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Estimating and Forecasting Aggregate Productivity Growth Trends in the US and Germany

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Discussion Papers

471

Georg Erber*
Ulrich Fritsche**

Estimating and Forecasting
Aggregate Productivity Growth Trends
in the US and Germany¹

Berlin, January 2005

¹ An earlier version of this paper was presented at the 1st Productivity Workshop at DIW Berlin, July 1st 2004. The authors would like to thank the participants for helpful comments. Special thanks to Rainer Schlittgen and Jirka Slacalek for helpful remarks and to Deborah Bowen who helped to draft the English version.

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German Institute
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Georg Erber*

Ulrich Fritsche**

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Aggregate Productivity Growth Trends
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Abstract: This paper addresses the issue of estimating and forecasting productivity growth trends in the US and Germany from the perspective of a business cycle researcher who wants to use the available information in time series of aggregate labor productivity to derive a model for short- and/or long-term forecasts of labour productivity. We will use stability tests and a deterministic model with structural breaks that is estimated using the methods mentioned in Hansen (2001). The methodological approach also draws on Gordon (2003) using a Kalman filter specification. We discuss the implications of unit-root assumptions for long-term forecasts and argue in favor of a near unit-root modelling. That implies a convergence of productivity growth rates in both countries within the next 15 years.

JEL Classification: C22, C32, E23, E24, E30, E37

Berlin, January 2005

¹⁾ An earlier version of this paper was presented at the 1st Productivity Workshop at DIW Berlin, July, 1st 2004. The authors would like to thank the participants for helpful comments. Special thanks to Rainer Schlittgen and Jirka Slacalek for helpful remarks and to Deborah Bowen who helped to draft the English version.

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Introduction

Productivity growth can be analyzed from different perspectives and for different purposes. An approach based on behavioral assumptions like cost minimization or profit maximization uses a production function or, more generally, a set of production possibilities that constrain resource allocation in order to produce a certain set of outputs. This strand of the literature, which usually comes under the heading of growth accounting, tries to identify the different origins of productivity growth – such as factor accumulation, embodied or disembodied technological change, quality changes in factor inputs, and impacts from different types of externalities – and then discuss their implications for micro, industrial, and aggregate productivity growth (see e.g. OECD, 2004).

Economic growth theory, however, focuses on the steady state of long-term growth trajectories. It offers few testable empirical models for how adjustment processes occur after exogenous transitory or persistent shocks. In the real world, there are not just predictable shocks, but a multitude of different shocks at different times and in different intensities. This deviates from the quasi-laboratory conditions where individual predictable shocks and their impacts on a highly specified mathematical model are studied. Residuals obtained in growth accounting exercises, however, are often termed by some critics as “measures of ignorance” (see e.g. Griliches, 1995, Lipsey, Carlaw, 2001) because no single direct input factor can be attributed to them, and because they have to be broken down into pure random shocks, i.e. white noise, on the one hand, and, a systematic component on the other, i.e. residual trend, attributed by most authors to technological change or total factor productivity growth, TFP.¹

Especially the assumptions of perfect foresight and permanent efficient factor allocations pose severe impediments that prevent theoretical growth models from matching real-world situations – whether the models are Solovian with exogenous technological change (Solow, 1956) or growth models with endogenous growth (see e.g. Romer, 1996; Grossman, Helpman, 1991; Erber, Hagemann, Seiter, 1995; Aghion, Howitt, 1998). They also make it difficult to separate short-term fluctuations in productive efficiency due to business cycles (e.g. productivity

¹ Lipsey, Carlaw (2001, p.3) distinguish three different groups of economists “One group holds that changes in TFP measure the rate of technical change. ...We refer to this as the ‘conventional view’. The second group holds that TFP measures only the free lunches of technical change, which are mainly associated with externalities and scale effects. The third group is skeptical that TFP measures anything useful.”

shocks as the real business cycle theories assume, see Muth, 1961, Lucas, 1975), and other exogenous shocks (oil price or exchange rate shocks for example) from the medium- to long-term economic development, i.e. the trend. Even if all economic agents were willing to act according to these principles, they would still be unable to, due to information deficits and the incapability to adjust accordingly in a world with fixed factors.

This paper addresses the issue from the perspective of a business cycle researcher who wants to use the available information in time series of aggregate labor productivity to derive a model for short- and/or long-term forecasts of labour productivity.² We will use stability tests and a deterministic model with structural breaks that is estimated using the methods mentioned in Hansen (2001). The methodological approach also draws on Gordon (2003) using a Kalman filter specification.

This approach studies a single time series of labour productivity growth. As such, it is a significant reduction of complex issues raised in other theoretical economic models – for example models in the growth accounting tradition using a more or less complete structural economic model to explain labor productivity growth, or in econometrics, using a structural vector autoregression model (SVAR). All in all, one should keep in mind that in the standard production function framework the rate of change of labour productivity³, g_{lp} , depends on for the rate of technological change, g_{TFP} , measured by the total factor productivity (TFP) and the rate of change in the capital-labour intensity, $g_{K/L}$, weighted by its respective factor share, κ . Since all variables change over time, a time subscript is added to each variable.

$$g_{lp,t} = g_{TFP,t} + \kappa_t \cdot g_{K/L,t}$$

Labour productivity growth is therefore driven in this framework primarily by the two key factors: technological change and capital accumulation⁴ relative to the labor inputs used.

In contrast, the univariate time series approach is one with a radically reduced form, with all the strengths and weaknesses that have been discussed widely in the literature. The great ad-

² For the sake of brevity, we use the term productivity synonymously with labour productivity if not mentioned otherwise.

³ The annualized growth rates are calculated as logarithmic differences of the original index time series of labour productivity.

⁴ Under capital we might here understand all kinds of capital, i.e. physical, human, intangible, organizational or social capital. Most empirical growth accounting exercises, however, just take into account a subset of capital goods, so that in the standard literature often just physical capital goods are incorporated into the calculations.

vantage, however, is that for business cycle analysis, labor productivity data is available on a high-frequency basis like quarterly data, while an approach using total factor productivity (TFP) as an appropriate measure for technological progress as a key driver has difficulty obtaining reliable information about quarterly capital stock growth at such a high frequency. For a structural analysis, it would of course be much more appropriate to study the interactions between the different sources of labour productivity growth and to look for the potential improvements in forecasting accuracy if these structural relations are taken into account. This makes it more difficult for the latter approach to derive short-term forecasts that include information about the most recent developments. For example, if a recession starts in the third quarter of a year, a model based on annual data has to wait until the year is completed or use average estimates until this information enters the dataset. Often single equation estimates show robust forecasting properties that are not inferior to multivariate structural models.

The univariate time series modeling approach, however, fits the data to a standard time series decomposition in random (ε), cyclical (ϕ) and trend components (μ), ignoring seasonality for the moment (see e.g. Chatfield, 1975, chap. 2).

$$g_{lp,t} = \mu_t + \phi_t + \varepsilon_t$$

Thus, compared to multivariate models, univariate time series models of labor productivity growth do not place high demands on their databases in terms of additional economic variables. They do, however, make it necessary to identify restrictions on the nature of the trend and business cycle component.

