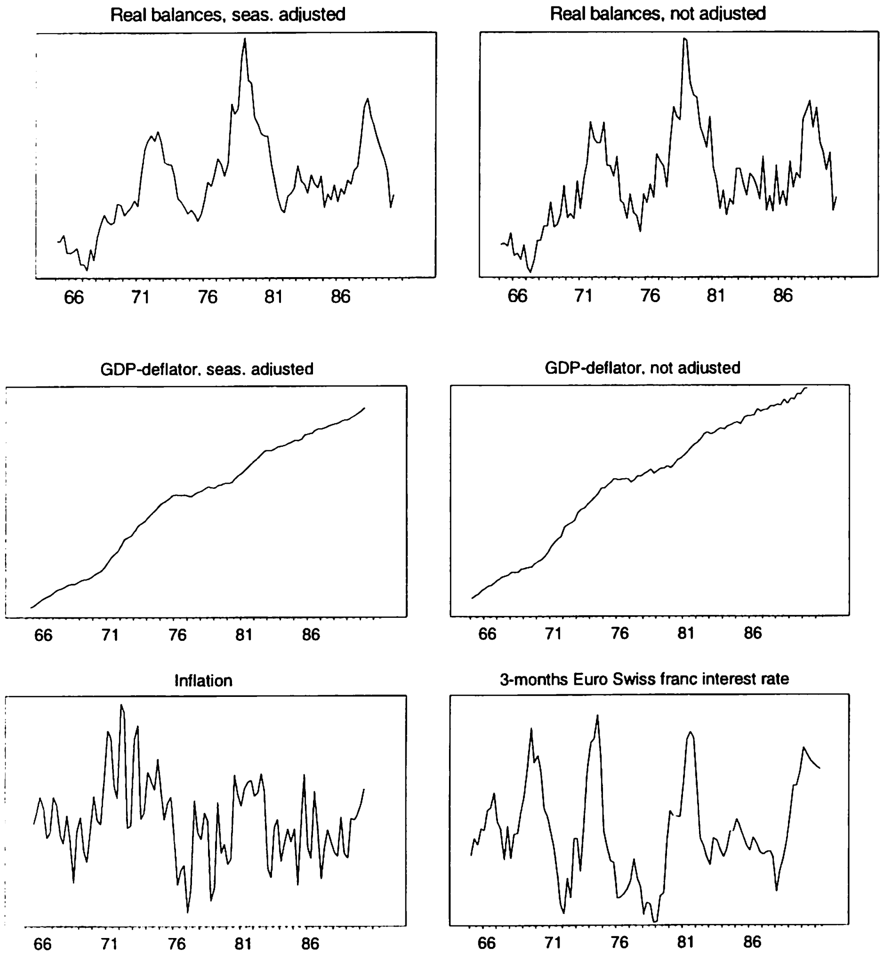
6. The deterministic seasonal component is estimated by an unobserved component model using the EM-algorithm proposed in WATSON and ENGLE (1983).

**Figure B.1: Plots of adjusted and unadjusted time series**




the unit root hypotheses cannot be rejected at frequencies $\pi / 2$ and $\pi$, corresponding to one and to two cycles per year, respectively. Before adjusting for deterministic seasonality, consumption is filtered by $(1 + L^2)$ and the price level by $(1 + L)$. As the interest rate is independent of quarterly cycles and does not display a typical seasonal pattern, this series is not adjusted for the analysis. By comparing the adjusted with the unadjusted series in figure B.1, we can see that consumption and investment have both important

**Figure B.1: (continued) Plots of adjusted and unadjusted time series**




seasonal components. However, after adjustment, consumption does not display a seasonal pattern any more, while obviously, investment retains a stationary stochastic seasonal component.

### *4.2 Unit root and cointegration tests*

After seasonally adjusting the series, GDP, consumption, investment and real balances are transformed to per capita series dividing them by the working age population[7]. Before analyzing the cointegration properties, Dickey-Fuller and Phillips-Perron tests for a unit root were performed in order to test for the order of integration of the per capita series[8]. Again the unit root hypotheses for the level of all series are not rejected. According to Dickey-Fuller even an $I(2)$-process is not rejected for consumption and the price level. A nonstationary inflation rate is consistent with economic theory. A further investigation will follow in the multivariate analysis. In contrast, an $I(2)$-process for consumption is inconsistent with the property of stationary great ratios derived in section 2. Therefore, according to the Phillips-Perron results that reject a unit root for the first differences of the series, an $I(1)$-process will be assumed for consumption in the following. Worth mentioning are also the ambiguous results for the interest rate but as the unit root hypothesis cannot definitely be rejected, we also assume nonstationarity for this series.

