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384/2011

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WIFO Working Papers, No. 384
January 2011

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2011/002/W/0

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On the Change in the Austrian Business Cycle

Sandra Bilek-Steindl*

January 10, 2011

Abstract

This paper analyzes the change in the Austrian business cycle over time using data back to 1954. The change in the cyclical pattern is captured using a nonlinear univariate structural time series model where the time of the break point is estimated. Results for GDP series suggest a break in the frequency of the cycle and in the parameter covering the variance of the disturbances of the cycle taking place in the mid 70s and early 80s, respectively. Using data for GDP components a break in these variables is found too, but the timing of the break differs among the series. In a further step the paper assesses the relevance of these findings for forecasting purposes. It is shown that during certain periods the out-of-sample forecasting performance of GDP does improve when a break in one of the two parameters is explicitly modeled.

Keywords Structural time series models, Business cycles, Forecasting performance

JEL classification C51, C53, E32

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1 Introduction

Since the mid-1980s cyclical fluctuations in the United States tend to be less pronounced compared to the decades earlier. This observation is referred to as the *Great Moderation* and has been heavily investigated by the empirical literature. The first studies reporting the decline in macroeconomic volatility of US time series comprise Kim & Nelson (1999), McConnell & Perez-Quiros (2000), Blanchard & Simon (2001) and Stock & Watson (2002), where the change was either reported to be a trend decline (Blanchard & Simon 2001, Stock & Watson 2002) or a discrete step reduction (Kim & Nelson 1999, McConnell & Perez-Quiros 2000). Blanchard & Simon (2001) show that this steady decline was interrupted in the 1970s and early 1980s and returned back to the trend line in the late 1980s and 1990s. The most common way to measure macroeconomic volatility in the literature is using the standard deviation of an output gap, the cyclical component of the GDP series or of the changes in GDP itself. Creal et al. (2008) introduce stochastically time-varying variances of the cyclical and the irregular component in a multivariate structural time series model to capture the *Great Moderation* in US time series. Besides dynamics in the volatility of the common cycle, they report changes in the volatility of the irregular components.

In Europe and other non European OECD countries cyclical fluctuations have became more damped, too (Dalsgaard et al. 2002, Barrell & Gottschalk 2004, European Commission 2007, Malgarini 2007, Barrell et al. 2009, Bodman 2009). For Germany Buch et al. (2004) and Aßmann et al. (2009) give evidence of a downward trend in output volatility. Also for Austria some empirical literature on the decline in macroeconomic volatility exits, but so far no explicit timing of the regime shift was observed. Hahn & Walterskirchen (1992) use a quarterly data set spanning 1960-1992. Comparing the standard deviation of the cyclical GDP component over three time periods, they reported a higher variation in the period 1974-1982 compared to the periods 1960-1973 and 1983-1992. Leitner (2007) divide the total time series of 1970-2004 into two parts. Using the standard deviation of real GDP growth and its expenditure components, she found for most series a higher volatility in the subperiod 1970-1983 compared to the subperiod 1983-2004. Similarly, the European Commission (2007) reports a sharp decrease in the standard deviation of year-on-year GDP growth rates since the end of the 1970s.

While there is general evidence that the volatility (or the amplitude) of the business cycle has decreased over time, there is not much evidence regarding the duration (or the frequency) of the cycle. From observed changes in the persistence of output gaps (measured using the first order auto-correlation) Dalsgaard et al. (2002) suggest an increase in the duration of the business cycle in certain countries (Australia, Austria, Canada, France, New Zealand, Norway, Sweden and United Kingdom), while the persistence of the cycle has been found more or less unchanged in the Euro Area (aggregate), Italy, Japan, Spain and the United States. Using a multivariate time series model and dividing the US data set in two subperiods, Creal et al. (2008) noted a decrease in the frequency parameter (increase in the average period between business cycles) in the sample after the year 1984.

Economic moderation has been stopped abruptly by the end of 2008, but there is still the question if it will continue after the phase-out of the global recession. Even if much more pronounced, this would be a break similar to that reported by Blanchard & Simon (2001) in the 1970s and early 1980s. The answer to that question depends on the reason of the decline in volatility beforehand, which is still not clear. The literature refers to many reasons for the change in the volatility of macroeconomic time series. They cover *good policy, good luck* and *good practices.* The first point usually refers to improvements in monetary policy (Clarida et al. 2000), the second stresses good luck in terms of smaller and fewer shocks (Stock & Watson 2002), while the third regards changes in the economic structure like sectoral shifts (Buch et al. 2004), globalisation and openness to trade (Buch 2002, Cavallo & Frankel 2008), technological developments (Arias et al. 2007), inventory management (Kahn et al. 2002, Irvine & Schuh 2005), demographic changes (Jaimovich & Siu 2009) or financial openness and innovations (Buch et al. 2005, Dynan et al. 2006) as the main factors for the reduced cyclical volatility. Especially the latter were recently discussed in the course of the financial crisis and the global recession starting at the end of 2008. On the one hand, financial innovations have lessened macroeconomic volatility, but on the other hand, they make financial crises much larger and more severe (Hahn 2008).

In this paper the potential change in the cyclical pattern in Austria is captured using a nonlinear univariate structural time series model. In the first place, the linear model following Harvey (1989) and Harvey & Trimbur (2003) is extended to allow for a break in the frequency of the cycle and in the parameter covering the variance of the disturbances of the cycle. Results for GDP suggest a longer average duration of the cycle after the mid 70s and a decrease in the amplitude in the early 80s. Using series of GDP components (private consumption, investment in machinery and equipment, construction investment, total exports and total imports) these results were found too, but the timing of the break differs both, among the components, and compared to GDP. Secondly, I assess the relevance of these findings for forecasting GDP. It can be shown that the nonlinear models outperform the linear models during certain periods, but not globally.

The outline of the paper is as follows: Section 2 describes the used data set, section 3 shows the model specifications of the standard model following Harvey (1989) and Harvey & Trimbur (2003) as well as two nonlinear extensions to decompose the time series into its structural components and to determine the break point of a regime switch. Section 4 and 5 give the results for Austrian GDP and its components, respectively. Section 6 evaluates the forecast performance of the nonlinear models using GDP series, section 7 concludes.