This type of traditional time series modeling has ignited another debate around the question of the stability and nature of trends, since these assumptions govern the decomposition. With the emergence of time series modeling by random walk and stochastic trend models, the topic of the nature of trends in economic time series has led to a heated debate (for a brief summary of the debate, see e.g. Hansen, 2001, p. 124–26). The existence of statistically significant unit roots in a large number of macroeconomic time series posed the new challenge of either accepting the trade-off between deterministic trends combined with a number of structural breaks on the one hand, or modeling time series using a random walk approach, leading to stochastic trends, on the other. In this paper, the options will be discussed in detail based on data from the US and Germany.

The following are the most important benchmarks for choosing between the alternative model specifications: a good fit with the available data; generation of reliable robust forecasts of long-term shifts in productivity trends; and plausibility of these decomposition results with respect to the information available to the researcher. The question of a model's appropriateness can therefore never be separated from the prior information that is available to the researcher. Insights from economic theory are crucial for decision making when data-driven statistical methods cannot deliver clear-cut answers as to which statistical model is the best in a given case.

The paper is organized as follows: Section 1 discusses possible changes in the labor productivity growth together with stylized facts about the data (sources and definitions are given in an appendix). Section 2 presents Gordon's approach to determining the long-term trend in labor productivity growth (Gordon, 2003b). Section 3 presents the results of alternative modeling approaches using quarterly data for the US and Germany. These approaches include deterministic models with structural breaks and stochastic models like the random walk model and state space modeling. Sections 4, 5 and 6 discuss the comparative advantages and disadvantages of these alternative models with regard to data consistency, and the implications of different models for long-term and short-term forecasts.

One key argument is that if alternative modeling approaches allow for sufficient flexibility – i.e. a large number of break points, or perfect unit roots versus near-unit roots – then statistical tests will be unable to provide the information needed to choose among their specifications. However, with regard to forecasting properties, the implications of these different models would lead to very different long-term forecasts of the labor productivity trend rate. Taking account of the most important economic considerations, this means that mean reversion cannot be rejected even if a very long time period is needed to observe it. Thus, we prefer forecasts based on a Kalman-filter model with near unit root properties to the alternatives – including deterministic broken trends and a perfect random walk stochastic trend.

1 Changes in labor productivity growth and time series properties

1.1 Has the long-term trend of labor productivity growth changed?

Productivity growth is highly volatile. Economists know well that a multitude of factors influence productivity growth – especially when measured at high frequency, i.e. with quarterly data. Furthermore one of the most frequently cited "facts" of business cycle research is that productivity moves in a pro-cyclical fashion. Some authors such as Gordon (2003b) argue that productivity growth also reflects future business cycle changes. The business cycle component of productivity growth therefore leads the cycle. It is, however, more an art than a science to evaluate whether a change in productivity growth is due to a change in the cycle or in the long-term trend.

The topic of determining changes in the long-term productivity growth rate gained increased importance for public and policy makers after the recent dramatic surge in US productivity, which is widely attributed to a significant increase in the use of ICT-technologies.⁵ Others like Robert Gordon (2000) raised substantial doubts as to the sustainability of the late-1990s surge in productivity growth. Things became even more complicated after the burst of the New Economy Bubble. The setback of US GDP growth in 2001 – which was even much more pronounced in Germany and Europe – raised further doubts that labour productivity growth would stay on the high levels of the late-1990s.

However, to the great surprise of many professional observers, even during the mild recession of the US economy in 2001 and afterwards, labour productivity growth accelerated instead of declining. This raised the even more pressing question of what has changed and how long this new surge in productivity growth will last.⁶ On the other hand, Europe's much-acclaimed

⁵ See Oliner; Sichel (2000), Council of Economic Advisers (2001), Jorgenson, Stiroh (2000).

⁶ Gordon (2003b). His second puzzle relates to this question: "*Why did productivity growth accelerate after 2000 when the ICT investment boom was collapsing?*" *ibid.* p. 11. A major source for this divergence between ICT investment and productivity growth according to Gordon relates to the different approaches of ICT capital stock measurement. If investment in software and other (in particular communications) equipment had been incorporated into the ICT capital stock, the collapse in ICT investments would be much more moderate than if it had not been incorporated. Other omitted intangible investments in ICT and a delay in the efficiency impacts due to a gradual increase caused by learning-by-using (Rosenberg, 1994) and learning-by-doing (Arrow, 1962) might delay a deceleration of productivity growth beyond the peak of actual ICT investments until these effects have worked out. For a recent study on the new economy growth impact in Finland, see Daveri, Silva (2004). Their

process of catching up with the US economy (see Lisbon Summit Declaration of 2000⁷) by transforming its old economy into one based on a new modern information society is still far from complete.⁸ The new economy bubble led to a significant setback in US economic growth after the year 2000. Therefore it has become very important to distinguish between short-term movements of productivity growth attributable to a high-tech bubble and/or cyclical movements on the one hand, and long-term shifts in productivity growth rates on the other (see Erber, Hagemann, 2004).

The consequences of long-term shifts in the productivity growth rate are dramatic. Consider Gordon's question:

"Will potential output grow in the future at a four percent annual rate, as several of the more optimistic business economists assume, or at the pathetic 1.8 percent annual rate assumed into the distant future by the trustees of the Social Security Administration? Put differently, will real GDP in seventy-five years be 20 times its current level or a mere 3 ½ times?" Gordon (2003a), p. 207.

An answer on this question would speak volumes about the economic situation that our generation and the generations to come will face, and the efforts needed to prepare for the future. Long-term trends like population decline and the aging of society would be significantly less frightening if financial planners could build their financial schemes on a rapidly growing economy with high productivity growth (see e.g. Kotlikoff, Burns, 2004). The current huge US fiscal deficit, for example, would be easier to conquer if the US government could consolidate its position by stabilizing expenditure growth and waiting for economic growth to close the public deficit gap. If such an approach were just a pipe dream, the future perspectives for the US economy would look rather bleak. Much of the policy debate in the current US election campaign depends on implicit assumptions about the US economy's future

findings cast doubt on the hypothesis that the ICT-productivity spillover effects on the whole economy are as significant as reported for the US.

⁷ In March 2000, the EU Heads of States and Governments agreed to make the EU "the most competitive and dynamic knowledge-driven economy by 2010". Although some progress was made on innovating Europe's economy, there is, however, growing concern that the reform process is not going fast enough and that the ambitious targets will not be reached.

⁸ European productivity growth relative to the US has changed dramatically since 1995. Germany has now become the main laggard in economic growth, and there is little hope that a strong recovery will take place in the near future. For the majority of Europe, the long-term process of catching up with US productivity has come to an end (see e.g. O'Mahoney, van Ark, 2003). Gordon recently makes the following remark:

"After a half century following World War II of catching up to the level of the US productivity, since 1995 Europe has experienced a productivity growth slowdown while the United States has experienced a marked acceleration. ... Starting from 71 percent of the US level of productivity in 1870, Europe fell back to 44 percent in 1950, caught up to 94 percent in 1995, and has now fallen back to 85 percent. What were the causes of this stunning setback?" Gordon (2004, p. 1)

growth perspectives and the efficiency increases that can be expected from high productivity growth.