For the cointegration and the following multivariate analysis the lag length $p$ is chosen according to the Hannan-Quinn criterion. In table A.2, Johansen's trace statistic gives evidence for 3 cointegration vectors. The evidence is enforced when applying Stock-Watson's tests for common trends. The hypothesis of 3 against 2 common trends is not rejected. Tests concerning the structure of the cointegration vectors are given in table A.3. In Panel A the stationarity of the variables is tested once more in the multivariate framework. Again, the hypothesis of non-stationarity for the levels of the real variables as well as for real balances and the inflation rate cannot be rejected. For the interest rate, however, the $I(1)$ hypothesis is rejected at a high significance level. Nevertheless, according to the univariate results and the theoretical exposition in section 2, an $I(1)$-process for the interest rate will be maintained. In panel B we test wether the cointegrating vectors postulated by theory are vectors of the cointegration space. The hypotheses of stationary great ratios (using the first two vectors) and a stationary real interest rate (using the last vector) are rejected. The restrictions that the great ratios and the real interest rate may have a stationary relationship with real balances are also rejected (see table A.3, panel C, $\bar{H}_{3.1}$). Only the weaker restrictions, that the great ratios have stationary relationships with all other variables are not rejected. For the subsequent analysis the cointegration vectors are therefore estimated subject to these restrictions.

7. As the working age population is available only as seasonally adjusted time series, the transformation to per capita series is made after seasonal adjustment of the other variables.
8. The results are not displayed in the paper in order to save space. They are obtainable upon request from the author.

**Table A.2: Multivariate cointegration tests: Johansen's und Stock-Watson's statistics**

$$\Delta X_t = \rho + \Sigma_{i=1}^{p-1} B_i \Delta X_{t-i} - \Pi X_{t-p} + \varepsilon_t$$

$\Pi = \alpha\beta'$ $\beta$: $(n \times r)$ matrix of the cointegration vectors

$$X'_t = [y, c, i, m - p, R, \Delta p]$$

| $p$ | $r$ | trace-statistic | $k$ | $q_\tau^c\,(k, k - 1)$ statistic | $q_\tau^f\,(6,3)$ statistic |
|---|---|---|---|---|---|
| 3 | ≤5 | 0.35 | 6 | -91.75*** | |
| | ≤4 | 6.97 | 5 | -95.94*** | |
| | ≤3 | 24.77 | 4 | -82.76*** | -26.47 ($P_{0.1}$= -27.7) |
| | ≤2 | 50.38** | 3 | -21.61 | |
| | ≤1 | 77.78*** | | | |

*, **, *** means significant at the 90%, 95% and 99% significance level, respectively.

**Table A.3: Hypotheses testing in the 6-variables system**

**A: Stationarity of the variables**

| | $y$ | $c$ | $i$ | $m$-$p$ | $R$ | $\Delta p$ |
|---|---|---|---|---|---|---|
| statistic | 18.60 | 13.67 | 22.10 | 16.29 | 2.38 | 8.59 |
| significance | (0.00) | (0.00) | (0.00) | (0.00) | (0.50) | (0.04) |

**B: Testing cointegration vectors**

| | | statistic | significance |
|---|---|---|---|
| $\underline{H}_{3.2}$ | $\underline{H} = [-1\ 1\ 0\ 0\ 0\ 0]'$ | 10.40 | (0.02) |
| $\underline{H}_{3.3}$ | $\underline{H} = [-1\ 0\ 1\ 0\ 0\ 0]'$ | 17.06 | (0.00) |
| $\underline{H}_{3.4}$ | $\underline{H} = [0\ 0\ 0\ 0\ 1\ -1]'$ | 13.93 | (0.00) |

**C: Testing the cointegration space**

| | | statistic | significance |
|---|---|---|---|
| $\overline{H}_{3.1}$ | $\overline{H} = \begin{bmatrix} -1 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$ | 20.87 | (0.00) |
| $\overline{H}_{3.2}$ | $\overline{H} = \begin{bmatrix} -1 & -1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$ | 3.72 | (0.29) |

### *4.3 Impulse response functions and variance decomposition*

The VECM in (1) is estimated[9] using the restricted cointegration vectors of table A.4. Because the postulated cointegrating vectors are not found in the data, their interpretation is not obvious any more and the estimation of the structural model becomes more complex[10]. However, as we find evidence for 3 common trends, the interpretation of the

9. I wish to thank MARK WATSON and ANDERS WARNE for sending me computer programs which were helpful for the following analysis.
10. See MELLANDER et al. (1992) and WARNE (1991).

structural shocks driving the system is left unchanged. The additional two restrictions, that the inflation shock has no permanent effect on real GDP and that the interest rate shock has no permanent effect on the inflation rate, identify the structural model. Using these restrictions together with the empirical cointegration vectors, the restrictions on the matrix of long-run multipliers and on the covariance matrix of the structural innovations yields the following estimated common trends model:

$$X_t = X_0 + t\hat{\mu} + \begin{bmatrix} \underset{(0.0085)}{0.0168} & \underset{(-)}{0.0000} & \underset{(-)}{0.0000} \\ \underset{(0.0204)}{0.0318} & \underset{(0.0033)}{0.0082} & \underset{(0.0024)}{0.0097} \\ \underset{(0.0177)}{0.0269} & \underset{(0.0032)}{0.0023} & \underset{(0.0026)}{0.0103} \\ \underset{(0.0139)}{0.0162} & \underset{(0.0045)}{0.0230} & \underset{(0.0014)}{-0.0057} \\ \underset{(0.0003)}{-0.0004} & \underset{(0.0001)}{-0.0006} & \underset{(0.00003)}{0.0001} \\ \underset{(0.0017)}{0.0024} & \underset{(0.0005)}{0.0025} & \underset{(-)}{0.0000} \end{bmatrix} \cdot \begin{bmatrix} \hat{\tau}_{pr,t} \\ \hat{\tau}_{in,t} \\ \hat{\tau}_{ir,t} \end{bmatrix} + \hat{\Gamma}^*(L)\hat{\eta}_t$$

