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Evidence for Switzerland

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Author(s):

Siliverstovs, Boriss

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Boriss Siliverstovs



KOF

ETH Zurich
KOF Swiss Economic Institute
WEH D 4
Weinbergstrasse 35
8092 Zurich
Switzerland

Phone +41 44 632 42 39
Fax +41 44 632 12 18
www.kof.ethz.ch
kof@kof.ethz.ch

Dating Business Cycles in a Historical Perspective: Evidence for Switzerland[§]

BORISS SILIVERSTOVS
ETH Zurich
KOF Swiss Economic Institute
Weinbergstrasse 35
8092 Zurich, Switzerland
boriss.siliverstovs@kof.ethz.ch

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Abstract

In this study we suggest a chronology of the classical business cycle in Switzerland. To this end we use two approaches: the approach of Artis et al. (2004) and an approach based on Markov-switching models (Hamilton, 1989). Our results show that similar conclusions can be reached by applying the two methodologies. Another result is that the chronology obtained displays high concordance with the chronology derived for the Euro Area by the CEPR Business Cycle Dating Committee. A further contribution of our study is that we determine the sensitivity of the chronology obtained with respect to a particular GDP vintage used. For this purpose we employ the real-time database that contains 53 vintages of GDP data starting from 1997Q4 until 2010Q4. The main result of this robustness exercise is that the chronology obtained is stable across different vintages, although some minor differences across vintages can be detected.

Keywords: Classical business cycle, turning points, GDP revisions, Switzerland

JEL code: E32, C22.

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1 Introduction

In this paper we establish a business cycle chronology for Switzerland. We apply the business cycle dating approach recently proposed in Artis, Marcellino, and Proietti (2004), which is an elaboration of the non-parametric dating methodology of Harding and Pagan (2002). Detection of business cycle phases is based on a simulated Markov chain such that the resulting chronology has to satisfy a number of constraints. These constraints include alternation of peaks and troughs, minimum duration of recession and expansion phases as well as of the whole cycle. An important advantage of the proposed algorithm is that it allows for assessment of uncertainty around turning points.

A distinctive feature of our study is that when creating our chronology we explicitly address the well-known fact that GDP data often undergo substantial revisions. As a result, a chronology based on particular vintage of GDP data may be different from a chronology based on another GDP vintage released at some later point. This seems to be of a particular importance to a small and open economy like Switzerland where according to Cuche-Curti, Hall, and Zanetti (2008) revisions tend to be large and volatile. For example, in June 2010 the first release of quarterly growth rate of real GDP in Switzerland for the first quarter of 2010 was 0.41. Three months later in the next GDP release this figure was modified to 1.03. We use the following figure in order to illustrate volatility of the revision process in Switzerland. Figure 1 displays the historical vintages of the quarterly growth rate of seasonally adjusted GDP. This real-time dataset includes 53 GDP vintages starting from the fourth quarter of 1997 until the recent one that includes the fourth quarter of 2010. A starting point of the dataset is the first quarter of 1980. In the figure, for every quarter we report all estimates of the GDP growth rate that were released at some point of time. As seen, revisions are rather large and volatile, supporting the earlier conclusion of Cuche-Curti et al. (2008). For about of 61% of all quarters in the period from 1980Q1 until 2010Q4 the sign of the estimated growth rate is preserved across all vintages published; for the rest of the quarters there are both positive and negative estimates of the growth rate depending on a particular vintage. Given such an outcome it is necessary to examine to what extent the recorded business cycle chronology varies depending on a particular GDP vintage. It also should help assess the effectiveness and timeliness of policies implemented in order to soften the effects of a recession or measures undertaken to stimulate the economy.

Amstad (2000) is an earlier attempt to create a business cycle chronology for Switzerland. Using GDP and industrial production time series Amstad (2000) establishes recession and expansion phases for several definitions of the business cycle. The business cycle chronology of Amstad (2000) ended in 1997. As a consequence, there is a scope for a new study on business cycle dating that incorporates more recent time periods, including the Great Recession. The current paper extends the work of Amstad (2000) in several directions.

The paper contributes to the literature in the following aspects. First, using recent GDP data vintage we date the phases of the classical business cycle in Switzerland. We compare the chronology obtained with that reported for the Euro Area by the CEPR Business Cycle Dating Committee. Second, in order to check the robustness of the dating algorithm to the use of different data vintages, we run the business cycle dating

algorithm on all historical GDP vintages available to us. Third, we compare the chronology based on the algorithm of Artis et al. (2004) with that based on Markov-switching models.

The paper proceeds as follows. In Section 2 methodology of business cycle dating is explained. Section 3 presents the estimation results. The final section concludes.

2 Dating methodology

The dating methodology applied here for identification of the classical turning points is based on a three-step procedure that is similar to one outlined in Proietti (2005) and Proietti (2009b). In the first step a model-based low-pass filter is applied to the log level of the GDP time series in order to extract the trend components free from high-frequency fluctuations. In the second step a preliminary set of turning points is identified by means of the business cycle dating algorithm of Artis et al. (2004). At this stage we also apply the simulation smoother of de Jong and Shephard (1995) in order to assess uncertainty around turning points arising from prefiltering. In the third step we select the most likely candidates for final identification of turning points using the original time series.

2.1 Model-based low-pass filter

A model-based decomposition of a time series into orthogonal trend and cycle components by means of an optimal class of filters was suggested in Proietti (2009a). Assume that a time series y_t allows an ARIMA(p, q, d) representation

$$\phi(L)(\Delta^d y_t - \beta) = \theta(L)\xi_t, \quad \xi_t \sim NID(0, \sigma^2), \quad (1)$$

where β is a constant, $\phi(L)$ and $\theta(L)$ are the lag polynomials satisfying the requirements of stationarity and invertibility, respectively. As shown in Proietti (2009a), the white-noise disturbance ξ_t in Equation (1) can be decomposed into two orthogonal stationary processes

$$\xi_t = \frac{(1+L)^r \varsigma_t + (1-L)^m \kappa_t}{\varphi(L)}$$

with

$$|\varphi(L)|^2 = \varphi(L)\varphi(L^{-1}) = |1+L|^{2r} + \lambda|1-L|^{2m}.$$

Further assume that the time series y_t can be decomposed into two orthogonal components

$$y_t = \mu_t + \psi_t, \quad (2)$$

representing a low-frequency (trend) component μ_t and a high-frequency (cycle) component ψ_t . Then the trend-cycle decomposition of the ARIMA representation in Equation (1) can be written as follows

$$\begin{aligned}\phi(L)\varphi(L)(\Delta^d\mu_t - \beta) &= (1+L)^r\theta(L)\varsigma_t, & \varsigma_t &\sim NID(0, \sigma^2), \\ \phi(L)\varphi(L)\psi_t &= \Delta^{m-d}\theta(L)\kappa_t, & \kappa_t &\sim NID(0, \lambda\sigma^2).\end{aligned}$$

Observe that the trend component μ_t has the same order of integration as the original time series y_t . The high-frequency component is stationary under the maintained assumption that $m \geq d$.

The trend-cycle decomposition can be cast into a state-space form and the corresponding estimates of the low- and high-pass components can be obtained by means of the Kalman filter and smoother. These estimates and the associated mean square errors in finite samples will depend on the ARIMA model maintained for y_t . For fixed values of r and m one can define a cut-off frequency $\omega_c = 2\pi/(1.25 * s)$, where s is a frequency of the series y_t . Then in the extracted low-pass component the amplitude of the high-frequency fluctuations with periodicity less than 5 quarters will be dampened. The corresponding smoothing parameter λ is given by

$$\lambda = 2^{r-m} \left[\frac{(1 + \cos \omega_c)^r}{(1 - \cos \omega_c)^m} \right].$$

2.2 Business cycle dating algorithm

Artis et al. (2004) propose an algorithm for dating business cycle turning points as a further development of the algorithm proposed in Harding and Pagan (2002), which in turn is a modification of the algorithm of Bry and Boschan (1971). There are two building blocks in the algorithm of Artis et al. (2004): a Markov chain and a stochastic procedure of scoring Markov-chain transition probabilities.

