Regional Business Cycles - An Analysis for the Austrian Economy

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Abstract

There exists a wealth of literature dealing with the analysis of business cycles, dating their turning points and measuring their synchronisation, but most work concentrates on the countrywide level. Only a few comprehensive studies have been conducted investigating business cycles of regions. So far, to my best knowledge, no empirical investigation focusing on regional business cycles in the Austrian economy has been conducted. The aim of this paper is to fill this gap and to identify business cycle turning points for the Austrian regions and to analyse the co-movement and degree of its change for each region with respect to the national aggregate. First, I derive the business cycle component following the *classical* as well as the *deviation* cycle approach. Second, I establish a business cycle chronology for each region and contrast their cyclical properties. For the subsequent analysis of business cycle synchronisation I use HP-filtered data and turning points obtained with the Bry-Boschan dating routine as input and investigate the degree of synchronisation employing cross-correlation, coherence and concordance measures. The empirical analysis uses quarterly real gross value added data for the period 1988:Q1-2009:Q4 for the nine Austrian federal provinces and the corresponding NUTS 1 aggregates (East-/South-/West-Austria).

The results show that the regional cycles are quite heterogeneous. The degree of regional co-movement with the national business cycle is rather weak in the 90s, but increases (substantially) for most of the regions from 2000 onwards. On a provinces scale, Upper Austria and Vorarlberg exhibit the most consistent synchronised movement with the Austrian business cycle. Burgenland, in contrast, shows the least conformity. On NUTS level 1, the aggregate of Western Austria matches the national business cycle close to unity; East- and South-Austria follow with some distance.

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1 INTRODUCTION

The aim of this paper is to characterise and compare regional business cycles in Austria during the period 1988-2009. To this end I am interested in two core questions often addressed in business cycle studies: (1) how does the business cycle look like, i.e. at which point in time turns the cycle up and down, and (2) to want extent is the business cycle synchronised with cycles of other countries over time. Given the focus of this work is on the regional level, I am primarily interested in identifying business cycle turning points for the Austrian regions and analysing the comovement and degree of its change for each region with respect to the national aggregate.

There exists a wealth of literature dealing with the analysis of business cycles, dating their turning points and measure their synchronisation, but most work concentrates on the countrywide level.[1] Only a few comprehensive studies have been conducted investigating business cycles of regions within a country. Norman and Walker (2007), in studying the synchronisation of Australian state business cycles, comment that despite the importance for national policy-makers little focus has been given to the question of cyclical co-movement among regional and countrywide economic activity. The authors argue that knowing more about the extent of synchronisation at the regional level would provide a better understanding of the economy as a whole and has implications for the role of national policy instruments in smoothing the business cycle. Although Norman and Walker (2007) provide their argument in the case for the Australian economy it is easily transferable to other industrialised countries as well.
Other notable examples of studies focusing on the regional level are for U.S. regions Wynne and Koo (2000), Hess and Shin (1998), Kouparitsas (2002), Carlino and Still (1997) and Owyang et al. (2003). Papers dealing with regional business cycles within or across European countries are, for example, Fatás (1997), Clark and van Wincoop (1999), Barrios and de Lucio (2003), Barrios et al. (2003), Mastromarco and Woitek (2007), Montoya and De Haan (2008), Artis and Okubo (2009), Artis et al. (2009) and Schirwitz et al. (2009a, 2009b, 2009c).

So far, to my best knowledge, no empirical investigation focusing on regional business cycles in the Austrian economy has been conducted. However, there exist a number of studies dating

[1] See e.g. De Haan et al. (2008) or Fidrmuc and Korhonen (2006) for a literature overview of business cycle synchronisation for the euro area.

the business cycle, i.e. identifying turning points, for the Austrian economy. Among them are Breuss (1984), Hahn and Walterskirchen (1992), Artis et al. (2004a, 2004b), Scheiblecker (2007) and Bierbaumer-Polly (2010). With the empirical part of this study I want to add a 'regional' element to the common understanding of the Austrian business cycle.

The remainder of this paper is organised as follows. In Section 2 I outline the characteristics of classical and deviation cycles. Further, I provide an overview of non-parametric turning point dating procedures and a detailed discussion on de-trending methods, such as the ad-hoc filters of Hodrick-Prescott (1980, 1997) and Baxter-King (1999). In Section 3 I review some methods for measuring business cycle synchronisation. Section 4 deals with the empirical analysis of regional business cycles in the Austrian economy. First, I provide a description of the dataset, identify the turning points in the reference series using classical as well as deviation cycle methods and contrast their properties. Second, I derive a business cycle chronology for each Austrian region using HP-filtered data and a modified version of the Bry-Boschan (1971) dating routine. Third, I analyse regional business cycle synchronisation with the Austrian aggregate in using statistical measures such as cross-correlations, coherence and concordance over different sample periods. In Section 5 I summarise and conclude.

2 BUSINESS CYCLES AND TURNING POINTS

2.1 Defining the business cycle

The business cycle is usually described as representing more or less regular patterns in economic output within a specified range of periodicities. Burns and Mitchell (1946) provide in their seminal work of business cycle studies a widely recognised definition:[2]

> "Business cycles are a type of fluctuations found in the aggregate economic activity of nations that organise their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten to twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own." (Burns and Mitchell, 1946, p. 3).

In other words, cyclical instability is analysed in terms of expansions and contractions in the level of economic activity which are observed in a broad set of macroeconomic time series

[2] Burns and Mitchells work (1946) formed the basis of the methods used at the National Bureau of Economic Research (NBER) to compile an official business cycle chronology for the United States.

across different sectors at roughly the same time. These cycles are known as *classical* business cycles.
Following Burns and Mitchell's definition of the business cycle the following stylised chronology can be established: The business cycle consists of a peak (P: upper turning point) in economic activity, which is followed by a contraction that leads into a recessionary phase ending in a trough (T: lower turning point) in the cycle. A recovery phase takes place once the lower turning point has been reached which is followed by a period of expansion leading to the next cyclical peak. As such, the business cycle can be represented with respect to the turning points.

An alternative approach is to focus on periods of deviations of output from a permanent component or trend. In other words, the analysis is concerned with phases of above and below trend rates of growth. This category of business cycles is known as *deviation* cycles or *growth* cycles. Following this approach the crucial step relates to the question of how to determine the trend. As from now, I use the terminology of deviation cycle when referring to this method. This is also done in order to avoid a mix-up with a third type of business cycle definition which looks at turning points in the growth rate of economic activity, thus, often referred to as *growth rate* cycles.
Whatever approach one follows depends on the exact question on hand. As pointed out in Harding and Pagan (2005) policy makers most often focus on classical type cycles due to their interest in recessionary phases rather than in slowdowns relative to a trend. In contrast, academics tend to favour the deviation from trend approach. One problem with the former concept of the business cycle is that cyclical fluctuations following this approach hardly occurred and if so only in modest shape in the second half of the 20th century. As a consequence the latter approach also gained popularity amongst business cycle analysts (see e.g. Tichy, 1994; Zarnowitz, 1992). There is a large amount of literature discussing issues in measuring the business cycle following the various concepts. Recent examples are Canova (1998), Baxter and King (1999) and Harding and Pagan (1999, 2002, 2003).

In the empirical analysis (see Section 4) I will employ the classical as well as the deviation cycle approach for dating the reference series. This is done to highlight the differences between each methodology and to compare the business cycle properties derived from each approach, such as the timing of turning points and duration of cyclical phases.

2.2 Choosing a reference series

With either definition of the business cycle on hand it is important to choose a measure, i.e. to define a reference series, which best represents aggregate economic activity for a country or region in a timely manner. Typically the level of economic activity is either measured by a single indicator, e.g. GDP or industrial production, or by utilising a broad set of economic variables.[3] Bodart et al. (2003) comment that employing a single indicator such as GDP has the main advantage over using multivariate reference series that it avoids the uncertainty about the turning points in the business cycle. However, using, for example, GDP as reference series has some drawbacks. Such a series has a tendency to underestimate economic activity due to the missing accounts for goods and services produced outside the official market economy, such as household production or voluntary work. Furthermore, GDP is often if at all only available on a quarterly frequency and is available only with some publication lag. Hence, gaining a timely insight into the current state of the economy may be problematic following the single indicator approach.

2.3 Characterising the business cycle

In order to describe the chronology of the business cycle and to obtain its characteristics a lot of *a priori* choices have to be made. As mentioned above the choice of the business cycle approach, e.g. classical or deviation cycle, as well as the selection of the underlying reference series are important determinants in the cyclical analysis. Next, if one follows the deviation approach an immediate related question is the choice of the de-trending procedure, i.e. the extraction of the cyclical component. Finally, an exact dating rule has to be chosen in order to identify distinct phases in the cycle and to date its turning points accordingly.

Depending on the cyclical approach chosen the meaning of a turning point and phase is somewhat different (see Table 1). Turning points related to classical cycles are obtained when output level is at a local maximum or minimum. Further, the duration of the full cycle is just the interval from the initial trough to the final trough and the period between the trough and the peak is the expansion phase and the period between the peak and the trough is the contraction phase. In contrast, turning points in the deviation cycle are represented by extrema in output gaps. In a phase of a cyclical upturn the growth rate is above and in a period of a cyclical downturn below the long-run trend rate.

[3] If one follows the multivariate approach, often an index is created containing the individual economic variables.

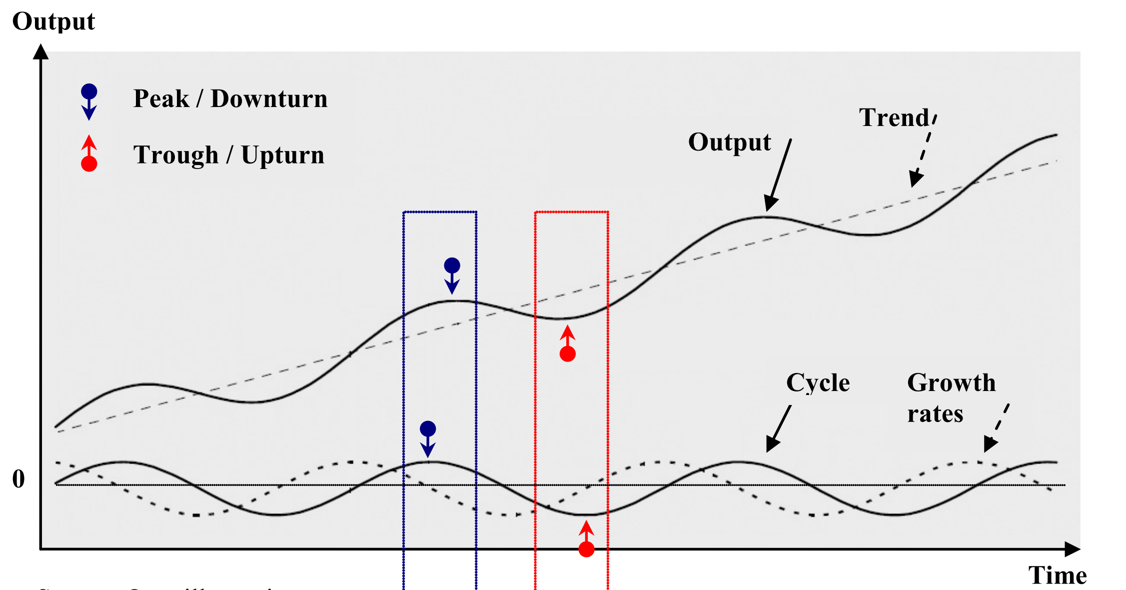
Table 1: Classification of Business Cycle Terminologies

Cycle Type	Analysis related to..	Turning Points	Phases
Classical	Level	Peaks (P) Troughs (T)	P-T: Contraction T-P: Expansion
Deviation / Growth	Cyclical component	Downturn (D) Upturn (U)	D-U: Low rate growth (below trend) U-D: High rate growth (above trend)

Source: Own illustration based on Cotis and Coppel (2005).