2 Data Description

I use quarterly seasonally adjusted data for Austria for the period 1954Q1-2009Q3[1]. Following Scheiblecker (2008) different data sets - all taken from the WIFO database - were used to construct one consistent quarterly time series starting 1954Q1. The most recent quarterly national accounts data going back to 1988Q1 were used (publication date November 2009). Their respective corresponding annual figures go back until 1976, with both, annual and quarterly figures measured in chained values with the year 2005 as reference year. For the time period before 1988 quarterly data are chained back using national accounts data of earlier releases: annual national accounts GNP series (1954-1978), annual national accounts data according to SNA 68 definition in 1976 prices (1964-1988), quarterly GNP series (1954Q1-1978Q4), quarterly national accounts data according to SNA 68 definition in 1976 prices (1964Q1-1989Q1) and quarterly national accounts data according to ESVG 79 definition measured in 1983 prices (1976Q1-1999Q3). First, the actual annual figures covering 1976-2008 were chained back to

[1] All time series were seasonally adjusted using Census X12.

receive one annual time series ranging from 1954-2008. Second, to obtain the quarterly pattern from 1954Q1-1987Q4 the Chow & Lin (1971) method of temporal disaggregation was used, with the chained national accounts data of the former releases being the indicator series. Thus, quarterly series summing up to the chained back annual figures are produced. Besides GDP, the constructed data set contains the following expenditure side GDP components: private consumption, investment in machinery and equipment, construction investment, total exports and total imports.

The quarter-on-quarter GDP growth rates (Figure 1) reveal a high cyclical volatility in the first part of the series (especially well pronounced at times of the oil price shocks in the 1970s), which is followed by a smoother cyclical pattern in the second part of the time series. The standard deviation of the growth rates is reduced from 0.013 (1954Q1-1979Q4) to 0.009 (1980Q1-2009Q3). A similar pattern exists in the components of GDP. Table 1 shows the evolution of the standard deviation of the quarter-on-quarter growth rates of GDP and its components over time.

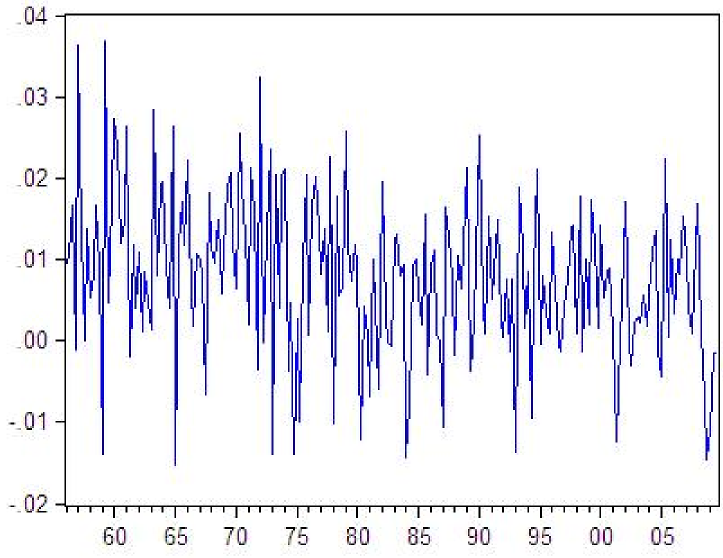

Figure 1: Quarter-on-quarter GDP growth rates, 1954Q1-2009Q3

Component	Sample	Stdev.	Sample	Stdev.
GDP	1954-1980	0.0133	1964-1985	0.0121
	1981-2008	0.0084	1986-2008	0.0083
Private Consumption	1954-1980	0.0201	1964-1985	0.0200
	1981-2008	0.0117	1986-2008	0.0109
Investment in Machinery and Equ.	1954-1980	0.0491	1964-1985	0.0379
	1981-2008	0.0466	1986-2008	0.0485
Construction Investment	1954-1980	0.0457	1964-1985	0.0288
	1981-2008	0.0325	1986-2008	0.0335
Total Exports	1954-1980	0.0336	1964-1985	0.0342
	1981-2008	0.0258	1986-2008	0.0238
Total Imports	1954-1980	0.0454	1964-1985	0.0391
	1981-2008	0.0265	1986-2008	0.0273

Table 1: Standard deviation of quarter-on-quarter growth rates of GDP and its components

3 Model Specifications

3.1 Standard Model

I use a structural time series model which is formulated in terms of components that have a direct interpretation. The estimation results of the hyperparameters reveal information about the two characteristics of the cycle, which are in the interest of the paper: its frequency and its amplitude.

Following the commonly used model by Harvey (1989) the seasonally adjusted log GDP series is decomposed into a trend component, a cyclical component and an irregular component in an additive form[2]:

$$z_t = \mu_t + \psi_t + \epsilon_t,\ \ \epsilon_t \sim \text{NID}(\mathbf{0}, \sigma^2_\epsilon). \tag{1}$$

The components are allowed to evolve stochastically over time. μ_t, the trend component, is specified as

$$\mu_t = \mu_{t-1} + \kappa_{t-1} + \eta_t,\ \ \eta_t \sim \text{NID}(\mathbf{0}, \sigma^2_\eta), \tag{2}$$

$$\kappa_t = \kappa_{t-1} + \delta_t,\ \ \delta_t \sim \text{NID}(\mathbf{0}, \sigma^2_\delta), \tag{3}$$

with κ_t, the slope of the trend and ϵ_t, η_t and δ_t mutually uncorrelated, and the cyclical component, ψ_t is specified as

$$\begin{bmatrix} \psi_t \\ \psi^*_t \end{bmatrix} = \left\{ \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ \text{-}\sin\lambda & \cos\lambda \end{bmatrix} \right\} \begin{bmatrix} \psi_{t-1} \\ \psi^*_{t-1} \end{bmatrix} + \begin{bmatrix} \theta_{t-1} \\ \theta^*_{t-1} \end{bmatrix}, \tag{4}$$

$$\begin{bmatrix} \theta_{t-1} \\ \theta^*_{t-1} \end{bmatrix} \sim \text{NID} \begin{bmatrix} \mathbf{0}, & \begin{matrix} \sigma^2_\theta & 0 \\ 0 & \sigma^2_\theta \end{matrix} \end{bmatrix},$$

[2]There is still an ongoing debate of the possibility of the neat separation between business cycles and long-run economic growth. See for example chapter 8 in Aghion & Howitt (1998).

where $\rho \in (0,1]$ (the damping factor) and $\lambda \in [0,\pi]$ (the cyclical frequency in radians with $2\pi/\lambda$ as the period of the cycle) are constants and $E(\theta_t\theta_t^*) = 0$.

Without imposing any restrictions on the variances in equation (2) and (3), the trend component is a random walk with variable drift, which is equivalent to an ARIMA(0,2,1) process. If $\sigma_\delta^2 = 0$ the trend component reduces to a random walk with drift. Furthermore, if $\sigma_\eta^2 = 0$ as well, the trend process of the variable reduces to a linear deterministic time trend. If only $\sigma_\eta^2 = 0$, the resulting model exhibits a smoothing changing I(2) trend. The cycle ψ_t is modeled as mixture of sine and cosine waves. It can also be represented as ARMA(2,1) process. The auxiliary process ψ_t^* appears by construction.