Assume that there are only two mutually exclusive states of the economy: expansion E_t and recession R_t . Further, the last observation of an expansion phase is defined as a peak P_t and, accordingly, the last observation of a recession phase is a trough T_t :

$$\begin{aligned}E_t &\equiv \begin{cases} EC_t & \text{Expansion Continues} \\ P_t & \text{Peak,} \end{cases} \\ R_t &\equiv \begin{cases} RC_t & \text{Recession Continues} \\ T_t & \text{Trough.} \end{cases}\end{aligned}$$

From EC_t a transition is possible either to a peak P_{t+1} , ending the expansion phase, or to EC_{t+1} , continuing expansion. Similarly, from RC_t a transition either to T_{t+1} or to RC_{t+1} is possible. From P_t we end up in RC_{t+1} with probability one. From T_t only a transition to EC_{t+1} is possible. Table 1 presents a transition matrix of the first-order Markov chain with four states S_t , where $p_{EP} = Prob(P_{t+1}|EC_t)$ and $p_{EE} = Prob(EC_{t+1}|EC_t)$ are probabilities of visiting a peak, terminating the expansion phase, or continuing expansion. Observe that $p_{EP} + p_{EE} = 1$. Similarly, we can define $p_{RT} = Prob(T_{t+1}|RC_t)$ and $p_{RR} = Prob(RC_{t+1}|RC_t) = 1 - p_{RT}$. Such a specification of transition probabilities enforces alternating

pattern of peaks and troughs. It also enforces a minimum duration of each phase of two quarters.

The algorithm of Artis et al. (2004) also requires that the minimum duration of a whole business cycle should be five quarters. Such a requirement implies that we need a fifth-order Markov chain in order to describe state-to-state transition. However, using the states S_t defined above it can be written as a first-order chain with the following states:

$$S_t^* = \{S_{t-4}, S_{t-3}, S_{t-2}, S_{t-1}, S_t\}.$$

The minimum cycle duration rules reduce the number of admissible states of the Markov chain to 24. For example, the state $\{P_{t-4}, RC_{t-3}, T_{t-2}, EC_{t-1}, P_t\}$ is not admissible, whereas the state $\{P_{t-4}, RC_{t-3}, T_{t-2}, EC_{t-1}, EC_t\}$ is admissible. All 24 admissible states are listed in Artis et al. (2004, Table 1) for the quarterly case with the above mentioned minimum duration requirements. The transition dynamics of this chain is uniquely driven by the probabilities p_{EP} and p_{RT} specified above.

Hence, the next step is to estimate the transition probabilities p_{EP} and p_{RT} for the time series of interest. Similarly to Harding and Pagan (2002), two sequences suggesting candidates for peak and trough are defined as follows:

$$\begin{aligned} ETS_t &= \{(\Delta y_{t+1} < 0) \cap (\Delta_2 y_{t+2} < 0)\} \\ RTS_t &= \{(\Delta y_{t+1} > 0) \cap (\Delta_2 y_{t+2} > 0)\}, \end{aligned}$$

where ETS_t is an expansion-terminating sequence and RTS_t is a recession-terminating sequence. The operators Δ and Δ_2 are defined as follows: $\Delta = y_t - y_{t-1}$ and $\Delta_2 = y_t - y_{t-2}$.

The transition probabilities p_{EP} and p_{RT} depend on the joint distribution of the sequences $\{ETS_t, RTS_t; t = 1, \dots, T\}$, which is determined by the stochastic process governing y_t and is usually not analytically tractable. Given this, Artis et al. (2004) suggest to use stochastic simulation for estimation of p_{EP} and p_{RT} .¹

The dating algorithm of Artis et al. (2004) has an additional feature compared to the dating algorithms suggested earlier. It allows to assess the uncertainty around the identified turning points. Recall that the dating algorithm is applied to a prefiltered time series, or a trend component μ_t in Equation (2), where cycles with a periodicity of, say, 5 quarters have been dampened. Prefiltering introduces uncertainty in the identification of the turning points that can be assessed by means of the simulation smoother suggested in de Jong and Shephard (1995). The simulation smoother is a Monte Carlo procedure that repeatedly draws simulated samples from the posterior distribution of the trend component $\tilde{\mu}_t^{(i)} \sim \mu_t | y_1, \dots, y_T$. For each quarter in our sample we therefore obtain the relative frequency of this quarter being labeled as a peak or a trough. Correspondingly, we can determine the frequency with which each quarter is identified as a recession period, for example.

¹For the sake of saving space we chose not to report it here. The details can be found in Artis et al. (2004, Section 2.2).

2.3 Final identification of turning points

The final set of turning points is identified using the original seasonally adjusted time series by the following two-step procedure. First tentative turning points are identified iteratively, starting with the highest relative frequency with which a particular quarter q is selected as a peak or a trough by the simulation smoother in the low-pass component. Then a local maximum for a peak (and a local minimum for a trough) in the original time series y_1, \dots, y_T is identified in the neighbourhood $\{y_{t-1}^q, y_t^q, y_{t+1}^q\}$ of that quarter. At this stage, we enforce the minimum duration constraints on each phase and on the business cycle. We also disregard turning points within the minimum phase at the beginning and the end of the sample. In addition, only those recession phases are retained that satisfy a minimum recession depth constraint stating that the output drop at the trough compared to the previous peak should be at least 0.5%.

3 Results

In this section we describe the results in the following order. First we provide a chronology of the classical business cycle using the latest available GDP vintage. We relate the suggested chronology for Switzerland with that established for the Euro Area by the Business Cycle Dating Committee at the CEPR.² In the second step we check whether the chronology is stable across different GDP vintages. Finally, we compare it with the chronology based on a Markov-Switching model.

3.1 Turning points of the classical business cycle

Before the launch of the dating algorithm, a model for the seasonally adjusted time series has to be selected. We fitted the same set of models as in Proietti (2009b) to the time series in question, i.e. ARIMA(0,1,0), ARIMA(1,1,0), and ARIMA(2,1,2). The preferred model for which we report chronology is an ARIMA(1,1,0) model with estimated autoregressive coefficient $\hat{\phi} = 0.57923$ and standard error of the residuals $\hat{\sigma} = 0.047761$. The following reasons justify our choice. The random walk model is misspecified, as there is strong evidence of remaining first-order autocorrelation in residuals from the model. The parameter estimates of the ARIMA(2,1,2) model turned out to be unstable when the model was fitted to different historical GDP vintages. In contrast, the autoregressive model delivers stable coefficient estimates across different vintages. In the end, the final set of identified turning points turns out to be the same for all three ARIMA models.

An ARIMA(1,1,0) model-based low-pass filter is applied to the most recent vintage (available in Spring 2011 for 1980Q1—2010Q4) of the original seasonally adjusted time series. In the low-pass component the amplitude of the high-frequency fluctuations with periodicity less than 5 quarters is dampened. The uncertainty around the turning points is assessed using the simulation smoother with 2000 Monte Carlo draws from the posterior distribution of the low-pass component. The outcome of the dating procedure is displayed in Figures 2 and 3. In the former figure, the relative frequency with which each quarter is designated as a recession quarter is shown. In the latter figure, the relative frequency with which each quarter is selected as a peak or a trough (shown on the inverse scale) is presented.