$$\begin{bmatrix} \hat{\tau}_{pr,t} \\ \hat{\tau}_{in,t} \\ \hat{\tau}_{ir,t} \end{bmatrix} = \begin{bmatrix} \hat{\tau}_{pr,t-1} \\ \hat{\tau}_{in,t-1} \\ \hat{\tau}_{ir,t-1} \end{bmatrix} + \begin{bmatrix} \hat{\eta}_{1t} \\ \hat{\eta}_{2t} \\ \hat{\eta}_{3t} \end{bmatrix}.$$

**Table A.4: Restricted cointegrating vectors under $\overline{H}_{3.2}$.**

$$\beta = \begin{bmatrix} -3.8209 & -2.2627 & -2.3781 \\ 1.3876 & 0.9524 & -6.3450 \\ 2.4333 & 1.3103 & 8.7231 \\ 11.2133 & 0.0126 & 2.7983 \\ 178.2204 & -161.7033 & -88.4660 \\ -70.3884 & -40.4013 & -32.3992 \end{bmatrix}$$

**Table A.5: Variance decomposition of dummy adjusted variables**

**A. Fraction attributable to productivity shock**

| Horizon | $y$ | $c$ | $i$ | $m$-$p$ | $R$ | $\Delta p$ |
|---|---|---|---|---|---|---|
| 1 | 0.58 | 0.45 | 0.36 | 0.17 | 0.19 | 0.00 |
| 4 | 0.63 | 0.64 | 0.40 | 0.25 | 0.16 | 0.07 |
| 8 | 0.81 | 0.76 | 0.57 | 0.27 | 0.13 | 0.13 |
| 12 | 0.89 | 0.80 | 0.66 | 0.26 | 0.14 | 0.27 |
| 16 | 0.92 | 0.81 | 0.70 | 0.25 | 0.14 | 0.37 |
| 20 | 0.94 | 0.82 | 0.72 | 0.25 | 0.14 | 0.41 |
| 24 | 0.95 | 0.83 | 0.73 | 0.26 | 0.14 | 0.42 |
| 120 | 0.99 | 0.86 | 0.82 | 0.30 | 0.21 | 0.46 |
| $\infty$ | 1.00 | 0.86 | 0.87 | 0.32 | 0.32 | 0.45 |

**B. Fraction attributable to inflation shock**

| Horizon | $y$ | $c$ | $i$ | $m$-$p$ | $R$ | $\Delta p$ |
|---|---|---|---|---|---|---|
| 1 | 0.09 | 0.08 | 0.06 | 0.46 | 0.18 | 0.17 |
| 4 | 0.14 | 0.06 | 0.07 | 0.59 | 0.34 | 0.16 |
| 8 | 0.07 | 0.07 | 0.04 | 0.61 | 0.38 | 0.13 |
| 12 | 0.04 | 0.09 | 0.04 | 0.64 | 0.37 | 0.15 |
| 16 | 0.03 | 0.09 | 0.03 | 0.65 | 0.37 | 0.20 |
| 20 | 0.02 | 0.09 | 0.03 | 0.65 | 0.38 | 0.23 |
| 24 | 0.02 | 0.08 | 0.03 | 0.65 | 0.39 | 0.26 |
| 120 | 0.00 | 0.06 | 0.01 | 0.65 | 0.52 | 0.44 |
| $\infty$ | 0.00 | 0.06 | 0.01 | 0.64 | 0.64 | 0.55 |

**C. Fraction attributable to real interest rate shock**

| Horizon | $y$ | $c$ | $i$ | $m$-$p$ | $R$ | $\Delta p$ |
|---|---|---|---|---|---|---|
| 1 | 0.15 | 0.10 | 0.10 | 0.03 | 0.01 | 0.00 |
| 4 | 0.05 | 0.08 | 0.21 | 0.04 | 0.03 | 0.01 |
| 8 | 0.02 | 0.07 | 0.19 | 0.04 | 0.05 | 0.03 |
| 12 | 0.01 | 0.06 | 0.16 | 0.05 | 0.05 | 0.04 |
| 16 | 0.01 | 0.06 | 0.15 | 0.05 | 0.05 | 0.03 |
| 20 | 0.01 | 0.06 | 0.15 | 0.05 | 0.05 | 0.03 |
| 24 | 0.01 | 0.06 | 0.15 | 0.05 | 0.05 | 0.02 |
| 120 | 0.00 | 0.08 | 0.13 | 0.04 | 0.05 | 0.01 |
| $\infty$ | 0.00 | 0.08 | 0.13 | 0.04 | 0.04 | 0.00 |

In the long run, the productivity shock ($\hat{\eta}_{1t}$) has a significant positive effect only on GDP, the estimated t-ratios for consumption and investment being 1.56 and 1.51, respectively. Moreover, here the interpretation of the second ($\hat{\eta}_{2t}$) and the third shock ($\hat{\eta}_{3t}$) as an inflation and an interest rate shock becomes doubtful. The inflation shock seems to have a significant positive effect on consumption and the interest rate has a significant positive long-run effect on consumption and investment.