Harvey & Trimbur (2003) further extend the general model given above towards a model with stochastic cycles of higher order. This specification has been found useful in modeling cyclical behaviour of US investment series. The extracted cycle was smoother and more clearly defined, which allows to date turning points more easily. A cycle of order 2 can be written as a stochastic cycle of order 1 – as described in equation (4), with the variance of the disturbance term for the auxiliary process $\psi_{2,t}^*$ set to zero instead of θ_{t-1}^* – where the error process itself follows a stochastic cycle:

$$\begin{bmatrix} \psi_{2,t} \\ \psi_{2,t}^* \end{bmatrix} = \left\{ \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ \text{-}\sin\lambda & \cos\lambda \end{bmatrix} \right\} \begin{bmatrix} \psi_{2,t-1} \\ \psi_{2,t-1}^* \end{bmatrix} + \begin{bmatrix} \psi_{1,t} \\ 0 \end{bmatrix}, \tag{5}$$

$$\begin{bmatrix} \psi_{1,t} \\ \psi_{1,t}^* \end{bmatrix} = \left\{ \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ \text{-}\sin\lambda & \cos\lambda \end{bmatrix} \right\} \begin{bmatrix} \psi_{1,t-1} \\ \psi_{1,t-1}^* \end{bmatrix} + \begin{bmatrix} \theta_{t-1} \\ 0 \end{bmatrix}.$$

The model represented by equations 1-4 and 1-5, respectively, is transformated into state-space form and the hyperparameters σ_ϵ^2, σ_η^2, σ_δ^2, σ_θ^2, λ and ρ are estimated using maximum likelihood.

3.2 Nonlinear Extensions

The model stated above can be extended to allow for breaks in structure and switching regimes. In order to account for a break in the cyclical pattern, first I substitute λ in equation (4) and (5) by

$$\lambda(\tau) = \lambda_1 I(t \leq \tau) + \lambda_2 I(t > \tau), \tag{6}$$

where $I(t)$ is an indicator function taking the value one before the break point τ, and zero after the break point τ. τ is estimated using a grid search over the time variable. Differences between λ_1 and λ_2 imply differences in the cycle length before and after τ.

Second, following the idea by Creal et al. (2008), a break in the variance of the cycle is assessed. According to Harvey (1989), the variance of the cycle is determined by the variance of its error process and the damping factor: $Var(\psi_t) = \sigma_\theta^2/(1-\rho^2)$. Thus, I allow for a break in the variance of the error process of the cyclical component σ_θ^2 and replace the parameter in equation (4) and (5) by

$$\sigma_\theta^2(\tau) = \sigma_{\theta_1}^2 I(t \leq \tau) + \sigma_{\theta_2}^2 I(t > \tau). \tag{7}$$

4 Estimation Results for GDP

4.1 Standard Model (Type A)

I first estimate the standard model characterized by equations (1) to (4) for the whole time period 1954Q1-2009Q3 (model 1A) in the time domain. The model with the smooth trend ($\sigma_\eta^2 = 0$) provides the most accurate fit. The obtained cycle and the dating of its turning points coincide with those of former studies summarized in Scheiblecker (2008). But with an estimated length of 28.5 quarters the duration is longer compared to the mentioned studies, where the average cycle length ranges from 13 to 26 quarters. I further estimate the same model over the shorter time period 1964Q1-2008Q4 (model 2A) because of two reasons: first, the national accounts definition changes between 1954 and 1963 and the time beyond (see section 2), and second, data for 2009 are obtained from an early vintage and are subject to further revisions. The observed peaks and troughs of the obtained cycle again confirm those detected in the studies summarized in Scheiblecker (2008). It deviates from the trend by a maximum of 2.5 percent. The duration of the business cycle is estimated to amount 20.9 quarters. Then model $2A^2$ is estimated over the same time sample as model 2A (1964Q1-2008Q4), imposing stochastic cycles of second order according to equation (5). As expected the cycle is smoother compared to the one obtained by the models 1A and 2A and the estimated variance $Var(\psi_t)$ is smaller. Again, peaks and throuhgs coincide with previous studies. The left column of figure 2 shows the cyclical components extracted by the three linear models. Vertical lines denote peaks (continuous lines) and troughs (dashed lines) previously determined and summarized in Scheiblecker (2008).

In order to assess a possible change in the parameters over the whole sample, the time series is split into two subsamples, with the first covering the period 1964Q1-1979Q4 (model 3A) and the second 1980Q1-2008Q4 (model 4A). The lower coefficient estimate for the frequency parameter λ in the second subsample (0.22 in model 4A compared to 0.35 in model 3A) supports the idea of a different data generating process in the two samples. The average duration of the cycle is found to be 17.9 quarters in the first sample (model 3A) and increases to 28.5 quarters in the second time period (model 4A). Further, the persistence parameter ρ is lower in the second subsample, suggesting a dampened cyclical volatility. This can also be seen in the estimated variance of the cycle, $Var(\psi_t)$, which is smaller in model 4A, covering the second subsample. The maximum likelihood estimates of the hyperparmeters of all linear models are summarized in the first lines in table 2.

Goodness of fit of all models is assessed by the estimated prediction error variance of the signal σ^2, the coefficient of determination R_D^2 and the AIC. Further, diagnostic tests concerning autocorrelation, homoscedasticity and normality of the standardized residuals are carried out. According to R_D^2 all models show an improvement in goodness of fit over a random walk plus drift. The assumption of independence is violated for all models apart from model $2A^2$ imposing stochastic cycles of second order and model 3A covering only the time span 1964Q1-1979Q4. Homoscedasticity is checked against the F-distribution, again not all models fulfill this criterion. Considering normality, a more satisfactory situation is found. All results are summarized in the Appendix, table A.5.

4.2 Nonlinear Extensions (Type B and C)

I estimate the model with the nonlinear generalization covered in equation (6) to determine the break point τ and the two representations of the cycle. First I cover the whole sample period 1954Q1-2009Q3 (model 1B). Second, I consider the shorter time span 1964Q1-2008Q4 (model 2B). The results are similar. I find a break occurring at 1972Q3 (model 1B) and 1974Q3 (model 2B), respectively. Before this point of time, the estimate of the frequency parameter λ_1 is close to zero, which means the cycle follows an AR(1) process. For the later time period the estimate of λ_2 is 0.24 (model 1B) and 0.21 (model 2B) corresponding to a cycle length of 26.5 (model 1B) and 29.9 quarters (model 2B). The cycle length of both models seems to be reasonable. As robustness check I further estimate the model imposing stochastic cycles of second order (model 2B^2). The breakpoint was found in 1974Q2. Before this point of time the cycle follows an AR(1) process, too. Later, λ_2 is 0.38, corresponding to an average cycle length of 16.5 quarters. Looking at the variance of the cycle, $Var(\psi_t)$, again it is smaller in the model imposing stochastic cycles of second order. With a point in the early 70s in all three models, the break occurred earlier then expected, but the models provide a reasonable fit to the data, concerning the dating of the cycle. Figure 2 (second column) gives a picture of the obtained cycles of 2A, 2B and 2B^2. The observed peaks and troughs confirm those detected in the linear model (type A). The results of the estimated parameters are summarized in the middle of table 2.