²For more information, we refer to the website <http://www.cepr.org/data/dating/>.

Figure 2 allows us to tentatively identify five recession periods: in the early 1980s, in the early 1990s, around the year 2002, and, finally, the recent Great Recession. There is also some evidence of a recessionary period around 1995 and 1996, but for all corresponding quarters the recession frequencies fall below 0.5. Judging from Figure 3 peaks and troughs are generally well defined, especially for the recent crisis. The exceptions are a slight uncertain dating of a trough around the fourth quarter of 1982 and of a peak around the beginning of 2002.

The final set of turning points is identified using the procedure outlined in Section 2.3 above, see Figure 4. The corresponding chronology along with the characteristics of recessions in terms of deepness, duration, and steepness is presented in Table 2. The duration of the recessions ranges from three to six months. The most prolonged recession is in the beginning of 1980s. The recent recession is the most severe one, exceeding previous recessions both in terms of deepness and steepness.

The timing of the recessions in Switzerland closely matches the chronology of Euro Area business cycle published by CEPR. Both recession chronologies are shown in Figure 5. In the period under investigation the CEPR Business Cycle Dating Committee identified the following three pairs of peaks and troughs: 1980Q1-1982Q3, 1992Q1-1993Q3, and 2008Q1-2009Q2. It also mentions the period from 2001Q1-2003Q2 as a potential candidate for a recession, but argues that it is better classified as a period of slow growth in economic activity in the Euro Area rather than a full-fledged recession.³ For Switzerland, the dating algorithm suggests to identify the period from 2002Q2 until 2003Q2 as a recession. In terms of both deepness and steepness measures it is the mildest recession in comparison to the remaining four identified recessions. Thus the only major difference between our chronology for Switzerland and that posted by CEPR for the Euro area is the recession period from 1990Q3 until 1991Q2 when Switzerland experienced a sharp decline in GDP of about 1.55% during three subsequent quarters. This recession was a result of the bursting of the real-estate market bubble in Switzerland fueled by extensive mortgage loan practice by Swiss banks during the 1980s. The real-estate crisis was followed by a banking crisis leading to the wave of bank consolidations in the country (see Bank for International Settlements, 2004). In the period from 1991 till 1996, the bank losses were estimated to total around 42 billion Swiss francs.

3.2 Determining recession periods using the real-time vintages

The revisions of GDP data are rather volatile in Switzerland. Therefore it is instructive to check to what extent the business cycle chronology derived using the recent vintage is robust across historical vintages. To this end we use GDP vintages from the database collected at the KOF Swiss Economic Institute at ETH Zurich. The earliest GDP observation in this database is available for 1980Q1. The earliest historical GDP vintage has the last valid observation in 1997Q4 (implying that it was available in March 1998, at the latest) and the most recent vintage has observations until 2010Q4. We denote the vintages as follows: GDP.YYQ, where YYQ correspond to the quarter with the last available observation in that vintage. For example, the vintage with the last observation in 1997Q4 is denoted as ‘GDP.974’. Similarly, the vintage with the last observation in 2000Q4 is denoted as ‘GDP.004’. All in all, we have 53 historical vintages. For each vintage,

³For more information, see <http://www.cepr.org/data/dating/growth-pause.asp>.

the relative recession probabilities were calculated using the steps described in Sections 2.1 and 2.2 above.

The relative recession frequencies are displayed in Figure 6 for every historical vintage. The overall impression is that the timing of recessions is stable across historical vintages. Nevertheless, some differences can be observed. The recession in the beginning of the 1980s starts one (two) quarters earlier according to the later vintages. A similar observation can be made for the recession in 1990. The slowdown in the economic activity in the beginning of 1999 was only evident for intermediate vintages starting from GDP.034 till GDP.084. Vintages until GDP.084 suggest a recession in 2001 that can be related to the burst of the dot-com bubble. In later vintages there is a little evidence of a recession in that period.

3.3 Determining business cycle phases using Markov-switching models

In this section we report the results of determining business cycle phases using an alternative methodology based on Markov-switching (MS) models. The use of MS models for turning point detection was popularised in the seminal contribution of Hamilton (1989). The model suggested in Hamilton (1989) allows for a regime-specific mean growth rate, where switching between different regimes are governed by a latent variable that follows a discrete Markov-switching process.

Hamilton (1989) detects phases of the U.S. business cycle using the following model, which allows for two regimes of low and high growth:

$$y_t - \mu(s_t) = \sum_{i=1}^4 \phi_i (y_{t-i} - \mu(s_{t-i})) + \epsilon_t, \epsilon_t \sim N(0, \sigma^2), \quad (3)$$

where y_t denotes the quarterly GDP growth rate, $\mu(s_t)$ is the regime-dependent mean growth rate, s_t is a latent variable that follows a Markov chain and takes values either zero or one. In Krolzig (1997) such models are labelled $MSM(k) - AR(p)$ with $k = 2$ and $p = 4$ denoting the number of regimes and the length of autoregressive lag augmentation, respectively. The model in Equation (3) can be straightforwardly extended to allow for a regime-specific variance of the error term $\sigma^2(s_t)$, and more regimes. Also the autoregressive coefficients ϕ_i can be made regime-dependent.

In the sequel we report the estimation results and the classification of the business cycle dynamics in Switzerland for the following two models: $MSMH(2) - AR(0)$ and $MSMH(3) - AR(0)$, where H denotes that we allow for a regime-specific variance of the error term in the models. Also observe that in both models the lag augmentation has been set to zero, i.e. $p = 0$. Such a restrictive model appeared to describe adequately the regime switching in the GDP growth rate. Interestingly, Amstad (2000) came to a similar conclusion and reported the results obtained by Markov-switching models without any autoregressive lags.

The classification of the business cycle phases is shown in Figures 7 and 8 for the models $MSMH(2) - AR(0)$ and $MSMH(3) - AR(0)$, respectively. The corresponding model parameters estimates of the regime-specific mean growth rate $\hat{\mu}(s_t)$ and the error standard deviation $\hat{\sigma}(s_t)$ are reported in Table 3. The estimated transition probabilities of the Markov chain are given in Table 4. In this table the transition probabilities are denoted as follows $p_{i|j} = Prob(\text{Regime } i \text{ at } t + 1 | \text{Regime } j \text{ at } t)$. For example, for the three-regime model the entry $p_{2|0} = 0$ signifies that there is a zero transition probability from the high-growth phase (Regime

0) in the current quarter into the recession phase (Regime 2) in the next quarter.

According to the $MSMH(2) - AR(0)$ model the mean growth rate in the high-growth regime is about 0.85% and in the low-growth regime about zero. The sample period is about equally split into two parts: the high-growth regime is attributed to 61 quarters (49.59%) with average phase duration about 7.63 quarters, the low-growth regime is assigned to 62 quarters (50.41%) with average phase duration 8.86 quarters. The low-growth phases are defined as follows: 1981Q1-1983Q3[11], 1986Q3-1987Q1[3], 1990Q2-1996Q4[27], 1998Q3-1999Q2[4], 2000Q4-2003Q2[11], 2004Q3-2004Q4[2], 2008Q3-2009Q2[4], with the corresponding duration reported for each phase in squared brackets. The longest period of low growth is attributed to the period 1990Q2-1996Q4 in the aftermath of the burst of the domestic real-estate bubble and the banking crisis.