Cotis and Coppel (2005) note, that it is important to bear in mind the different conceptual foundations between the classical and deviation approaches to the business cycle. The former is purely descriptive whereas the latter involves a separation between the trend and cyclical components of the underlying reference series and as such embodies a lot of statistical difficulties (e.g. choosing a proper model for trend elimination). Further, it is important to remember that, depending on the approach, cyclical turns occur at different points in time.

Figure 1: Stylised Illustration of Business Cycle Definitions[4]



Source: Own illustration.

For example, as shown in Figure 1, deviation cycle downturns appear earlier in the cycle than classical cycle peaks. It follows that classical recessions are always a subset of deviation cycle recessions, and, as Cotis and Coppel (2005) note, there may be multiple classical contraction episodes within a deviation cycle recession. For that reason, from an economic policy point of

[4] For a detailed discussion of a stylised business cycle illustration contrasting classical and deviation cycle approaches see, for example, Boehm and Liew (1994).

view, e.g. for some kind of policy intervention, the growth cycle concept shall be preferred, as cyclical downturns lead those obtained from the analysis of fluctuations in the absolute levels of economic activity (Scheiblecker, 2007). Contrary, it should be expected that expansion phases tend to be longer-lived than high rate growth, i.e. above trend, phases.

2.4 Identifying turning points / dating the business cycle

In general, given a reference series of economic activity turning points can be determined for each of the business cycle approaches. There exist a number of different dating procedures which can be classified as either belonging to the group of non-parametric or parametric methods. Non-parametric models have been criticised for using ad-hoc dating rules while parametric procedures like the Hamilton (1989) switching regime method have the inconvenience that all the cyclical analysis depends on the underlying statistical model chosen.[5] In the discussion which follows I concentrate on the non-parametric (ad-hoc) dating methods.

The standard non-parametric method to determine cyclical turns is the algorithm of Bry and Boschan (1971). Basically, the Bry and Boschan (BB) algorithm consists of successive application of moving average filters of different length and the treatment of extreme values, i.e. outliers in the relevant series. The BB algorithm places the following censoring rules on potential turning points: (1) a full business cycle (P-P, T-T) should last at least fifteen months; (2) each business cycle phase (P-T, T-P) should last at least five months; and (3) the peaks and troughs in the cycle should alternate. These BB criteria have been developed to identify business cycle turns in the level of economic activity, hence, referring to the classical business cycle approach.[6]

The BB dating methodology was developed originally for monthly time series but modifications have been proposed since then to apply the algorithm to other data frequencies as well. For example, Harding and Pagan (2001, 2002) discuss amendments necessary to generalise the algorithm to quarterly or annual data. These authors label their quarterly version of the original BB as BBQ.[7] The BBQ includes similar to BB algorithm a simple rule to define peaks and troughs and a censoring procedure to guarantee that the phases and the

[5] For alternative methods see e.g. Diebold and Rudebusch (2001) and Hess and Iwata (1997).
[6] For a detailed overview of the BB procedure I refer to Bry and Boschan (1971).
[7] Quite a few studies revert to the BBQ dating algorithm when dealing with quarterly data frequencies and analysing the business cycle in the spirit of the classical approach (see e.g. Schirwitz, 2009; Krolzig and Toro, 2005; Galvao, 2002).

cycles have a minimum length, but does not include a smoothing step because it assumes that quarterly series are already smooth enough. The determination of a peak and a trough at period t is based on the following rules:

Peak: $$\Delta_2 y_t > 0 \cap \Delta y_t > 0 \cap \Delta y_{t+1} < 0 \cap \Delta_2 y_{t+2} < 0 \quad \textbf{(2-1)}$$

Trough: $$\Delta_2 y_t < 0 \cap \Delta y_t < 0 \cap \Delta y_{t+1} > 0 \cap \Delta_2 y_{t+2} > 0 \quad \textbf{(2-2)}$$

where $\Delta_2 y_t = y_t - y_{t-2}$ and $\Delta y_t = y_t - y_{t-1}$. Each identified turning point has then to fulfil certain criteria such that peaks and troughs alternate, phases are at least two quarters long and a full cycle lasts at least five quarters, and the level at peak must be higher than at the adjacent trough. The application of the BB or BBQ algorithm is not only restricted to date classical style business cycles. It is also common practice to apply the BB dating routine, or some modified version of it, to deviation or growth rate cycles (see e.g. Zarnowitz and Ozyildirim, 2002; Altissimo et al., 2001; Scheiblecker, 2007).

An even simpler dating rule which has been proposed, for example, in Wecker (1979) locates peaks and troughs at period t according to the following simplified rule set:

Peak: $$\Delta y_t > 0 \cap \Delta y_{t+1} < 0 \cap \Delta y_{t+2} < 0 \quad \textbf{(2-3)}$$

Trough: $$\Delta y_t < 0 \cap \Delta y_{t+1} > 0 \cap \Delta y_{t+2} > 0 \quad \textbf{(2-4)}$$

with the only restriction in place that peaks and troughs have to alternate. This definition is in line with the often used classification of a recession, i.e. the period between a peak and a trough, in the general public and media, hence, the label ‘newspaper’ method. It states that a period of at least two quarters of declining economic activity, following a period of increasing and positive growth rates, is denoted as a recession (see e.g. Schirwitz, 2009; Bonenkamp et al., 2001). Similarly, a contraction is terminated with at least two consecutive quarters of positive growth in economic activity.[8]

[8] Boldin (1994) proposed some modifications to the simple two-in-a-row rule. As such he suggested using a two-out-of three quarters change of sign in the business cycle as well as a threshold growth rate greater than zero for dating a trough.

2.5 More comments on the deviation cycle approach: de-trending issues

Deviation cycles as already noted above are defined in terms of movements around the underlying trend component. As such, a separation of the business cycle fluctuations from the trend component is required. The problem, however, is that the trend cannot be directly measured since it is unobservable and has to be inferred from the data. There exist quite a few approaches in the literature of how to decompose a time series into its trend and cycle components but no single procedure is unequivocally superior to its counterparts.

Following Cotis et al. (2004) trend-cycle decomposition techniques can be classified according to three general approaches which are based on: (1) estimating a structural model of the supply side; (2) using statistical techniques; and (3) using survey data. In this paper I will focus on the second approach, hence, providing a selection of de-trending techniques which identify the trend by decomposing the series into various components. In other words, those methods split the underlying series in a long-run trend component and some short-run disturbances around this long-run equilibrium. In a stylised decomposition, this may look like:

$$y_t = \tau_t + c_t \qquad \textbf{(2-5)}$$

where y_t represents the series of interest, τ_t the trend and c_t the cyclical component. Note that according to this decomposition the cyclical component (c_t) also contains seasonal fluctuations as well as idiosyncratic noise. The process of extracting a cycle from a data series is often referred to as a process of *filtering* where the signal is extracted up to a particular point in the data series (Massmann et al., 2003). In contrast, the term *smoothing* is used if the process exploits information over the whole data range. In order to extract the trend (τ_t) or cyclical component (c_t) a parametric or non-parametric statistical model has to be specified.[9]

2.5.1 Parametric methods

Signal extraction following parametric approaches requires in the first place a fully specified model for the time series of interest as well as for each component, e.g. trend and cycle, therein. This is followed by the estimation of the set of parameters, and, finally, consisting of a choice of different weighting methods for the observations to be filtered. Various parametric models exist; the most widely used ones are phrased in terms of the state-space form and the Kalman filter (Harvey, 1989). Examples of signal extraction using state-space modelling are the unobserved components model (Harvey, 1993; Koopman et al., 1999), common factors

[9] An elaborated discussion of each of the parametric and non-parametric signal extraction approaches can be found, for example, in Massmann et al. (2003).

models (Sargent and Sims, 1977; Stock and Watson, 1993), and state-dependent Markov-switching models (Hamilton, 1989). Another similar approach, which does however not require a state-space representation, is the ARIMA Beveridge-Nelson decomposition (Beveridge and Nelson, 1981),

2.5.2 Non-parametric methods – "ad-hoc" Filter

This class of signal extraction contains the most widely used de-trending approaches such as the simple first-order differencing filter; the Hodrick-Prescott (1980, 1997) filter; and the Baxter-King (1999) and Christiano-Fitzgerald (2003) approximation of an ideal band-pass filter. Before providing a detailed discussion on these non-parametric filtering methods several remarks are appropriate.

In general, as in the case with parametric methods, non-parametric filters can be viewed as weighted moving averages and the extraction of the components trend and cycle (τ_t, c_t) from y_t can be represented by

$$c_t = a(L)y_t \tag{2-6}$$

$$a(L)_{-r}^{s} = a_{-r}L^{-r} + \ldots + a_0 + a_1 L + \ldots + a_s L^s \tag{2-7}$$

$$\tau_t = [1 - a(L)]y_t \tag{2-8}$$

where $a(L)$ is a polynomial in the lag operator L that specifies the number of lags [$-r$, s] included in the model, i.e. representing the filter in its respective form. Typically, most filters are two-sided and symmetric, i.e. the value of the trend component depends on both past and future values. This ensures that no phase shift between the original and the filtered series occurs (see e.g. Baxter and King, 1999).

But some problems arise near the beginning and end of the series where the filter becomes asymmetric, i.e. one-sided, without further amendments. This refers to the well-known endpoint problem. As such the addition of new or revised data points changes the filtered values of observations at the end of the series and leads to phase shifts.[10] Possible solutions to the end-point issue are to either remove a certain number of observations at the start and end of the series or to extrapolate the original series using, for example, an autoregressive (AR) process (see e.g. Kaiser and Maravall, 2000).

[10] Kranendonk et al. (2004) provide an empirical discussion of the end-point bias in contrasting the Hodrick-Prescott (HP) filter with the Baxter-King (BK) and the Christiano-Fitzgerald (CF) filter. The authors find that the HP filter is more sensitive in this respect compared to the other two.

First-order differencing filter

An easy and still widely used filtering technique despite its drawbacks is calculating first differences. That is simply 'generating' the cyclical component by $c_t = (1-L)y_t$.[11] However, as pointed out, for example, in Baxter and King (1999) a major problem with the differencing filter is that it induces a phase shift in the series and puts a large weight on the very high frequencies. This results in a filtered series, which usually displays a rather erratic style as it emphasises the 'noise' over the cyclical component.