The impulse responses of the real variables to the permanent structural shocks shown in figure B.2 are depicted with +/– one estimated standard error[11]. All functions reach their new levels after 3-5 years. However, the standard errors adjust very slowly to their long-run estimate. The long-run standard error for the response of GDP to the productivity shock is approximately 0.01 while after ten years it is about 0.08, e.g. eight times as big. Worth mentioning is, even if small, the negative effect of the inflation shock on GDP in the short run. This contrasts to the widely expected effect of an inflationary policy. The variance decomposition in table A.5 confirms that even in the short run, only a minor part of the forecast error variance of GDP is attributable to the inflation shock. The greatest part for all real variables is attributable to the productivity shock over the whole forecast horizon, despite nominal variables were also included in the analysis. After one year the productivity shock explains more than 50 percent of the forecast error variance of GDP. It explains more than 50 percent of the forecast error variance in consumption and gross investment after one and two years, respectively.

These results contrast those found in previous studies using Census X-11 adjusted data (KUGLER [1992], BONJOUR and KUGLER [1993]) in which monetary shocks explain part of the forecast error variance in real variables at least in the short run. In order to get evidence for the robustness of the results with respect to the method of seasonal adjustment, the same model was estimated with a set of quarterly data adjusted by the Census X-11 method[12]. The data cover the period from 72:1 to 92:2. The inflation rate seems to be stationary, so the price level is differenced only once for the multivariate estimation. The results obtained are now in line with the above mentioned studies. Looking at the impulse responses in figure B.3 it seems that the price level shock has a positive effect on GDP in the short run. Looking at the variance decompositions in table A.6 we can see that the productivity shock still explains the major part of the forecast error variance of the real variables in the long run but that in the short run (up to a horizon of 8 quarters) the price level shock explains a substantial part of the forecast error variance in real GDP. And up to a horizon of 4 quarters it explains 14 percent and 26 percent of the forecast error variance of consumption and investment, respectively. Moreover, the influence of the interest rate shock in explaining the forecast error variance of investment does not vanish even in the long run.

11. See the appendix of WARNE (1991), Theorem 3.
12. Data source: BAK, Basel.

**Figure B.2: Impulse response functions of dummy adjusted variables to a one standard deviation shock to the permanent components (depicted with +/- one standard deviation).**

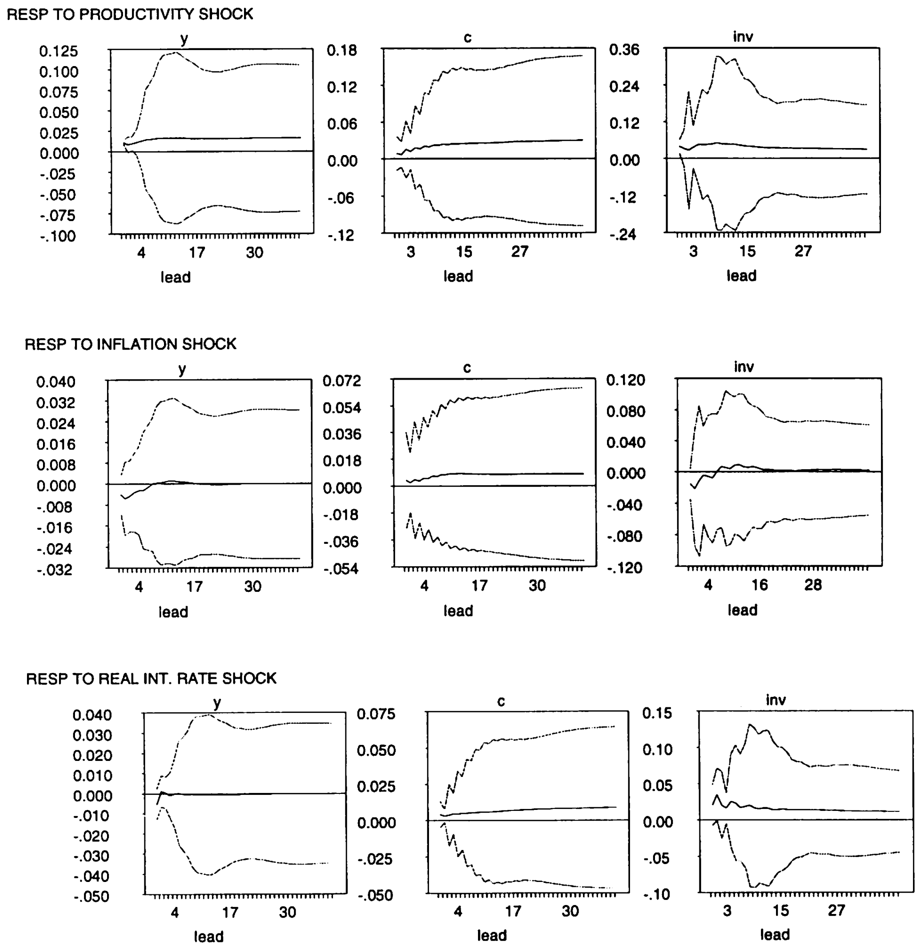


**Figure B.3: Impulse response functions of Census X-11 adjusted variables to a one standard deviation shock to the permanent components (depicted with +/- one standard deviation).**

