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A comprehensive German business cycle chronology

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Abstract Business cycle chronologies offer reference points for empirical studies used as benchmarks for business cycle and recession theory. A quasi-official chronology exists for the US economy, but not for most European countries, including Germany. While most papers dealing with business cycle dates rely on one specific method, I present and discuss a number of different dating approaches based on the classical business cycle. These are applied to German GDP data comprising 1970–2006. Finally, based on the results of the different methods, a consensus business cycle chronology for the German economy is suggested.

Keywords Business cycles · Turning points · Business cycle dating algorithm · Non-parametric · Markov-switching

JEL Classification E32 · C14 · C22

1 Introduction

Business cycles have been on the research agenda for at least a couple of decades now and there is a long list of theories that try to explain the phenomenon of fluctuations in the economy. Still, a number of questions remain to be resolved satisfyingly in a broad

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framework: Why does the economic output decline even when no plants are destroyed, no knowledge is forgotten and the potential workforce does not decline? Why does involuntary unemployment rise during recessions? Are recessions distinctive phases of the business cycles or just the mirror image of expansions?

Hence, there is still need for further research on business cycles. A prerequisite to evaluate the usefulness of a theoretical model, which aims to explain this economic aspect, is a thorough analysis of the empirical business cycle. By far the most work done so far is based on US data, while studies from other countries are rather rare. This is problematic as the implementation of the market economy in continental Europe partially deviates strongly from the Anglo-Saxon model. Business cycle chronologies are often the starting point for further analysis of the cycle and its components. Having such a reference for a variety of countries helps to extract commonalities and country specifics of the business cycle phenomenon.

A general difficulty in business cycle research is the broad usage of the term 'business cycle' and anything connected to it. As Harding and Pagan (2005) point out, a variety of definitions exists in current cycle research. Furthermore research on economic fluctuations includes various topics. These differences in the concepts and tasks naturally lead to different approaches to extract the business cycle from the data.

My aim is to develop a business cycle chronology for Germany comprising the years 1970–2006. Several methods known from the literature are adopted, all of them according to the concept of the classical business cycle and based on the gross domestic product (GDP). I provide a reference point for the use of German data for recession analysis and the derivation and evaluation of business cycle theories. Due to the general availability of GDP and since the analysis mainly builds on routines that can be automated, the procedure could easily be extended to other economies as well (cf. Appendix A for the used software and programmes). Therefore a set of consistent business cycle chronologies, to be used in further standardized research, could be built following this example.

2 Approaches to the business cycle

Arthur Burns and Wesley Mitchell are considered by most authors as the pioneers in empirical research on the business cycle. Their definition of the business cycle as 'a type of fluctuation found in aggregate economic activity' given in Burns and Mitchell (1946) is probably the most cited one. Despite common roots the successors of Burns and Mitchell developed different directions to continue their research on economic fluctuations.

A first delineation is the selection of one or more appropriate series to indicate the business cycle. Burns and Mitchell derived the economic activity from a range of time series. A group of researchers deduced from this approach that co-movement among economic aggregates was one of the main characteristics of the business cycle.[1] However, as Harding and Pagan (2002) note, Burns and Mitchell's approach might also be understood as reflecting the paucity of suitable comprehensive data available

[1] Cf. e.g. Diebold and Rudebusch (1996), Cooley and Prescott (1995).

at the time they conducted their research. By now, the quarterly availability of GDP, comprising the total value of all goods and services produced within an economic area, has closed this gap. Accordingly, the use of GDP as a direct measurement of the economic situation offers a suitable univariate alternative to multivariate methods.[2] The final choice of the appropriate data set is also decisively influenced by the particular research objective. For ex-post analyses and comparisons GDP is the optimal candidate. If instead the task is to construct a (monthly) indicator to evaluate the current economic state prior to official GDP releases or for forecasting purposes, then multivariate approaches based on additional and higher-frequency data published with a shorter delay are usually preferred.[3]

For dating and analysing the business cycle most often a 2-phases scheme is used. This scheme distinguishes expansions and recessions, which together make up the complete cycle. However, research concepts also differ in how they identify the cycle in the time series chosen for inspection, which also influences the resulting phase classifications. What is often termed the 'classical' approach considers business cycles in level data, where recessions are periods of absolute decline in the economic activity. Other approaches instead emphasize that level data was the sum of a long-run trend and short-run deviations from it. Recessions are then periods in which actual output is below the trend level. As the trend is not directly observable, a range of methods has been developed to de-trend and to filter the data, or to estimate potential output via a production function.[4] To distinguish this approach from the classical cycle, the term 'growth cycle' has started to prevail when deviations from the trend are the subject of investigation.