Hodrick-Prescott (HP) filter

Perhaps the most widely used and best known non-parametric filter for the analysis of business cycles is the HP filter (Hodrick-Prescott 1980, 1997). Technically, the HP filter is a two-sided symmetric linear high-pass filter that generates the smoothed series by minimising the variance of the underlying series around the trend component, depending on a penalty factor that constrains the second difference of the trend. The HP filter solves the minimisation problem:

$$\min_{\{\tau_t\}} \sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \qquad \textbf{(2-9)}$$

where y_t is the original trend afflicted series, τ_t is the 'smoothed' trend to be estimated, and the penalty parameter λ controls the degree of smoothness of the trend; the larger λ, the smoother is the trend component. The residual $y_t - \tau_t$, i.e. the deviation from trend, is then referred to as the business cycle component. In using the lag polynomial notation, the solution to (2-12) yields $c_t = a(L)y_t$ where the log polynomial is defined as follows:

$$a(L) = \frac{\lambda L^{-2}(1-L)^4}{\lambda L^{-2}(1-L)^4 + 1} \qquad \textbf{(2-10)}$$

From (2-10) it is apparent that the HP filter contains four differencing operators and can therefore render stationary any integrated process up to fourth order (King and Rebelo, 1993). The choice of λ depends on data frequency.[12] For quarterly data λ is usually set to 1600. Hodrick and Prescott (1980) proposed this value based on the argument that a 5 percent standard deviation from trend is moderately large as is an 1/8th of a percent change in the

[11] Note that if the first-differencing de-trending filter, $(1-L)y_t \equiv \Delta y_t \equiv y_t - y_{t-1}$, is applied to a series in logarithmic form the output series can be interpreted as growth rates. As such this type of filter can be related also to the growth rate cycle approach (see e.g. Harding and Pagan, 2005).

[12] However, irrespective the data frequency, when $\lambda=\infty$ the solution to the minimisation problem in (2-12) is a linear trend, while with $\lambda=0$ the trend component reflects the original series.

standard deviation of the quarterly trend growth rate. Using Hodrick and Prescott's arguments the following standard values for λ can be obtained as:

Quarterly: $\lambda_q = 5^2/[0.5/4]^2 = 1600$ **(2-11)**

Monthly: $\lambda_m = 5^2/[0.5/12]^2 = 14{,}400$ **(2-12)**

Annually: $\lambda_a = 5^2/[0.5]^2 = 100$ **(2-13)**

However, as Ravn and Uhlig (1997), among others, have pointed out there is some disagreement in the literature about the appropriate value for λ, especially when dealing with non quarterly data. In their study they base the analysis on the frequency domain[13] to provide a rule to obtain λ in the case the quarterly frequency of observations is altered:

$$\lambda_s = s^m \times \lambda_q \qquad \textbf{(2-14)}$$

where s is the alternative sampling frequency (annual or monthly) as the ratio of the frequency of observation compared to quarterly data (s=0.25 for annual data or s=3 for monthly data); m represents the power the transfer function is raised to;[14] and λ_q is set to 1600 the value for quarterly data. Ravn and Uhlig (1997) recommend using a power value m=4. Using Ravn and Uhlig's suggestion the following altered values for λ can be derived:

Monthly: $\lambda_{m'} = 3^4 \times 1600 = 129{,}600$ **(2-15)**

Annually: $\lambda_{a'} = 0.25^4 \times 1600 = 6.25$ **(2-16)**

Another characteristic of the HP filter as pointed out, for example, by Prescott (1986) is that the filter approximates an ideal high-pass filter. As such the HP filter allows high frequencies to pass and attenuates fluctuations at low frequencies.

This raises the question, which cut-off frequency relates, for example, to the λ value proposed by Hodrick and Prescott (1980) for quarterly data. Maravell and del Rio (2001) provide an answer to this question. In using the frequency response function of the HP filter the authors show how the filter affects certain frequencies, which frequencies are retained and which are let through. The cut-off frequency is defined as the frequency where 50% is let trough and 50% is retained from the cyclical period, i.e. identifying the frequency for which 1/2 of the

[13] The frequency domain is a term used to describe the analysis of functions with respect to frequency, rather than time. The Fourier transformation maps a time series into the series of frequencies (their amplitudes and phases) that composed the time series. Analogous, the inverse Fourier transformation maps the series of frequencies back into the equivalent time series. The two functions are inverses of each other (Hamilton, 1994).

[14] Using m=2 reveals the original Hodrick-Prescott values for λ.

filter gain has been achieved.[15] As such Maravell and del Rio (2001) show how the λ parameter can be aligned to filter out cycles in a certain frequency range with the help of the transformation into the frequency domain.

Having either the λ parameter or a particular cut-off frequency ω_0 in mind one can easily work out the other value by using the following formula:

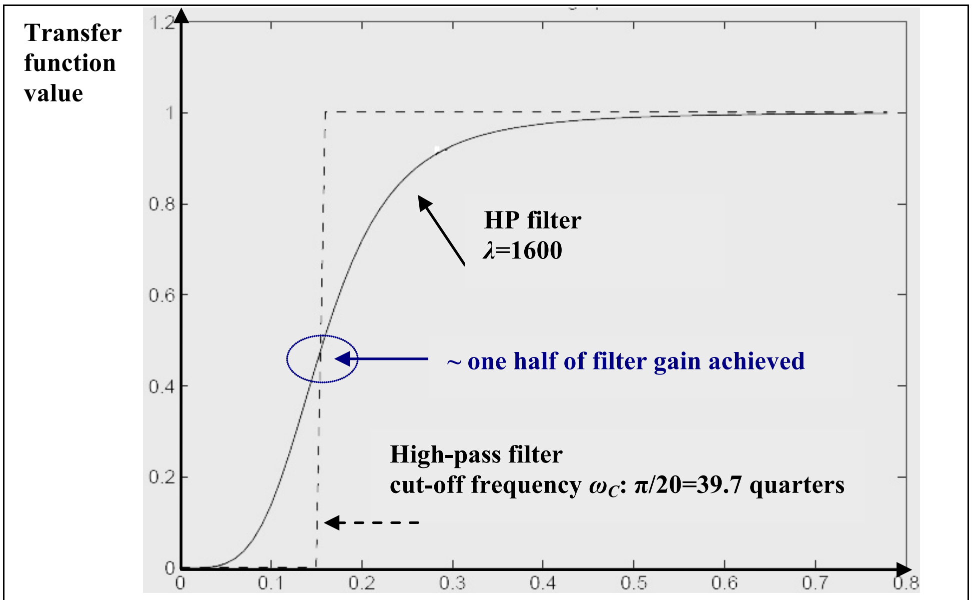
$$\lambda = \left[4(1-\cos(\omega_C))^2\right]^{-1} \tag{2-17}$$

Furthermore, the λ parameter can be used to directly find the period it takes for the completion of the full cycle, denoted as φ, of the chosen cut-off frequency ω_C. Using the relationship $\varphi = 2\pi / \omega$, one can obtain the period φ directly as a function of λ, as

$$\varphi = 2\pi / a\cos\left(1 - \tfrac{1}{2\sqrt{\lambda}}\right). \tag{2-18}$$

Applying (2-18), for example, to quarterly data with λ=1600, results to a corresponding cut-off period of $\varphi = 39.7$ quarters. This means as Maravell and del Rio (2001) put it that peak-to-peak cyclical movements of less than ten years of duration will remain in the business cycle component obtained from the HP filter. Figure 2 illustrates the approach taken by these authors and displays the HP-filter versus an ideal high-pass filter.

Figure 2: HP filter versus ideal High-pass filter



Source: Own illustration.

[15] Maravall and del Rio (2001) refer to the cycle associated with the cut-off frequency as the 'cycle of reference'.

Before turning the discussion to the class of band-pass filters, some final remarks on the HP filter should be made. At first, given that seasonal fluctuations should not contaminate the cyclical signal, the HP filter should be applied to seasonally adjusted series (see e.g. Kaiser and Maravall, 2001). Second, the choice of the 'correct' value for the smoothing parameter λ is despite some general agreements found in the literature not that clear. One has to bear in mind that depending on the λ value chosen the cyclical components derived may considerably differ. Next, given that the HP filter can only be interpreted as an approximation to an ideal high-pass filter some cyclical periods around the cut-off frequency may only partially excluded from the trend or included in the cyclical component.

Finally, despite some criticism relating to spurious cyclical behaviour, especially at the end-points of the series (see e.g. Canova, 1998; Harvey and Jaeger, 1993), the HP filter is still, due to its simple estimation, widely used amongst business cycle researchers and practitioners.

Baxter-King (BK) filter

The BK filter relates to the class of band-pass filters which allow extracting components of a time series between predetermined cut-off points. Baxter and King (1999) argue that using such a filter that both eliminate low-frequencies as well as high-frequencies in the data should lead to an improved outcome of the business cyclical component of interest. In particular, Baxter and King (1999) suggest isolating periodic fluctuation between 6 and 32 quarters (1.5 to 8 years). This is in line to the business cycle frequency range proposed in the seminal work of the NBER researchers Burns and Mitchell (1946).[16]

Formally, the BK filter is a linear, two-sided moving average of finite sample-length. As such it only represents an approximation of an ideal band-pass. Note that the ideal filter of infinite length should retain the desired range of frequencies [ω_L, ω_U], i.e. the range of periodicities, and perfectly eliminate the remaining while inducing no phase shifts. This yields the following weighing rule $v(\omega)$ and filter weights for the moving average in the frequency domain, v_j, and time domain, $a(L)$, of the ideal band-pass filter:

$$v(\omega) = \begin{cases} 1, & \omega_L \leq |\omega| \leq \omega_U \\ 0, & otherwise. \end{cases} \qquad \textbf{(2-19)}$$

[16] It is to note that in more recent papers concerning cyclical analysis it is argued that modern business cycles may last longer and have shorter cyclical fluctuations. For example, Agresti and Mojon (2001) propose for the European business cycle to use an upper bound of 10 years.

$$v_j = \int_{-\pi}^{\pi} v(\omega) \exp^{ij\omega} d\omega \qquad \textbf{(2-20)}$$

$$a(L) = \sum_{-\infty}^{\infty} v_j L^j \qquad \textbf{(2-21)}$$

As can be seen from (2-21) the ideal band-pass filter requires a moving average of infinite order [-∞,∞]. The approximation to this ideal filter as derived by Baxter and King (1999) has filter weights of length *K* given by

$$\widetilde{a}(L) = \frac{\sin L\omega_U - \sin L\omega_L}{L\pi} - \frac{1}{2K+1} \sum_{L=-K}^{K} \frac{\sin L\omega_U - \sin L\omega_L}{L\pi} \qquad \textbf{(2-22)}$$

where symmetry is imposed so that the filter does not induce a phase shift.[17] However, this means that end-of-sample estimates are unavailable. More specifically, filtered values are only obtainable for periods *K+1* to *T-K*.

Christiano-Fitzgerald (CF) filter

Another type of approximation to an ideal band-pass filter is the Christiano-Fitzgerald (2003) filter. In contrast to the BK filter, the CF filter uses an asymmetrical weighting scheme, which employs all observations for the calculations of the filtered values. Hence, the CF filter has the advantage that is does not lead to the loss of observations at the beginning and at the end of the sample period. The filter weights are as well estimated using frequency domain arguments. Despite the somewhat different assumptions underlying the BK and CF filter method, Christiano and Fitzgerald (2003) point out that both filters provide quantitatively similar cyclical statistics. A drawback in the application of the CF filter, and similar to that of the HP and BK filter, is the endpoint issue, when new observations become available. This means that even though cyclical estimators for the central periods are final, the estimates for the most recent periods will be revised.[18]

[17] Baxter and King (1999) propose for quarterly data the following set of parameters: K=12, ω_U=π/16 and ω_L=π/3, where ω_U and ω_L correspond to 32 and 6 quarters, respectively. They also constrain the weights to sum to zero, so that the resulting approximation is a de-trending filter.

[18] Kaiser and Maravall (2001) show how a series can be extended with forecasts and backcasts to possible reduce revisions at the endpoint of the data series, thus, making the estimated cyclical component more robust.