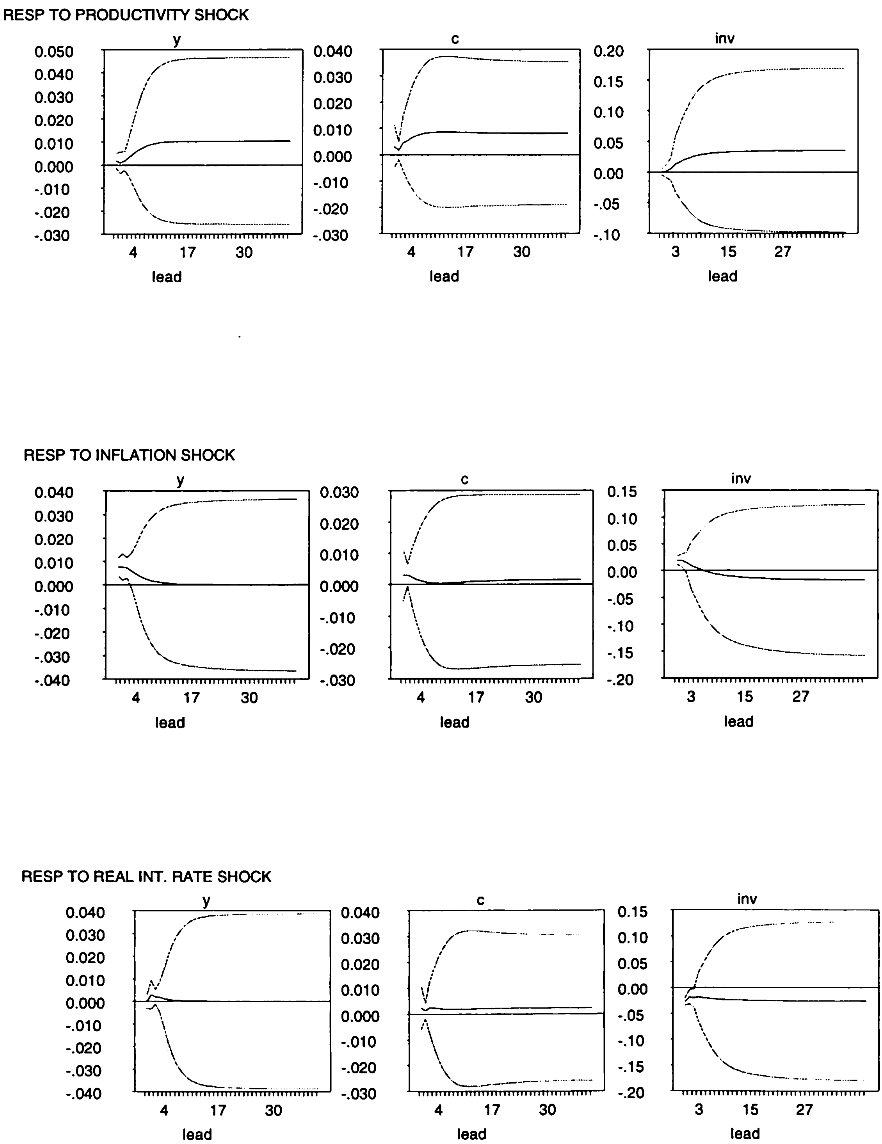


**Table A.6: Variance decomposition of Census X-11 adjusted variables**

**A. Fraction attributable to productivity shock**

| Horizon | $y$ | $c$ | $i$ | $m\text{-}p$ | $R$ | $\Delta p$ |
|---|---|---|---|---|---|---|
| 1 | 0.02 | 0.13 | 0.00 | 0.01 | 0.57 | 0.00 |
| 4 | 0.06 | 0.33 | 0.05 | 0.20 | 0.49 | 0.11 |
| 8 | 0.35 | 0.65 | 0.26 | 0.30 | 0.49 | 0.25 |
| 12 | 0.60 | 0.77 | 0.40 | 0.33 | 0.48 | 0.30 |
| 16 | 0.72 | 0.82 | 0.46 | 0.35 | 0.48 | 0.32 |
| 20 | 0.78 | 0.84 | 0.50 | 0.36 | 0.48 | 0.33 |
| 24 | 0.83 | 0.85 | 0.51 | 0.37 | 0.47 | 0.33 |
| 120 | 1.00 | 0.89 | 0.56 | 0.42 | 0.45 | 0.34 |
| $\infty$ | 1.00 | 0.89 | 0.56 | 0.43 | 0.43 | 0.34 |