1.2 Time series properties and a first look at stylized facts on US and German labor productivity

To a large extent, the choice of appropriate methods of time series investigation depends on stationarity assumptions. As a first step, we take the available time series of labor productivity (see Appendix for details concerning the data) and test for time series properties, namely the existence of unit roots.

Table 1
Unit Root Tests

Variable	Augmented Dickey-Fuller test (H0: series has a unit root)		Kwiatkowski-Phillips-Schmidt-Shin test (H0: series is stationary)	
	Specification	Test statistic	Specification	Test statistic
USA				
log (Productivity)	constant, trend, lags = 0 (based on minimum SIC)	-2.32	constant, trend, bandwidth = 11 (Newey-West using Bartlett kernel)	0.41***
Δ log (Productivity)	constant, lags = 0 (based on minimum SIC)	-16.56***	constant, bandwidth = 2 (Newey-West using Bartlett kernel)	0.24
Germany				
log (Productivity)	constant, lags = 9 (based on minimum SIC)	-2.93**	constant, bandwidth = 10 (Newey-West using Bartlett kernel)	1.65***
Δ log (Productivity)	constant, lags = 8 (based on minimum SIC)	-2.02	constant, bandwidth = 7 (Newey-West using Bartlett kernel)	1.41***
$\Delta\Delta$ log (Productivity)	lags = 7 (based on minimum SIC)	-7.46***	constant, bandwidth = 23 (Newey-West using Bartlett kernel)	0.11
***, **, * denotes significance at the 1, 5, 10 per cent level.				

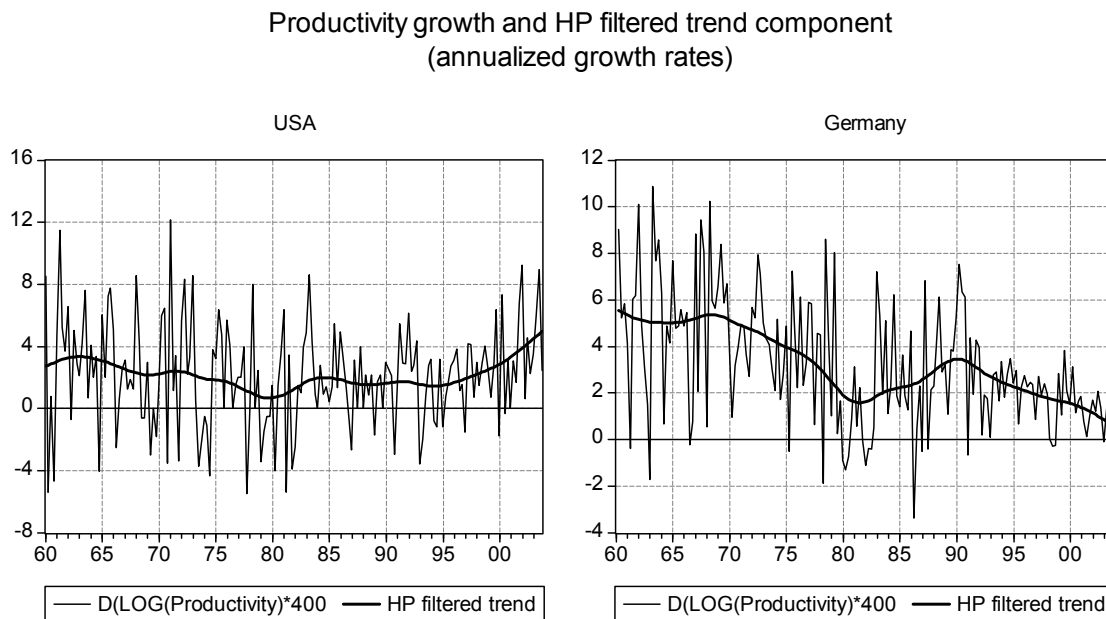
We use the augmented Dickey-Fuller procedure as well as the test proposed by Kwiatkowski et al (1992) – abbreviated as ADF and KPSS-tests. The tests have opposite null hypotheses:

whereas the ADF test decides under the null that the time series has a unit root, KPSS decide under the null that the time series is stationary.⁹ The results are given in Table 1. The test results suggest that the US data seems to be I(1), whereas the data for Germany seems to be I(2).

However, unit root tests are, in the end, only valid under the assumption of no structural change. For empirical investigation, there is no conclusive way to discriminate between a random walk model and a segmented deterministic model.

To get a better impression of the long-term and short-term dynamics of productivity growth in both countries, we used a Hodrick-Prescott-Filter under standard settings (see Appendix for details) to derive an initial time-varying trend estimate.

Figure 1
Productivity growth and HP filtered trend component



Comparing the results of productivity growth in the US and Germany using the Hodrick-Prescott-Filter, one observes that

for the US:

- The long-term productivity trend rate has recovered moderately in the early 1980s after a significant decline from the early 1960s to the late 1970s.

⁹ Dickey and Fuller (1979), Kwiatkowski, Perron, Schmidt, Shin (1992).

- From about 1983 until 1995, the long-term productivity growth rate stagnated more or less 2 percent.
- From 1995 onwards, a significant acceleration of long-term productivity growth occurred and was not even affected when the new economy bubble burst in spring 2000.

for Germany:

- High productivity growth in the 1960s and early 1970s slowed down dramatically compared to US rates after the first oil price shock in 1974.
- This deceleration of productivity growth became even more pronounced in 1982, with the deep (double-dip) recession that followed the second oil-price shock. From 1982 to 1989, productivity growth was in a state of recovery.
- With German reunification, productivity growth started to decline again. In the mid-1990s, Germany's comparative advantage in productivity growth relative to the US was lost, and fell below levels never seen before – less than 1 percent in 2003. Germany is no longer catching up to US productivity levels, but continues to fall more and more behind.
- The burst of the new economy bubble in spring 2000 further accelerated the decline in long-term labor productivity growth.

There is, however, a debate among experts about whether the HP filter is an appropriate method for business cycle filtering. Like other symmetric filters, the HP filter is very sensible for changes at the endpoints – which is of great importance for practitioners who are mainly concerned about the assessment of the actual situation. Furthermore, the univariate HP filter does not take into account additional information about the economy (which is present e.g. in co-movements with other variables) to decompose productivity growth fluctuations into a cyclical and a long-term component.