Adding a third regime into the Markov-switching model leads to the following results. The high-growth regime remains largely unchanged; the estimated mean growth rate is about 0.88%, and it accounts for 59 quarters (47.97%) with average phase duration of 7.38 quarters. However, the low-growth regime is further divided into two sub-regimes, which we can label as the normal-growth and recession phases. In the normal-growth phase the mean growth rate is 0.18%, whereas in the recession phase it is -0.61%. The following periods are identified as belonging to the recession regime: 1981Q4-1982Q2[3], 1990Q4-1991Q2[3], 1992Q3-1992Q4[2], 1995Q1[1], 2003Q1[1], 2008Q3-2009Q2[4]. With the exception of the quarter 1995Q1 there is a substantial overlap with the business cycle chronology obtained using the approach of Artis et al. (2004), see Table 2.

A further interesting observation can be made. According to the matrix of estimated transition probabilities for the three-regime model reported in Table 4, the Swiss economy never went directly from a high-growth phase to a recession phase in the past 30 years. This is indicated by the corresponding zero entry in place of $p_{2|0}$ in the probability transition matrix. The phase of the normal-growth rate always serves as a buffer between these two extreme regimes. The movement in the opposite direction is not often observed either. In fact, such a transition never took place before the Great Recession that the world economy experienced recently. As our analysis shows, this previously unseen pattern has been broken in the post-Great Recession period, when the Swiss economy made a staggering transition to the high-growth phase directly from the deepest recession it experienced.

4 Conclusions

In this study we suggest a chronology of the classical business cycle in Switzerland. We use two approaches: the approach of Artis et al. (2004), where the detection of business cycle phases is based on a simulated Markov chain that has to satisfy a number of constraints such as alternation of peaks and troughs and minimum duration of recession and expansion phases as well as of the whole cycle, and an approach based on Markov-switching models inspired by the seminal paper by Hamilton (1989). Our results show that that similar conclusions can be reached by applying either of the two methodologies. An additional result is that the chronology displays high concordance with the chronology derived for the euro area by the CEPR

Business Cycle Dating Committee, reflecting a high degree of integration of the Swiss economy with the Euro Area.

An additional contribution of our study is that we determined the sensitivity of the chronology with respect to a GDP vintage used. For this purpose we employ a real-time database that contains 53 vintages of GDP data starting from 1997Q4 until 2010Q4. The main result of this robustness exercise is that the chronology is rather across different vintages, although some minor differences can be detected.

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Table 1: Transition matrix

| | EC_{t+1} | P_{t+1} | RC_{t+1} | T_{t+1} |
|--------|------------|-----------|------------|-----------|
| EC_t | p_{EE} | p_{EP} | 0 | 0 |
| P_t | 0 | 0 | 1 | 0 |
| RC_t | 0 | 0 | p_{RR} | p_{RT} |
| T_t | 1 | 0 | 0 | 0 |

Table 2: Classical business cycle in Switzerland

| Peak | Trough | Recession | | |
|--------|--------|---------------------------|----------|----------------------------|
| | | Deepness ^a (%) | Duration | Steepness ^b (%) |
| 1981Q2 | 1982Q4 | 1.74 | 6 | 0.29 |
| 1990Q3 | 1991Q2 | 1.55 | 3 | 0.52 |
| 1992Q1 | 1993Q1 | 1.54 | 4 | 0.38 |
| 2002Q1 | 2003Q2 | 0.83 | 5 | 0.17 |
| 2008Q2 | 2009Q2 | 3.29 | 4 | 0.82 |

Notes: A recessions terminates in a trough, an expansion terminates in a peak.

^a Measure of deepness is defined as the difference between a peak and a trough in log level of GDP.

^b Measure of steepness is obtained by dividing deepness by duration.

Table 3: Markov-switching models: coefficient estimates

| | $\hat{\mu}(0)$ | $\hat{\mu}(1)$ | $\hat{\mu}(2)$ | $\hat{\sigma}(0)$ | $\hat{\sigma}(1)$ | $\hat{\sigma}(2)$ |
|-------------------|------------------|------------------|-------------------|-------------------|-------------------|-------------------|
| $MSMH(2) - AR(0)$ | 0.848 (0.059) | 0.004 (0.065) | | 0.362 (0.061) | 0.430 (0.038) | |
| $MSMH(3) - AR(0)$ | 0.875 (0.044) | 0.175 (0.052) | -0.614 (0.074) | 0.346 (0.056) | 0.274 (0.036) | 0.238 (0.057) |

Notes: Standard errors are reported below the coefficient estimates.

Table 4: Markov-switching models: transition probabilities
 $p_{i|j} = P(\text{Regime } i \text{ at } t + 1 | \text{Regime } j \text{ at } t)$

| <i>MSMH</i> (2) – <i>AR</i> (0) | Regime 0, <i>t</i> | Regime 1, <i>t</i> | |
|---------------------------------|--------------------|--------------------|--------------------|
| Regime 0, <i>t</i> + 1 | 0.873 | 0.124 | |
| Regime 1, <i>t</i> + 1 | 0.127 | 0.876 | |
| <i>MSMH</i> (3) – <i>AR</i> (0) | Regime 0, <i>t</i> | Regime 1, <i>t</i> | Regime 2, <i>t</i> |
| Regime 0, <i>t</i> + 1 | 0.856 | 0.152 | 0.054 |
| Regime 1, <i>t</i> + 1 | 0.144 | 0.735 | 0.371 |
| Regime 2, <i>t</i> + 1 | 0.000 | 0.113 | 0.574 |