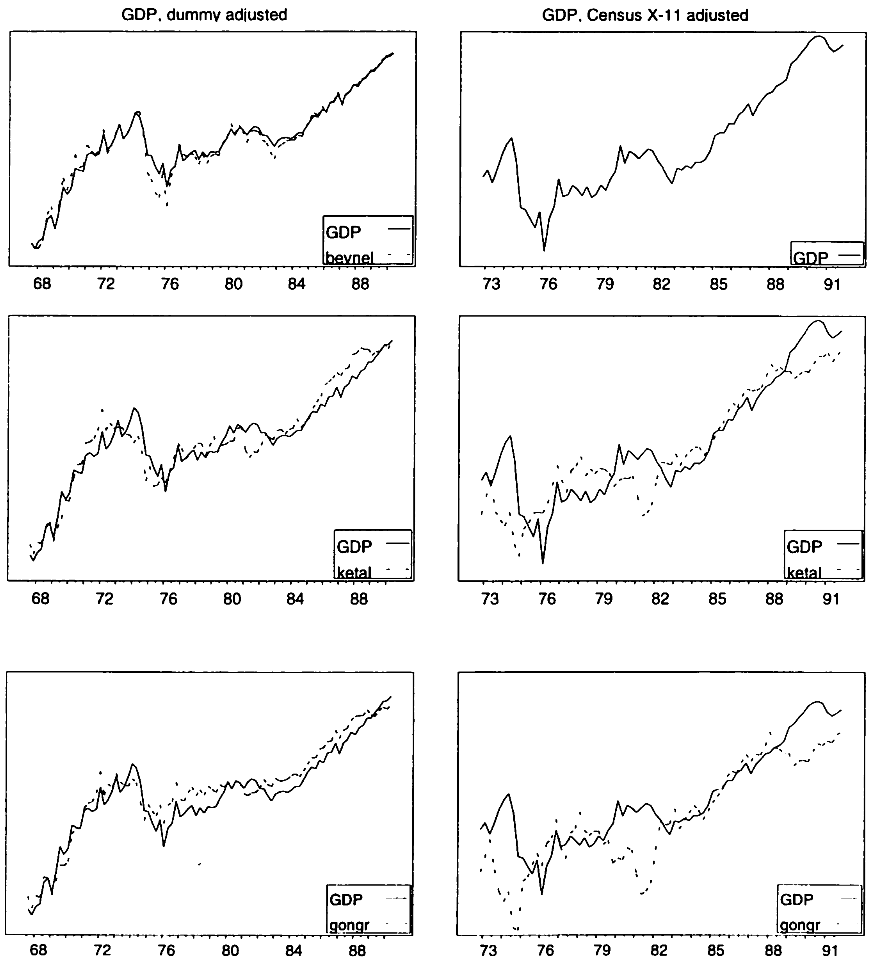
**B. Fraction attributable to price level shock**

| Horizon | $y$ | $c$ | $i$ | $m\text{-}p$ | $R$ | $\Delta p$ |
|---|---|---|---|---|---|---|
| 1 | 0.52 | 0.12 | 0.22 | 0.37 | 0.35 | 0.33 |
| 4 | 0.61 | 0.14 | 0.26 | 0.48 | 0.38 | 0.52 |
| 8 | 0.43 | 0.07 | 0.14 | 0.47 | 0.39 | 0.61 |
| 12 | 0.27 | 0.04 | 0.10 | 0.46 | 0.40 | 0.63 |
| 16 | 0.19 | 0.03 | 0.09 | 0.45 | 0.40 | 0.64 |
| 20 | 0.15 | 0.03 | 0.10 | 0.44 | 0.40 | 0.64 |
| 24 | 0.12 | 0.03 | 0.10 | 0.44 | 0.40 | 0.64 |
| 120 | 0.02 | 0.04 | 0.13 | 0.40 | 0.41 | 0.65 |
| $\infty$ | 0.00 | 0.04 | 0.14 | 0.39 | 0.42 | 0.66 |

**C. Fraction attributable to real interest rate shock**

| Horizon | $y$ | $c$ | $i$ | $m\text{-}p$ | $R$ | $\Delta p$ |
|---|---|---|---|---|---|---|
| 1 | 0.00 | 0.08 | 0.46 | 0.17 | 0.02 | 0.09 |
| 4 | 0.05 | 0.11 | 0.44 | 0.21 | 0.06 | 0.10 |
| 8 | 0.04 | 0.09 | 0.44 | 0.18 | 0.06 | 0.04 |
| 12 | 0.02 | 0.07 | 0.41 | 0.18 | 0.07 | 0.02 |
| 16 | 0.02 | 0.07 | 0.38 | 0.17 | 0.07 | 0.01 |
| 20 | 0.01 | 0.07 | 0.36 | 0.17 | 0.08 | 0.01 |
| 24 | 0.01 | 0.07 | 0.35 | 0.17 | 0.08 | 0.01 |
| 120 | 0.00 | 0.07 | 0.30 | 0.18 | 0.12 | 0.00 |
| $\infty$ | 0.00 | 0.08 | 0.30 | 0.18 | 0.15 | 0.00 |