2 Gordon's approach to determining trend rates

As a starting point, we use a simple semi-structural approach very similar to Gordon (2003a). According to Gordon, one of the stylized facts of business cycle research is that the cyclical component of productivity growth is *pro-cyclical* and has a *lead* in relation to the changes in output gap. Under the label of Verdoorn's or Kaldor's law, this phenomenon has been known for a long time (see e.g. McCombie, Pugno, Soro, 2002, Cornwall, 1976, Erber 2003). One explanation is offered by the literature on real business cycles, where productivity shocks are at the root of cyclical fluctuations (Kydland and Prescott, 1982) or labor hoarding in combination with slow price adjustment (Rotemberg and Summers, 1988, 1990). This leads to the following specification where "Gap" stands for the output gap.¹⁰

$$g_{lp,t} = c_t + \beta_0 \Delta \text{Gap}_t + \beta_1 \Delta \text{Gap}_{t+1} + \beta_2 \Delta \text{Gap}_{t+2} + \beta_3 \Delta \text{Gap}_{t+3} + \beta_4 \Delta \text{Gap}_{t+4} + \varepsilon_t$$

In this specification c_t captures the trend component and all the other coefficients are intended to capture the cyclical component. We decided to use four leads of the change in output gap – as Gordon did – which seems to be a bit arbitrary. We also experimented with additional lag lengths but this simple model seems to fit the data quite well.

¹⁰ See appendix for details.

3 Breaks in productivity growth: deterministic vs. stochastic trends

3.1 A deterministic broken trend model

Economic time series are quite often significantly changed in their development pattern due to transitory or persistent exogenous shocks in the time series during the observation range. German unification, for example, changed the economic area, the population and the economic system fundamentally between 1989 and 1990. Many consider this to have created a persistent shock to the German economy from which it has not yet recovered. Similar extraordinary events like the two oil price shocks of the 1970s and the impacts of terrorist attacks of September 11, 2001, change the dynamics of the economic system in ways that are out of reach of standard macroeconomic explanations.

If structural breaks in time series modeling were not accounted for, simpler models of time series analysis would produce highly biased results. Traditionally, structural break testing uses the Chow test. In the last decade, however, a number of new testing procedures have been developed in part because of an inherent problem with the Chow test: it is only statistically valid if the breakpoint is known in advance. Such *a priori* knowledge is often unavailable in applied research.

Structural break tests can now be done with a number of alternative structural breaks tests:

- Hansen (1992) developed a test of the null hypothesis that no single structural break is present in the respective time series. Rejecting the null hypothesis indicates structural instability without specifying the form of this instability.
- Bai and Perron (2003) developed a simultaneous multiple breakpoint test and estimation method. The procedure investigates all possible models under the assumption of a given number of breakpoints and a given minimum distance between the break points. The 'optimal' model is chosen according to the (minimum of the) sum of squared residuals and according to information criteria. Therefore, we have to assume a maximum acceptable number of breakpoints. Otherwise the algorithm could not determine a reasonable global minimum since each single observation point could be considered to be a local optimum for a break point.

Testing for structural breaks, we use the above-mentioned model in a two-stage approach:¹¹

$$g_{lp,t} = \beta_0 \Delta \text{Gap}_t + \beta_1 \Delta \text{Gap}_{t+1} + \beta_2 \Delta \text{Gap}_{t+2} + \beta_3 \Delta \text{Gap}_{t+3} + \beta_4 \Delta \text{Gap}_{t+4} + u_t$$

$$u_t = c + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2)$$

The model specification in the first equation omits a constant term because otherwise, the parameter c in the second could not be estimated independently.

We applied the Hansen test as well as the Bai-Perron test on the second equation. For the Bai-Perron test, we opted for a maximum of 10 breakpoints with a data range of about 40 years. The minimum distance between two breakpoints was set equal to 3 years – as we assume a little stability over the cycle. For each model, the Bayesian Information Criteria (BIC) were calculated to check which of the estimated breakpoint models should be viewed as the best one.

For the Hansen test statistics, we obtained the following results (see Table 2).

Table 2
Results of Hansen (1992) stability test

Variable	Test statistic	
	US data	German data
c	0.62**	4.66***
σ_ε^2	1.13***	1.28***
Joint test	1.48***	5.02***

/ denote significance at 5% resp. 1%.

For both countries, we find at least one significant structural break in the labour productivity time series. Both residual parameter estimates are statistically significant at the 5% and/or 1% level. Therefore we need to identify structural breakpoints using the other two tests.

From the Bai-Perron test we obtain the following breakpoints and optimum number of breakpoints for both countries.

¹¹ The structural break tests were done using RATS 5.04 and the freely available procedures for the described Hansen and the Bai-Perron tests.

Table 3

Results of Bai-Perron (2003) multiple structural break test

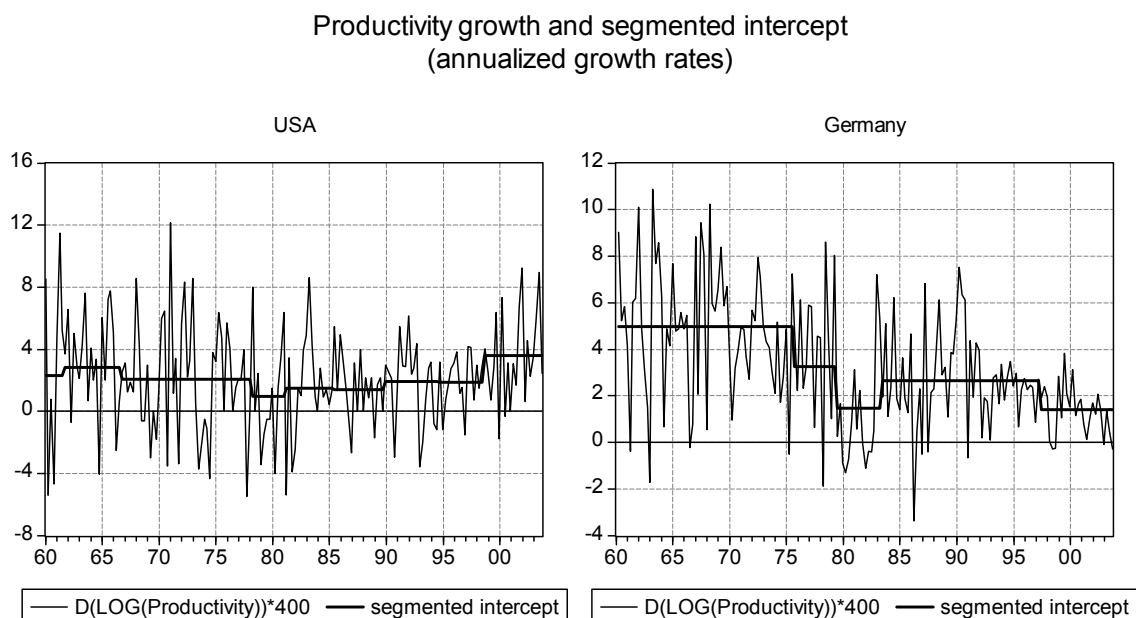
	"Optimal model" (according to the minimum of BIC)	
	US data	German data
Number of breaks	8	4
Breakdates	1961:3 1966:3 1978:1 1981:1 1985:2 1989:4 1994:3 1998:3	1975:3 1979:2 1983:2 1997:2

Summing up, the tests give us the following results:

- In the US, eight significant structural breaks occurred in the sample: two in the 60s, one in the 70s, three in the 80s, and two in the 90s.
- In Germany, four significant structural breaks can be identified: three in the 70s and 80s and one in the 90s.