This variety of approaches to the business cycle naturally results in an array of research directions, each applying and expanding the knowledge and methods specific to the chosen concept of the cycle. Each of the existing approaches has its merits in exploring the nature of economic fluctuations. The classical cycle directly follows the spirit of Burns and Mitchell and allows the study of periods of absolute decline in economic performance. Such analyses are of particular interest to the public and are also in line with theoretical models emphasizing the links between growth trends and fluctuations. However, economic weakness does not necessarily involve a decrease in activity; it might also be characterized by prolonged periods in which output falls short of its potential. Therefore the analysis of deviations from the long-run trend complements the research on economic fluctuations, despite the difficulties connected to isolating the unobservable trend. Likewise the different research tasks like dating, dissecting or forecasting all improve our knowledge of the business cycle. Each of

[2] A second popular single-series meter for the business cycle is industrial production, as industry sectors in general fluctuate more than service activities, see e.g. Artis et al. (1997) and Fritsche and Kouzine (2005).

[3] For the latter strand of research see also the rich literature on the construction of composite indices. Important stimulation came from Stock and Watson (1989), recent contributions and extensions include Altissimo et al. (2001, 2006), Kholodilin (2005), Kholodilin and Yao (2005) and Mariano and Murasawa (2003).

[4] Some arbitrarily chosen examples are the HP filter, band-pass-filters like the Baxter-King and the Christiano-Fitzgerald filter, the method of unobserved components and production functions like the Cobb-Douglas based approach of the European Commission (see Denis et al. 2002). Current research includes Döpke (2004), Harvey and Trimbur (2003) and Azuvedo et al. (2006) amongst others.

them is connected to particular methods. Hence, to find the appropriate approach and for meaningful comparison of the results, it is always necessary to be clear about the respective object of an analysis.

I identify the classical German business cycle 1970–2006. As the aim is to offer a reference for ex-post analysis I base my evaluation on GDP data. Its widespread availability for many countries and regions and the application of common standards in its ascertainment[5] also ease the construction of a multi-country data set based on a uniform framework as an extension to the current analysis.

3 Methods to date the cycle

3.1 Official releases

To date the business cycle means to locate the turning points that signal the switch from one business cycle phase (sometimes also called 'state' or 'regime') to another; with *peaks* completing expansions and *troughs* ending recessions. A number of different procedures to determine the dates of an economy's business cycle exists, and there are (quasi-)official and unofficial chronologies. For the U.S. economy the National Bureau of Economic Research (NBER) is considered the authority for dating the national business cycle. In accordance with the classical cycle its Business Cycle Dating Committee defines a recession as 'a significant decline in economic activity', cf. NBER (2006). Despite the advantage of having a generally accepted chronology of the business cycle, the NBER dating features at least two important drawbacks: First, because it is mainly based on experts' evaluation, it is not very transparent and not necessarily uniform. Second, and for current research maybe the more important issue, there is a significant time lag in the announcement of the turning points.[6]

Furthermore, the existence of an institution like the NBER for the U.S. business cycle is rather unique. This fact, as well as the desire to make business cycle chronologies comparable across countries and regions, cause the need for alternative dating methods.

3.2 Non-parametric methods

There are two groups of methods used to date the business cycle: non-parametric and parametric methods. Non-parametric procedures often rest on some kind of pattern recognition algorithm. One example is the popular 'newspaper' definition, which states that in order for a recession to be present, there must be two consecutive quarters of negative GDP growth.

A main advantage of non-parametric methods is the general simplicity of their rules, which supports understanding and replication of the results. As they do not impute certain characteristics on the time series, non-parametric rules are not very

[5] Cf. the current System of National Accounts 1993.

[6] For instance, the November 2001 trough was announced only in July 2003, i.e. almost one and a half year after the date passed.

Table 1 Non-parametric rules to date the business cycle in log-level GDP $\{y_t\}$

Conditions for a peak in t	
Newspaper	$\Delta y_t > 0 \cap \Delta y_{t+1} < 0 \cap \Delta y_{t+2} < 0$
Boldin	$\Delta y_t > 0 \cap \Delta y_{t+1} < 0 \cap \left[\Delta y_{t+2} < 0 \cup \Delta y_{t+3} < 0\right]$
BBQ	$\Delta_2 y_t > 0 \cap \Delta y_t > 0 \cap \Delta y_{t+1} < 0 \cap \Delta_2 y_{t+2} < 0$
Conditions for a trough in t	
Newspaper	$\Delta y_t < 0 \cap \Delta y_{t+1} > 0 \cap \Delta y_{t+2} > 0$
Boldin	$\Delta y_t < 0.5\% \cap \Delta y_{t+1} > 0.5\% \cap \left[\Delta y_{t+2} > 0.5\% \cup \Delta y_{t+3} > 0.5\%\right]$
BBQ	$\Delta_2 y_t < 0 \cap \Delta y_t < 0 \cap \Delta y_{t+1} > 0 \cap \Delta_2 y_{t+2} > 0$
Explicit censoring rules	
Newspaper	Peaks and troughs must alternate
Boldin	Peaks and troughs must alternate
BBQ	Peaks and troughs must alternate
	Completed phases must not be shorter than two quarters
	A complete cycle must not be shorter than five quarters
	Level at peak must be higher than at proximate trough