2.6 Final remarks of Section 2

Quah (1992) and Canova (1998), amongst others, point out that different de-trending methods may extract substantially different business cycle components, i.e. short-run disturbances, from the same underlying time series which in turn effects the dating of the turning points and other business cycle characteristics. Furthermore, the various de-trending procedures may also differ in terms of whether or not the cyclical component extracted is stationary, i.e. the moments of the series such as mean and variance do not depend on time. As a consequence the choice of one method over another depends most often on the purpose of the analysis and on the specific characteristics of the time series. However, contrary to the critique found in Canova (1998), De Haan et al. (2008), for example, comment that studies that use standard filters such as the HP, BK or CF filter are likely to yield similar results. In the empirical part of this study (see Section 4) I will take account for this circumstance and use the output of different de-trending methods, in particular non-parametric approaches, as input into the dating procedure. In the analysis of business cycle characteristics for the reference series I will comment on differences obtained.

3 METHODS FOR MEASURING BUSINESS CYCLE SYNCHRONISATION

In general, a variety of methodologies exist in the literature to examine the comovement of two or more time series. In what follows is an outline of some basic synchronisation measures but it also includes methods which have been specifically designed for the task of analysing conformity between business cycles.

3.1 Cross-correlations

The *cross-correlations* measure constitutes one of the more common approaches adapted to estimating the relationships between the cycles of two economic variables. I denote the series of interest *i* and the reference series *r*. Basically, for the couple, the cross-correlations measure estimates the linear relationship between the variables, i.e. the degree to which the movements of the two variables are in sync. In this way, they allow one to verify whether the movements of the variable tend to be produced at the same time as the changes of the variable. They are calculated as follows:

$$\rho_{ir}^{(k)} = \frac{\sum_t (r_t - \mu_r)(i_{t+k} - \mu_i)}{\sum_t (r_t - \mu_r)^2 (i_t - \mu_i)^2}, \text{ with } k = 0, \pm 1, \pm 2, \ldots \qquad \textbf{(3-1)}$$

where μ_r and μ_i are the respective means of r and i. When k=0, a measure of the degree of the simultaneous, i.e. contemporaneous evolution of the two variables is derived.

3.2 Coherence

The frequency domain provides further useful measures for business cycle analysis.[19] One statistic typically used therein is the pair-wise *coherence* among the variables of interest and the reference series both being derived from the cross-spectrum. In general, coherence measures the proportion of the variance explained by the individual indicator series i to the frequencies given by the reference series r. Or in other words, it measures the linear relatedness of two stationary series at a special frequency across all leads and lags of the series.[20] The coherence measure is bounded between 0 and 1. The closer it is to 1 the stronger is the linear relationship and the more information is contained in the variable of interest which is strongly linked to the cyclical behaviour of the reference series. Technically, the coherence measure for a certain frequency, $\eta_{ir}(\omega)$, is defined by the squared cross-spectrum, $s_{ir}(\omega)$, divided by the product of the spectral density function for both series i and r and can be expressed as

$$\eta_{ir}(\omega) = \frac{|s_{ir}(\omega)|^2}{s_{ii}(\omega)s_{rr}(\omega)}, \text{ with} \tag{3-2}$$

$$s_{ir}(\omega) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\rho_{ir}^{k}e^{-i\omega k} \tag{3-3}$$

where the frequency ω in (3-2) is bounded to the range $[0,\pi]$ and for the cross-spectra in (3-3) being within $\pm\pi$; $i=\sqrt{-1}$; and ρ_{ir}^{k} is the cross-covariance of the series i and r of k-th order which being the cross-correlation as defined in (3-1). Hallet and Richter (2006) point out that the coherence is nothing else than the R^2 of the time domain. It measures, for each frequency, the R^2 between each of the corresponding cyclical components embodied in the indicator and reference series.[21] One has to keep in mind though that the coherence statistic abstracts from phase differences between two series, i.e. it does not provide a measure of simultaneous movements at different frequencies (Croux et al., 1999).

[19] As noted previously, spectral analysis allows analysing time series behaviour in frequency rather than in standard time domain. An exhaustive description can be found in Hamilton (1994).

[20] Typically, the frequencies used for calculating the coherence to analyse business cycle synchronicity range between 1.5 and 8 years.

[21] For a better understanding what coherence means Hallet and Richter (2006) use the following example: suppose the coherence statistic equals 0.6 at frequency 1.2 (this roughly equals 15.7 months), then this means that country X's business cycle at a frequency of 1.2 determines the business cycle of the reference country at this point in time by 60%.

3.3 Concordance

Burns and Mitchell (1946) provide in their seminal work two different methods of measuring conformity between two series. The first method takes into account the direction and rate of movement of a series during successive expansions and contractions with respect to the reference cycle. The second method assigns different values to cyclical movements, i.e. +100 for each rise, -100 for each fall and 0 when there is no change in the series. An arithmetic mean of all entries produces an expansion index and by changing the signs a contraction index can be calculated accordingly. A problem with these indices as noted in Krolzig and Toro (2005) is that the indices only consider the net difference between the averages at cyclical trough and peaks and miss out the intermediate values from peak to trough or trough to peak. The *concordance* measure by Harding and Pagan (2002, 2003) provides an alternative measure. Harding and Pagan's concordance index measures the degree of which regional cycles are in sync with the national cycle by the proportion of time that the two economies were in the same regime. Specifically, the degree of concordance between the business cycles of region i and reference region r is expressed as

$$C_{ir} = \frac{1}{T}\sum_{t=1}^{T}\left[S_{i,t}S_{r,t} + (1 - S_{i,t})(1 - S_{r,t})\right] \qquad \textbf{(3-4)}$$

where $S_{i,t}$ ($S_{r,t}$) is the state in region i (r) during time t; the state S variable can take on value 1 or 0, where 1 denotes an expansionary and 0 a contractionary phase; T denotes the total number of periods. The concordance index is bounded between 1 and 0, where 1 indicates maximum concordance. Harding and Pagan (2002) suggested using this index to measure conformity in classical style business cycles. Nevertheless, it is possible to apply their concordance index on series for which the business cycle component, for example, has been extracted using some de-trending method. As such, the only thing to do would be to set S=1 to periods above trend growth and S=0 to times where growth is below trend.[22]

3.4 Synchronicity and Co-movement according to Mink et al. (2007)

In analysing convergence of business cycles for countries within the euro area Mink et al. (2007) propose, in focusing on deviation from trend, a new method to assess the similarity of business cycles. The authors define two measures: one of *cycle synchronicity* and one of *cycle co-movement*. The former shows the fraction of time that the output gaps of two economies

[22] In the empirical analysis I will calculate the concordance index for the Austrian Länder using business cycle components extracted with the HP filter (λ=1600).

have the same sign and the latter takes differences between cycle amplitudes as well as synchronicity of cycles into account. Both measures are designed for the multivariate case, i.e. these statistics can be simultaneously applied to a group of countries or regions. Formally, the cycle synchronicity (φ_t) and co-movement (γ_t) measure can be expressed as

$$\varphi_t = \frac{1}{n}\sum_{i=1}^{n}\frac{c_{i,t}c_{r,t}}{\left|c_{i,t}c_{r,t}\right|} \qquad \textbf{(3-5)}$$

$$\gamma_t = -\frac{\sum_{i=1}^{n}\left|c_{i,t}-c_{r,t}\right|}{\sum_{i=1}^{n}\left|c_{i,t}\right|} \qquad \textbf{(3-6)}$$

where $c_{i,t}$ denotes the business cycle of region *i* in period *t*, and $c_{r,t}$ the cycle of the reference region *r* at time *t*. In (3-5) the term right to the summation sign is equal to 1 when both cyclical components have the same sign and -1 otherwise. As such, the cycle synchronicity measure is bounded between -1 and 1. Transforming the measure to a [0, 1] scale provides the proportion of regions with a business cycle component that share the same sign as the reference region at time *t*.[23] The co-movement measure in (3-6) represents the total distance between the cycles of the regions and the corresponding cycle in the reference series, scaled by the overall distance of the regions. The minus sign is required in order that both measures move in the same direction. In a bivariate setting (3-5) and (3-6) simplify to

$$\varphi_{ir,t} = \frac{c_{i,t}c_{r,t}}{\left|c_{i,t}c_{r,t}\right|} \qquad \textbf{(3-7)}$$

$$\gamma_{ir,t} = -\frac{n\left|c_{i,t}-c_{r,t}\right|}{\sum_{i=1}^{n}\left|c_{i,t}\right|}. \qquad \textbf{(3-8)}$$

Note that the bivariate cycle synchronicity measure in (3-7) is basically similar to the concordance index proposed by Harding and Pagan (2002). The only difference is that Harding and Pagan (2002) examine comovement between classical cycles whereas Mink et al. (2007) use deviation cycles.

[23] Mink et al. (2007) argue that their synchronicity measure provides a better quantification of cyclical conformity than correlation measures because the latter one may be influenced by the magnitude of the cyclical amplitude. The authors provide an example where positive and negative output gaps of two series perfectly coincide but the correlation coefficient reveals only 0.53.

3.5 Final remarks of Section 3

The list of the methods described above is by no means exhaustive and there exist quite a few other techniques in the literature to measure comovement in economic variables. But in the empirical analysis which follows I decided to employ cross-correlations, concordance and coherence statistics and as such it was naturally to discuss these methods more in depth. Other measures of synchronisation can be found, for example, in Artis et al. (2004a) where the authors use a 2x2 contingency table for analysing synchronisation in the business cycle. The table basically reflects the number of periods when both series are in the same phase, i.e. contraction or expansion, and how often they are in different phases over the whole time span. In deriving the Pearson's contingency coefficient a measure of the strength of association can be obtained, where 0 indicates no association and 1 represents maximum synchronisation. Koopman and Azevedo (2003) use phase-adjusted time-varying correlations to investigate the process of synchronisation and the degree of converging cycles. They assume that there exists a difference in the shift between the cyclical components of two variables from one period to another. This means that the business cycles are shifted from each other by some fraction of time in an earlier period while the cycles match without shifts in later periods. Artis et al. (2003), as a final example, use diffusion indices to measure how widespread business cycle movements are throughout the economy, where the business cycle diffusion measures the proportion of economic time series being in a certain regime (e.g. above trend growth).

4 EMPIRICAL ANALYSIS

4.1 The dataset

The dataset used for analysing regional business cycles in the Austrian economy contains quarterly data of real gross value added (*GVA*).[24] The data are primarily taken out from the WIFO Economic Database – Section "Regional indicators". Data for the nine Austrian federal provinces (Länder) as well as for the national aggregate are available back to 1988. Consequently, the period 1988:Q1 to 2009:Q4 (in total 85 observations) will be used in the analysis. The data series of total Austrian gross value added, GVA_{AT}, serves as the reference series. The regional statistical data for the Austrian Länder correspond to the NUTS level 2 classification established by Eurostat.[25] In addition, data aggregates are also used matching

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[24] The data series of gross value added does not include data for the primary sector, i.e. it excludes sectors of agriculture, hunting, forestry and fishing (ÖNACE A-B).

