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Declining output volatility in Germany: impulses, propagation, and the role of monetary policy

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The decline in output volatility in Germany is analysed. A lower level of variance in an autoregressive model of output growth can be either due to a change in the structure of the economy (a change in the propagation mechanism) or a reduced error term variance (reduced impulses). In Germany the decline output volatility is due to a decline in the persistence of the growth process. This is in contrast to the US results, where a break in the variance seems to dominate the decline in persistence. A change in the conduct of monetary policy (the establishment of another monetary policy regime) could be part of an explanation for the change in propagation. Stochastic simulations with a New Keynesian DSGE model support the hypothesis.

I. Outline

Output volatility declined in most industrialized countries over the last decades. This was not unexpected. Arthur Burns (1960) in his Presidential Address to the American Economic Association already noticed and predicted a further decline in US output volatility which he labelled as being of a secular nature. He argued that a trend decline in output volatility is indeed under way due to composition effects, the steady shift to a service economy, improvements in capital markets and a higher ability to 'smooth' consumption during periods of uncertain and variable income.

Recently, several authors have investigated the decline in output volatility in the US economy and in other industrialized countries (McConnell and Perez-Quiros, 2000; Blanchard and Simon, 2001; Simon, 2001; Stock and Watson, 2002, 2003a, 2003b; Doyle and Faust, 2003; Barrell and Gottschalk, 2004). Most authors offer explanations for the decline in US output volatility including changes in the conduct of monetary policy (Taylor, 2000; Stock and Watson, 2002), a reduction in inflation volatility (Blanchard and Simon, 2001; Barrell and Gottschalk, 2004), an improved inventory management (McConnell and Perez-Quiros, 2000) and several other factors – including 'good luck' or a lower intensity of shocks hitting the economy.

With the notable exception of Buch *et al.* (2004) there is – to the best of the author's knowledge – little work about this phenomenon in Germany. The present paper differs from the mentioned paper as follows: Buch *et al.* (2004) use SNA 95 data, recalculated for West Germany by the German Statistical Office. These data were seasonally adjusted using Census X11 under standard settings by the authors and an Hodrick–Prescott–Filter was applied

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to analyse the change in business cycle volatility. Here, long time series of seasonally adjusted GDP were used for West Germany (1970–1991) which were made officially available in August 2003 by the German Statistical Office. In contrast to the data set used in Buch *et al.* (2004), the present time series were corrected for outliers and calendar effects by the Bundesbank and the German Statistical Office. A Hodrick–Prescott–Filter is not applied because such a strategy seemed to be too restrictive. Furthermore, other structural break tests than Buch *et al.* (2004) and a completely different modelling strategy has been used.

In this paper the focus is first and foremost on changes in the conduct of monetary policy as the driving force of decreasing output volatility. This does not mean that other possible factors are excluded. The main findings can be summarized as follows: There is a decline in output volatility which is mainly due to a less persistent data generating process. The boom period associated with the re-unification process, however, showed again an increase in volatility. It can reasonably be argued that this was an exceptional period. From an econometric point of view, that makes it extremely difficult to exactly identify the break points or transition periods in volatility. The results of frequency domain analysis show a decline in variance at business cycle frequency. This can be interpreted in a way that the hypothesis that a change in the conduct of monetary policy might be a factor responsible for the reduced volatility is supported. This is at least one explanatory factor. A deeper investigation of this hypothesis calls for a structural model, however. Using a dynamic stochastic general equilibrium (DSGE) model along the lines proposed by McCallum (2001) it can at least give some hints more concerning what might be behind the change in output growth persistence.

The paper is organized as follows: First, some data properties are discussed and it is asked if the reduced volatility – especially at business cycle frequency – might be either due to a change in the propagation mechanism or the strength of the shocks hitting the economy. To that end, an autoregressive framework as in Blanchard and Simon (2001) will be used to investigate the sources of Germany's volatility decrease. Recursive estimates as well as rolling window estimates are used to detect possible changes in the process of output growth. Furthermore, the results of stability and structural break tests are reported and the dates of the breaks are investigated. In the next sections the estimation results for a Markov-switching model as well as a state space model are presented and some results from a smooth transition (STAR) model reported. The results in general support the hypothesis of a shift toward less persistent growth. Furthermore spectral analysis is used to investigate at which frequency the variance diminished mostly. Since the investigation was done in a reduced form interest is in changes of the structural equations as well. To that end, in a final section stochastic simulation results are presented stemming from a model proposed by McCallum (2001) to analyse the changes which might stand behind the volatility change.

A concluding section discusses the results and gives some theoretical considerations about the possible sources of the structural change in the output-generating process. Further research should concentrate on the changes in the structure of the propagation mechanism to clarify if the supply side, the demand side or the change in the conduct of policy is responsible for the changed patterns. This, however, calls for the empirical investigation of structural changes in a fully specified structural model and is clearly beyond the scope of this paper.

II. Declining Growth Volatility: Persistence or Shocks?

The model

A decline in growth volatility can be attributed to different factors. To illustrate this argument, assume that output growth follows an autoregressive process given by:

$$\Delta y_t = g + a(L)\Delta y_{t-1} + \epsilon_t, \qquad (1)$$

where y_t denotes the log of GDP in quarter t, Δ is the difference operator and g the underlying growth rate of output. ϵ_t is a white noise process with the standard deviation σ_ϵ, and $a(L)$ a lag polynomial. Assume further, that output growth follows a first order autoregressive process which leads to $a(L) = a$ and $\Delta y_t = g + a \cdot \Delta y_{t-1} + \epsilon_t$. For output volatility that yields $\sigma_Y = \sigma_\epsilon/(1 - a^2)^{1/2}$, so the higher the value of a, the higher is the standard deviation of output.[1] A change in the output volatility in that model could therefore be attributed either to changes in the intensity of shocks hitting the economy

[1] Without loss of generality this holds for high-order autoregressive processes as well, cf. Blanchard and Simon (2001).