Note: $\Delta y_i = y_i - y_{i-1}$, $\Delta_2 y_i = y_i - y_{i-2}$

demanding concerning the underlying data. The results are rather robust, insensitive to changes in the sample size and easily comparable among different data sets. Still, the simplicity and non-specificity in terms of their underlying purpose is also the focus of critics of non-parametric approaches. Hamilton (2003) rejects such a method by stating that 'one could use this rule to find business cycles in records of rainfall in Mongolia or the counts of spots on a shuffled deck of cards'. However, as Harding and Pagan (2003b) argue, employing a pattern that defines a recession for appropriate data is clear enough for '*collecting* evidence on the phenomena of interest', which is at the centre of business cycle dating. Hence, their convenience makes non-parametric methods a popular tool for this task.[7]

I consider three non-parametric approaches in my analysis. The first one is the mentioned *newspaper* method. In line with the declaration of a recession's beginning, the contraction is terminated with two consecutive quarters of positive growth. These rules can be transferred into a set of conditions a data point t has to meet to qualify as a turning point. Table 1 sums up these conditions, together with those of the non-parametric approaches to come.[8]

After applying the newspaper method to U.S. data and comparing it with NBER dates, Boldin (1994) suggested some modifications. In addition to relaxing the strict two-in-a-row constraints into two-out-of-three requests, he claims that 'growth should

[7] Examples apart from those considered in this section include Artis et al. (1997, 2004), Bengoechea et al. (2006) amongst many others.

[8] Note that the use of growth rates in these algorithms is no contradiction to the classical business cycle: a decline in the level of a time series translates into negative growth rates, while the cycle is still detected in the level.

be higher than average after a recession ends.' The latter introduces a threshold growth rate higher than zero into the dating rule for a trough. Although primarily intended to better match the NBER dates, *Boldin's* modifications implement some additional features of business cycle thinking worth considering. The general idea of a recession as an economic downturn still applies if two quarters with negative growth rates are interrupted by one with (mostly weak) positive growth. The introduction of a positive growth rate threshold for the termination of a recession is in line with the observation that immediately after recessions growth rates would be particularly high, cf. e.g. Sichel (1994). When applying these rules to German data I follow Boldin's proposal and set the threshold on the mean quarterly growth rate at 0.5%, cf. Table 1.

Probably the most cited academic representative of a non-parametric dating algorithm used for monthly data is that of Bry and Boschan (1971). I employ a quarterly version of it, proposed by Harding and Pagan (2002), the *BBQ* approach. Based on this method, turning points are local maxima or minima, respectively, of the considered time series. Table 1 also gives a number of explicit censoring rules and cleansing procedures to make sure that the standard assumptions of the business cycle are met.

3.3 Parametric methods—Markov-switching models

Parametric procedures base their examination on a data generating process (DGP), which is assumed to have created the data. The most often employed procedure for business cycle dating is the idea of Markov-switching (MS) processes underlying the evolution of the economy, initiated by Hamilton (1989).[9]

An advantage of parametric approaches for business cycle research is that a successful application implies characteristics about the underlying processes which can be directly transferred to theoretical models. Prior information may be utilized to assist in the dating process. MS models, for example, explicitly consider existing evidence on asymmetries in the business cycle, see for example Romer (2006, p. 177) for the U.S. cycle. Individual features of the underlying data set may also be taken into account. The drawback of these features is that the results might lack stability when faced with changes in the sample size or the data set itself.[10] Also, dating results of the MS approach do not necessarily coincide with business cycle phases when the assumption on the DGP is wrong and the data is additionally influenced by long-run structural changes or breaks. A final disadvantage of complex methods like MS is their opacity.[11] Still current research improves the fit of parametric models to economic time series which makes them a valuable instrument for a variety of business cycle analyses and forecasts.

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[9] Less often used parametric approaches to the business cycle include variations of threshold autoregressive models (TAR) and smooth transition autoregressive models (STAR), cf. e.g. Potter (1995) and Teräsvirta and Anderson (1992).

[10] As Harding and Pagan (2003a) note, extensions of basic MS models also were induced by the inability to replicate the Hamilton (1989) results with a larger U.S. data sample or for other countries.

[11] Harding and Pagan (2003a) show for the results in Hamilton (1989) how the BBQ rule relates to the MS dating rule. They are able to deduce a simple rule based on the magnitude of a weighted average of the growth rates. But the choice of the weights derived from the application of MS remains rather intransparent and is of course dependent on the chosen data sample and its particular MS parameter values.