[25] NUTS is short for "Nomenclature des unités territoriales statistiques" or Nomenclature for Territorial Units for Statistics. The NUTS classification divides up the economic territory of the EU Member States into three levels:

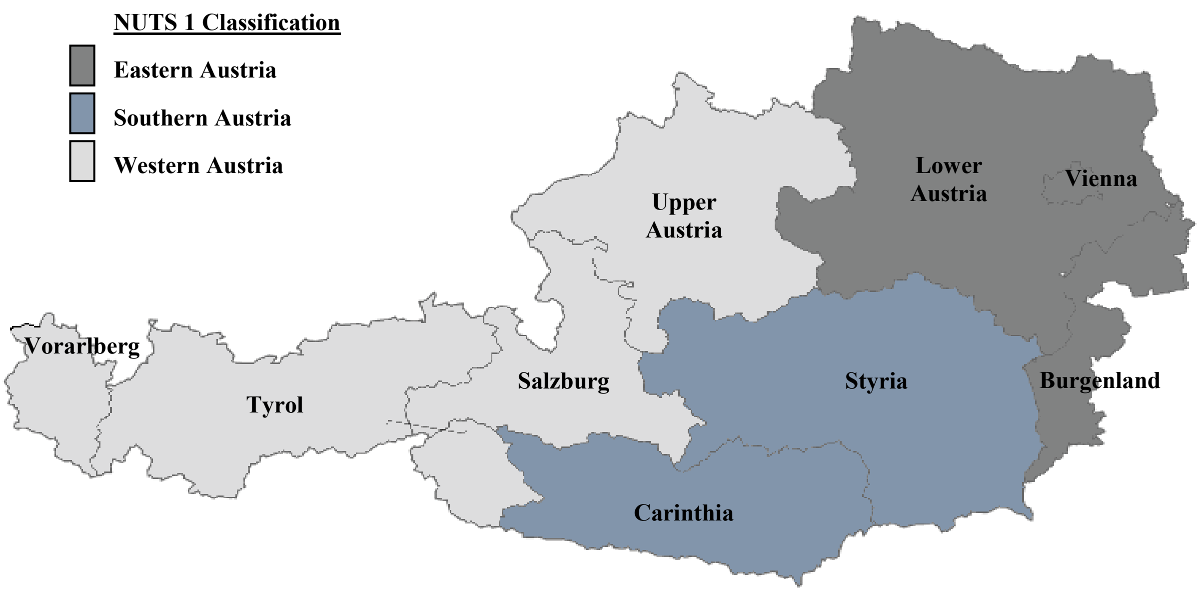
NUTS level 1. For Austria, this relates to the regional unit of Eastern- (containing Vienna, Lower Austria and Burgenland), Southern- (containing Styria and Carinthia) and Western- (containing Upper Austria, Salzburg, Tyrol and Vorarlberg) Austria. Table 2 provides an overview of the Austrian regional areas and aggregates used in this paper and Figure 3 represents them graphically.

Table 2: Overview of Austrian Regions and Top-level Aggregates

Regions ≡ NUTS Level 2	NUTS Level 1 Aggregates			Industrial Aggregate [1)]	Area in km2	Resident population [2)]
	Eastern	Southern	Western			
Vienna	■				414.65	1,687,271
Lower Austria	■			■	19,186.26	1,605,122
Burgenland	■				3,961.80	283,118
Styria		■		■	16,401.04	1,207,479
Carinthia		■			9,538.01	560,605
Upper Austria			■	■	11,979.91	1,410,403
Salzburg			■		7,156.03	529,217
Tyrol			■		12,640.17	704,472
Vorarlberg			■	■	2,601.12	367,573
					83,878.99	8,355,260

[1)] Region selection based on the share of the manufacturing sector on the respective regional GVA; Threshold >=25%.
[2)] As per 1 January 2009.
Source: Own illustration based on Statistics Austria.
http://www.statistik.at/web_en/statistics/regional/regional_breakdown/nuts_units/index.html

Figure 3: Map of Austrian Regions



Source: Own illustration.

NUTS levels 1, 2 and 3. The second and third levels are subdivisions of the first and second levels respectively. See http://europa.eu/legislation_summaries/regional_policy/management/g24218_en.htm.

Besides the geographical aggregates corresponding to NUTS level 1 and 2 regions I decided to construct an 'industrial' aggregate containing Austrian Länder which exhibit a predominate share of the manufacturing sector in their respective GVA_{REG}. One motivation behind this rests in the fact that the manufacturing sector plays an important role for the export orientated Austrian economy and as such is often seen as business cycle maker. In other words, the group of "Industriebundesländer" should mirror the Austrian cycle to a great extent. It is expected that the 'industrial' aggregate shows a high co-movement with the total Austrian aggregate of GVA_{AT}.

Table 3: Proportion of the Manufacturing Sector on Regional Gross Value Added (GVA_{REG})

		Descriptive Statistics [1]									
		Mean Y96-09	**Std. Dev.**	**95% Interval +/- 2 StdDev.**		**Jarque-Bera [2]**			**Mean Y96-97**	**Mean Y08-09**	**ΔMean**
						t-stat	**p-Value**				
	Regions	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)	(9)
	Austria	20.4	1.0	18.5	22.4	6.039	0.0488	***	19.6	21.6	+2.0
NUTS 2	Vienna	10.0	0.7	8.7	11.4	1.116	0.5723	*	11.0	10.0	-1.0
	Lower Austria	24.4	1.1	22.1	26.6	2.839	0.2419	*	23.9	25.3	+1.3
	Burgenland	18.2	1.2	15.9	20.6	2.010	0.3660	*	17.7	17.3	-0.5
	Styria	26.2	1.6	23.1	29.3	1.657	0.4368	*	23.9	27.7	+3.8
	Carinthia	20.8	1.3	18.2	23.5	2.031	0.3622	*	19.2	21.7	+2.5
	Upper Austria	30.5	1.5	27.6	33.5	3.434	0.1796	*	29.2	32.1	+2.9
	Salzburg	17.6	1.7	14.3	20.9	0.567	0.7532	*	15.9	19.2	+3.2
	Tyrol	18.7	2.3	14.2	23.2	0.791	0.6733	*	17.1	20.7	+3.6
	Vorarlberg	27.8	2.3	23.2	32.5	0.159	0.9237	*	26.4	30.4	+4.0
NUTS 1	Eastern Austria	15.2	0.6	14.1	16.4	3.332	0.1890	*	15.5	15.6	+0.1
	Southern Austria	24.5	1.4	21.6	27.4	1.282	0.5266	*	22.4	25.8	+3.4
	Western Austria	24.8	1.7	21.5	28.2	0.489	0.7831	*	23.3	26.7	+3.4
	Industrial Austria	27.2	1.3	24.6	29.8	5.142	0.0764	**	25.9	28.7	+2.8

[1] Numbers shown in column (1) and (7)-(9) represent the percentage share of the manufacturing sector w.r.t. to total Gross Value Added for the respective region; data ranges from 1996:Q1 to 2009:Q4.

[2] Jarque-Bera statistic: test statistic for normality of a series based on the sample kurtosis and skewness. Under the null hypothesis of normality, the statistic is $\chi 2(2)$-distributed. The reported p-Value is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null - small probability value leads to the rejection of the null hypothesis of a normal distribution. Statistically significance at the 1%, 5% or 10% level is indicated by ***, ** or *, respectively.

Source: WIFO Database. Own calculations based on original level data prior seasonal adjustment procedure.

As can be seen in Table 3 four regions, namely Lower Austria, Upper Austria, Styria, and Vorarlberg are classified as "Industriebundesländer". Each of these selected regions has a manufacturing share in their GVA_{REG} close to or above 25 per cent. Given that a sectoral breakdown of Länder data are only available from 1996:Q1 onwards the sector analysis is based on this curtailed time-period. Table 3 provides detailed results for the share of the manufacturing sector in each region. It can be seen from column (1) that on average the manufacturing sector constitutes around one fifth to total *GVA* for Austria. This share is greater for each member of the group of “Industriebundesländer” with the highest manufacturing share being associated to Upper Austria with a bit more than 30%. This is followed by Vorarlberg, Styria, and Lower Austria with about 27%, 26%, and 24%, respectively. All “Industriebundesländer” combined, GVA_{IND}, represent a proportion of the manufacturing sector of roughly 27%. On the other end of the Länder scale ranks Vienna with a share in this sector of around 10%. The NUTS 1 aggregate of Eastern Austria marks with around 15% a below average share whereas the regions of Southern and Western Austria have a share of nearly one quarter.

Table 3 also reports the standard deviation around the mean of the manufacturing share to investigate the degree of which the ratios may vary. In most cases the standard deviation lies roughly between 0.5 and 1.5 per-cent points. Tyrol and Vorarlberg mark the exception with a deviation from the mean of 2.3 per-cent points, hence exhibiting a much wider interval. Therefore, the manufacturing share for these two Länder has ± 2 standard deviation range of about 10%. Finally, column (7)-(9) in Table 3 provide an indication of the mean change of the manufacturing sector comparing the mean over the years 1996-97 with 2008-09. It can be seen that all regions, except Vienna and Burgenland, increased their share in the manufacturing sector. Especially, the regions in Western Austria and Styria raised their manufacturing share between 3 and 4 per-cent. This result illustrates the still and even increasing importance of the manufacturing sector in the Austrian economy.

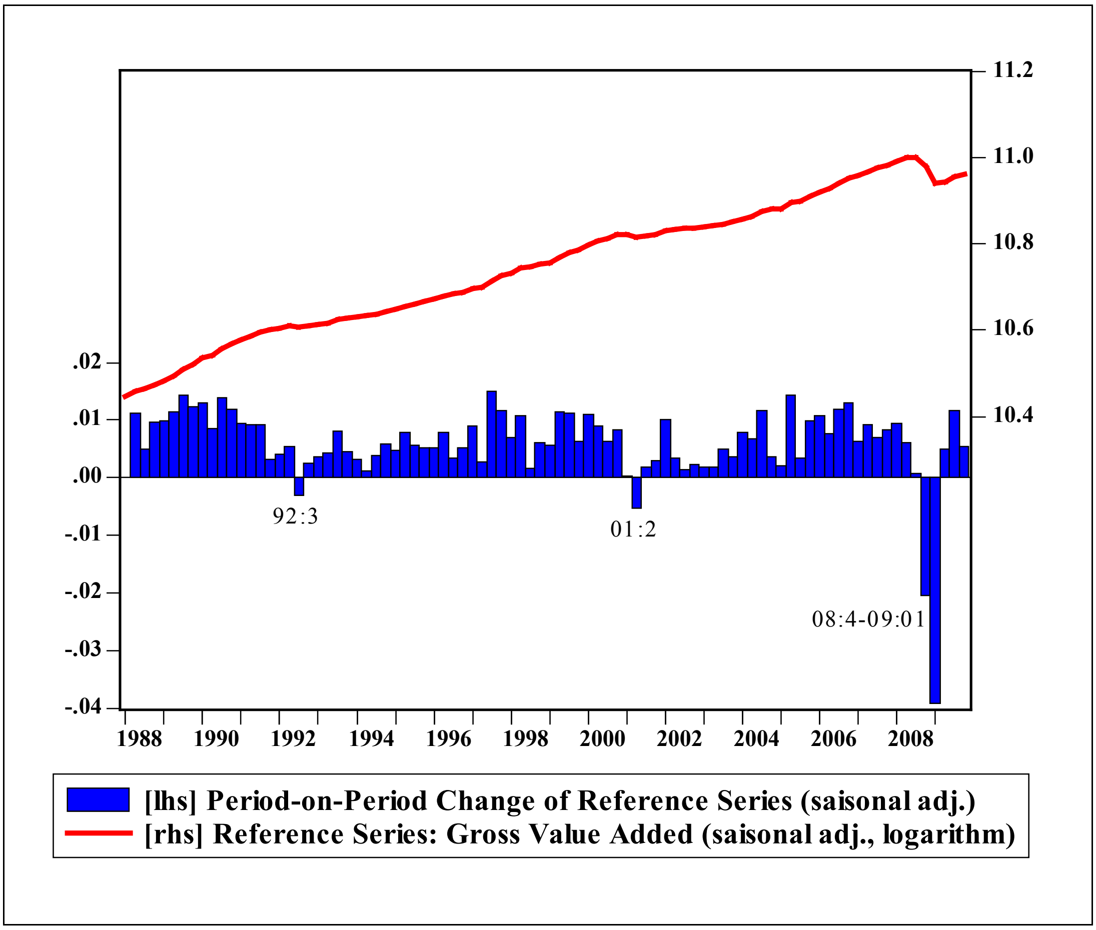
Appendix A presents the results for the other sectors as well. In short, the data reveal that the construction and energy sector has a share of roughly 10 per-cents with the proportion being on average the lowest in Vienna (7.2%) and highest in Burgenland (13.0%). Further, it can be observed that a moderate decline of around one-percent in the share of the construction and energy sector took place between 1996/97 and 2008/09. The retail industry constitutes around 11 to 16 per-cent to total GVA_{REG}. An industry share above the Austrian average, which is 13.1%, can be found for Salzburg, Vienna and Lower Austria with a proportion of 16.0%, 15.3%, and 14.1%, respectively. On the other end, Vorarlberg and Tyrol, for example, have a share in their retail sector of around 11 per-cents. The group of other market orientated services, which includes sectors such as tourism, transport, financial services or real estates, has a share in GVA_{AT} of a bit more than one third. By looking on the regional aggregate, it can be seen that this share is, as one would expect, higher for Länder which belong to the group of "Tourismusbundesländer". These are, amongst others, Vienna, Salzburg and Tyrol which have a proportion in their GVA_{REG} of 42.1%, 37.4%, and 39.9%, respectively. However, it is to note that by looking on a more disaggregated level the high share in the case of Vienna is also reflected by the fact that Vienna plays a dominant role within Austria in the real estate and financial services sector. About 40% of Austrians total gross value added for each of these sectors is made up in Vienna. As such, these two sectors contribute together more than 30% to Vienna's GVA_{REG} and as a consequence producing the high share in the group of other market orientated services.