Figure 2

Productivity growth and segmented intercept



Using the results of the Bai-Perron multiple break point test and plotting them against the time series data, we obtain a step function that is consistent with the major shifts in the long-term productivity growth rate found using the HP filtering technique. However, especially at

the boundary – i.e. the years after the burst of the new economy bubble in 2000 – the shift in the long-term productivity growth rates in the US and Germany are not as dramatic as they appear using the HP filtering technique (see figure 2, below). Thus it makes sense to look for a different estimation method that is more in line with the results found by using deterministic breakpoints to determine shifts in the long-term productivity growth rate.

3.2 A state space model using a Kalman filter

However, the productivity trend could change in a stochastic rather than a deterministic manner. To investigate this, a state space model with a time-varying coefficient for the trend growth rate was estimated.¹² The system consists of two equations: the signal 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 signal equation is given by:

$$g_{ip,t} = \alpha_t + \beta_0 \Delta \text{Gap}_t + \beta_1 \Delta \text{Gap}_{t+1} + \beta_2 \Delta \text{Gap}_{t+2} + \beta_3 \Delta \text{Gap}_{t+3} + \beta_4 \Delta \text{Gap}_{t+4} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, \sigma_\varepsilon^2) \quad \text{with} \quad \sigma_\varepsilon^2 = e^\gamma$$

and

the state equation is given by:

$$\alpha_t = \alpha_{t-1} + v_t \quad v_t \sim N(0, \sigma_v^2) \quad \text{with} \quad \sigma_v^2 = e^\phi$$

In the signal equation, productivity growth is regressed on the change in output gap, to eliminate business cycle fluctuations. The time-varying part of the model just explains productivity changes that are not due to changes in the business cycle. It is assumed to follow a random walk – a strong assumption but one that allows great flexibility.¹³ Using a ML estimator, the variances of the error terms are estimated simultaneously with the other model parameters. The exponential function is employed to impose positivity restrictions on the estimated variances.¹⁴

Tables 4 and 5 show the estimated coefficients for the US and Germany. For the latter, the coefficients β_2 and β_3 were found to be statistically insignificant and therefore restricted to

¹² An introduction can be found in Hamilton (1994), chapter 13.

¹³ The variance of the state equation determines the smoothness of the time-varying coefficient. In contrast to Gordon (2003) the variance here was freely estimated.

zero. The final state of the coefficient α_t gives the value of the time-varying coefficient at the last observation in sample (2003:04).

Table 4

State space model: USA

Method: Maximum likelihood (Marquardt)				
Sample: 1947:1 2003:4				
Included observations: 228				
Valid observations: 227				
Convergence achieved after 66 iterations				
	Coefficient	Std. Error	z-Statistic	Prob.
β_0	2.78	0.22	12.42	0.00
β_1	-0.60	0.22	-2.76	0.01
β_2	0.42	0.19	2.16	0.03
β_3	0.40	0.21	1.90	0.06
β_4	0.50	0.19	2.57	0.01
γ	1.91	0.06	34.41	0.00
ϕ	-3.31	0.93	-3.57	0.00
	Final State	Root MSE	z-Statistic	Prob.
α_t	3.43	0.72	4.77	0.0000
Log likelihood	-554.67	Akaike info criterion		4.95
Parameters	7	Schwarz criterion		5.06
Diffuse priors	1	Hannan-Quinn criter.		5.00

¹⁴ All state space estimates were done using EViews 4.1.

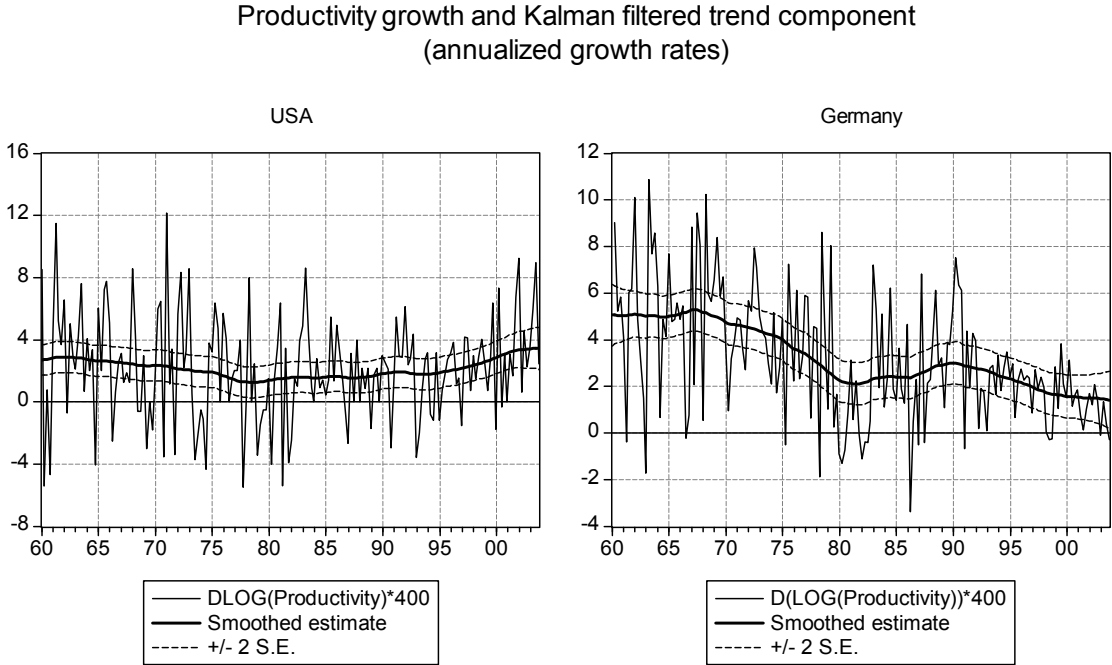
Table 5

State space model: Germany

Method: Maximum likelihood (Marquardt)				
Sample: 1960:1 2004:4				
Included observations: 180				
Valid observations: 175				
Convergence achieved after 25 iterations				
	Coefficient	Std. Error	z-Statistic	Prob.
β_0	1.25	0.20	6.35	0.00
β_1	0.92	0.20	4.67	0.00
β_4	-0.41	0.23	-1.80	0.07
γ	1.37	0.09	15.27	0.00
ϕ	-3.16	0.74	-4.25	0.00
	Final State	Root MSE	z-Statistic	Prob.
α_t	1.41	0.77	1.82	0.07
Log likelihood	-384.78	Akaike info criterion		4.45
Parameters	5	Schwarz criterion		4.55
Diffuse priors	1	Hannan-Quinn criter.		4.49

Looking at the following graphs of the estimates of the long-term productivity growth rate measured by α_t (see figure 3), one notices that the estimates follow in general the pattern already found by the HP filter and the step function as implied by the results of the Bai-Perron multiple breakpoint test. No statistical differences between the results of all methods can be found – especially because confidence bounds would be even greater if estimation uncertainty for some methods would be taken into account.