As the focus of this paper is to present and compare different approaches to date the business cycle that are stable and easily transferable to other data sets, I will only consider simple versions of MS models.[12] Basic MS models are built on autoregressive (AR) processes of order p. The parameter values of the processes (partly) depend on the current but unobservable regime s_t the economy is in. In our context, we can think of two regimes, namely recession ($s_t = 1$) and expansion ($s_t = 2$). The probability p_{ij} for a switch from $s_t = i$ to state $s_{t+1} = j$ is exogenous and depends only on s_t. I use two main classes of MS models. The first one discriminates between different regimes by the assignment of regime dependent means μ_{s_t}, with

$$\Delta y_t - \mu_{s_t} = A_1 \left[\Delta y_{t-1} - \mu_{s_{t-1}}\right] + \cdots + A_p \left[\Delta y_{t-p} - \mu_{s_{t-p}}\right] + u_t,$$

where Δy_t denotes the growth rate of log-level GDP, the A_i represent parameter values and u_t is an error term. I follow the classification of Krolzig (1997) and label the models as MSM if $u_t \sim N(0, \Sigma)$ for all states. I also consider so called MSMH models, in which additionally the error variance depends on the current regime, i.e. $u_t \sim N(0, \Sigma_{s_t})$. The second class of models is based on a regime-dependent intercept ν_{s_t} and reads

$$\Delta y_t = \nu_{s_t} + A_1 \Delta y_{t-1} + \cdots + A_p \Delta y_{t-p} + u_t.$$

Here, too, I consider a version with constant error variance, called MSI, and one with regime-dependent Σ_{s_t}, labelled MSIH. Fitting the model to the data includes finding the underlying process for each of the regimes as well as assigning the individual data points to the regimes. For an introduction into the solution algorithm as well as current developments of regime switching models for business cycle research in general see for instance Hamilton and Raj (2002).

To date the German business cycle I use the MSVAR package for the software Ox, cf. Krolzig (2005) and Doornik (2002), to estimate various MS specifications with up to 8 AR-lags. The non-linearity of multiple regime-dependent processes is the basis for using MS in business cycle dating. Hence I only consider those MS models that offer a significantly better fit than their respective linear counterpart. I use the likelihood ratio (LR) linearity test implemented in MSVAR, denoting p-values following Davies (1977, 1987), to decide on goodness of fit.[13] Included models are significant at least at a 90% level. There are a number of additional specification tests which could be employed to optimize the fit of MS models to the underlying data, see e.g. Breunig et al. (2003). The full application of these methods, however, is beyond the scope of this paper, where MS models are considered one of several types of business cycle dating procedures.

First I considered MS specifications which try to identify two regimes in the underlying German data. I found, in general, that MSM and MSI models distinguish between a low-growth and a high-growth regime. MSMH and MSIH models turned

12 See Kholodilin (2005) for a current more advanced and individual application in particular on the German business cycle, referring to composite indicators rather than to GDP.

13 Alternative likelihood ratio linearity tests are proposed by Hansen (1992, 1996).

out to be unsuitable in the current business cycle dating task. While most of them actually pass the LR linearity test, they generally divide the whole time period only once, placing the segregation line between 1993:2 and 1994:2. Apparently, before this time growth rates were higher on average but also more volatile. I additionally included a dummy into the analysis for the periods after the most often placed regime border 1993:3.[14] Then the resulting level dampening effect of the dummy is so strong that no more switches since 1993 can be identified by the otherwise significant regime-switching specifications. MSMH and MSIH models remain highly significant but rather unsuitable for the dating of business cycle phases.

Finally I considered the adaptation of a third regime, as the basic specifications only offered low-growth rather than negative-growth phases. Although these models are in general superior to their linear counterpart and have one regime with a negative parameter, this value is so extremely low, that most often recessions are defined only as one-quarter events.

Estimation results for significantly non-linear MS specifications, whose results might be interpreted meaningfully in business cycle context, are given in Table 4 in Appendix B. Table 5 in Appendix C gives the suggested business cycle phases of these models. In accordance with the non-parametric methods and business cycle thinking in general, I only included phases that last more than one quarter. Due to space considerations and for purposes of clarity, for Sect. 4 MS results were aggregated based on majority dates.[15]

4 Application: the German business cycle

4.1 Business cycle dates of the different methods

To identify the German business cycle phases for the years 1970–2006 I use quarterly seasonally-, calendar- and price-adjusted GDP of the German Federal Republic, i.e. until 1990 West Germany and from 1991 on unified Germany.[16] However, growth rates are always calculated territorially consistently. Figure 1 gives a visual impression of the respective German growth rates.

As the application of the presented business cycle dating methods indicates, over the last decades Germany experienced several business cycles. Table 2 summarizes the German business cycle chronology suggested by the different approaches. The dating methods generally agree on the approximate timing of economic downturns in Germany. Even though each dating approach focuses on distinctive features, they form a rather comprehensive concept of the classical business cycle. However, they somewhat differ in their judgement regarding where exactly to place the turning points

[14] The dummy is denoted as 'X' in the label of a model, e.g. MSM-ARX(1) for a MSM specification with one autoregressive lag and the dummy.