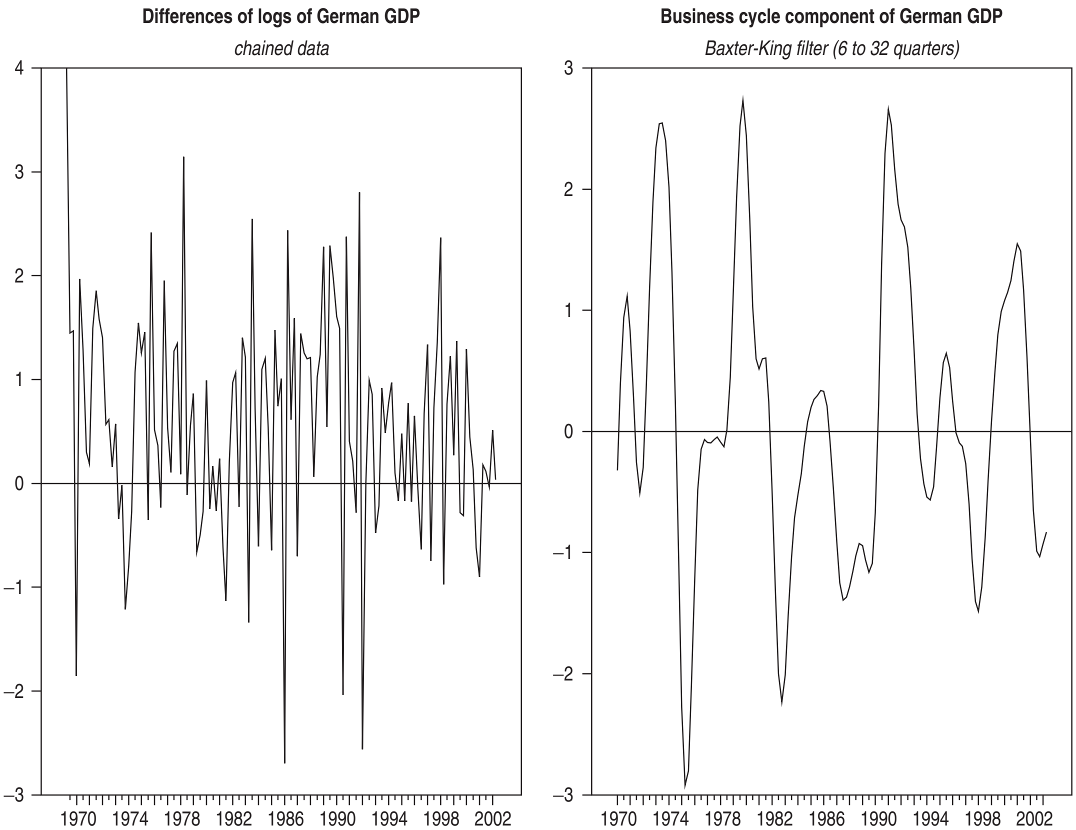

Fig. 1. Data graphs

(impulses) or to changes in the autoregressive structure of output growth (propagation).[2] The autoregressive model can therefore be seen as a simple impulse-propagation framework and serves as a starting point for the investigation.

The data

The data are quarterly real GDP values, adjusted for outliers and calendar effects and seasonally adjusted using X12-ARIMA. The whole time series is calculated according to the new SNA 95 standard for GDP calculation. From 1970 to 1990 the data are West German data, from 1991 onwards the data for Germany until the second quarter 2003 are used. All data are in logs. The time series were chained using the relationship of the 1991 values of German real GDP to West German real GDP as a conversion factor. For a preliminary analysis, a Baxter–King (1995) band pass filter was applied to extract a business cycle component out of the data. First differences and the business cycle component according to the band pass filter are plotted in Fig. 1. The visual inspection shows that output volatility is lower in the second half of the sample when measured at the business cycle frequency – especially if it is taken into account that the reunification boom was an extraordinary event in German history.

Linear model estimates and stability test results

In a related paper, Hess and Iwata (1997) argue that in general an AR(1) process should be able to capture the dynamics of output growth quite well and can serve as a proxy for the impulse-propagation framework used here. At least in history, this process performed no worse than much more complicated non-linear formulations of the

[2] Blanchard and Simon (2001) argue that the decrease in volatility could also be influenced by the underlying growth rate, g, that affects the probability of negative growth occurrences given the other parameters. The authors argue, that the length of expansions is not independent from the underlying growth rates, because the probability of negative growth occurrences (that is, 'recessions' in their definition) increases as the underlying growth rate decreases. Because an economy – once trapped in a recession – shows a different volatility, the overall volatility is at the end not independent from the recession probability. The following sections focus on changes in the autoregressive parameter and in the innovation variance only.

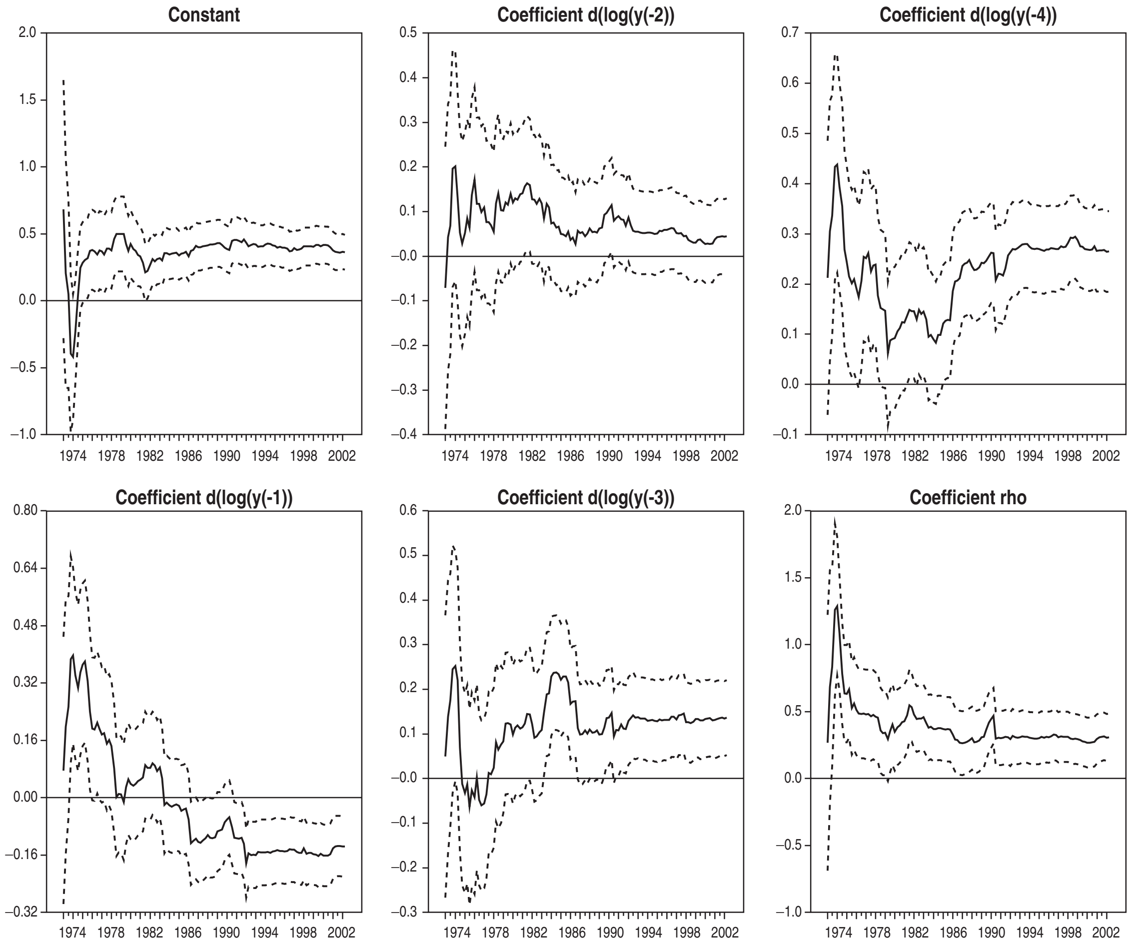

Fig. 2. Recursive estimation results

output growth process. The appropriate lag length for the German output growth process was investigated using lag selection tests.[3] The results indicate that an AR(4) seems to be appropriate. The estimated model has the following properties:

$$\Delta y_t = \underset{(0.001)}{0.004} - \underset{(0.08)}{0.14}\Delta y_{t-1} + \underset{(0.08)}{0.04}\Delta y_{t-2} + \underset{(0.08)}{0.14}\Delta y_{t-3} + \underset{(0.08)}{0.27}\Delta y_{t-4} + \epsilon_t \qquad (2)$$

$$R^2 = 0.11,\ \mathrm{LM}(5) = 0.46[0.80],\ \mathrm{ARCH-LM}(5) = 0.71[0.61]$$

$$\mathrm{JB} = 7.40[0.02],\ \mathrm{AIC} = -6.37$$

According to the reported criteria the equation is well specified with some signs of non-normality.[4] In spite of the fact that some lags are not significant, it was decided to use the AR(4) specification in the next sections. The specification should be flexible enough to allow for changes in the dynamics over time which it is desired not to restrict prior to the investigation.

In the next stage of the investigation, structural stability was tested for in this impulse-propagation model. CUSUM and CUSUM square tests were applied; they gave no indication of any instability. More interesting are the results of recursive and rolling windows estimations which are shown in Figs 2 and 3. The recursive coefficients suggest that there might be a ‘change’ in the propagation

[3] Specifically, the minima of the Akaike and Schwarz criteria up to a lag order of 24, a Ljung–Box for residual serial correlation, a Langrange multiplier test for residual serial correlation and a general-to-simple reduction test were estimated.
[4] The following tests were performed serial correlation LM test, ARCH LM test, Jarque–Bera normality test. Furthermore the Akaike information criterion is reported.

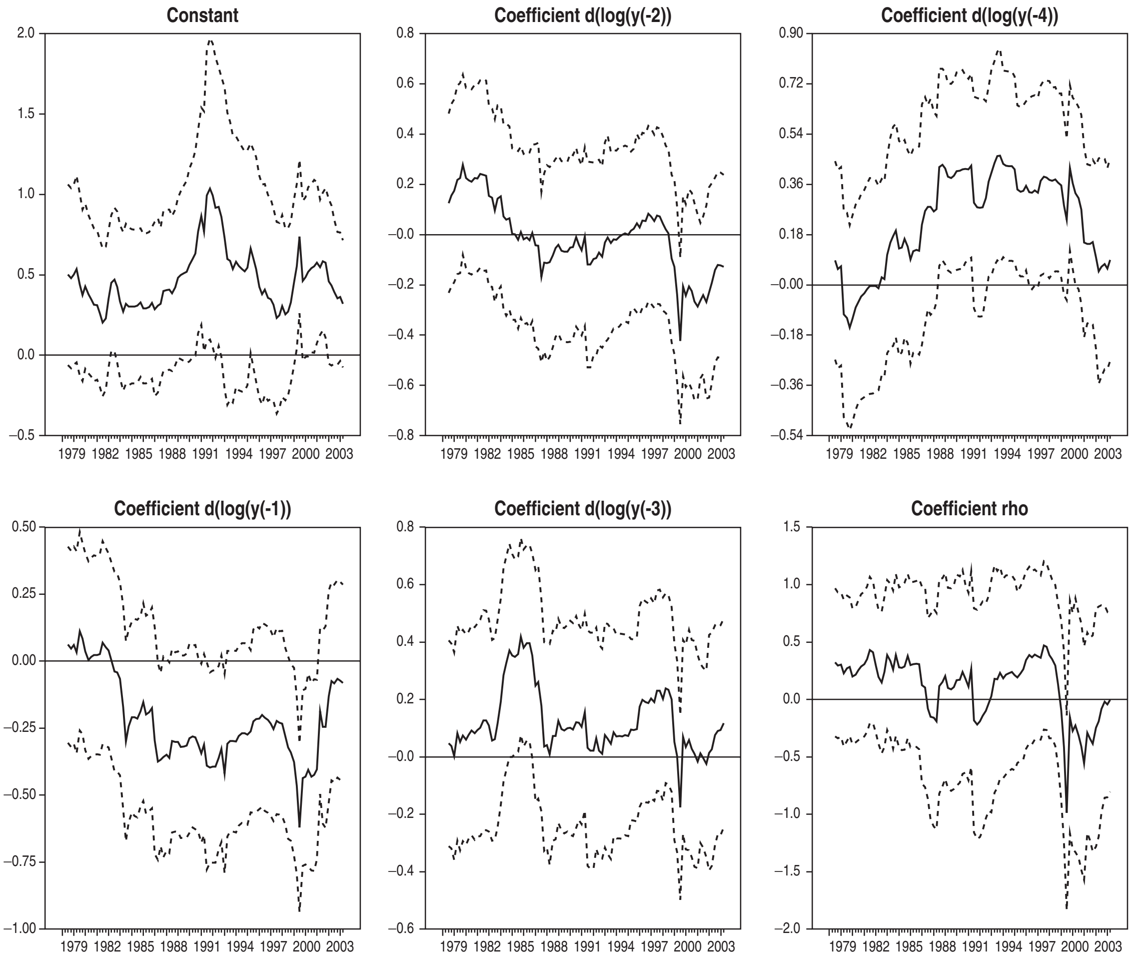

Fig. 3. Moving window estimation results

structure – the coefficient of the first lag is relatively high in the early 1970 but declines steadily over time. The result is confirmed but less pronounced by the results from rolling window estimates.[5]

The hypothesis of a change in the propagation structure also within a transformed version of the AR(4) model was tested where the overall persistence is measured in one single parameter (ρ). The transformed (error correction) representation is given by:

$$\Delta y_t = g + (\rho_1 + \rho_2 + \rho_3 + \rho_4)\Delta y_{t-1} - (\rho_2 + \rho_3 + \rho_4)\Delta^2 y_{t-1} - (\rho_3 + \rho_4)\Delta^2 y_{t-2} - \rho_4 \Delta^2 y_{t-3} + \epsilon_t \tag{3}$$

$$\Delta y_t = g + \rho \Delta y_{t-1} + \phi_1 \Delta^2 y_{t-1} + \phi_2 \Delta^2 y_{t-2} + \phi_3 \Delta^2 y_{t-3} + \epsilon_t \tag{4}$$

In this specification Δ^2 stands for the second differences, i.e. $\Delta\Delta$ and ρ for the sum of the AR coefficients. The parameter ρ measures the overall persistence since it sums up all AR parameters.

This equation is of course identical to the AR(4) model. However, due to this 'trick' it is easier to explore the change in the *overall* persistence. The recursively estimated ρ – as can be seen in Fig. 2 – shows a clear tendency that the overall persistence declined over time. The result is confirmed by the rolling windows estimates (see Fig. 3) – however the decline is by far less pronounced.