**Figure B.4: Trend components of GDP**



### 4.4 *Estimated trend components*

Finally, we can compare the alternatively estimated trend components of GDP (see figure B.4). The trend components estimated by applying KING et al. and GONZALO and GRANGER show similar patterns. Both components increase, decrease or stagnate during the same periods. The greatest difference to the BEVERIDGE and NELSON trend component[13] is that the former two reach their peaks before the latter one. While the trend components estimated in a multivariate framework are already decreasing or at least stagnating (see the beginning of the 70ies and of the 80ies) the BEVERIDGE and NELSON trend component is still increasing. This difference between multivariate and univariate estimates of the stochastic trend component of GDP also shows up when using data seasonally adjusted with the Census X-11 method[14]. Note that it is quite surprising that the estimation of a factor model as proposed by GONZALO and GRANGER, which sets no economic identifying restrictions, brings out a trend component, that seems to fit well the evolution of economy.

## REFERENCES

BEVERIDGE, ST., CH.R. NELSON (1981), «A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the 'business cycle'», *Journal of Monetary Economics*, pages 151–174.

BLANCHARD, O.J., D. QUAH (1989), «The dynamic effects of aggregate demand and supply disturbances», *The American Economic Review*, 79:655–673.

BONJOUR, D., P. KUGLER (1993), «The dynamics of demand and supply shocks: a multicountry study», *Diskussionsschriften* 2, Universität Bern.

CAMPBELL, J.Y., N.G. MANKIW (1987a), «Permanent and transitory components in macroeconomic fluctuations», *American Economic Review, Papers and Proceedings*, LXXVII:111–117.

CAMPBELL, J.Y., N.G. MANKIW (1988), «International evidence on the persistence of economic fluctuations», *Working Paper* 2498, NBER.

CLARK, P.K. (1987), «The cyclical component of U.S. economic activity», *The Quarterly Journal of Economics*, pages 797–814.

COCHRANE, J.H. (1988), «How big is the random walk in GNP?», *Journal of Political Economy*, 96:893–920.

DICKEY, D.A., W.A. FULLER (1979), «Distribution of the estimators for autoregressive time series with a unit root», *Journal of the American Statistical Association*, 74:427–431.

13. This component was estimated from a Box-Jenkins estimation of a seasonal AR(1) process for real GDP.
14. The estimated BEVERIDGE and NELSON trend component of Census X-11 adjusted GDP is the series itself.

GONZALO, J., C.W.J. GRANGER, «Estimation of common long-memory components in cointegrated systems», *Discussion paper*, University of California, San Diego, October 1991.

HYLLEBERG, S., R.F. ENGLE, C.W.J. GRANGER, B.S. YOO (1990), «Seasonal integration and cointegration», *Journal of Econometrics*, 44:215–238.

JOHANSEN, J. and K. JUSELIUS (1990), «Hypothesis testing for cointegration vectors for Gaussian vector autoregressive processes with constant and seasonal dummies», *Oxford Bulletin of Economics and Statistics*, 52:169–210.

KING, R.G., CH. I. PLOSSER, J.H. STOCK, M.W. WATSON (1991), «Stochastic trends and economic fluctuations», *The American Economic Review*, 81:819–840.

KING, R.G., CH. I. PLOSSER, S.T. REBELO (1988), «Production, growth and business cycles: II. New directions», *Journal of Monetary Economics*, 21:309–341.

KUGLER, P. (1992), «The relative importance of demand and supply shocks: Some empirical evidence», *Empirical Economics*, 17:523–535.

KYDLAND, F.E., E.C. PRESCOTT (1982), «Time to build and aggregate fluctuations», *Econometrica*, 50:1345–1370.

LONG, J.B., CH.I. PLOSSER (1983), «Real business cycles», *Journal of Political Economy*, 91:39–69.

MELLANDER, E., A. VREDIN, A. WARNE (1992), «Stochastic trends and economic fluctuations in a small open economy», *Journal of Applied Econometrics*, 7:369–394.

NELSON, CH. R., CH.I. PLOSSER (1982), «Trends and random walks in macroeconomic time series: Some evidence and implications», *Journal of Monetary Economics*, 10:139–162.

PHILLIPS, P.C.B., P. PERRON (1988), «Testing for a unit root in time series regression», *Biometrika* 75:335–346.

SHAPIRO, M.D., M.W. WATSON (1988), «Sources of business cycle fluctuations», *Working Paper* 2589, NBER.

SOLOW, R.M. (1988), «Growth Theory: An Exposition», *Oxford University Press.*

STOCK, J.H., M.W. WATSON (1988), «Testing for common trends», *Journal of the American Statistical Association*, 83:1097–1107.

WARNE, A. (1991), «A common trends model: Identification, estimation and asymptotics», Unpublished manuscript, Stockholm School of Economics, Sweden.