[15] Exceptions from the majority rule were made for the time period after 1993, where I skipped those models from counting that were not able to find any more recession there.

[16] Federal Statistical Office Germany, National Accounts series, Fachserie 18 Reihe S.28, published September 5, 2006, for West German data up to 1991, and Fachserie 18 Reihe 1.3, published August 23, 2007, for German data from 1991 on.

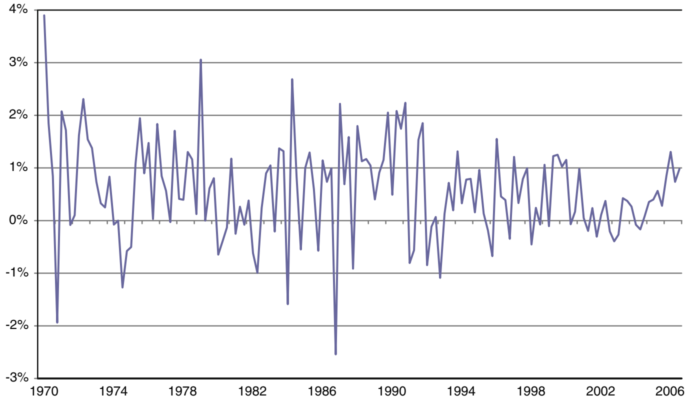

Fig. 1 Quarterly growth rates of real German GDP, seasonally and calendar-adjusted

Table 2 German business cycles 1970–2006

Newspaper		Boldin		BBQ		MS, aggregated	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
1974:3	1975:2	1974:1	1975:2	1974:1	1975:2	1974:1	1975:2
1980:1	1982:3	1980:1	1982:4	1980:1	1980:4	1980:1	1982:4
				1982:1	1982:3		
1991:1	1991:3	1991:1	1991:3			1991:1	1991:3
1992:1	1993:1	1992:1	1993:2	1992:1	1993:1	1992:1	1993:2
1995:3	1996:1	1995:3	1997:1	1995:3	1996:1	1995:2	1996:1
		1998:1	1998:4			1998:1	1998:4
2002:3	2003:2	2001:2	2005:2	2002:3	2003:2	2001:1	2005:2
2004:1	2004:3			2004:1	2004:3		

and also in their sensitivity when distinguishing between different states in low-growth periods.

The mid-1970s downturn is met fairly consistently by each method. Likewise, there is agreement that in the beginning of the 1980s another economic descent took place, with particularly 1980 and 1982 being recessionary years. In this period the different claims to call a phase switch—with respect to the robustness of sign or magnitude changes in the growth rates—become visible between the dating methods. While the BBQ algorithm as well as few MS-classifications indicate a short phase of recuperation between these years, the newspaper and the Boldin (1994) approach demand a more continuous or a stronger rise in the growth rates to detect an expansion.

Negative growth-quarters in the remaining 1980s, see Fig. 1, remained too sporadic and alternated with high-growth quarters to indicate times of recessions. Only one of the MS specifications suggests a regime shift at about 1986, see Table 5 in Appendix C. The suggested recession directly after German re-unification is somewhat surprising. Growth rates were negative in 1991:2 and 1991:3, long and pronounced enough for most approaches to signal a downturn. However, a closer look into the data reveals that this decline must be due to the breakdown of the East German economy, because a decline is not detectable when looking only at West German data. I conclude that this event is not actually cyclical and should be considered as special case.

There is agreement that the next actual recession started in 1992 and lasted about a year. A further commonly acknowledged downturn is placed in the mid-1990s. Later I again found negative growth quarters, in 1998 alternating with positive growth. These fluctuations were sufficient to suggest a recession in terms of Boldin's modified newspaper approach and some of the MS-specifications, but were not enough for the remaining methods to announce a switch of states.

All dating procedures indicate a recession after the turn of the millennium. While the MS- and the Boldin (1994)-method declare rather early the transition between expansion and recession, the newspaper and the BBQ approach follow later on. This deviation indicates the discontinuous development of the German GDP at that time, to which the considered approaches react differently. The disagreement continues in determining the end of the recession. Newspaper and the BBQ algorithm suggest a recession lasting about one year, followed by a short expansionary phase, before economic performance declined again. The last trough is eventually located at 2004:3 by both of these methods. Conversely, Boldin's approach and MS dating identify one long recession and consider it finished only in the middle of 2005. Apparently, growth rates were considerably lower until then, compared to the overall sample. Due to their construction, both procedures tend to add such low-growth quarters to preceding recessions.