There is a growing literature about the detection and dating of structural breaks – especially if the exact break point is unknown; see Hansen (2001) for an excellent survey. To test for breaks, the Andrews–Quandt tests were applied as described in Andrews (1993) to the AR(4) model and the error

[5] A window of 32 quarters or eight years was opted for respectively because this is the lower threshold for a typical business cycle frequency according to the concept of Burns and Mitchell (1946).

Table 1. Results of Andrews–Quandt test: asymptotic and bootstrapped p-values

	Asymptotic results		Bootstrapped results ($n = 2000$)	
Variable	Break date	AQ (p-value)	Break date	AQ (p-value)
Constant	1991:2	0.50	1983:1	0.88
Δy_{t-1}	1976:2	0.08	1976:2	0.05
Δy_{t-2}	1991:2	0.39	1991:2	0.69
Δy_{t-3}	1991:2	0.93	1976:3	0.93
Δy_{t-4}	1985:2	0.64	1985:2	0.45
ρ	1991:2	0.44	1991:2	0.36
All coeff.	1991:2	0.44	1991:2	0.40
Variance	1993:1	0.78	1993:1	0.34

correction representation of the AR(4) model. In short, these tests trim the range of the sample by 15% (suggested value in Andrews and Ploberger, 1994) from each side and perform Lagrange multiplier tests for each of the possible break points for the remaining middle range of the sample. The Andrews–Quandt test uses as the test statistic the maximum of the LM statistics. To consider the scepticism with regard to asymptotic distributions for these type of test (Diebold and Chen, 1996), bootstrapped p-values (2000 replications) were considered as well as asymptotic p-values taken from Hansen (1997).[6]

The results – see Table 1 – indicate that a structural break can be identified in the autoregressive structure (more precisely: it is found on a 5% significance level for the first lag coefficient), but not in the residuals variance. This is in contrast to the results for the US economy, where a break in the variance of the residuals is found by most methods (cf. McConnell and Perez-Quiros, 2000). For Germany, the breakpoint for the AR(1) coefficient is dated around 1976.[7] For the period from 1976 onwards no further break was detected at a conventionally applied significance level. Note, that the break date for the overall equation is estimated around the German unification. This result will be returned to later.

In the next step the procedure proposed by Bai and Perron (2003) was used to check if there are more structural breaks.[8] The test procedure investigates all possible models under the assumption of a given number of breakpoints and a given minimum distance between the break points. Then, the 'optimal' model is chosen according to the (minimum of the) sum of squared residuals and according to information criteria. Therefore, it was necessary to assume the number of breakpoints that would be allowed to occur in the model at maximum and the optimal break points calculated for each model. A maximum of four breakpoints was opted for with a data range of about 30 years. The minimum distance between two breakpoints was set equal to six years as some stability is assumed over the cycle. For each model, the Bayesian Information Criteria (BIC) was calculated to check which of the estimated breakpoint models could be seen as the best performing one.

The results are presented in Table 2. According to the BIC criteria the model with one break shows the best fit. The break occurred in 1991Q2. The break date corresponds to the result for the overall stability of Equation 2. However, according to the Andrews–Quandt test applied above, this break was not significant. All in all, the differences between the models chosen by the Bai and Perron (2003) method in terms of the squared residual sum are quite small – so the interpretation in favour of the one-break-model is weak. Nevertheless a general observation holds: the point estimates of the coefficient ρ are higher in the 1970s and 1980s and very low – even negative – in the period from 1991 onwards.

In a nutshell, the results from the stability tests indicate that there is structural instability in the dynamic structure of the economy and that there

[6] The RATS procedures THRESHOLD.SRC and APTEST.SRC downloadable from the Estima homepage (www.estima.-com) and RATS 6.01 were used to perform the calculations.
[7] This result also holds, if an expanded data set with data from 1960 onwards is used. However this data set was not considered for further explorations because the data from 1960 to 1969 are only available according to the old national account standards.
[8] Tom Doan of Estima is thanked for making the RATS code available to perform the Bai–Perron tests in previous versions of the paper. The procedure BAIPERRON.SRC became available on the Estima homepage (www.estima.com) since then.

Table 2. Results of Bai–Perron test

Model (breaks)	Model (1)	Model (2)	Model (3)	Model (4)
Sum of squared residuals	108.4	99.0	90.9	84.7
BIC	0.23	0.33	0.44	0.56
Breakpoint(s)	1991Q2	1983Q2 1991Q2	1978Q2 1985Q2 1991Q2	1978Q2 1985Q2 1991Q2 1999Q2

is a decline in the persistence of output growth. To shed further light on these issues different non-linear specifications were used, namely Markov-switching, smooth transition (STAR) and state space (time-varying coefficient) models.

Non-linear models

The results up to now indicate that there might have been a regime shift in volatility over time. Markov-switching models are often seen as appropriate for this kind of problem (McConnell and Perez-Quiros, 2000). Strictly speaking, Markov-switching models are not appropriate if the regime-shift is seen as irreversible due to the ergodic nature of the Markov chain. However, to compare the results up to now and to get a deeper insight into the nature of the problem, this class of model was used as well.

In the following, the Markov-switching version of Equation 4 with a regime-dependent ρ-coefficient was estimated.[9]

$$\Delta y_t = g + \rho(s_t)\Delta y_{t-1} + \phi_1 \Delta^2 y_{t-1} + \phi_2 \Delta^2 y_{t-2} + \phi_3 \Delta^2 y_{t-3} + u_t, \ \ s_t \in \{1, 2\} \qquad (5)$$

where s_t denotes the realizations of the underlying unobservable discrete Markov chain. Two regimes are allowed.[10] The transition probabilities were estimated using a logit transformation: $p_{jj} = e^{\varphi_j}/(1 + e^{\varphi_j})$. Using Maximum Likelihood estimation technique under normality assumption, the estimation results were received and the corresponding smoothed probabilities as shown in Table 3 and Fig. 4.

The results indicate that there were two major periods where the persistence of the data generating process was high: the early 1970s and the reunification boom in the early 1990s. Also the recession period of the early 1980s as well as after the millennium sees an increase in persistence which is however much less pronounced than the other two episodes.