In the next stage I allow for a break in the variance of the error process of the cyclical component σ^2_θ (equation (7)). In the same manner as above, first I cover the whole sample period 1954Q1-2009Q3 (model 1C), second, the shorter time span 1964Q1-2008Q4 (model 2C) and third, I estimate the model imposing stochastic cycles of second order (model 2C^2). In all three cases estimation results suggest a break in the variance in the mid 80s: 1985Q2 (model C1), 1982Q2 (model C2) and respectively, 1985Q3 (model 2C^2). In all three cases the results for $\sigma^2_{\theta_1}$ and $\sigma^2_{\theta_2}$ confirm the assumption that the variance of the cyclical part decreased after the break point τ: from 68.5 to 21.2 (model 1C), from 70.1 to 21.7 (model 2C) and from 63.2 to 21.5 (model 2C^2). All parameter results are summarized in the bottom of table 2. Figure 2 (left column) shows a picture of the obtained cycles of the three models 2C, 2C and 2C^2. Again, peaks and troughs coincide with those of the other models.

Diagnostic tests of the models of type B and C are summarized in the Appendix, table A.5. Like in the linear case (models type A) there are some problems concerning the assumption of independence.

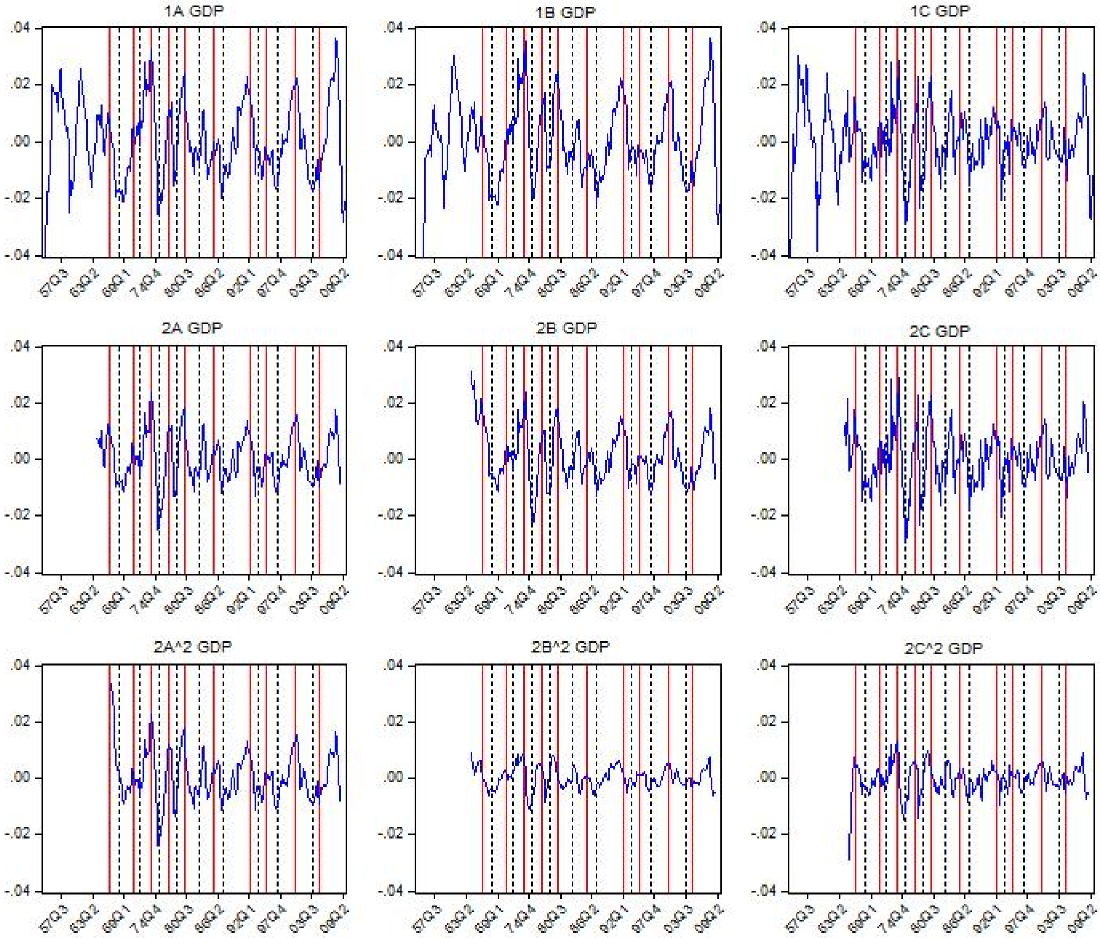

Figure 2: Cyclical component of GDP, extracted from linear (type A) and nonlinear models (type B and C)

Note: Vertical lines denote peaks (continuous lines) and troughs (dashed lines) previously determined and summarized in Scheiblecker (2008).

		σ^2_ϵ	σ^2_δ	ρ	λ	$2\pi/\lambda$	λ_1	λ_2	$2\pi/\lambda_2$	σ^2_θ	$\sigma^2_{\theta_1}$	$\sigma^2_{\theta_2}$	τ	$Var(\psi_t) = \sigma^2_\theta/(1-\rho^2)$
1A	54Q1-09Q3	18.9*	0.3	0.87**	0.22**	28.5	-	-	-	60.2**	-	-	-	0.015
2A	64Q2-08Q4	23.0**	0.9*	0.81**	0.30**	20.9	-	-	-	40.1**	-	-	-	0.005
2A^2	64Q2-08Q4	26.9**	0.9*	0.71**	0.26*	24.4	-	-	-	24.0**	-	-	-	0.001
3A	64Q1-79Q4	45.4**	2.2	0.84**	0.35**	17.9	-	-	-	33.2	-	-	-	0.004
4A	80Q1-08Q4	0.0	2.8**	0.80**	0.22**	28.5	-	-	-	30.0**	-	-	-	0.002
1B	54Q1-09Q3	20.9**	0.3	0.88**	-	-	0.0	0.24**	26.5	57.1**	-	-	72Q3	0.014
2B	64Q1-08Q4	24.6**	0.7*	0.81**	-	-	0.0	0.21**	29.9	38.4**	-	-	74Q3	0.004
2B^2	64Q1-08Q4	25.6**	1.0 *	0.73**	-	-	0.0	0.38**	16.5	2.2**	-	-	74Q2	0.001
1C	54Q1-09Q3	0.0	1.9**	0.82**	0.27**	23.6	-	-	-	-	68.5**	21.2 **	85Q2	-
2C	64Q1-08Q4	0.0	1.9**	0.85**	0.25**	24.7	-	-	-	-	70.1**	21.7**	82Q2	-
2C^2	64Q1-08Q4	0.0	1.1**	0.62**	0.25**	24.8	-	-	-	-	63.2**	21.5**	85Q3	-

Table 2: Estimation results of the structural time series models, GDP

Note: All variances are multiplied with 10^5.
** denotes significance at 5 percent level, * denotes significance at 10 percent level.
Considering the naming of the models, note that:
The alphabetic character denotes the model characteristics while the number stands for the sample period (1 covers 54Q1-09Q3, 2 covers 64Q1-08Q4, 3 covers 64Q1-79Q4 and 4 covers 80Q1-08Q4.
The model type A is the linear model, B indicates the nonlinear model with a break in λ, C indicates the model with a break in σ^2_θ.
The extension ^{2} denotes a model with second order stochastic cycles.