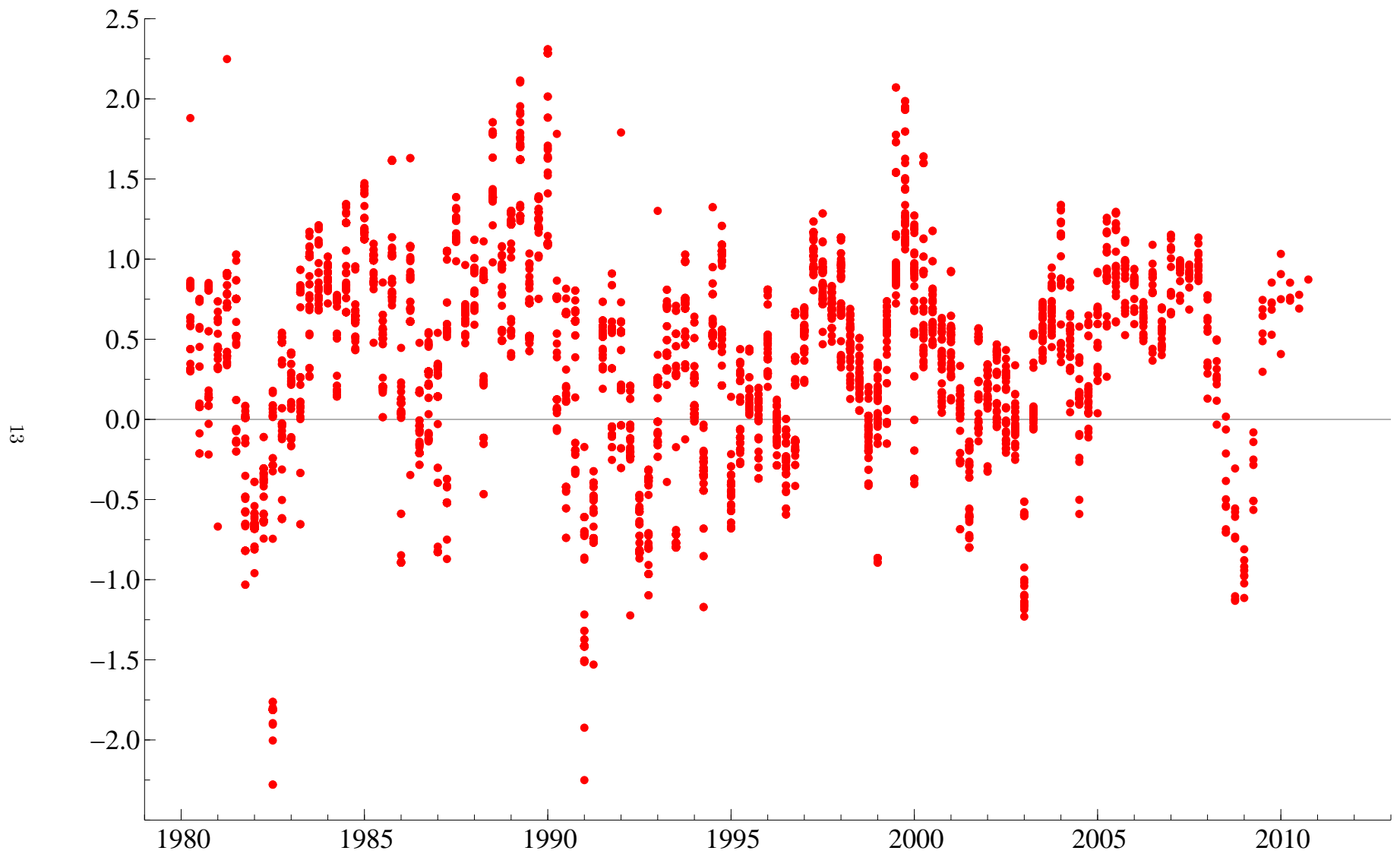


Figure 1: GDP vintages: the quarterly growth rate, seasonally adjusted

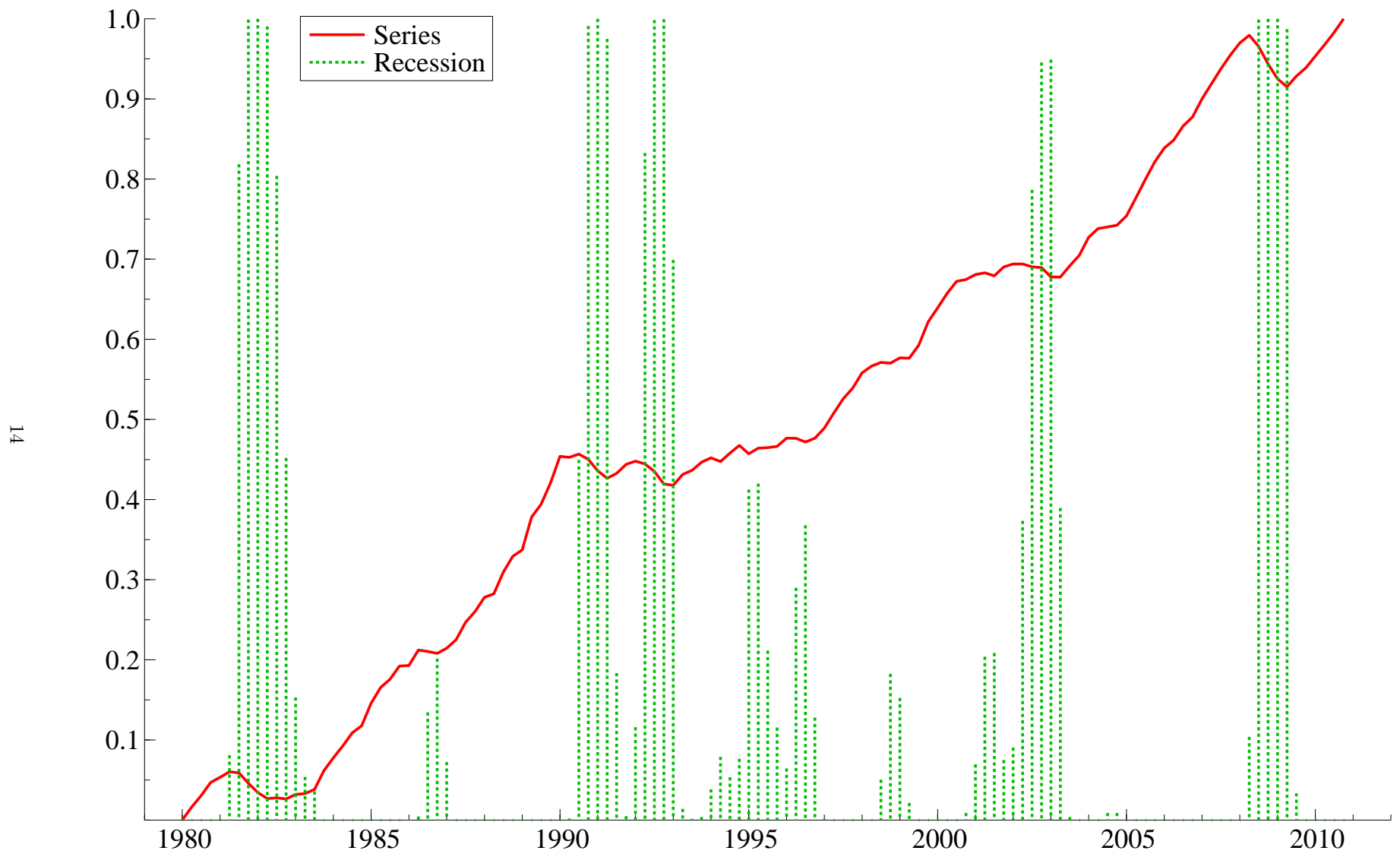


Figure 2: Real GDP index (seasonally adjusted): 1980Q1—2010Q4. Classical business cycle: Relative frequency with which each quarter is identified as a recession quarter by the simulation smoother of de Jong and Shephard (1995) based on 2000 Monte Carlo repetitions.