Table 3. Estimation results of the Markov-switching model Equation 5

Coefficient	Value	Std. error
g	0.004	0.001
$\rho(s_t = 1)$	0.61	0.21
$\rho(s_t = 2)$	−0.005	0.21
ϕ_1	−0.36	0.16
ϕ_2	−0.39	0.12
ϕ_3	−0.28	0.08
γ	−9.42	0.14
p_{11}	0.89	–
p_{22}	0.94	–
Log $L(\hat{\Theta})$	417.16	–
AIC	−6.33	–

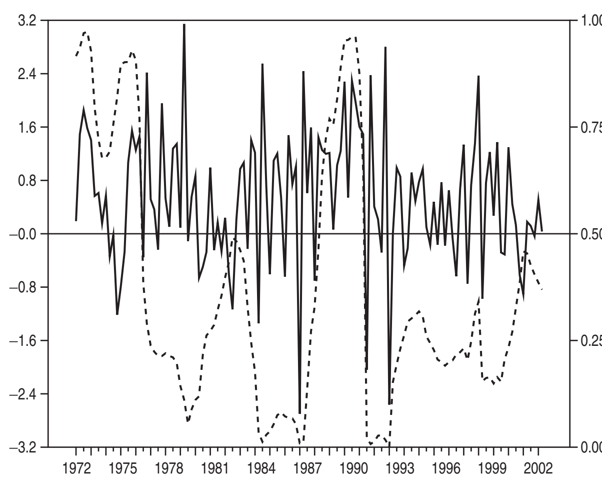

Fig. 4. Markov-switching model results: GDP growth and high persistence regime probabilities (Equation 5): (——) GDP growth (– – –) Smoothed probability.

Output volatility is high either in very pronounced booms or recessions and low in other periods. Since there was only one of these 'extraordinary' episodes in the second half of the sample it is not

[9] This is an MSA-model. It was implicitly assumed that only ρ_1 from the specification in Equation 3 is changing in dependence from the regime (Krolzig, 1997).

[10] More regimes were considered but the results were not decisive.

astonishing that the volatility at the typical business cycle frequency is lower. If the early 1990s period is interpreted as a special period where the business cycle was mainly driven by the reunification boom, the result is in line with the Andrews–Quandt test results (break in 1976). If a second break is allowed for, the found break date corresponds to the results of the Bai–Perron test.

An explicit counterpart of the Markov-switching model estimated above is the smooth transition autoregressive model (STAR, cf. Teräsvirta, 1998), because in contrast to the previous case an observable transition variable and not an unobservable Markov chain is assumed to determine the regime change mechanism. Employing the time trend as the transition variable, the irreversibility of the detected regime change is explicitly assumed. The estimated regression equation posses the following form:

$$\Delta y_t = g + F(t)\Delta y_{t-1} + (1 - F(t))\Delta y_{t-1} + \phi_1 \Delta^2 y_{t-1} + \phi_2 \Delta^2 y_{t-2} + \phi_3 \Delta^2 y_{t-3} + u_t \qquad (6)$$

where the disturbance term is assumed to be i.i.d. and

$$F(t) = (1 + \exp[-\gamma(c - t)])^{-1}$$

in which c represents the location parameter of the structural change (starting with 1971Q2 = 1) and γ determines the smoothness of the corresponding change. Equation 6 represents a non-linear model and can in principle be estimated using non-linear least squares.

However, the non-linear least squares estimation turned out to be quite difficult because of the existence of multiple minima for the sum of squared residuals, a corresponding sensitivity to starting values, and due to the estimated value of γ, which tends to go to infinity, implying a threshold model. Therefore it was decided to use a grid search procedure, implemented for example in JMULTI 3.11, for the first estimation of the parameters.[11] The results of the grid search in terms of parameter values of c and γ can be found in Fig. 5. The multiple local extrema and the corresponding values of γ tending to infinity can be clearly seen.

The results indicate that the global maximum of the negative sum of squares corresponds to the first break date indicated by Markov-switching model in 1976Q2 (it also corresponds to the break date of the AR(1) coefficient according to the Andrews–Quandt test), whereas the second largest extremum is probably due to the unification boom in the early 1990s. It could mean that the unification boom requires a separate treatment as an individual regime, however, it would be beyond the scope of this paper and therefore attention is concentrated only to the irreversible change in the middle of the 1970s. Because the estimated value of γ tends to go to infinity, the estimation was proceeded with using a step dummy which is one before 1976Q2 and zero after it. The results of the linear estimation can be found in Table 4. A clear decline of the output persistence is found after 1976Q2.

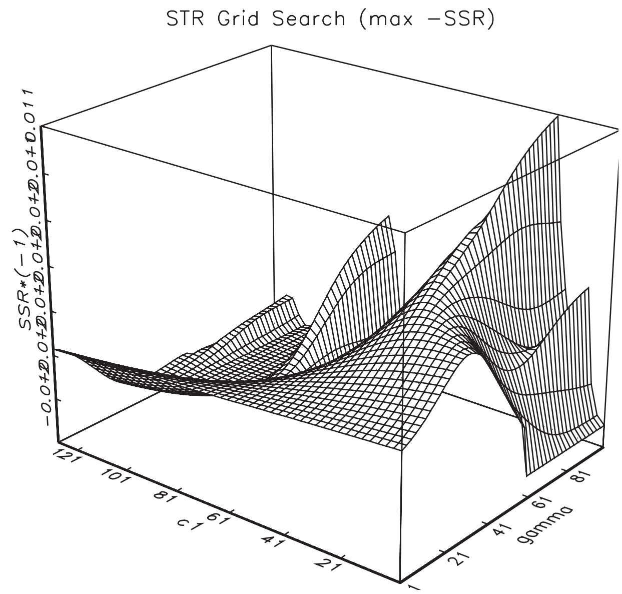

Fig. 5. Results of grid search: c and γ (Equation 6)

Table 4. Estimation results for $\gamma = \infty$ (Equation 6)

Coefficient	Value	Std. error
g	0.0037	0.0013
$\rho \cdot I_{(1976Q2)}$	0.78	0.24
$\rho \cdot [1 - I_{(1976Q2)}]$	0.21	0.18
ϕ_1	−0.44	0.15
ϕ_2	−0.43	0.12
ϕ_3	−0.29	0.08
AIC	−6.42	–

Furthermore a state space model (as described e.g. in Hamilton, 1994) with a time-varying coefficient ρ was estimated. The system consists of two equations: the space equation, which is the observable part of the model and the state equation, which gives some structure to the unobservable part of the model. The space equation is given

[11] The programme JMULTI (cf. Lütkepohl and Krätzig, 2004) is freely available at www.jmulti.de

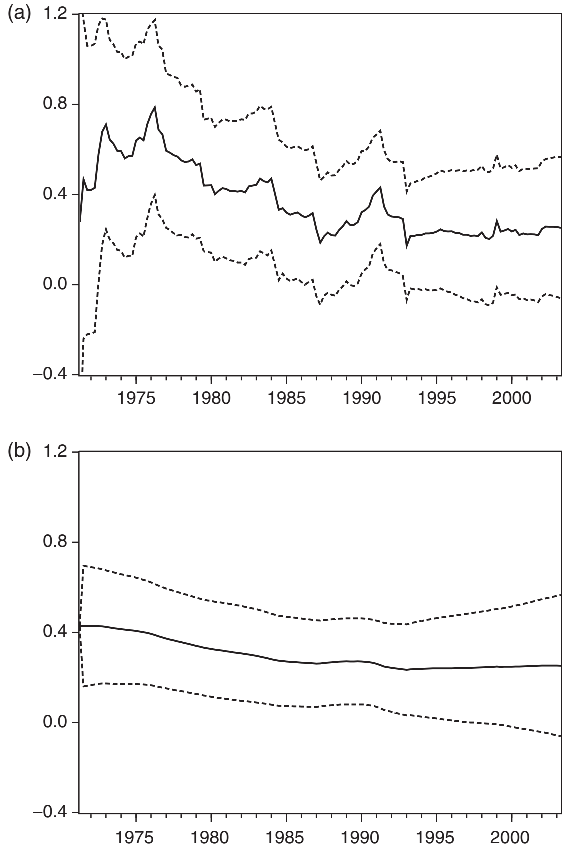

Fig. 6. State space model: estimation results for ρ including confidence bounds (± 2 RMSE) (Equation 7): (a) Filtered estimate; (b) Smoothed estimate