The original series have been transformed seasonally adjusted with Tramo-Seats[26]. Unit root tests showed that all series, i.e. GVA_{AT} and individual GVA_{REG}, are as one would expect integrated of order one. The order of integration has been determined by the Augmented Dickey-Fuller (ADF) test.[27] See Appendix B for details on the unit root test results obtained. Further, for all series used in this study the natural logarithms are taken, i.e. y_t=ln(Y_t).

Figure 4 (upper panel) shows the reference series, GVA_{AT}, in seasonal adjusted and natural logarithm form. The single indicator of GVA_{AT} is used in this study as a proxy for representing economic activity of the Austrian economy. As one can see, GVA_{AT} exhibits an almost constant upward growth trend with only minor disturbances, except the period at the end of the sample. The sudden decline in GVA_{AT} at around 2008/09 reflects the shakedown in economic activity as a consequence of the economic crisis prevailing at this time. By looking at the period-on-period change in economic activity (see Figure 4 – bottom panel) it can be observed that there exist only three periods of negative growth. One can be found in the third quarter of 1992 and the next is located in the second quarter of 2001. The last period of negative growth in the level of economic activity ranges from 2008:Q4 to 2009:Q1, which marks actually the only period of two consecutive quarters of negative growth.

[26] The program Tramo-Seats was developed by Gomez & Maravall in the 90s. Information and sources of the program are found at www.bde.es/servicio/software/softwaree.htm.
[27] The appropriate lag length in the ADF specification has been automatically determined using the Schwarz Info Criterion (SIC) with the maximum number of lags set to 15. The critical values for the ADF t-statistic at the 1%, 5% and 10% level used are -3.45, -2.87 and -2.57, respectively.

Figure 4: Reference Series - Austrian Gross Value Added, GVA_{AT}



4.2 Constructing a business cycle chronology for the reference series GVA_{AT}

As discussed in Section 2, in order to identify turning points in the cyclical component or level of economic activity it is important to select, if one follows the deviation cycle approach, a proper method for trend elimination, and, irrespective of the business cycle approach applied, a dating procedure. Given the various techniques available for dating the business cycle I decided to identify turning points in the reference series using different methods following either the classical or the deviation cycle approach. More specifically, in the case for the classical cycle, I derive a business cycle chronology using the 'newspaper' (NP) method and the quarterly version of the Bry-Boschan (BBQ) routine as proposed by Harding and Pagan (2001, 2002). In the case of the deviation cycle approach, the cyclical component has been extracted with the aid of the software tool BUSY[28] by the following three non-parametric filtering techniques: (1) first-order differencing, (2) HP filter, and (3)

[28] The program BUSY (Release 4.1) is a software tool developed by the European Commission (FP5). It has been designed and implemented to serve as an official tool for the analysis of economic cycles (Fiorentini and Planas, 2003). The functionality embedded in the program allows the identification of the business cycle component in a series as well as the description, estimation and prediction of cycles of other variables in relation to a reference cycle. The two types of statistical procedures implemented are: an NBER-type of analysis and a dynamic factor model approach. Source: http://eemc.jrc.ec.europa.eu/EEMCArchive/Software/BUSY.

BK filter. The dating procedure applied to the business cycle component is a modified version of the original Bry-Boschan routine as implemented in BUSY.[29] The minimum cycle length has been set to 5 quarters and the one for the minimum phase length to 3 quarters.

The business cycle chronologies obtained from the five different dating procedures are shown in Table 4. At first glance it is apparent that the numbers of turning points identified varies quite significantly between the various methods.

Table 4: Turning Points in the Reference Series GVA_{AT}

Classical Cycle Approach													
NP 1)			▼92:3									▲08:3	▼09:1
BBQ 2)		▲92:2							▼01:2			▲08:3	▼09:1
Deviation Cycle Approach 3)													
1st-Diff.		▲89:2	▼92:2			▲97:2			▼02:2			▲06:3	▼08:4
HP filter	▼88:3	▲91:3	▼95:1	▲96:2	▼97:2			▲00:4	▼03:4			▲08:2	
BK filter	▼89:1	▲91:3	▼94:4	▲95:4	▼97:1	▲98:1	▼99:1	▲00:3	▼03:3	▲04:3	▼05:3	▲08:1	▼09:2

Note: ▲..indicates peak / downturn; ▼..indicates trough / upturn.
1)-2) Peaks and troughs identified according to the formulas described in Section 2.4.1.
3) Turning points identified based on NBER method implemented in BUSY software.
Source: Own calculations / BUSY software.

4.2.1 Classical Cycle Approach

Not surprisingly, and as expected, the dating procedures following the classical approach only identify turning points around periods of decline in economic activity. As already displayed in Figure 4 above, only three periods of declining activity can be observed in GVA_{AT}. Therefore, a maximum number of three troughs are possible in this category. The NP method marks 1992:Q3 as trough but does not reveal 2001:Q2. This is correct because turning points have to alternate and no peak point occurred in between. At the end of the sample, a peak has been identified at 2008:Q3 which is the quarter preceding the decline occurring in the two quarters around the turn of 2008-09. Finally, the end of the most recent recessionary phase has been marked by the NP method at the first quarter of 2009. This trough as well as the peak found in 2008:Q3 is in line with the turning points obtained using the BBQ dating procedure. However, there exists a difference at the other two periods of declining economic activity. The BBQ method identifies a peak in 1992:Q2 as opposed to the trough in 1992:Q3 found by the NP method. The difference rests in the underlying dating rule.

[29] The modifications are required to the original Bry-Boschan procedure in the case of quarterly data frequency. See Appendix C for a brief outline of the Bry-Boschan (1971) dating procedure implemented in BUSY.

In general, one can say that the results obtained following the classical cycle approach are quite similar and robust between the NP and BBQ procedures. But a major drawback exists. Given the sparse number of turning points obtainable in a time series with an underlying steady growth pattern one has to bear in mind that inference, for example, about cyclical co-movement between series may be problematic or misleading. Further, as shown in Table 5 it is hard to interpret turning point statistics, such as the average duration of phases and cycles, when only a few cyclical turns are at hand. For example, the NP method reports an average duration of contractionary phase of 2 quarters and expansionary phase of 64 quarters. In the case for the BBQ method these measures reveal 19 and 29 quarters, respectively.

Table 5: Average Duration of Phases and Cycles of the Reference Series GVA_{AT}

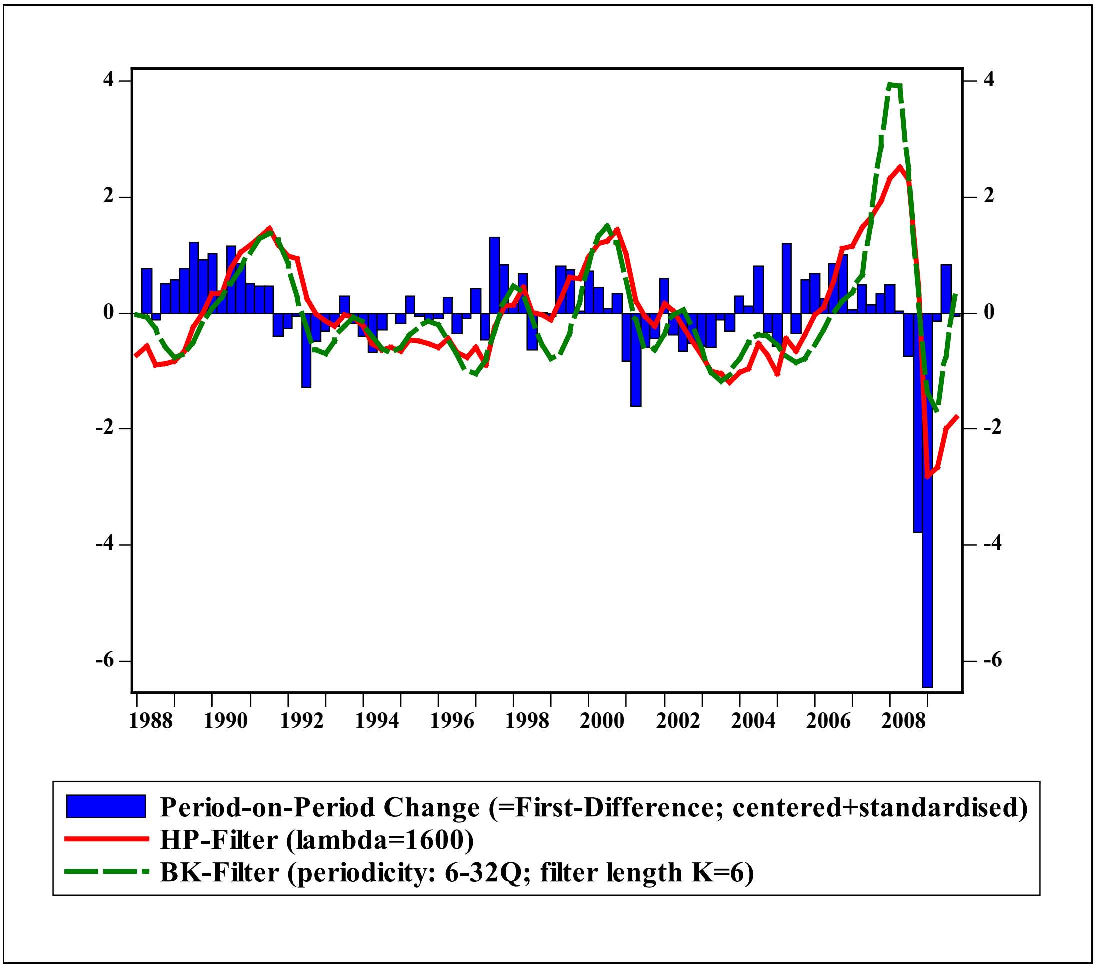
	Classical Cycle Approach		Deviation Cycle Approach		
Reference Series GVA_{AT}	NP	BBQ	1st-Diff.	HP filter	BK filter
Total Nr. of Turning Points					
▲ Peaks / Downturns	1	2	3	4	6
▼ Troughs / Upturns	2	2	3	4	7
Phases [1)]					
[▲-▼] Contraction	2.0	19.0	13.7	10.0	7.2
[▼-▲] Expansion	64.0	29.0	18.5	12.3	6.3
Cycles [2)]					
[▲-▲] Peak-to-Peak	-	65.0	34.0	21.7	12.4
[▼-▼] Trough-to-Trough	66.0	31.0	32.5	19.7	12.7

[1-2)] Average durations shown are in quarters.
Source: Own calculations / BUSY software.