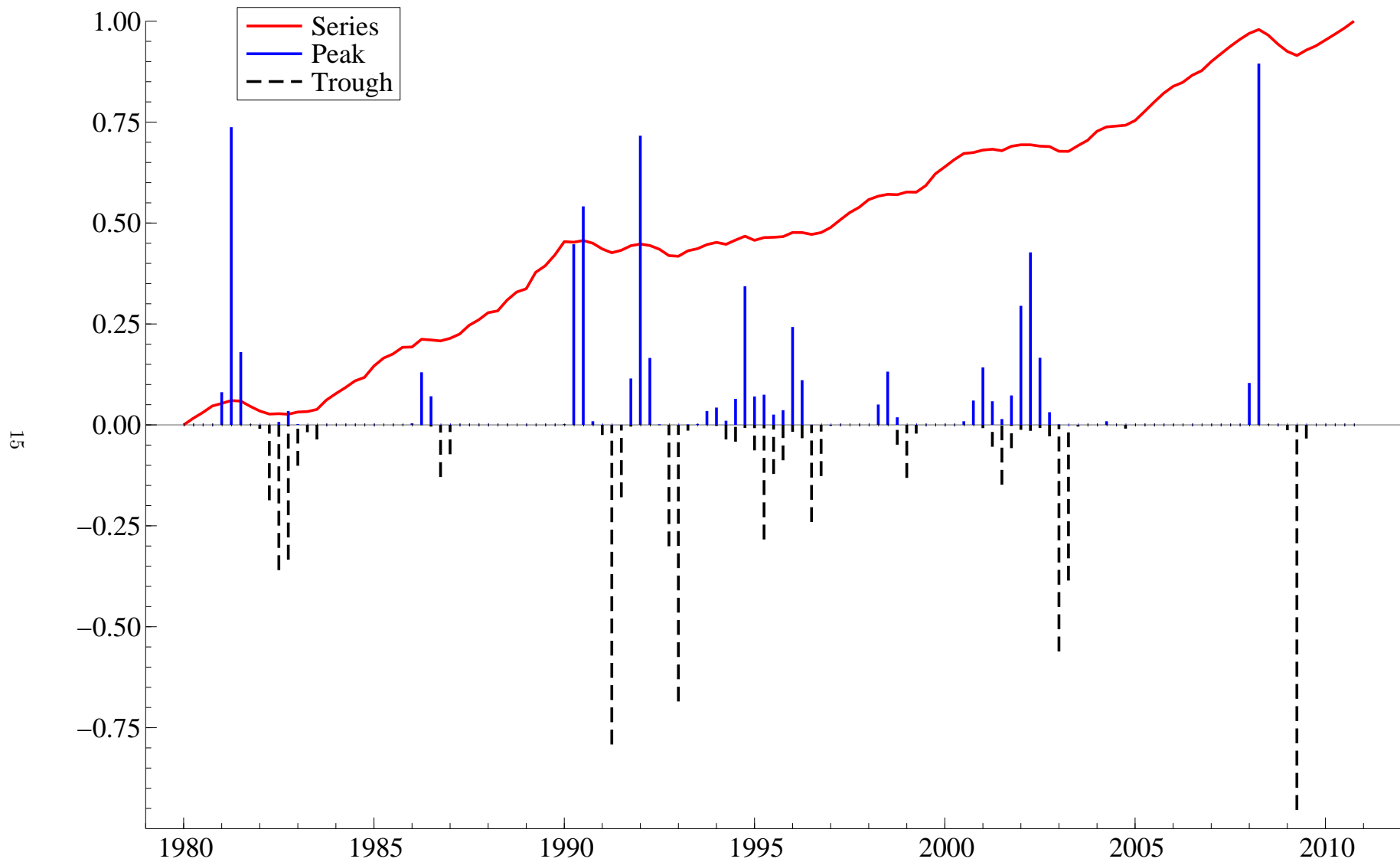


Figure 3: Real GDP index (seasonally adjusted): 1980Q1—2010Q4. Classical business cycle: Relative frequency with which a quarter is identified as a peak or a trough (inverted scale) by the simulation smoother of de Jong and Shephard (1995) based on 2000 Monte Carlo repetitions.

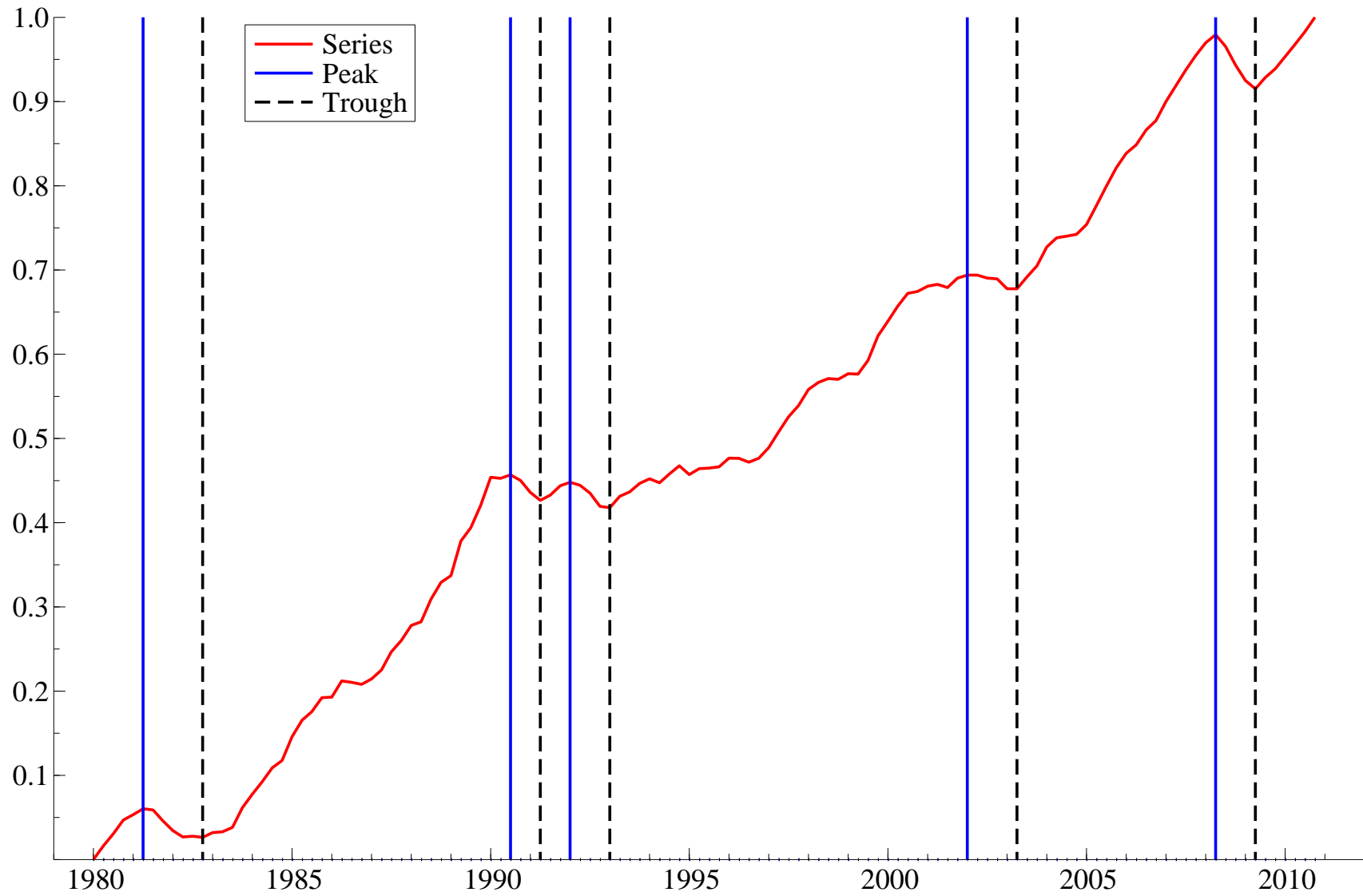


Figure 4: Real GDP index (seasonally adjusted): 1980Q1—2010Q4. Classical business cycle: Turning points identified using the procedure described in Section 2.3.