by the transformed autoregressive growth (error correction form) model. The coefficient ρ is modelled as a random walk and defined by the state equation:

$$\Delta y_t = g + \rho_t \Delta y_{t-1} + \phi_1 \Delta^2 y_{t-1} + \phi_2 \Delta^2 y_{t-2} + \phi_3 \Delta^2 y_{t-3} + u_t \quad (7)$$

$$\rho_t = \rho_{t-1} + v_t \quad (8)$$

where the disturbance vectors u_t, v_t are assumed to be serially independent. The variance of the space and the state equation are estimated as exponential functions to restrict the variance to non-negative numbers. The evolution of the estimated coefficient (Kalman filter result) is plotted in Fig. 6. The estimation results of the state space model are summarized in Table 5.

As can be seen from Fig. 6 there is a decline in persistence over time until the mid 1980s. The value of the respective coefficient is about 0.7 for the filtered or 0.4 for the smoothed estimates in the early 1970s, it declines in the course of the 1980s and is about 0.3 at the beginning of the 1990s. There is a temporary increase of the coefficient during the reunification boom – even in the smoothed estimates. This is all in line with the results from the Markov-switching model, the STAR model and the results from stability tests.

III. Spectral Analysis

A helpful tool to detect the sources of the change in persistence is furthermore given by spectral analysis (cf. König and Wolters, 1972). Analytically, the correllogram of a stationary time series can be transformed into the frequency domain using Fourier transformation. The spectra functions indicate the contribution of every frequency component to overall variance. By decomposing the overall variance into frequency portions it can be informally checked if long-run movement, business cycle fluctuations or seasonal dynamics are the driving forces of a time series' dynamics. Analysing the spectra functions is therefore a suitable instrument to find out at which frequency the changes took place.

In Fig. 7 are ploted empirical spectra functions for different periods including some grid lines which define a business cycle frequency from one and a half to eight years. According to the test results the sample was spilit in 1976. The empirical spectra functions are given in the first row of the graph. Critics might argue that a sample of six years is too short for any reasonable statement about the spectra function. Therefore the sample was spilit in the middle of the overall sample and the exercise repeated – see the figures in the second row. The results are fairly robust. There is a distinctive decline of variance at the business cycle frequency.[12]

Ahmed *et al.* (2002) used the spectra functions to investigate the change in US growth volatility and interpret a shift as in the present case – which occurs primarily at the business cycle frequency – as being induced by better a better managed macroeconomic (i.e. mainly monetary but also fiscal) policy. Critics might argue that it could well be the case that other factors – i.e. better business practices or improved inventory management – might dampen the business cycle fluctuations as well. This can of course never be ruled out. However, as Buch *et al.* (2004) already have shown, changes in inventory management do not seem to be factor behind the observed

[12] To estimate the spectra functions the code SPECTRUM.SRC in RATS 5.04 was used with standard settings. The window size as well as the smoothing parameters were set automatically according to the number of observations.

Table 5. Estimation results: state space model (Equation 7)

	Coefficient	Std. error	z-statistic	Prob.
g	1.47	0.58	2.52	0.012
ϕ_1	−0.43	0.15	−2.81	0.005
ϕ_2	−0.40	0.13	−3.05	0.002
ϕ_3	−0.27	0.08	−3.22	0.001
$\mathrm{Log}(\sigma^2(u_t))$	2.68	0.11	23.42	0.000
$\mathrm{Log}(\sigma^2(v_t))$	−7.47	1.99	−3.76	0.000
ρ_t	Final state	Root MSE	z-statistic	Prob.
	0.25	0.16	1.59	0.112
Log likelihood	−367.60	AIC	–	5.79
Parameters	6	Schwarz criterion	–	5.93
Diffuse priors	1	Hannan–Quinn criterion	–	5.85