4.2.2 Deviation Cycle Approach

Before contrasting the turning point chronologies and statistics (see again Table 4-5) derived from the three de-trending methods it is worth showing the different business cycle components extracted by each method. As can be seen in Figure 5, the first-order differenced data show the most erratic picture. The HP- and BK-filtered series move quite similar with some exception occurring in the mid and late 90s as well as around the year 2004/05. If I compare the data further, it shows that the HP-filtered series is a bit ‘noisier’ compared to the BK counterpart. This rests on the fact that the HP filter does not remove the high-frequencies by construction.

Figure 5: Deviation Cycle Approach - Extracted Business Cycle Components



The representation of the business cycle component in Figure 5 should provide some indication about the potential location of turning points in the cycle. For example, the cyclical peaks shown in HP- and BK-filtered data in the year 1991, 2000, or 2008 represent a good candidate for a turning point. As such it should be expected to find these peaks reflected in their respective business cycle chronology obtained. However, the illustration in Figure 5 should also make clear that phases in the different cycles exist where it is not that clear whether a turning point is present or not. The period between 1993 and 1997 or the two years of 2004-05 may be seen as such an example.

As already noted, it can be observed by looking at the business cycle chronologies shown in Table 4 that the number of turning points obtained varies across the different business cycle extraction methods. Applying the Bry-Boschan dating procedure implemented in BUSY to the BK-filtered data detects the largest number of turning points; in total 13 cyclical turns. In contrast to the BK-filtered data the dating routine identifies in using HP-filtered data two cycles less, missing one occurring in the years 1998-99 and one between 2004 and 2005.

Using the first-order differenced data as input into the turning point detection routine produces the lowest number of turning points, namely 6. But it can be observed that the turns in the cyclical component appear earlier compared to the HP and BK filter. This observation is in line with a general property of growth rate cycles[30], which is that turning points in growth rate cycles usually tend to lead those of other methods (Boehm and Liew, 1994). However, this nice property is not that rewarding given the rather erratic movements in the series. This may also explain the fewer turning points detected using this de-trended series because of the remaining noise in the data.

Comparing the individual turning points detected between HP- and BK-filtered data, but not considering the two missing cycles in the HP filter chronology, it can be seen that all cyclical turns occur within a time frame of ± two quarters. As such the average cycle and phase duration should be similar in magnitude. But given the fewer turning points detected for HP-filtered data these statistics are, as displayed in Table 5, significantly different. For example, a contractionary phase lasts on average about 7 quarters for BK-filtered data but has duration of 10 quarters in the case of HP-filtered data. Moreover, a full cycle, e.g. from peak-to-peak, has an average length of a bit more than 12 quarters by looking at the BK extracted business cycle component. But on the other hand it takes nearly 22 quarters for such a cycle to finish if one uses the HP-filtered data.
In overall, the turning point chronology derived for the reference series GVA_{AT} is similar to those found in other studies identifying business cycle turning points in the Austrian economy (see e.g. Artis et al., 2004b; Scheiblecker, 2007).

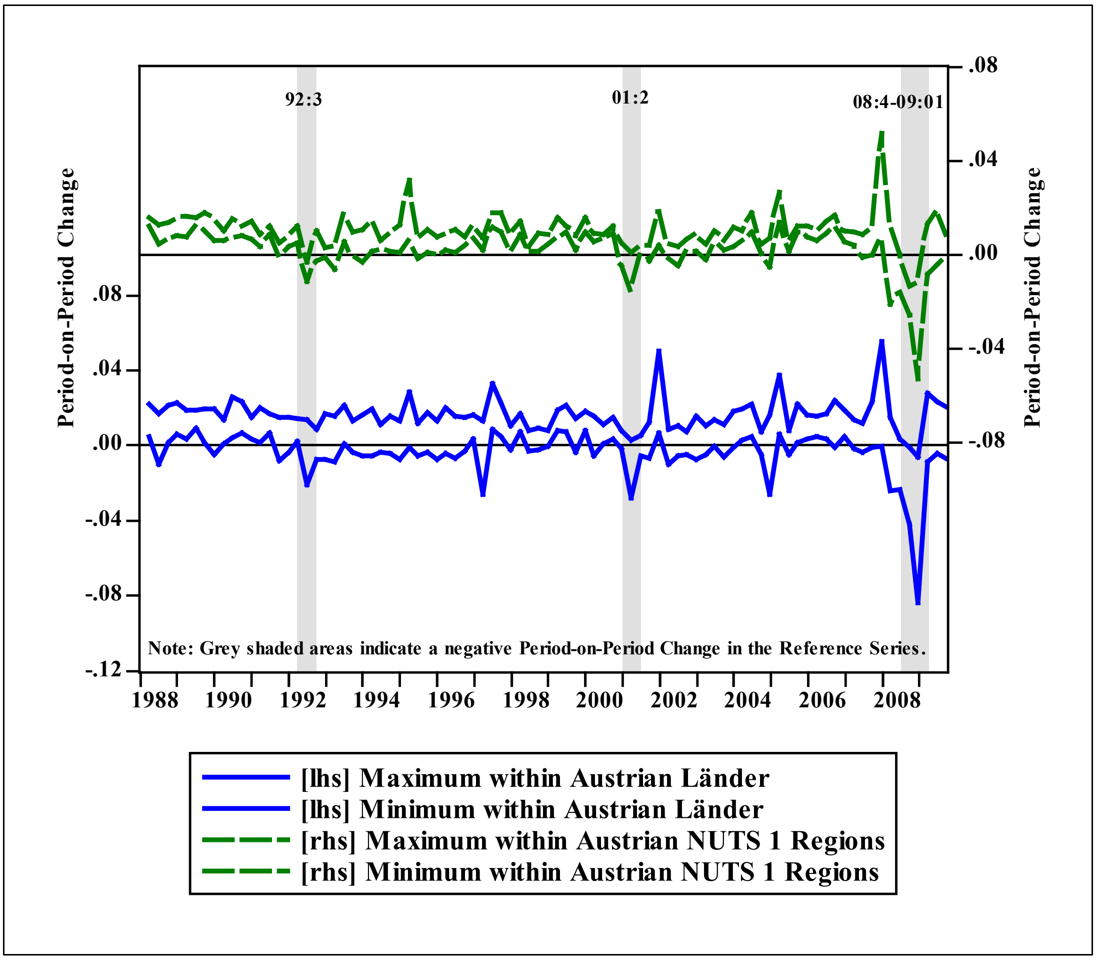
4.3 Dating the Regional Business Cycles

Having identified the business cycle chronology for the reference series, GVA_{AT}, the next step in the analysis is to obtain a sequence of turning points for the Austrian Länder and NUTS level 1 aggregates. For a starting point, it is interesting to determine how steady the regional aggregates of gross value added, GVA_{REG}, evolve over time and how does this compare to the national aggregate. To remember, for the reference series of Austrian gross value added only three periods of declining economic activity showed up in the data. In order to get a first idea of the possible different regional growth pattern it is best to look on period-on-period changes in the seasonal adjusted GVA_{REG} series. If regional economic activity is somehow similar to

[30] Remember, taking first difference of a series y_t, i.e. $\Delta y_t \equiv y_t - y_{t-1}$, where y_t=ln(Y_t), can be interpreted as growth rates.

the national aggregate only a few quarters of negative growth should be present. Figure 6 displays the highest and lowest period-on-period change in the respective quarter for the Austrian Länder (bottom panel) and NUTS level 1 aggregates (top panel). It can be observed that there exists quite a big spread in the period-on-period growth in the level of economic activity between the Austrian Länder. This difference narrows down in the case for the NUTS level 1 series.

Figure 6: Period-On-Period Changes in Regional Gross Value Added



By looking at the sign of the change in economic activity, Figure 6 reveals an interesting point. In most of the periods, especially from 1992 onwards, there exists at least one Austrian region which has a negative quarter-on-quarter change. But at the same time other regions exhibit positive growth in economic activity. Based on this simple illustration it can be assumed that the Austrian regions exhibit quite dissimilar business cycles and, with respect to the national aggregate, GVA_{AT}, the regional cycles may convey turning points not matching those obtained in the reference series.

Next, in order to derive a consistent turning point chronology for the Austrian regions I decided to use the HP filter for extracting the business cycle component, hence, following the deviation cycle approach.[31] As such the turning points identified in the HP-filtered reference series, GVA_{AT}, serve as the benchmark chronology.

Figure 7: HP-filtered Business Cycle Component for Austria and Austrian Länder

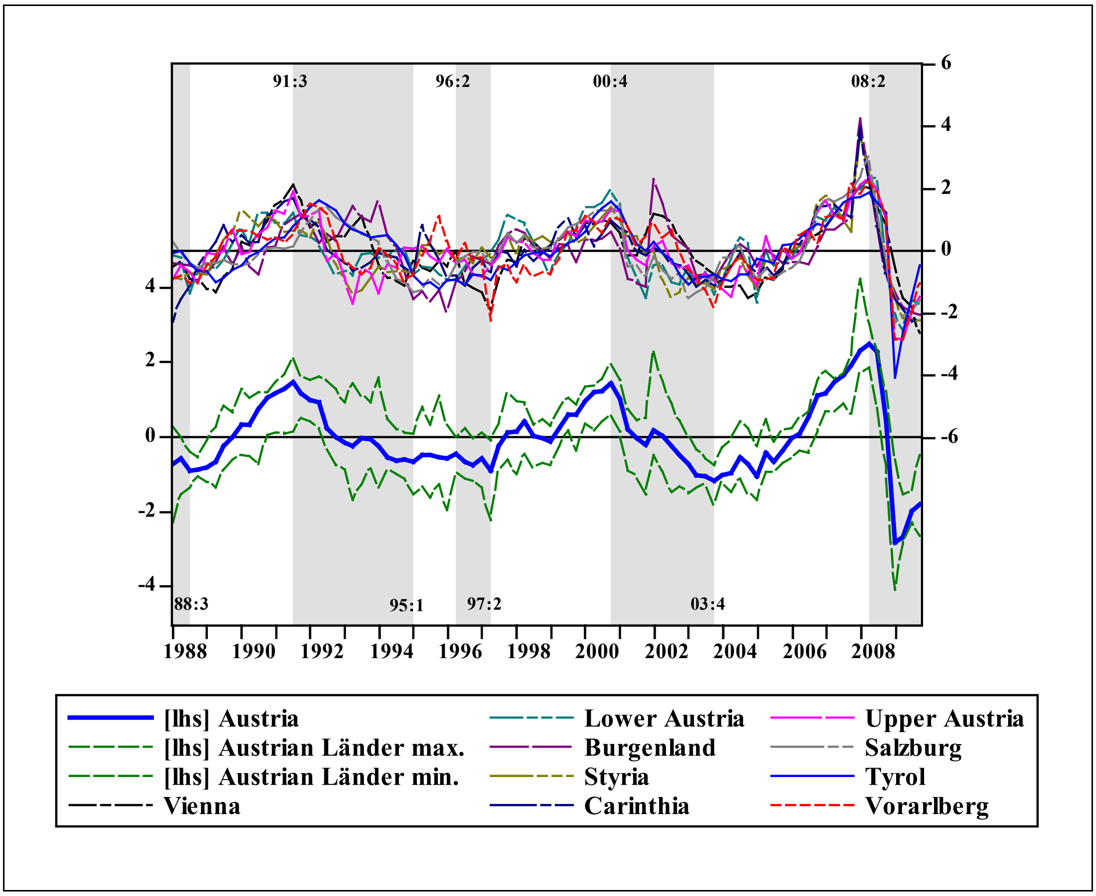


Figure 7 illustrates in the bottom panel the HP-filtered reference series, GVA_{AT}, in combination with the highest and lowest value of the business cycle component obtained amongst the Austrian Länder. This is done to reinforce the finding from Figure 6 which shows that at nearly any point in time, output in some Länder is above trend, while in others it is below trend. In other words, providing a very heterogeneous set of business cycles carried in the Austrian Länder data. The upper panel in Figure 7 depicts this variation in the individual business cycle components.