5 Estimation Results for GDP Components

This section examines the cyclical behavior of the following GDP components: private consumption, investment in machinery and equipment, construction investment, total exports and total imports. As documented already in table 1, a decline in the standard deviation of the growth rates over time is found, with a break-point a priori fixed in the 1980s.

To determine the time of the change in the cyclical behaviour, like in the case of GDP, nonlinear extensions of the standard structural components model with a break in λ (model 2B) and a break in the variance of the error process of the cyclical component σ_θ^2, respectively (model 2C) are estimated. First, the standard model (model 2A) is estimated. By observing the duration of the cycles of the GDP components the following pattern was observed: while the average duration of the business cycle in private consumption and imports are similar to the one of GDP, the average investment and export cycles are found to be longer. Using quarterly data for GDP components for 1964-1992, similar results for Austria were observed by Hahn & Walterskirchen (1992). All parameter results can be found in table 3.

Estimating model 2B (with a break in the frequency parameter λ) for all observed time series apart from private consumption, the break was found in 1974Q2 or 1974Q3. In the successive quarters, the estimate of λ_2 is smaller compared to estimate of λ in the standard model (model 2A). This means a longer duration of the cycle after 1974. Before 1974, the estimate of the frequency parameter λ_1 is close to zero and the cycle follows an AR(1) process. For the series of private consumption the break in λ was found to be only in 2004. Considering model 2C (with a break in σ_θ^2), for all time series a reduction in the estimated variance of the error process of the cyclical component σ_θ^2 has been found. To put it in other words, the variance of the cyclical part decreased after the break point. The timing of the break point varies over the components between 1978Q1 and 1995Q4 and apart from private consumption, for all time series it was found to occur after the break in λ. For total imports the break occurred in 1978Q1, for investment in machinery and equipment in 1982Q2, for total exports in 1986Q1, for construction investment in 1993Q3 and private consumption in 1995Q4, respectively. All parameter results are summarized in table 3, diagnostic tests are shown in the Appendix, table A.6. The obtained cycles of the models can be found in figure 3. The left column shows the cycles obtained from standard model (2A), the middle column those obtained from the model with a break in the frequency parameter λ (2B) and the right column those obtained from the model with a break in σ_θ^2 (2C).

	σ^2_ϵ	σ^2_δ	ρ	λ	$2\pi/\lambda$	λ_1	$2\pi/\lambda_1$	λ_2	$2\pi/\lambda_2$	σ^2_θ	$\sigma^2_{\theta_1}$	$\sigma^2_{\theta_2}$	τ
2A private consumption	0.0	2.9**	0.82**	0.32**	19.5	-	-	-	-	3.8**	-	-	-
2B private consumption	0.0	0.1**	0.79**	-	-	0.45**	14.0	-0.08	-	7.4**	-	-	04Q2
2C private consumption	0.0	1.6**	0.77	<u>0.32</u>	19.5	-	-	-	-	-	5.0**	3.0**	95Q4
2A construction investment	22.9 **	0.6**	0.82	<u>0.17</u>	37.0	-	-	-	-	28.4**	-	-	-
2B construction investment	26.1**	0.6**	0.82**	-	-	0.00	-	0.18	34.9	23.2*	-	-	74Q3
2C construction investment	21.3**	0.5*	0.82**	<u>0.17</u>	37.0	-	-	-	-	-	38.8**	15.0	93Q3
2A investment in m. and e.	86.1**	0.1	0.95**	0.19**	32.7	-	-	-	-	39.4*	-	-	-
2B investment in m. and e.	61.7**	0.1	0.84**	-	-	0.00	-	0.13*	48.3	86.1**	-	-	74Q2
2C investment in m. and e.	90.4**	0.0	0.94**	<u>0.19</u>	33.1	-	-	-	-	-	59.9**	24.9**	82Q1
2A total exports	17.7 **	0.1	0.90**	0.17	37.7	-	-	-	-	40.1**	-	-	-
2B total exports	18.0 **	0.0	0.91**	-	-	0.00	-	0.18**	34.9	39.6**	-	-	74Q3
2C total exports	8.1	0.2	0.89**	<u>0.17</u>	37.7	-	-	-	-	-	80.3**	32.5**	86Q1
2A total imports	29.0**	0.2	0.89**	0.24**	25.8	-	-	-	-	38.2**	-	-	-
2B total imports	29.1 **	0.3	0.83**	-	-	0.00	-	0.27**	22.7	-	-	-	74Q3
2C total imports	15.0 **	0.2*	0.87**	<u>0.24</u>	26.2	-	-	-	-	-	127.2 **	30.3**	78Q1

Table 3: Estimation results of the structural time series models, GDP components, 64Q2-08Q4

Note: All variances are multiplied with 10^5.

** denotes significance at 5 percent level, * denotes significance at 10 percent level, underlined parmaters are fixed.

The model type A is the linear model, B indicates the nonlinear model with a break in λ, C indicates the model with a break in σ^2_θ.