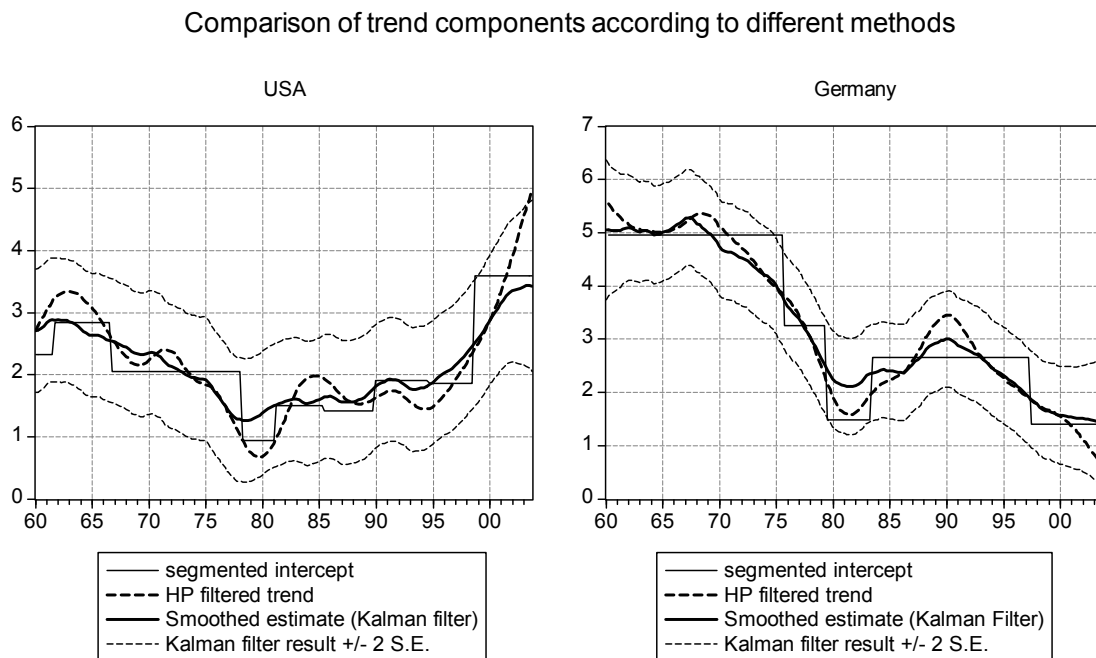
Figure 3
Productivity growth and Kalman filtered trend component



4 Model selection: Which one, what for?

The major differences between the three different approaches become more obvious if we plot all three different long-term trend estimates together (see Figure 4). Additionally we added a 2σ -confidence band from the Kalman Filter estimates. This covers the possible range of the true long-term rate with a probability of 99 percent, assuming they are asymptotically normally distributed.

Figure 4
Comparison of trend components according to different methods



Comparing the results of the HP filter with those of the Kalman filter, we observe that the HP filter long-term rates under the standard setting of $\lambda = 1600$ deviate from the Kalman filter values especially when turning points occur. The HP filter values are much more volatile during these periods than those of the Kalman filter. This raises the suspicion that they do not measure the true long-term rates efficiently and without bias. However, taking the confidence band as a benchmark for the range where the true long-term productivity growth rates may be located, all three methods give results inside this confidence range, with the sole exception of the point where the step function exceeds the confidence interval in Germany in 1975 .

However, the Kalman filtering technique seems to give a more robust estimator¹⁵ of the long-term rates compared to the other two methods. Especially for long-term planning, a robust estimate of the long-term productivity growth rate seems very important. This is in line with the recent findings of Gordon (2003). Beside the benefits of more reliable point estimates for long-term productivity values, the possibility of deriving confidence intervals provides social planners and forecasters an additional benefit: these boundaries can be used for alternative scenarios using the upper and lower bounds of the confidence interval as safe estimates to guard against potential risks of unexpected shifts in the long-term productivity growth rate.

4.1 Stochastic versus deterministic broken trends

Our current findings show the statistical problem of discriminating, given a limited data set, between two competing hypothesis that deliver quite similar results when applied to particular time series. The unit root revolution in macroeconomic time series analysis started with the article by Nelson and Plosser (1982). Before that, according to Hansen (2001, p.124) “*it was commonplace to assume that the trend was linear.*” Structural breaks were treated by incorporating a structural dummy variable into the set of explanatory variables to account for this particular structural break. Nelson and Plosser instead tested a large set of macroeconomic time series against the random walk hypothesis, i.e.

$$y_t = \alpha + \rho y_{t-1} + u_t \quad \text{with} \quad E(u_t^2) = \sigma_u^2 \quad \text{and} \quad \rho = 1$$

The existence of a unit root in the autoregression parameter determines the dynamic properties of an autoregressive stochastic process dramatically because past random shocks do not vanish over time. Each single shock is kept in the memory of the time series forever and will be not forgotten if $\rho = 1$. The time series following a random walk are strongly dependent und non-stationary due to this unit root path. A significant random shock – statistically a rare event – shifts the trajectory of such a time series persistently over a long period until a similarly large negative random shock would later compensate for it, or until a positive shock would drive the long-term growth rate of the time series even further away from its initial value if it had the same sign. Random walk time series are, for this reason, intrinsically non-

¹⁵ Smooth estimates over time for the long-term growth rate are better than those who are jumping up and down from period to period. (see e.g. Härdle, 1992).

ergodic, i.e. tend to end up at a finite expectation value. This property, however, was counter-intuitive for most economists in the early 80s.

The only alternative way of keeping the deterministic trend model intact was to assume that from time to time at certain breakpoints, structural breaks shifted the deterministic trend in a random fashion to a persistent new deterministic trend for some period. By incorporating the possibility of a sequence of broken trends into the test of the random walk hypothesis, the empirical results often ended in an indeterminate situation where it is empirically impossible to give one of the two hypothesis maintained a higher probability. Perron (1989) attempted such a defense against the random walk hypothesis in macroeconomics with some success. However, by adding more and more breakpoints into a deterministic trend model, it becomes asymptotically equal to a random walk model, where each single observation point is considered to represent a breakpoint.