4.2 Suggesting a consensus German business cycle chronology

Despite variation in the exact dates suggested by the different methods, together they still give a general idea about when the German economy suffered from economic downturns. According to my findings, I suggest the comprehensive turning points for the German business cycle as denoted in Table 3. In the absence of an overall agreement on the timing of a turning point, I basically followed two principles: First, due to the classical concept of the business cycle with recessions as periods with *declining* output, I put most weight on negative growth rates. Second, since periods of extremely short expansions that subsequently move into another recession are assumed to already experience some defect, or at least instability, these periods were adjoined

Table 3 Consensus German turning points 1970–2006

Peak	Trough
1974:1	1975:2
1980:1	1982:3
1992:1	1993:1
1995:3	1996:1
2002:3	2004:3

with the downturns that surround them. The chosen classification is supposed to give a starting point for further empirical research on recessions using German data.

5 Conclusion

Despite the long history of business cycle research, a number of questions still remain. In particular, governments and the public want to know what the mechanisms behind recessions are and how such economic and socially challenging times might be avoided, or at least dampened.

However, to analyze specifics about times of economic downturn, one first needs to indicate when such downturns occurred. Business cycle chronologies offer reference points for empirical studies and serve as benchmarks for business cycle and recession theory. While a quasi-official chronology exists for the U.S. economy with the NBER dates, this is not the case for Germany and most other European countries. As distinctive differences between the economies exist, it is desirable to further expand business cycle analysis for other countries. I presented a number of—parametric as well as non-parametric—common univariate business cycle dating methods, built on the original idea of business cycles as fluctuations in levels instead of filtered data and applied them to the German GDP. Discussing the findings and characteristics of the dating approaches I finally recommended a consensus business cycle chronology for Germany. Further research resting upon this result should include a detailed analysis of the business cycle and its distinctive phases. The results can be used to derive and improve suitable models which can help to explain what the reasons behind business cycles are and what happens on the way to and during recessions.

Appendix A: Used software

The methods for business cycle dating were implemented in a number of Ox programs, cf. Doornik (2002), which are available upon request. The code for the BBQ-method borrowed strongly from the GAUSS code provided for Harding and Pagan (2000). Markov-switching specifications were found using the MSVAR package, see Krolzig (2005).

Appendix B: Estimation results of Markow-switching models

Given are the parameter values (and standard errors) of those significantly non-linear MS specifications whose results might be interpreted as meaningful in the business cycle context. Business cycle phases should last more than one quarter. However, specifications that only identified recessions in the periods 1971:4–1972:1 (only 3-regime models), 1974:4–1975:2 and/or 1991:2–1991:3 were excluded. Their focus is limited to finding periods with continued very strong decline, which is a too strict requirement for my context.

Table 4 Parameter values of appropriable MS models

	MSM(2)-AR(3)	MSI(2)-AR(3)	MSMH(2)-AR(3)	MSIH(2)-AR(3)
μ_1 or ν_1	0.0740 (0.1135)	0.1456 (0.2445)	0.0032 (0.0967)	0.0319 (0.1429)
μ_2 or ν_2	0.9579 (0.1499)	1.3002 (0.2036)	0.8063 (0.1589)	0.9972 (0.3255)
μ_3 or ν_3				
A_1	−0.2836 (0.0926)	−0.2181 (0.0850)	−0.1982 (0.1017)	−0.1383 (0.1299)
A_2	−0.2311 (0.0870)	−0.1383 (0.0846)	−0.1926 (0.0965)	−0.1235 (0.1088)
A_3	−0.1725 (0.0824)	−0.0866 (0.0821)	−0.1197 (0.0924)	−0.0863 (0.1193)
A_4				
A_5				
dummy				
p_{11}	0.8284	0.8302	0.8469	0.8559
p_{22}	0.8466	0.8601	0.9243	0.9426
p_{33}				
SE	0.7387	0.7332		
SE_1			0.5420	0.5203
SE_2			0.8842	0.8996
SE_3				
ln L	−184.8099	−185.7865	−182.1552	−183.1135
LR lin. test	8.5135	6.5604	13.8230	11.9063
	MSM(2)-ARX(3)	MSI(2)-ARX(2)	MSI(2)-ARX(3)	MSM(3)-AR(3)
μ_1 or ν_1	−0.3028 (0.2929)	−0.4272 (0.2065)	−0.3496 (0.2246)	−0.2447 (0.4530)
μ_2 or ν_2	0.9539 (0.1451)	1.1878 (0.1485)	1.2667 (0.1653)	0.6646 (0.1247)
μ_3 or ν_3				1.5221 (0.3905)
A_1	−0.2173 (0.0847)	−0.1752 (0.0754)	−0.2006 (0.0768)	−0.6475 (0.2892)
A_2	−0.1105 (0.0910)	−0.0341 (0.0752)	−0.0772 (0.0905)	−0.5533 (0.2637)
A_3	−0.0855 (0.0855)		−0.0494 (0.0815)	−0.3489 (0.1463)
A_4				
A_5				
dummy	−0.6962 (0.2096)	−0.6648 (0.1674)	−0.7118 (0.1657)	
p_{11}	0.6166	0.5710	0.6613	0.6457
p_{22}	0.9137	0.9034	0.9276	0.7487
p_{33}				0.5592
SE	0.7240	0.6771	0.6903	0.5648
SE_1				
SE_2				
SE_3				
ln L	−184.1009	−185.2581	−182.8153	−180.0561
LR lin. test	8.2523	7.6551	10.8236	18.0211