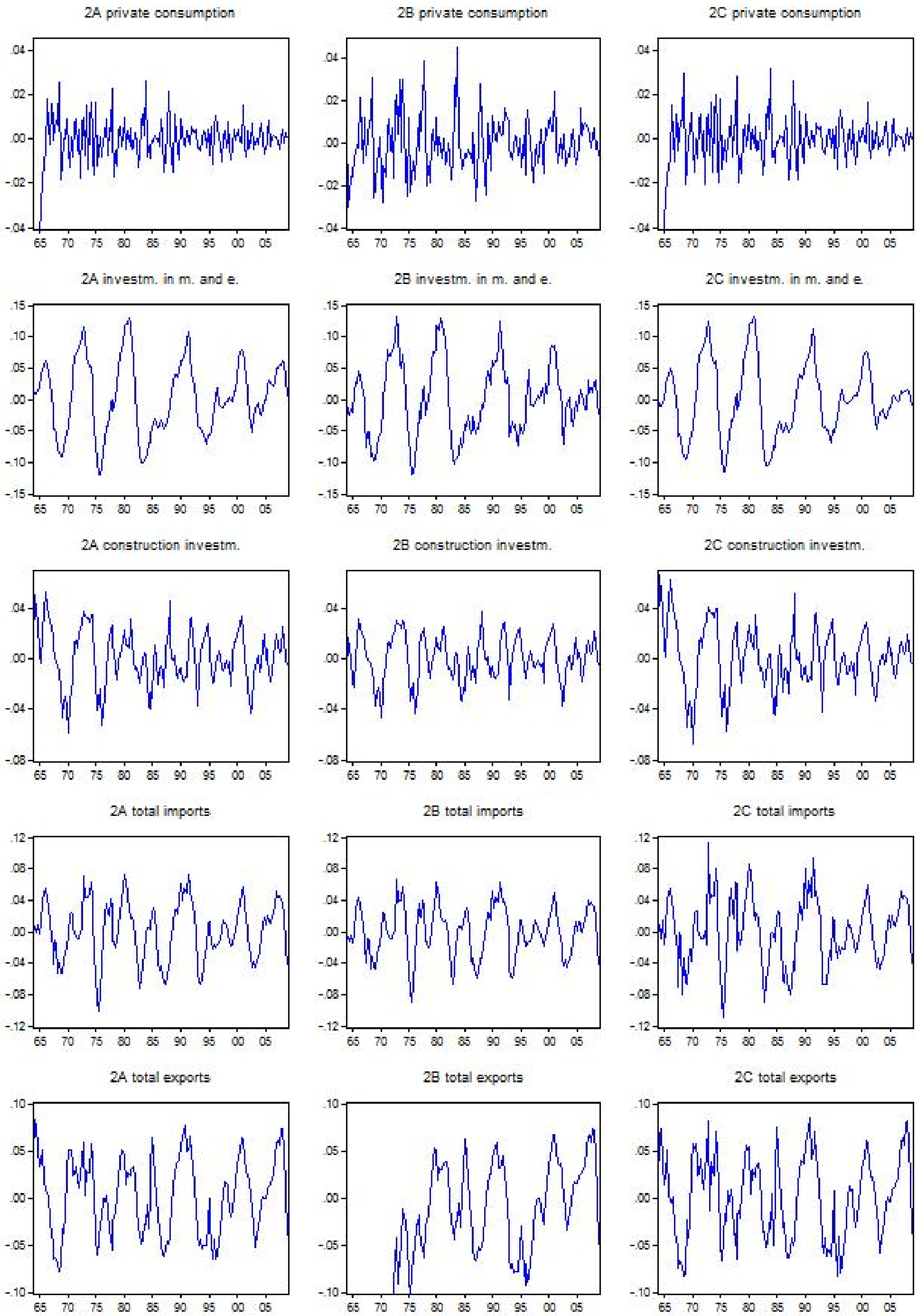

Figure 3: Cyclical component of GDP components, extracted from linear (type A) and nonlinear models (type B and C)

6 Does the Forecast Performance improve using Nonlinear Models?

In this section I evaluate whether the nonlinear models (1B, 1C, 2B, 2C, $2B^2$ and $2C^2$) help to improve GDP predictions compared to the standard models (1A and 2A). Therefore, I first estimate the models as specified above for the sample up to 1997Q1 (pre-forecast period). Based on these models, a k-step ahead forecast is carried out. As the interest lies in short-term forecasting, $k = 1 \dots 8$ (e.g. if $k = 8$: 1997Q2-1999Q1). Following, the pre-forecast period is extended for one period (up to 1997Q2). I estimate the model and carry out a k-step ahead forecast (e.g. if $k = 8$: 1997Q3-1999Q2) again. This procedure is repeated for 40 times, at the end yielding the out-of-sample period 2007Q1-2008Q4 (if $k = 8$). The whole out-of-sample period 1997Q2-2008Q4 is chosen to include two full cycles. For all 40 forecasts, each of the k-step ahead forecasts is evaluated by calculating the root mean squared forecasting error *RMSFE*:

$$RMSFE(y_{t+k}) = \sqrt{\sum_{i=1}^{N-1} \frac{(y^f_{t+k} - y_{t+k})^2}{N}}, \tag{8}$$

where $k = 1 \dots 8$ are the forecast steps, $N = 40$ and y^f_{t+k} denotes the k-step ahead forecast of y_t. I further calculate the *RMSFE* of the linear models (1A and 2A) and compare them with the results from the nonlinear models (1B, 1C, 2B, 2C, $2B^2$ and $2C^2$). Considering the time series starting in 1954Q1 and comparing the models 1B and 1C with 1A, for all 8-forecast steps, the forecast based on the linear model (1A) gives a lower *RMSFE.* The same result can be found when the sample starts in 1964Q1. The *RMSFE* of the forecast using model 2A is always smaller compared to forecast based on the models 2B $2B^2$, 2C and $2C^2$. These results can be seen in the first eight lines in table 4.

In the next step I observe if this result is still true for certain subperiods in the above mentioned out-of-sample period. Therefore the out-of-sample period 1997Q2-2008Q4 is split into three subsamples characterized by an upswing phase (1997Q3-2000Q3), a downswing phase (2000Q4-2003Q3) and an upswing phase (2005Q3-2008Q3) again. During the two upswing phases certain step ahead forecasts using the nonlinear models give a smaller *RMSFE* compared to the linear models. In the out-of-sample period 1997Q3-2000Q3, this is the case for model 1C, 2B, 2C, $2B^2$ and $2C^2$. Moreover, in the out-of-sample period 2005Q3-2008Q3 most of the forecast steps give smaller *RMSFE*s using the nonlinear models compared to use of their linear counterparts. In those cases where the *RMSFE*s are smaller from forecast of the nonlinear models (1B, 1C, 2B, 2C, $2B^2$ and $2C^2$) than of the linear models (1A and 2A) the numbers are marked bold in table 4. Considering the out-of-sample period 2000Q4-2003Q3 (downswing phase), using the nonlinear models 1B and 1C can improve the forecast efficiency compared to the use the linear model 1A, too. Again, this is indicated by the bold numbers in table 4. Although we can not find a general evidence that using nonlinear models help to improve forecasting GDP, in certain stances of the business cycle (an upswing or downswing phase) they may yield a better forecast performance in certain cases. Further it can not be observed from this analysis that one of the nonlinear models (type B versus type C) always yields a better forecast performance than the other one.