4.2 Unit root vs. near unit root

Accepting the unit root test hypothesis implies that the respective time series is a perfect random walk, i.e. $\rho = 1$. However, this assumption might be extreme for economic time series especially if the actual state of a random walk variable is at a maximum or minimum state never observed before in the actual data set. Using the actual state as a predictor for the long-term growth rate of labor productivity would lead to a dramatic surge or decline in productivity growth if the aim is to forecast not only a few quarters but rather decades, as social security agency forecasts, for example, have to do. The risk of a dramatic failure in the ex post long-term productivity growth rate would have dramatic impacts on decisions made now, and could put overly optimistic/pessimistic views into perspective. Normally a unit-root test does not focus on the error of the second kind even if the power of such a test drops dramatically with a declining distance between the two alternative hypotheses. In the standard augmented Dickey-Fuller test, the two hypothesis tested are:

$$H_0 : \rho = 1 \quad \wedge \quad G : \rho \leq 1$$

Accepting or rejecting the hypothesis of a unit root at a particular significance level α does not tell you anything about the power of the test or the associated error of the second kind, if are testing the implicit nested hypothesis that

$$H_0 : \rho = 1 \quad \wedge \quad G : \rho = 1 - \varepsilon \quad \text{with} \quad \varepsilon \leq 0.05$$

The power of the test would be low and the error of the second kind would be very large. Since the qualitative properties of non-stationarity or stationarity depend on an infinitely small difference from one, this delicate situation involves the high risk of making the wrong choice. If the time series shows mean reversion, a long-term swing in productivity growth back to a normal rate would lead to grossly different outcomes than the belief that the actual rate could be maintained indefinitely. Long-term mean reversals lasting many years or even decades, such as those observed in other macroeconomic time series, e.g. actual exchange rates with regard to purchasing power parities (see Rogoff, 1996), are very difficult to distinguish from true unit roots with the limited data set available. Under such circumstances, statistical tests do not provide sufficiently reliable answers for applied research because they always include the high risk of an error of the second kind, i.e. accepting a wrong hypothesis. The scarcity of data does not enable the applied econometrician to discriminate between two given hypotheses with the accuracy necessary to help decision-makers reach optimal decisions. One has to make additional judgements based on prior information or economic theory in order to choose between the two options of a unit root and a near unit root model.

4.3 Forecasting with unit root versus near unit root models

To illustrate the problem of discrimination between a unit-root approach on the one hand and either a segmented deterministic trend or a near unit-root approach (high persistence of adjustment but mean reversion), we did the following experiment: we estimated a state space model very similar to the model mentioned above where the only difference lies in the state equation. The evolution of the time-varying coefficient is now formulated as:

$$\alpha_t = c + \rho\alpha_{t-1} + \varepsilon_t \quad 0 < \rho < 1$$

The variance of ε_t was set close to the value of the original specification since this governs the smoothness of the trend estimate. The respective values for the values of the coefficients c and ρ for both countries are given in table 6.¹⁶

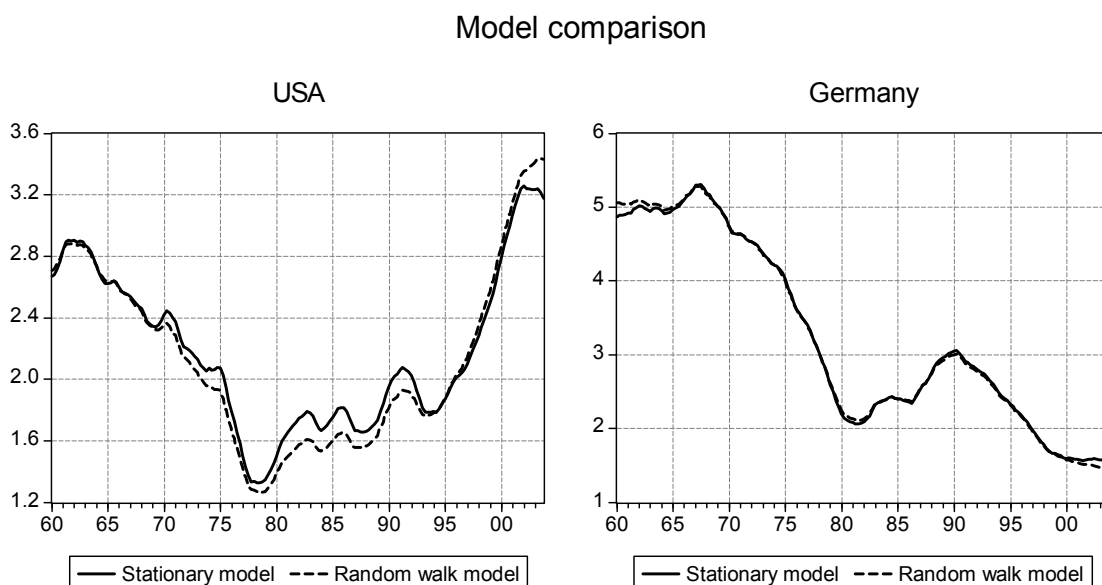
¹⁶ The detailed estimation results are of course available from the authors on request.

Table 6
Near Unit Root Estimates

	USA		Germany	
	coefficient	p-value (z-statistic)	coefficient	p-value (z-statistic)
c	0.10	0.18	0.03	0.58
ρ	0.96	0.00	0.99	0.00

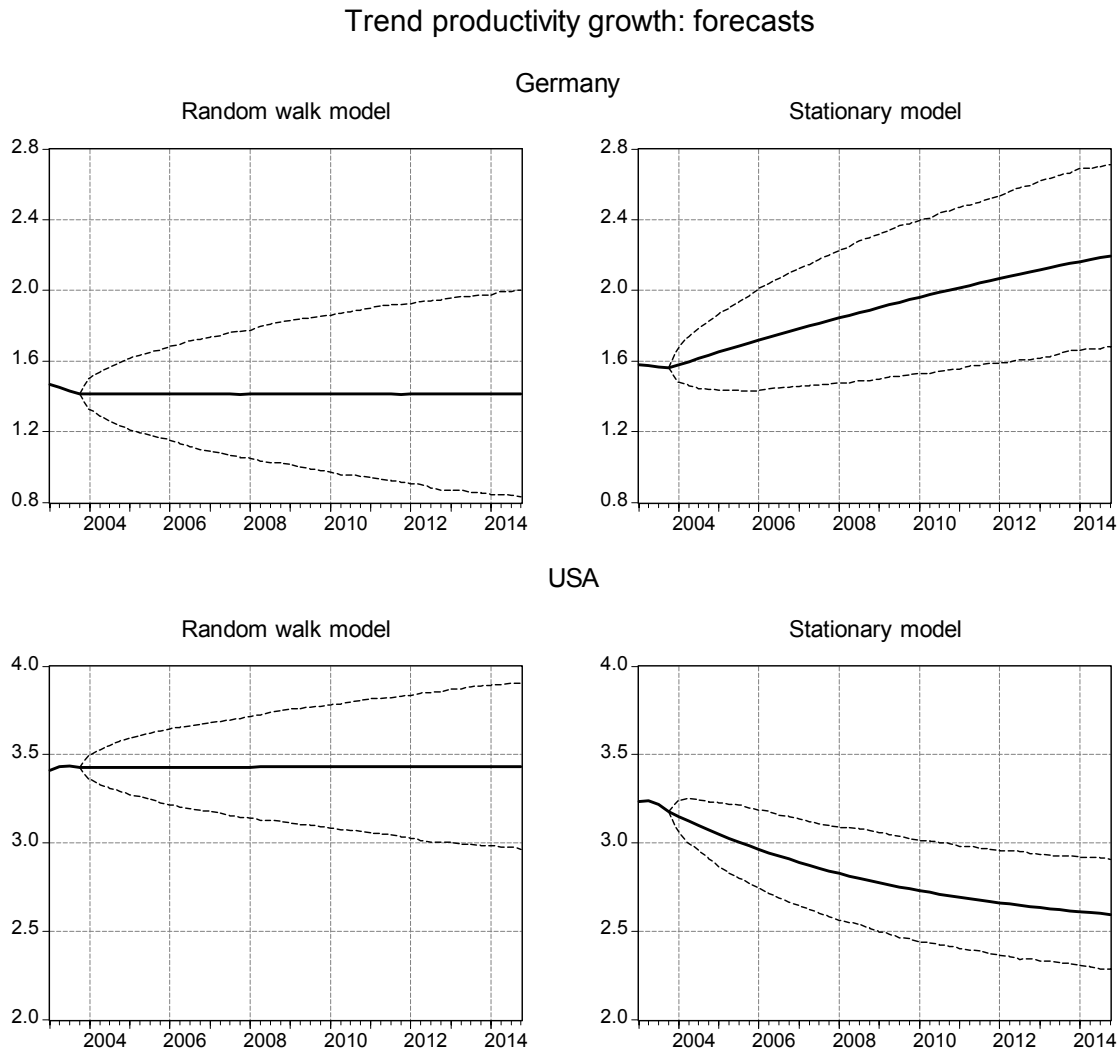
It is difficult or impossible to distinguish these estimates from the unit-root approach (see figure 5), especially for Germany.