Table 4 continued

	MSMH(3)-AR(3)	MSMH(3)-AR(4)	MSIH(3)-AR(4)	MSIH(3)-AR(5)
μ_1 or ν_1	−0.1083 (0.1373)	−0.5401 (0.2765)	−0.8568 (0.3295)	−0.8949 (0.2912)
μ_2 or ν_2	0.7729 (0.1117)	0.4223 (0.1191)	0.0398 (0.0821)	0.0314 (0.0824)
μ_3 or ν_3	0.9607 (0.1890)	0.7756 (0.2283)	0.9313 (0.1434)	0.9553 (0.1503)
A_1	−0.3248 (0.0910)	−0.0805 (0.0853)	−0.1938 (0.0780)	−0.2252 (0.0934)
A_2	−0.2907 (0.0857)	0.0351 (0.0766)	−0.0516 (0.0710)	−0.0619 (0.0728)
A_3	−0.1409 (0.0841)	0.0998 (0.0782)	0.0272 (0.0755)	0.0226 (0.0756)
A_4		0.1908 (0.0794)	0.2271 (0.0589)	0.2239 (0.0611)
A_5				0.0382 (0.0639)
dummy				
p_{11}	0.7630	0.5936	0.3774	0.3882
p_{22}	0.6330	1.0000	0.8273	0.8214
p_{33}	0.7422	0.9485	0.8861	0.8842
SE				
SE_1	0.4871	0.4693	0.6187	0.5915
SE_2	0.4389	0.5410	0.3231	0.3200
SE_3	1.1524	0.9193	0.6817	0.6790
ln L	−176.2207	−170.0112	−168.5028	−167.6517
LR lin. test	25.6919	17.5369	20.5537	19.7450

Appendix C: Business cycle dates of appropriable Markov-Switching Models

Given are the business cycle dates of the MS models described in Appendix B, considering phases that lasted at least two quarters.

Table 5 German business cycles 1970–2006, identified by MS models

MSM(2)-AR(3)		MSI(2)-AR(3)		MSMH(2)-AR(3)		MSIH(2)-AR(3)	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
1973:3	1975:2	1973:4	1975:2	1973:4	1975:2	1974:1	1975:2
1979:4	1983:1	1980:1	1983:1	1980:1	1982:4	1980:1	1982:4
1985:4	1987:1						
		1991:1	1991:3				
1992:1	1993:4	1992:1	1993:4	1992:1	1993:3	1992:1	1993:3
1994:4	1997:1	1995:2	1997:1	1995:2	1996:1		
1997:4	1999:1	1998:1	1999:2	1998:1	1998:4		
2000:2	2005:3	2000:3	2005:3	2000:4	2005:2	2001:1	2005:2

Table 5 continued

MSM(2)-ARX(3)		MSI(2)-ARX(2)		MSI(2)-ARX(3)		MSM(3)-AR(3)	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
1974:1	1975:2	1974:1	1975:2	1974:1	1975:2	1974:1	1975:2
1980:1	1982:4	1980:1	1982:4	1980:1	1982:4	1980:1	1980:4
						1981:3	1982:4
1991:1	1991:3	1991:1	1991:3	1991:1	1991:3		
1992:1	1993:2	1992:1	1993:2	1992:1	1993:2	1992:2	1993:2
						1995:2	1996:1
						1998:1	1998:4
						2001:1	2003:3
						2004:1	2004:4
MSMH(3)-AR(3)		MSMH(3)-AR(4)		MSIH(3)-AR(4)		MSIH(3)-AR(5)	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
1974:1	1975:2	1974:2	1975:2	1974:3	1975:2	1974:3	1975:2
1980:1	1982:4			1980:1	1980:4	1980:1	1980:4
						1982:1	1982:3
				1991:1	1991:3	1991:1	1991:3
1992:1	1993:2	1992:1	1993:1				
1995:2	1996:1						
1998:1	1998:4						
2001:1	2005:1						

References

Altissimo F, Bassanetti A, Cristadoro R et al (2001) A real time coincident indicator of the Euro area business cycle. CEPR Discussion Paper 3108

Altissimo F, Cristadoro R, Forni M et al (2006) New Eurocoin: tracking economic growth in real time. CEPR Discussion Paper 5633

Artis MJ, Kontolemis ZG, Osborn DR (1997) Business cycles for G7 and European countries. J Bus 70:249–279