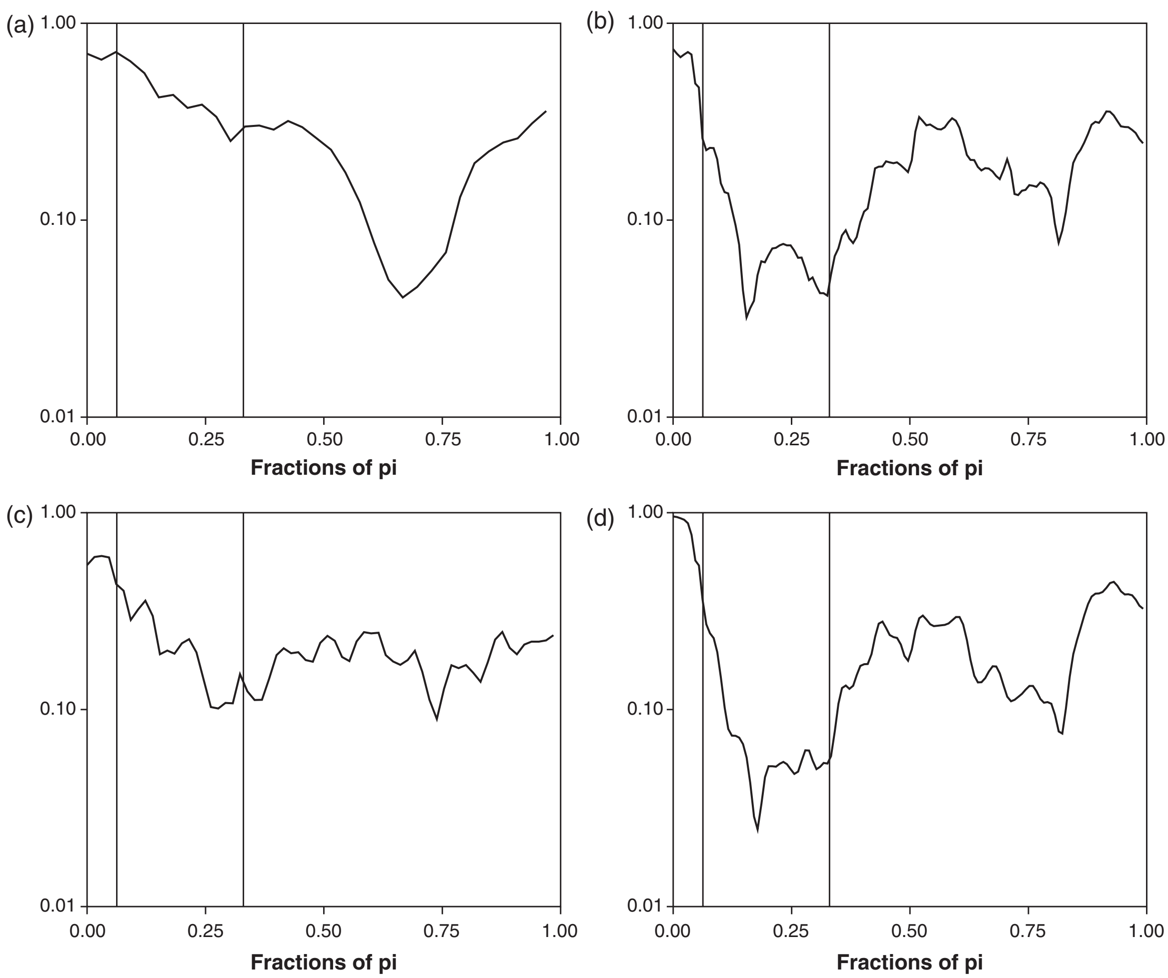

Fig. 7. Spectral density estimates: different subsamples: (a) spectrum: sample 1970–1976, (b) spectrum: sample 1976–2003, (c) spectrum: sample 1970–1985, (d) spectrum: sample 1986–2003

dampened cycle – at least not in Germany.[13] Therefore it is interesting to explore if monetary policy could be an important factor in explaining the decrease in volatility.

IV. A Theoretical Model

So far the result points to a decline of the persistence parameter ρ. The estimations were performed in a reduced form – so nothing can be said about the underlying structural changes. The spectral analysis results indicate that a change in monetary policy might play a role. There are two ways to investigate that issue further: either to estimate a structural model and test within the structural equations for changes or to calibrate a theoretical model and simulate the consequences of changes in the structural parameters. The second solution was opted for.

There is surely nothing new about the fact that there was a break in the conduct of monetary policy at the beginning of the 1980s. This is at least true for the USA, where Federal chairman Paul Volcker started a radical disinflation in 1979. The fact that there is a break in the conduct of monetary policy in other industrialized countries is, however, also confirmed by studies that estimated Taylor rules for other G7 countries (Clarida *et al.*, 1998). These studies showed that the monetary policy became more hawkish in the sense that central banks show more aggressive reaction toward fighting against inflation than during the heyday of Keynesian demand policy in the 1960s and the stagflationary 1970s (especially the reaction coefficient on inflation became larger). But can the reduced volatility and the detected change in propagation be explained by a change in the conduct of monetary policy? To analyse these aspects, the 'New Keynesian' (NK) model became the new workhorse in the last decade (a similar approach was used by Boivin and Giannoni, 2002).

In the following a calibrated model as developed by McCallum (2001) for example was used to analyse the effects of monetary policy on output. Here, it is required to explore the effects of changes in 'deep' structural parameters on output volatility. An attempt was made to keep the model as simple as possible. The model is given by the following equations:[14]

$$y_t = b_0 + b_1\left(R_t - E_t\Delta P_{t+1}\right) + E_t y_{t+1} + v_t \tag{9}$$

$$\Delta p_t = \beta E_t \Delta p_{t+1} + \alpha \tilde{y}_t + u_t \tag{10}$$

$$\begin{aligned} R_t = {} & \mu_0 + (1-\mu_3)(\mu_1 \Delta p_t + \mu_2 E_{t-1}\tilde{y}_t) \\ & + \mu_3 R_{t-1} + e_t \end{aligned} \tag{11}$$

Equation 9 states the intertemporal IS curve. Actual output y_t depends positively on future expected income $E_t y_{t+1}$ and negatively on the (short-term) real interest rate $R_t - E_t\Delta P_{t+1}$.[15] Equation 10 defines a forward-looking Phillips curve with Calvo price setting. Actual inflation depends on expected inflation $E_t\Delta p_{t+1}$ and the output gap $\tilde{y}_t$. Equation 11 gives a standard Taylor rule where the monetary authorities react on inflation and the output gap. Furthermore interest rate smoothing is assumed controlled by μ_3.

These equations are accompanied by the definition equation of the output gap and some laws of motion for the stochastic terms.

$$\begin{aligned} \tilde{y}_t &= y_t - \bar{y}_t \\ v_t &= 0 \cdot v_{t-1} + \nu_t \\ e_t &= 0 \cdot e_{t-1} + \epsilon_t \\ u_t &= 0 \cdot u_{t-1} + \psi_t \\ \bar{y}_t &= 0.95 \cdot \bar{y}_{t-1} + \eta_t \end{aligned} \tag{12}$$

The model was solved using the procedure proposed by McCallum (1998) and Klein (2000). First the model was solved under the following standard parameter settings as proposed by McCallum (2001): $b_0 = \mu_0 = 0,\ b_1 = -0.4,\ \beta = 0.99,\ \alpha = 0.03,\ \mu_1 = 0.5/4,\ \mu_2 = 0.5,\ \mu_3 = 0.8$. All impulse response functions show the expected signs and shapes as in McCallum (2001).[16]

[13] Taken together, these results [on the volatility of inventory investment, U.F.] are somewhat at odds with the hypothesis that the decrease in output volatility in Germany could be due to a decline in the volatility of inventory investment (Buch *et al.*, 2004, p. 475).

[14] The MATLAB files available from Bennett McCallums homepage and some modified versions of these files written by Jan Gottschalk were used. The authors' are greatful to Jan Gottschalk who kindly offered help to implement the files and handle the output.

[15] It is assumed that the long-term real interest rate depends on the short-term real interest rate.

[16] Note that the reaction functions of the model as specified above do not create very much persistence. McCallum (2001) used habit formation and a partly backward-looking Phillips curve (so-called Fuhrer–Moore specification), to get more persistence into the model. To keep the factors of influence as limited as possible, the simplest version of the model was opted for that could be found.

Table 6. Autocorrelation of $\tilde{y}$ at different lag lengths: results from stochastic simulations

ACF for ...				
Lag	Baseline $b_1 = -0.4$, $\mu_1 = 0.5$, $\mu_2 = 0.5$	$b_1 = -0.8$	$\mu_1 = 1$	$\mu_2 = 1$
1	0.72	0.66	0.69	0.69
4	0.34	0.21	0.29	0.31
8	0.15	0.04	0.10	0.13
12	0.08	0.00	0.04	0.07

In the next step, values were set for the variances of the different types of shocks. Again the settings as proposed by McCallum (2001) were opted for. The variances were set as follows: the variance of ν_t was set equal to 0.03, the variance of ϵ_t was set equal to 0.002, the variance of ψ_t was set equal to 0.0017, the variance of η was set equal to 0.007. Stochastic simulations done with the model (10 000 repetitions) and the autocorrelation functions saved. Specifically, interest was in the change of the autocorrelation function of the variable $\tilde{y}$ – the output gap. The focus is on the output gap because empirically it was found that changes at the business cycle frequency seem to be the driving force behind the change in persistence.