Figure 5
Model comparison



The implication for long-run forecasts, however, is important. We used the different specifications of the state space model for both countries to build a model and performed stochastic simulations (5000 repetitions). Figure 6 gives the forecasts of the time-varying coefficients – including the 95-per cent confidence bounds. In spite of the minor differences in specification, the implications for the long-run forecast are impressive.

Figure 6
Trend productivity growth: forecast



While in the short-run the differences between the two alternative models are not very dramatic, they will become dramatic in the long run. Especially in the current situation where both countries face opposite extreme states of productivity growth, accepting the unit root hypothesis would lead to very dramatic differences in long-run forecasts. The unit root forecast would be not in line with results obtained by other approaches based on more structural information and using growth accounting methods.

5 Conclusions

Summing up the results of our analysis for the US and Germany, we conclude:

- The dramatic surge in US labor productivity growth on the one hand, and the similarly dramatic decline in German labor productivity growth since the mid-1990s on the other, have led to a debate on the sustainability of these changes in both countries: Will the US continue to outpace Germany in labor productivity growth, leading to a persistent increasing productivity gap? Or, will this divide narrow again because of a long-term mean reversal that can be identified through near unit root models?
- Assuming for economic reasons that the recent surge in labor productivity in the US is not attributable to a persistent long-term shift as a perfect random walk model would suggest, it appears much more likely that sooner or later, some kind of mean reversal will take place, lowering the currently extreme high productivity growth rate in the US to one close to 2.5% in the next 10 years.
- Similarly, the currently existing structural crisis of the German economy will not persist forever so that if long-term mean reversal takes place, labor productivity growth will recover to rates of about 2.3% in the next 10 years – a little bit lower than the US long-term rate but a much less dramatic difference than at present.
- Using different methodological approaches like deterministic broken trends, stochastic trends as unit roots or near unit roots have a hard time using currently available statistical methods to decide whether the approaches are sufficiently flexible to fit the available data well.
- If one accepts the view that there are always limits to growth – in the sense that highly favourable episodes do not last forever, whether due to a positive new economy productivity shock or to positive impacts from the unprecedented global outsourcing of production – there are good reasons to doubt that the good times in the US and the bad times in Germany will roll on for ever.¹⁷ Some kind of convergence will probably take place sooner or later.

¹⁷ The demographic impact of an aging society is one good argument that major shifts in the US and Germany are underway (see e.g. Kotlikoff, Burns, 2004).

- Faced with the problem of making long-term forecasts of labor productivity growth for both countries, it seems justified to accept a near unit root model rather than a perfect one.

This would demand a more cautious view of the recent US productivity miracle and a less pessimistic view of the German productivity conundrum. Our interpretation puts us in good company, with such US experts as Gordon¹⁸ and Jorgenson.

¹⁸ *"I have argued that the underlying trend in productivity growth will decline from the recent rate of 3.0 percent a year to about 2.5 percent in the next two decades, because of the unwinding of temporary factors bolstering recent productivity growth, and because of potential diminishing returns in the exploitation of New Economy innovation, as well as the implications of a plateau in educational attainment for sharply slowing future growth in labor quality."* Gordon (2003a,p.274)

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Data definitions and sources

For the Kalman filter model as well as the structural break tests, we needed productivity data as well as output gap data.

1) Quarterly aggregate hourly labor productivity data for the US and Germany:

Quarterly aggregate hourly labor productivity data for the US and Germany:

- For the US, time series from the first quarter of 1947 until the last quarter of 2003 were used in the estimation process. The aggregate data is from the non-farm business sector, which avoids particular problems related to data for farms and government. It was taken from the Bureau of Labour Statistics (BLS, www.bls.gov) website.¹⁹ The base year is 1992. The data has been seasonally adjusted according to the US standard procedure Census-X12-ARIMA (Findley et al, 1998).
- For Germany, data for hourly labor productivity for the whole economy from the first quarter of 1991 to the last quarter of 2003 was available from the German Statistical Office (Destatis, 2004). This data is based on the new European SNA 95 framework for national accounting. The data from 1960 to 1990 is based on the old National Accounting System for West Germany (DIW Berlin, several issues). Both series were chained by setting them equal to 100 for the base year 1991. This eliminates by construction the level shift in productivity and thus also the structural break of German reunification. However, as the structural break also concerned the average growth rate for the period from 1991 onwards, this aspect of the break is not eliminated.
- The German data differs from the US data systematically because the farm sector as well as the government sector is included. This might make it some more difficult to catch the more market-based labor productivity development of the business sector, if particular effects in the determination of working hours and output growth from the government and farm sectors have significant impacts on the dynamic development of the time series. The data is seasonally adjusted by the BV4 seasonal adjustment filter (Nullau et al, 1969).

2) Output gap data for the US and Germany:

¹⁹ For more information about the US data see Gordon (2003a), p. 275-276.

- For the US time series, a HP filter (see below) with $\lambda = 1600$ was applied to quarterly real GDP data from 1947 to 2003. The data is available from the Bureau of Economic Analysis, (BEA, www.bea.gov). We relied on the HP filter method because we wanted to apply an easily applicable method to both countries. To avoid the end-point problem, the time series of output was prolonged until 2015 by an ARIMA model, where the lag structure was chosen automatically according to the minimum of the Akaike criterion.
- For Germany, real GDP data was taken from the same sources as the productivity data. The time series were also chained as in the case of the productivity data. This was necessary because otherwise, the HP filter created very implausible results around the reunification break. As in the case of the US data, the data was prolonged using an ARIMA model to avoid the end-point problem.