Artis MJ, Marcellino M, Proietti T (2004) Dating business cycles: a methodological contribution with an application to the Euro area. Oxf Bull Econ Stat 66:537–565

Azuvedo JV, Koopman SJ, Rua A (2006) Tracking the business cycle of the Euro area: a multivariate model-based band-pass filter. J Bus Econ Stat 24:278–290

Bengoechea P, Camacho M, Perez-Quiros G (2006) A useful tool for forecasting the Euro-area business cycle phases. Int J Forecast 22:735–749

Boldin MD (1994) Dating turning points in the business cycle. J Bus 67:97–131

Breunig R, Najarian S, Pagan A (2003) Specification testing of Markov switching models. Oxf Bull Econ Stat 65:703–725

Bry G, Boschan C (1971) Cyclical analysis of time series: selected procedures and computer programs. National Bureau of Economic Research, New York

Burns AF, Mitchell WC (1946) Measuring business cycles. National Bureau of Economic Research, New York

Cooley TF, Prescott EC (1995) Economic growth and business cycles. In: Cooley TF, Prescott EC (eds) Frontiers of business cycle research. Princeton University Press, Princeton, pp 1–38

Davies RB (1977) Hypothesis testing when a nuisance parameter is present only under the alternative. Biometrika 64:247–254
Davies RB (1987) Hypothesis testing when a nuisance parameter is present only under the alternative. Biometrika 74:33–43
Denis C, McMorrow K, Röger W (2002) Production function approach to calculating potential growth and output gaps—estimates for the EU member States and the US. European Commission Economic Papers 176
Diebold FX, Rudebusch GD (1996) Measuring business cycles: a modern perspective. Rev Econ Stat 78: 67–77
Doornik JA (2002) Object-oriented matrix programming using Ox. http://www.doornik.com
Döpke J (2004) Real-time data and business cycle analysis in Germany. J Bus Cycle Meas Anal 1:337–361
Fritsche U, Kouzine V (2005) Prediction of business cycle turning points in Germany. Jahrb für Nationalökonomie und Stat 225:22–43
Hamilton JD (1989) A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica 57:357–384
Hamilton JD (2003) Comment on a comparison of two business cycle dating methods. J Econ Dyn Control 27:1691–1693
Hamilton JD, Raj B (2002) New directions in business cycle research and financial analysis. Empir Econ 27:149–162
Hansen BE (1992) The likelihood ratio test under nonstandard conditions: testing the Markov switching model of GNP. J Appl Econom 7:S61–82
Hansen BE (1996) Erratum: the likelihood ratio test under nonstandard conditions: testing the Markov switching model of GNP. J Appl Econom 11:195–98
Harding D, Pagan A (2000) Knowing the cycle. In: Backhouse RE, Salanti A (eds) Macroeconomics in the real world. Oxford University Press, Oxford, pp 23–41
Harding D, Pagan A (2002) Dissection the cycle: a methodological investigation. J Monet Econ 49:365–381
Harding D, Pagan A (2003a) A comparison of two business cycle dating methods. J Econ Dyn Control 27:1681–1690
Harding D, Pagan A (2003b) Rejoinder to James Hamilton. J Econ Dyn Control 27:1695–1698
Harding D, Pagan A (2005) A suggested framework for classifying the modes of cycle research. J Appl Econom 20:151–159
Harvey AC, Trimbur TM (2003) General model-based filters for extracting cycles and trends in economic time series. Rev Econ Stat 85:244–255
Kholodilin KA (2005) Forecasting the turns of German business cycle: dynamic bi-factor model with Markov switching. Jahrb für Nationalökonomie und Stat 225:653–674
Kholodilin KA, Yao VW (2005) Measuring and predicting turning points using a dynamic bi-factor model. Int J Forecast 21:525–537
Krolzig HM (1997) Markov-switching vector autoregressions: modelling, statistical inference, and application to business cycle analysis. Springer, Berlin
Krolzig HM (2005) MSVAR package for Ox. http://www.krolzig.co.uk
Mariano RS, Murasawa Y (2003) A new coincident index of business cycles based on monthly and quarterly series. J Appl Econom 18:427–443
Potter SM (1995) A nonlinear approach to US GNP. J Appl Econom 10:109–125
Romer D (2006) Advanced macroeconomics, 3rd edn. McGraw-Hill, New York
Sichel DE (1994) Inventories and the three phases of the business cycle. J Bus Econ Stat 12:269–77
Stock JH, Watson MW (1989) New indexes of coincident and leading economic indicators. In: Blanchard OJ, Fischer S (eds) NBER macroeconomics annual. MIT Press, Cambridge/London, pp 351–394
Teräsvirta T, Anderson HM (1992) Characterizing nonlinearities in business cycles using smooth transition autoregressive models. J Appl Econom 7:119–136