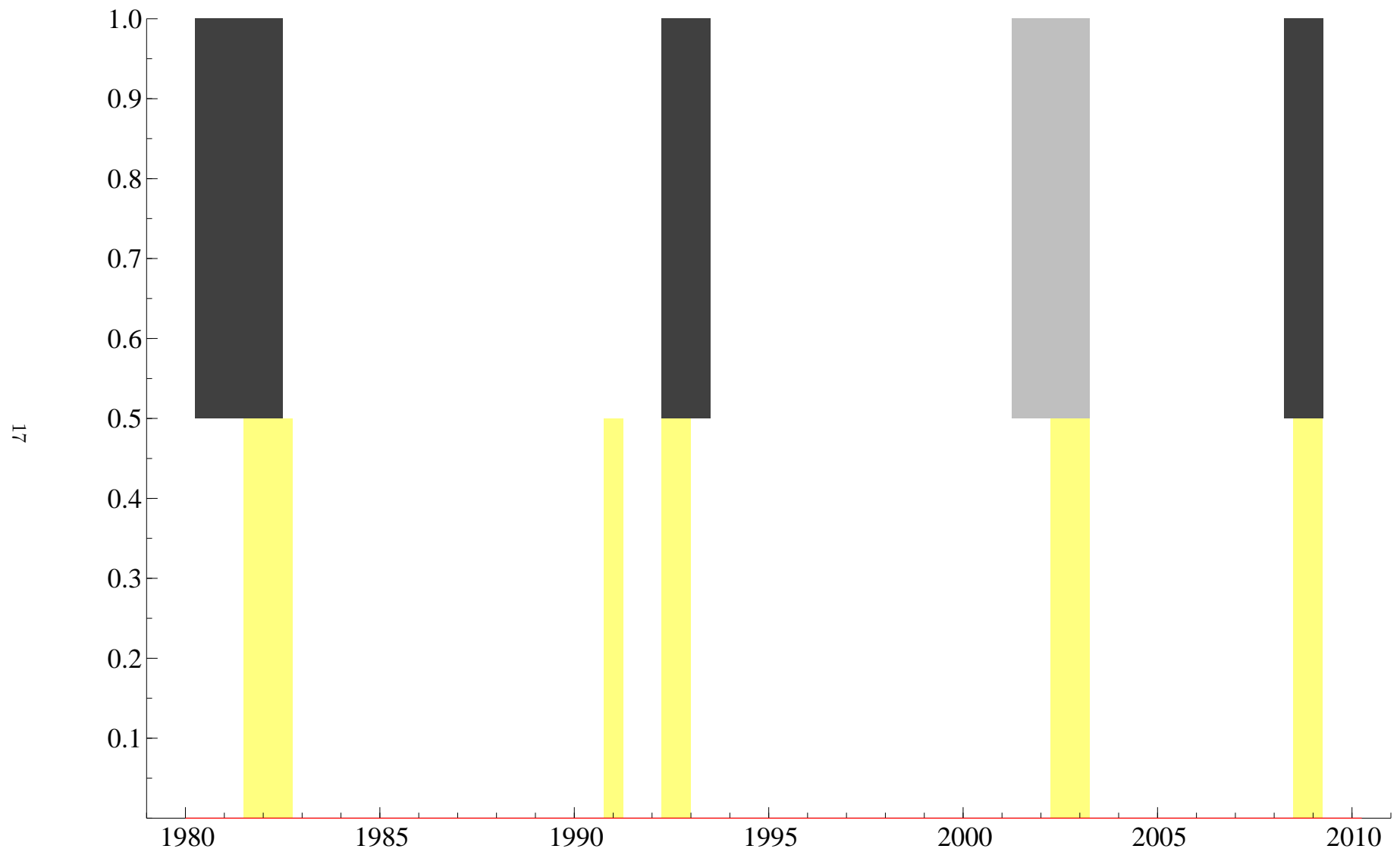


Figure 5: Recession chronology: Euro Area (upper part) and Switzerland (lower part). The ‘slow growth’ phase in 2001—2003 in economic activity in the Euro Area is also shown.

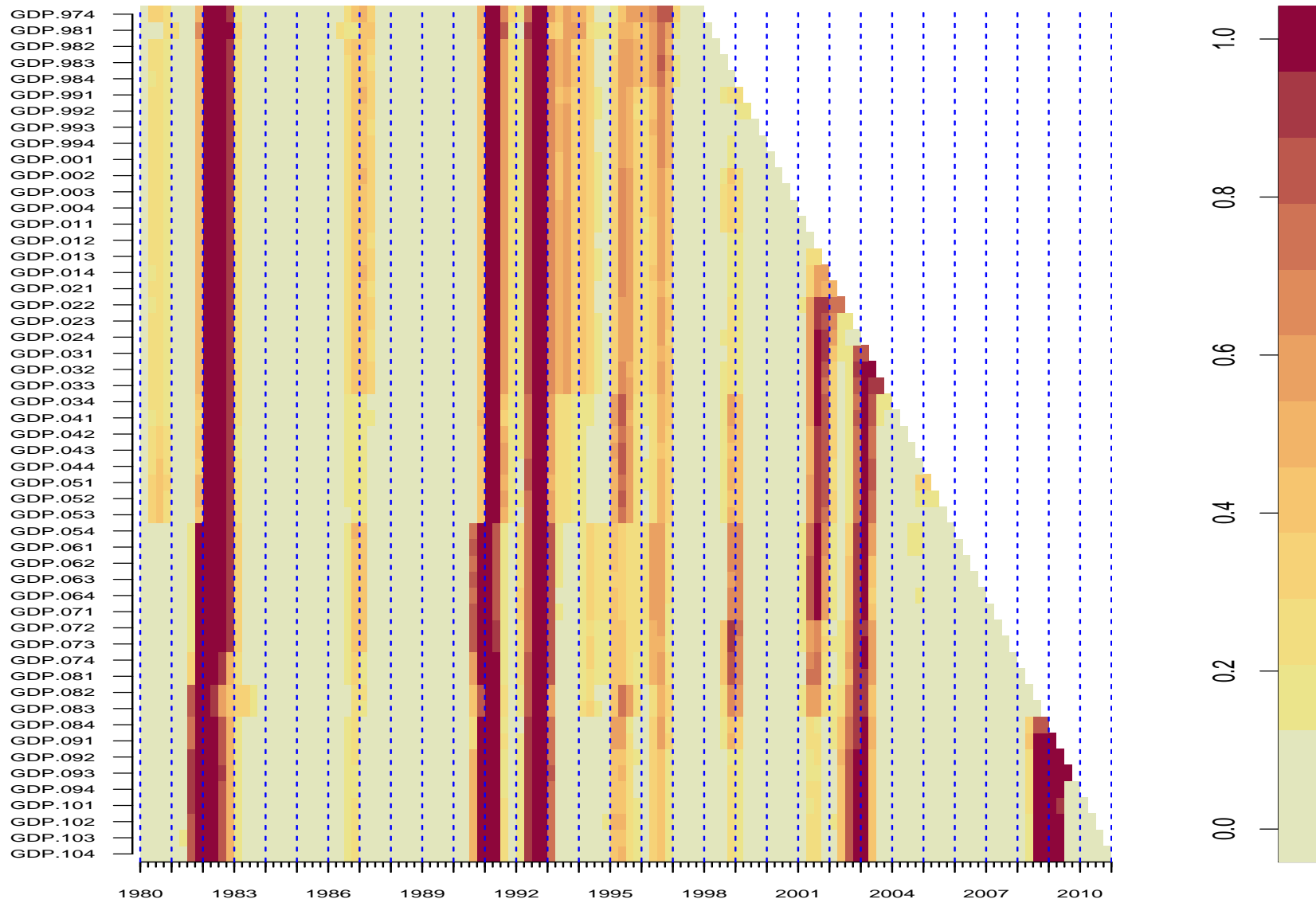


Figure 6: Vintage-specific relative frequency of recession: the first vintage ends in 1997Q4, the last vintage ends in 2010Q4.