Then, some parameters of the model were changed to see if and how much the persistence changes. Specifically, the value of b_1 was doubled to –0.8. In two other simulations, the values of μ_1 and μ_2 were doubled to 1. So, in the simulation exercise, changes in volatility might be either due to a change in the way households *react* to monetary policy (parameter b_1) or due to the way monetary policy is set (parameters μ_1 and μ_2). Always only one parameter was changed and the autocorrelation functions together with those from the baseline at different lags reported. The results are shown in Table 5. All changes lead to a decrease in persistence and are potential candidates as explanatory factors for the decrease in output volatility. It is interesting to note that a change in b_1 and μ_1 have a stronger effect on the persistence of $\tilde{y}$ than a change in μ_1.

V. Discussion

The decline in output volatility in Germany has been investigated. The results from the structural break tests, the Markov-switching model as well as the state space models show that the decline is probably more of a gradual nature than a sudden break. Results from spectral analysis estimations indicate that monetary policy might have played a role. However, in contrast to the US results, it is the transmission mechanism of shocks, not the variance of shocks itself which changed. To investigate the possible sources of structural changes which might be responsible for the observed pattern a calibrated DSGE model was used. The results of the stochastic simulations are interpreted in the following way: changes in policy reaction parameters – as reported for most industrialized countries around the late 1970s – should have had an influence on output volatility. Probably these changes also influenced the interest rate sensitivity of the IS curve and this in turn reduced volatility further. This could be a typical case for a Lucas critique phenomenon because it is very plausible that a change toward another policy regime would influence the behaviour of households. These changes, however, must have been quite pronounced to generate a remarkable fall in volatility – at least according to the simple model used here.[17]

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References

Ahmed, S., Levin, A. and Wilson, B. A. (2002) Recent US macroeconomic stability: good policies, good practices, or good luck?, Federal Reserve Board IFD Paper No. 730, July.

Andrews, D. W. K. (1993) Tests for parameter instability and structural change with unknown change point, *Econometrica*, **61**, 821–56.

Andrews, D. W. K. and Ploberger, W. (1994) Optimal tests when a nuisance parameter is present only under the alternative, *Econometrica*, **62**, 1383–414.

[17] More complicated models with habit formation and/or more persistence in the Phillips curve could generate different result. Such investigation is however beyond the scope of this paper.

Bai, J. and Perron, P. (2003) Computation and analysis of multiple structural change models, *Journal of Applied Econometrics*, **18**, 1–22.

Barrell, R. and Gottschalk, S. (2004) The volatility of the output gap in the G7, National Institute Economic Review No. 188, April, 100–7.

Baxter, M. and King, R. G. (1995) Measuring business cycles approximate band pass-filters for economic time series, NBER Working Paper No. 5022, Cambridge, MA.

Blanchard, O. and Simon, J. (2001) The long and large decline in US output volatility, *Brookings Papers on Economic Activity*, 135–73.

Boivin, J. and Giannoni, M. (2002) Assessing changes in the monetary transmission mechanism: a VAR approach, *FRBNY Economic Review*, May, 97–111.

Buch, C., Döpke, J. and Pierdzioch, C. (2004) Business cycle volatility in Germany, *German Economic Review*, **5**(4), 451–80.

Burns, A. (1960) Progress towards economic stability, *American Economic Review*, **50**(1), 2–19.

Burns, A. F. and Mitchell, W. C. (1946) *Measuring Business Cycles*, NBER, New York.

Clarida, R., Gali, J. and Gertler, M. (1998) Monetary policy rules in practice: some international evidence, *European Economic Review*, **42**, 1033–67.

Diebold, F. and Chen, C. (1996) Testing structural stability with endogenous breakpoint: a size comparison of analytic and bootstrap procedures, *Journal of Econometrics*, **70**, 221–41.

Doyle, B. and Faust, J. (2003) Breaks in the variability and co-movement of G-7 economic growth, Board of Governors of the Federal Reserve System (US), International Finance Discussion Papers No. 786.

Hamilton, J. (1994) *Time Series Analysis*, Princeton University Press, Princeton, NJ.

Hansen, B. (1997) Approximate asymptotic *P*-values for structural change tests, *Journal of Business and Economic Statistics*, **15**, 60–7.

Hansen, B. (2001) The new econometrics of structural change: dating changes in US labor productivity, *Journal of Economic Perspectives*, **15**, 117–28.

Hess, G. and Iwata, S. (1997) Asymmetric persistence in GDP? A deeper look at depth, *Journal of Monetary Economics*, **40**(3), 535–54.

Klein, P. (2000) Using the generalized Schur form to solve a multivariate linear rational expectations model, *Journal of Economic Dynamics and Control*, **24**(10), 1405–23.

König, H. and Wolters, J. (1972) *Einführung in die Spektralanalyse Ökonomischer Zeitreihen*, Meisenheim am Glan, Anton Hain.

Krolzig, H.-M. (1997) Markov-switching vector autoregressions: modelling, statistical inference and application to business cycle analysis, Lecture Notes in Economics and Mathematical Systems No. 454, Berlin.

Lütkepohl, H. and Krätzig, M. (2004) *Applied Time Series Econometrics*, Cambridge University Press, Cambridge.

McCallum, B. (1998) Solutions to linear rational expectations models: a compact exposition, *Economics Letters*, **61**(2), 143–7.

McCallum, B. (2001) Should monetary policy respond strongly to output gaps, *The American Economic Review*, **91**(2), 258–62.

McConnell, M. and Perez-Quiros, G. (2000) Output fluctuations in the United States: what has changed since the early 1980s?, *American Economic Review*, **90**(5), 1464–76.

Simon, J. (2001) The decline in Australian output volatility, Reserve Bank of Australia, RBA Research Discussion Papers, http://www.rba.gov.au/rdp/RDP2001-01.pdf

Stock, J. and Watson, M. (2002) Has the business cycle changed and why?, *NBER Macroeconomics Annual 2002*, 159–218.

Stock, J. and Watson, M. (2003a) Has the business cycle changed? Evidence and explanations, *Monetary Policy and Uncertainty*, Federal Reserve Bank of Kansas City, pp. 9–56.

Stock, J. and Watson, M. (2003b) Understanding changes in international business cycle dynamics, NBER Working Paper No. 9859, July, Cambridge, MA.

Taylor, J. (2000) Remarks for the panel discussion on recent changes in trend and cycle, *Conference on Structural Change and Monetary Policy*, Federal Reserve Bank of San Francisco and Stanford Institute for Economic Policy Research, 3 March, http://www.frbsf.org/economics/conferences/000303/papers/recent_taylor.pdf

Teräsvirta, T. (1998) Modeling economic relationships with STR, in *Handbook of Applied Economic Statistics* (Eds) A. Ullah and D. E. A. Giles, Chapter 15, Marcel Dekker, Inc, New York, pp. 507–52.