Out-of-sample period 1997Q2-2008Q4	1A	1B	1C	2A	2B	$2B^2$	2C	$2C^2$
1-step ahead forecast	0.00763	0.00766	0.00793	0.00758	0.00795	0.00803	0.00794	0.00769
2-step ahead forecast	0.01073	0.01103	0.01155	0.01060	0.01133	0.01176	0.01155	0.01101
3-step ahead forecast	0.01336	0.01389	0.01513	0.01328	0.01428	0.01478	0.01521	0.01414
4-step ahead forecast	0.01536	0.01607	0.01696	0.01520	0.01669	0.01740	0.01706	0.01622
5-step ahead forecast	0.01809	0.01903	0.01955	0.01794	0.01992	0.02045	0.01970	0.01922
6-step ahead forecast	0.02076	0.02188	0.02254	0.02067	0.02314	0.02370	0.02270	0.02230
7-step ahead forecast	0.02358	0.02489	0.02646	0.02336	0.02677	0.02734	0.02663	0.02609
8-step ahead forecast	0.02635	0.02752	0.03098	0.02639	0.03034	0.03109	0.03115	0.03028
Out-of-sample period 1997Q3-2000Q3	1A	1B	1C	2A	2B	$2B^2$	2C	$2C^2$
Upswing								
1-step ahead forecast	0.00786	0.00813	0.00893	0.00809	0.00814	**0.00728**	0.00893	0.00842
2-step ahead forecast	0.00903	0.00940	**0.00889**	0.00910	0.00962	**0.00761**	**0.00890**	**0.00816**
3-step ahead forecast	0.01147	0.01239	0.01273	0.01188	0.01188	**0.00985**	0.01276	**0.01070**
4-step ahead forecast	0.01486	0.01629	**0.01451**	0.01503	**0.01493**	**0.01258**	**0.01455**	**0.01240**
5-step ahead forecast	0.01538	0.01722	**0.01395**	0.01555	**0.01500**	**0.01240**	**0.01402**	**0.01236**
6-step ahead forecast	0.01933	0.02169	**0.01734**	0.01937	**0.01857**	**0.01596**	**0.01737**	**0.01584**
7-step ahead forecast	0.02168	0.02448	**0.01492**	0.02162	**0.02059**	**0.01763**	**0.01495**	**0.01576**
8-step ahead forecast	0.02671	0.02971	**0.02125**	0.02669	**0.02566**	**0.02199**	**0.02129**	**0.02138**
Out-of-sample period 2000Q4-2003Q3								
Downswing								
1-step ahead forecast	0.01085	**0.01040**	**0.00894**	0.01067	0.01269	0.01236	**0.00893**	**0.00936**
2-step ahead forecast	0.01808	**0.01786**	0.01897	0.01786	0.02047	0.02045	0.01895	0.01852
3-step ahead forecast	0.02264	**0.02212**	0.02617	0.02202	0.02559	0.02633	0.02616	0.02442
4-step ahead forecast	0.02377	**0.02294**	0.02670	0.02276	0.02727	0.02886	0.02668	0.02616
5-step ahead forecast	0.02543	**0.02465**	0.02580	0.02438	0.02928	0.03176	0.02575	0.02778
6-step ahead forecast	0.02905	**0.02871**	**0.02800**	0.02729	0.03323	0.03625	0.02795	0.03143
7-step ahead forecast	0.03552	0.03564	**0.03457**	0.03335	0.04028	0.04354	0.03452	0.03856
8-step ahead forecast	0.04090	0.04145	**0.04038**	0.03860	0.04621	0.04957	0.04031	0.04460
Out-of-sample period 2005Q3-2008Q3								
Upswing								
1-step ahead forecast	0.00597	**0.00578**	0.00603	0.00599	0.00613	**0.00527**	0.00609	0.00601
2-step ahead forecast	0.01012	**0.00981**	**0.00727**	0.01013	0.01053	**0.00876**	**0.00734**	**0.00810**
3-step ahead forecast	0.01375	**0.01350**	**0.01089**	0.01372	0.01419	**0.01109**	**0.01098**	**0.01172**
4-step ahead forecast	0.01648	**0.01621**	**0.01232**	0.01649	0.01726	**0.01311**	**0.01234**	**0.01358**
5-step ahead forecast	0.01961	**0.01954**	**0.01455**	0.01963	0.02058	**0.01514**	**0.01462**	**0.01580**
6-step ahead forecast	0.02405	0.02440	**0.01635**	0.02390	0.02500	**0.01816**	**0.01654**	**0.01849**
7-step ahead forecast	0.02632	0.02723	**0.01735**	0.02598	0.02721	**0.01880**	**0.01764**	**0.01974**
8-step ahead forecast	0.02640	0.02776	**0.01781**	0.02607	0.02738	**0.01799**	**0.01810**	**0.01961**

Table 4: *RMSFE* of the forecasts, GDP

Note: The model type A is the linear model, B indicates the nonlinear model with a break in λ, C indicates the model with a break in σ_θ^2.
The extension ^{2} denotes a model with second order stochastic cycles.
The bold numbers indicate that the *RMSFE* from the nonlinear model is smaller compared to the *RMSFE* of the linear model.

7 Conclusions

The paper analyses the change in the cyclical behaviour of the Austrian business cycle. Using quarterly data for GDP and its components starting in 1954 (or in 1964 in the case of the GDP components), for all series a break in the average duration of the cycle as well as in the variance of the cycle was observed. Using a nonlinear extension of the standard model Harvey (1989) and Harvey & Trimbur (2003), results for GDP series suggest that a break in the frequency parameter λ occurred in the mid 70s, while a break in the parameter covering the variance of the disturbances of the cycle was found in the early 80s. To put it in other words, after the mid 70s the duration of the business cycle increased, while after the early 80s the amplitude of the cycle decreased. Using series of GDP components (private consumption, investment in machinery and equipment, construction investment, total exports and total imports) similar results were found, but the timing of the break differs both, among the components, and compared to GDP.

Modeling nonlinearities does not help to improve the forecast performance over the business cycle. But results for GDP suggest, that there are certain stances of the business cycle (during an upswing or a downswing phase) where nonlinear models may yield a better forecast performance than the linear models.

References

Aghion, P. & Howitt, P. (1998), *Endogenous growth theory*, MIT Press.

Arias, A., Hansen, G. & Ohanian, L. (2007), 'Why have business cycle fluctuations become less volatile?', *Economic Theory* **32**(1), 43–58.

Aßmann, C., Hogrefe, J. & Liesenfeld, R. (2009), 'The decline in German output volatility: a Bayesian analysis', *Empirical Economics* **37**(3), 653–679.

Barrell, R. & Gottschalk, S. (2004), 'The volatility of output gap in the G7', *National Institute Economic Review* **188**, 100–107.

Barrell, R., Holland, D., Liadze, I. & Pomerantz, O. (2009), 'Volatility, growth and cycles', *Empirica* **36**(2), 177–192.

Blanchard, O. & Simon, J. (2001), 'The long and large decline in US output volatility', *Brooking Papers on Economic Activity* **1(2001)**, 135–164.

Bodman, P. (2009), 'Output volatility in Australia', *Applied Economics* **41**(24), 3117–3129.

Buch, C. M. (2002), Business cycle volatility and globalization: A survey, Kiel Working Papers 1107, Kiel Institute for the World Economy.

Buch, C. M., Doepke, J. & Pierdzioch, C. (2004), 'Business cycle volatility in Germany', *German Economic Review* **5**(4), 451–479.

Buch, C. M., Doepke, J. & Pierdzioch, C. (2005), 'Financial openness and business cycle volatility', *Journal of International Money and Finance* **24**(5), 744–765.

Cavallo, E. A. & Frankel, J. A. (2008), 'Does openness to trade make countries more vulnerable to sudden stops, or less? Using gravity to establish causality', *Journal of International Money and Finance* **27**(8), 1430–1452.