WATSON, M.W. (1986), «Univariate detrending methods with stochastic trends», *Journal of Monetary Economics*, 18:49–75.

WATSON, M.W., R.F. ENGLE (1983), «Alternative algorithms for the estimation of dynamic factor, MIMIC and varying coefficient regression models», *Journal of Econometrics*, 23:385–400.

SUMMARY

In this paper the estimation of stochastic trend components of Swiss time series, especially of real per capita GDP, is performed within a multivariate framework. The model includes real per capita consumption, real per capita investment, real per capita balances, and also a short-term interest rate and a measure for inflation. All series but the interest rate are adjusted for only deterministic seasonality. The cointegration analysis gives evidence for 3 cointegrating relationships and hence for 3 common trends. These are identified as being induced by a real productivity shock, an inflation shock and a real interest rate shock. To isolate the structural shocks the method proposed by KING et al. (1991) is used. The impulse response functions depict that the main part of fluctuations in real variables is due to the productivity shock. The variance decomposition attributes the main fraction of the forecast error variance to the productivity shock, in the long as well as in the short run. Even in the short run, the inflation and the real interest rate shock have only a minor influence on fluctuations in the time series. This could be interpreted as evidence for the assertion of real business cycles theory, that real permanent shocks are the most important source of business cycles fluctuations. However, nominal shocks seem to have a positive short-run effect on GDP and can explain part of the forecast error variance in real variables when applying the method to a set of Census X-11 adjusted data. Finally, the comparison of trend components of GDP estimated by alternative methods shows that the paths of multivariate estimates are similar and reach their peaks before contraction periods sooner than an univariate estimate. While the former are already decreasing or at least stagnating, the latter trend component is still increasing.

ZUSAMMENFASSUNG

In dieser Arbeit werden die stochastischen Trendkomponenten von Schweizer Zeitreihen, insbesondere vom realen BIP, in einem multivariaten Rahmen geschätzt. Der reale Konsum, die realen Investitionen, die reale Kassenhaltung (alle in pro Kopf Grössen transformiert), ein kurzfristiger Zinssatz und der BIP-Deflator als Mass für die Inflation werden zusätzlich in die Schätzung einbezogen. Alle Zeitreihen ausser dem Zinssatz werden von der deterministischen Saisonalität bereinigt. Die Kointegrationsanalyse gibt Evidenz für drei Kointegrationsvektoren, damit sind drei gemeinsame Trends in den Daten vorhanden. Diese werden identifiziert als ein Produktivitäts-, ein Inflations- und ein realer Zinsschock. Um die strukturellen Komponenten zu schätzen, wird die Methode von KING et al. (1991) angewandt. Die Reaktionsfunktionen zeigen, dass der Produktivitätsschock die grösste Auswirkung auf Schwankungen in den Zeitreihen hat und die Varianzdekomposition bestätigt, dass der reale Schock den grössten Anteil der Prognosefehlervarianz in den realen Variablen sowohl in der kurzen wie auch in der langen Frist erklärt. Der Inflationsschock und der reale Zinsschock scheinen nur einen geringen Teil der Schwankungen in den realen Variablen zu erklären. Der nominale Schock hat jedoch kurzfristig einen positiven Effekt auf das BIP und erklärt einen Teil in der Prognosefehlervarianz vom BIP, wenn die Methode auf ein Datenset angewandt wird, das durch das Census X-11-Verfahren saisonal bereinigt wurde. Schliesslich zeigt der Vergleich alternativ geschätzter Trendkomponenten des BIPs, dass die multivariaten Schätzungen ähnliche Verläufe zeigen und die Wendepunkte vor Kontraktionsperioden früher erreichen als die univariat geschätzte Trendkomponente. Während die zwei ersten schon fallen oder zumindest stagnieren, steigt letztere immer noch an.

RESUME

La tendance stochastique de plusieurs séries suisses, notamment du PIB, est estimée dans un contexte multivarié, dans lequel sont également inclus la consommation réelle par personne, les investissements réels par personne, la demande de liquidité réelle par personne, un taux d'intérêt à court terme et le déflateur du PIB comme mesure d'inflation. La saisonalité déterministique est relevée de toutes les séries, sauf du taux d'intérêt. Trois relations de cointegrations sont trouvées dans les variables. Donc trois tendances communes peuvent être identifiées, un choc de productivité, un choc inflationniste et un choc d'intérêt réel étant à l'origine de celles-ci. La méthode présentée par KING et al. (1991) est appliquée pour estimer ces composentes structurelles. La majeure partie de l'effet à court terme de même que de l'effet à long terme sur les variables réelles peut être attribué au choc de productivité. Le choc inflationniste et le choc d'intérêt réel ne semblent pas avoir d'effet rélévant sur les variables réelles. Par contre, en appliquant la méthode sur des séries désaisonalisées par Census X-11, le choc inflationniste a un effet positif à court terme sur le PIB. Finalement, la comparaison des tendances stochastiques du PIB estimées par des méthodes diverses montre que les tendances estimées dans un cadre multivarié atteignent leurs zéniths avant les périodes contractionnaires plus tôt que la tendance estimée dans un cadre univarié.