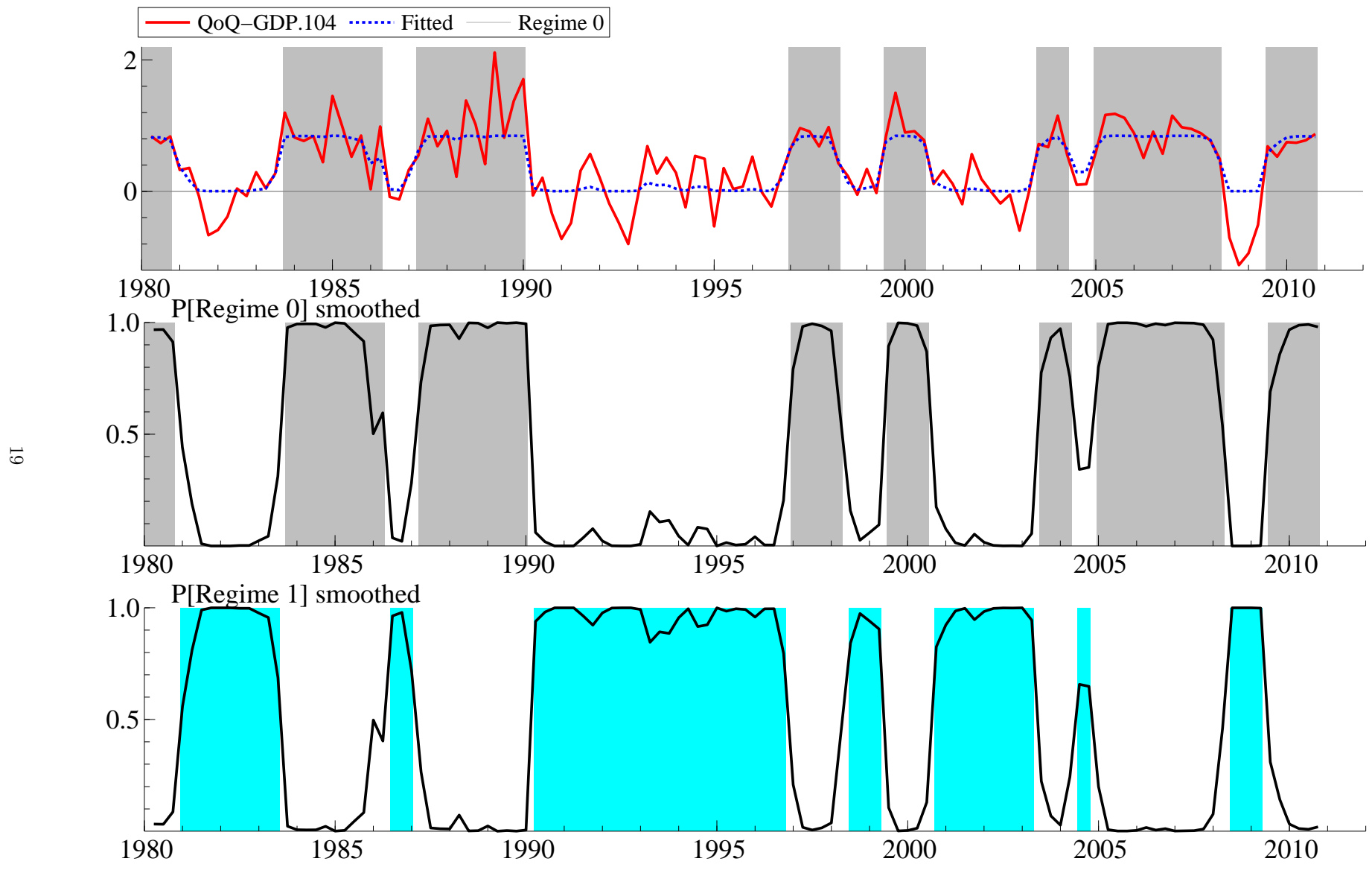


Figure 7: Markov-switching model, MSMH(2)-AR(0): Upper panel—the quarterly GDP growth rate and fitted values; Middle panel—smoothed probability of regime 0 (high growth); Lower panel—smoothed probability of regime 1 (low growth).

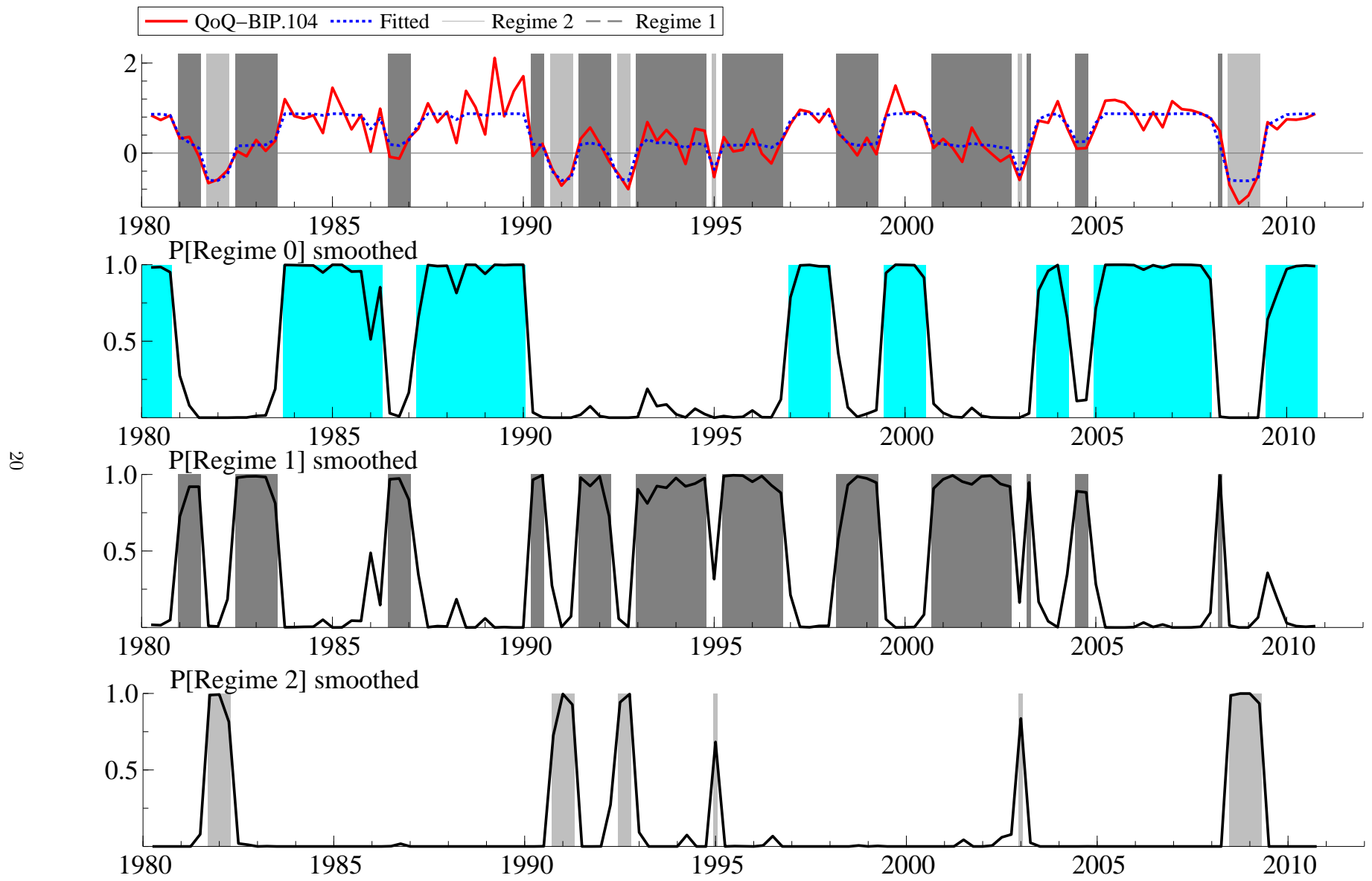


Figure 8: Markov-switching model, MSMH(3)-AR(0): Upper panel—the quarterly GDP growth rate and fitted values; Middle-Upper panel—smoothed probability of regime 0 (high growth); Middle-Lower panel—smoothed probability of regime 1 (normal growth); Lower panel—smoothed probability of regime 2 (recession).