Chow, G. C. & Lin, A.-l. (1971), 'Best linear unbiased interpolation, distribution, and extrapolation of time series by related series', *The Review of Economics and Statistics* **53**(4), 372–75.

Clarida, R., Gal, J. & Gertler, M. (2000), 'Monetary policy rules and macroeconomic stability: Evidence and some theory', *The Quarterly Journal of Economics* **115**(1), 147–180.

Creal, D., Koopman, S. J. & Zivot, E. (2008), The effect of the great moderation on the U.S. business cycle in a time-varying multivariate trend-cycle model, Tinbergen Institute Discussion Papers 08-069/4, Tinbergen Institute.

Dalsgaard, T., Elmeskov, J. & Park, C.-Y. (2002), *Ongoing changes in the business cycle - evidence and causes*, number 20 *in* 'SUERF Studies', SUERF - The European Money and Finance Forum.

Dynan, K. E., Elmendorf, D. W. & Sichel, D. E. (2006), 'Can financial innovation help to explain the reduced volatility of economic activity?', *Journal of Monetary Economics* **53**(1), 123–150.

European Commission (2007), 'The reduced volatility of output growth in the Euro area', *Quarterly Report on the Euro Area, European Commission, Directorate General for Economic and Financial Affairs* **I/2007**, 37–46.

Hahn, F. R. (2008), A primer on financial system meltdown. The economists' view, WIFO Working Papers 333, WIFO.

Hahn, F. R. & Walterskirchen, E. (1992), Stylized Facts der Konjunkturschwankungen in Österreich, Deutschland und den USA, WIFO Working Papers 58, WIFO.

Harvey, A. C. (1989), *Forecasting structural time series models and the Kalman filter*, Cambridge University Press.

Harvey, A. C. & Trimbur, T. M. (2003), 'General model-based filters for extracting cycles and trends in economic time series', *The Review of Economics and Statistics* **85**(2), 244–255.

Irvine, O. & Schuh, S. (2005), 'Inventory investment and output volatility', *International Journal of Production Economics* **93**(1), 75–86.

Jaimovich, N. & Siu, H. E. (2009), 'The young, the old, and the restless: Demographics and business cycle volatility', *American Economic Review* **99**(3), 804–826.

Kahn, J. A., McConnell, M. M. & Perez-Quiros, G. (2002), 'On the causes of the increased stability of the U.S. economy', *Economic Policy Review* (May), 183–202.

Kim, C.-J. & Nelson, C. R. (1999), 'Has the U.S. economy become more stable? A Bayesian approach based on a markov-switching model of the business cycle', *The Review of Economics and Statistics* **81**(4), 608–616.

Leitner, S. M. (2007), The Austrian business cycle - a role for technology shocks?, Economics Working Papers 2007-19, Department of Economics, Johannes Kepler University Linz, Austria.

Malgarini, M. (2007), 'Inventories and business cycle volatility: An analysis based on ISAE survey data', *Journal of Business Cycle Measurement and Analysis* **3**(2), 175–198.

McConnell, M. M. & Perez-Quiros, G. (2000), 'Output fluctuations in the United States: What has changed since the early 1980's?', *American Economic Review* **90**(5), 1464–1476.

Scheiblecker, M. (2008), *The Austrian business cycle in the European context*, Peter Lang, Forschungsergebnisse der Wirtschaftsuniversität Wien.

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

A Appendix

		σ^2	R^2_D	AIC	$Q(10)$	$Q(15)$	$H(h)$	N
1A	54Q1-09Q3	0.00012	0.143	-5.783	-	16.100	1.473	9.143
2A	64Q2-08Q4	0.00011	0.006	-5.765	-	16.627	2.343	7.402
2A^2	64Q2-08Q4	0.00011	0.003	-5.575	-	14.314	2.268	9.902
3A	64Q1-79Q4	0.00015	0.046	-4.417	8.527	-	2.592	13.688
4A	80Q1-08Q4	0.00005	0.306	-5.606	21.702	-	1.340	1.147
1B	54Q1-09Q3	0.00011	0.135	-5.884	-	18.651	1.559	13.744
2B	64Q1-08Q4	0.00010	0.072	-5.933	-	19.419	2.545	11.400
2B^2	64Q2-08Q4	0.00011	0.026	-5.761	-	17.729	2.312	5.757
1C	54Q1-09Q3	0.00003	0.774	-5.088	-	38.086	1.757	10.792
2C	64Q1-08Q4	0.00004	0.662	-5.394	-	37.578	1.047	0.285
2C^2	64Q2-08Q4	0.00005	0.579	-5.494	-	22.929	1.013	1.454

Table A.5: Diagnostic tests of the structural time series models, GDP

Note: The Box-Ljung statistic $Q(P)$, based on the first P autocorrelations, is calculated for $P = 10$ and $P = 15$. The statistics is compared to the χ^2 statistic with ($P+1-$ number of estimated hyperparameters) degrees of freedom. In case of the linear models (type A) $Q(10)$ is tested against $\chi^2_{6;0.05} = 12.592$ and $Q(15)$ against $\chi^2_{9;0.05} = 16.919$. In the case of the nonlinear models (type B and C) $Q(15)$ is tested against $\chi^2_{8;0.05} = 15.507$. Homoscedasticity is checked against the F-distribution, which is close to 2. Normality is tested against the χ^2 statistic: $\chi^2_{5;0.05} = 11.070$ (type A), $\chi^2_{6;0.05} = 12.592$ (type B and C).

	σ^2	R_D^2	AIC	$Q(15)$	$H(h)$	N
2A private consumption	0.00011	0.493	-3.653	68.063	4.059	9.074
2B private consumption	0.00009	0.574	-4.781	49.367	3.793	7.305
2C private consumption	0.00008	0.644	-4.087	58.370	3.101	8.391
2A construction investment	0.00082	0.039	-3.800	15.610	1.447	0.901
2B construction investment	0.00081	0.044	-3.891	15.722	1.539	0.540
2C construction investment	0.00061	0.287	-3.811	15.659	1.101	0.735
2A investment in m. and e.	0.00198	0.120	-2.902	35.746	1.021	2.083
2B investment in m. and e.	0.00200	0.111	-2.969	45.700	1.193	2.258
2C investment in m. and e.	0.00175	0.225	-2.921	34.844	1.171	1.900
2A total exports	0.00085	0.019	-3.749	10.423	1.764	24.903
2B total exports	0.00084	0.031	-3.812	11.147	1.719	17.563
2C total exports	0.00058	0.329	-3.792	11.795	1.286	31.330
2A total imports	0.00107	0.062	-3.513	22.540	3.448	14.882
2B total imports	0.00106	0.067	-3.625	34.575	3.270	43.009
2C total imports	0.00071	0.371	-3.605	27.435	1.720	13.194

Table A.6: Diagnostic tests of the structural time series models, GDP components, 64Q2-08Q4