Using the HP-filtered business cycle component as input to the Bry-Boschan dating procedure provides a set of turning points for each region of interest. Table 6 shows the complete list of

[31] For the HP filtering procedure of the regional data series I use again the smoothing parameter λ=1600 for extracting the business cycle component.

each regions business cycle chronology. Based on the regional variation found in the data it is expected that this difference is also reflected in the detected turning points. On the one hand, the business cycle chronology should deviate from the chronology identified in the reference series, GVA_{AT}. But on the other hand, the turning points should also differ amongst the regions. A first sight at Table 7 depicts that there exit quite a few ‘holes’ in the turning point calendar established. In other words, the number of turning points detected varies considerably across the regions.

Table 6: Business Cycle Chronology for the Austrian Regions [1)]

	Regions	Turning Points [2)]												
	Austria	▼88:3	▲91:3	▪	▪	▼95:1	▲96:2	▼97:2	▲00:4	▪	▪	▼03:4	▲08:2	▪
NUTS 2	Vienna	▼89:2	▲91:3	▼92:3	▲93:3	▼94:4	▲96:2	▼97:2	▲00:3	▪	▪	▼04:4	▲08:1	▪
	Lower Austria	▼88:3	▲91:3	▼93:2	▲94:4	▼96:1	▲97:4	▼99:1	▲00:4	▪	▪	▼05:1	▲08:2	▼09:2
	Burgenland	▼89:1	▪	▪	▲94:1	▼96:1	▲98:1	▼99:1	▲00:4	▪	▪	▼06:3	▲08:1	▪
	Styria	▪	▲90:1	▼93:2	▲95:3	▼96:4	▪	▪	▲00:4	▪	▪	▼02:3	▲08:1	▪
	Carinthia	▪	▲91:3	▼93:2	▲95:2	▼96:3	▪	▪	▲99:3	▼03:2	▲04:3	▼05:3	▲08:1	▪
	Upper Austria	▪	▲91:3	▼93:2	▲95:2	▪	▪	▼98:4	▲00:4	▪	▪	▼04:2	▲08:2	▼09:2
	Salzburg	▼88:4	▲92:3	▪	▪	▼95:1	▲97:4	▼98:4	▲01:1	▼03:1	▲04:3	▼05:3	▪	▪
	Tyrol	▼89:2	▲92:2	▪	▪	▼95:4	▪	▪	▲00:4	▪	▪	▼03:1	▪	▪
	Vorarlberg	▼88:3	▲90:1	▪	▪	▼94:4	▲95:4	▼97:2	▲00:1	▪	▪	▼03:4	▲08:2	▼09:2
NUTS 1	Eastern Austria	▼89:1	▲91:3	▪	▪	▪	▪	▼97:2	▲00:4	▪	▪	▼05:1	▲08:1	▪
	Southern Austria	▪	▲91:3	▼93:2	▪	▪	▲95:2	▼96:3	▲00:4	▪	▪	▼03:2	▲08:1	▪
	Western Austria	▼88:4	▲92:1	▼95:1	▪	▪	▲96:2	▼97:2	▲00:4	▪	▪	▼03:4	▲08:2	▪
	Industrial Austria	▪	▲91:3	▼93:2	▲95:2	▼96:2	▲97:4	▼99:1	▲00:4	▪	▪	▼03:4	▲08:2	▪

[1)] Business cycle component extracted using HP filter (lambda=1600).
[2)] Turning points identified based on NBER method implemented in BUSY software;
▲..indicates peak / downturn; ▼..indicates trough / upturn; ▪ .. indicates that no turning point has been identified.
Source: Own calculation / BUSY software.

1988 - 1995

In referring to the turning points found in the Austrian aggregate of gross value added it is apparent that some regions have an additional cycle in some period but do not exhibit a cyclical phase in another period. For example, in the long lasting contractionary period between 1991:Q3 and 1995:Q1 found in GVA_{AT}, all Länder except Salzburg, Tyrol and Vorarlberg mark a cyclical up and downturn in between. According to the chronology obtained, Lower Austria, for example, ends its downturn in the second quarter of 1993 and finds the subsequent peak located at 1994:Q4. As a consequence, the following trough does not occur until 1996:Q1. This means a delay compared to GVA_{AT} of a full year. Similar turning points have been obtained within this period for other members classified as

“Industriebundesländer”, e.g. Styria or Upper Austria. The ‘industrial’ aggregate matches those cyclical turns accordingly. Vorarlberg in contrast, for which no intermediate turns have been identified from 1991 to 1995, started its downturn already at the beginning of 1990, i.e. almost a year and a half earlier than the national aggregate, and marks the end of this recessionary phase in 1994:Q4. However, contrary to Vorarlberg, Tyrol started the contractionary phase in the second quarter of 1992, which is about three quarters later than the reference series and more than two years delayed compared to the neighbour region of Vorarlberg. Furthermore, the upturn detected in 1995:4 for Tyrol, hence, ending the below trend regime, is again shifted by about a year.

Already this brief outline of the regional turning points obtained for the period 1991-1995 allows some remarks with respect to the differences embodied in the data: (1) it appears that the size of the region matters (e.g. Lower Austria vs. Vorarlberg); (2) regions with similar sectoral structure, e.g. high share of the manufacturing sector, exhibit similar cyclical characteristics; (3) neighbouring Länder do not necessarily match in their turning points (e.g. Vorarlberg vs. Tyrol); and (4) it appears that there exists some kind of East-West difference exist as has been shown with the extra cycle detected in most of the Eastern and Southern Länder.

However, it has to be noted that in order to get a deeper understanding of the cyclical differences prevailing at the regional aggregate one has to look closer and analyse the economic conditions present at that time in the respective regional area. For example, it might be that the reason for ending a contractionary phase in one region is primarily a result of a specific regional policy intervention. Or it might be the case that external factors, i.e. factors outside the national border, for example economic conditions present in important in-bound tourism countries, may affect one region more than the others. But this analysis at that level is beyond the scope of this work. Therefore, the discussion of the regional business cycle chronologies focuses primarily on a stylised description of the cyclical movements.

Having highlighted some differences in the characteristics of the turning points for the beginning of the sample period it is now worth looking if this picture is somewhat different in the second half of the 90s and how it looks like from 2000 onwards.

1995-2000

The business cycle chronology for the reference series, GVA_{AT}, shows a short lived contractionary phase between 1996:Q2 and 1997:Q2. Comparing these turning points with the regional chronologies allows the following classification with respect to the timing of the cyclical turns. Vorarlberg enters this recessionary phase two quarters earlier but finds its peak also around 1997:Q2. Vienna is the only region which mirrors the Austrian phase at this period of time. Lower Austria and Salzburg start their downturn at the end of 1997, with Burgenland following one quarter afterwards. Note that these regions turn below their trend after the Austrian business cycle has already entered the subsequent expansionary phase. Finally, there are regions at hand, namely Styria, Carinthia and Tyrol, which remained still in an above trend regime after their respective business cycle turned up in 1996/97, thus, these Länder bypass the national contraction. However, independent of the turning points detected up to 1999 all regions mark the end of their respective expansionary phase somewhere in the year 2000. For example, the national aggregate, GVA_{AT}, reaches its peak in 2000:Q4 before turning down below trend until 2003:Q3. The Länder Lower Austria, Burgenland, Styria, Upper Austria and Tyrol are exactly in line with the downturn identified in GVA_{AT}. This holds also for the NUTS level 1 aggregates. Vienna, Carinthia and Vorarlberg form the group of regions which have their downturn prior the national aggregate whereas only Salzburg lags by a short period of time.

If one looks at the turning points detected in the 90s using the NUTS level 1 aggregates it can be observed that these aggregates do not necessarily mirror the turning points identified in their incorporated regions. For example, Eastern Austria, which contains Vienna, Lower Austria and Burgenland, is according to the chronology derived in a below trend phase ranging from 1991:Q3 to 1997:Q4, i.e. remaining in some questionable seven years of a contractionary phase. The aggregate of Southern Austria provides a contrary picture. This NUTS 1 aggregate matches the turning points with their respective regions, namely Styria and Carinthia, quite well. Their individual turning points deviate if at all by a maximum of two quarters. Further, the turning point chronology for the 'industrial' aggregate basically reflects the turning points of Lower Austria one-by-one, although Lower Austria does not make up the highest proportion in this top-level aggregate.[32] Finally, and probably the most surprising observation, is the fact that Western Austria follows essentially the same business cycle chronology as the Austrian aggregate, GVA_{AT}. One simple line of argument might be that this

[32] On average, the industrial aggregate is made up of regional data representing 34% Upper Austria, 31% Lower Austria, 25% Styria and 10% Vorarlberg.

aggregate is made up of Länder which have a high share in a broad spectrum of the Austrian economy: tourism is most important in Tyrol, Salzburg has an above average share in the retail industry and services sector and Upper Austria as already seen is a very good representative of the manufacturing sector within Austria.

2000-2009

The structure of the business cycle chronology following the period of the 90s is rather simple. First, as already mentioned before, all Austrian Länder as well as the NUTS 1 aggregates basically have their cyclical peak around the third/fourth quarter of 2000. Only Carinthia and Salzburg deviate from this general notion by as much as four quarters. The below trend phase continues, for example, for the economy wide aggregate, GVA_{AT}, until 2003:Q4. This marks the third recessionary phase in the reference series. Comparing this trough with the Länder turning points detected for that period the following can be observed. The spread between the first and last region which turns back above their trend growth is quite broad. Styria, for example, ends its contractionary phase as early as 2002:Q3. But Burgenland, on the other side of the scale, takes until 2006:Q3 to re-gain momentum.

According to the chronology at hand the long period of economic growth experienced from 2004 onwards finds its end at the beginning of 2008. For the reference series, GVA_{AT}, this means that a cyclical downturn is located at 2008:Q2 with other regions, except Salzburg and Tyrol, following closely. For these two Länder no such turning point has been identified.

Finally, the dating procedure yields for three regions, namely Lower Austria, Upper Austria and Vorarlberg, a subsequent trough at 2009:Q3. But it has to be mentioned that turning points near the beginning and end of the sample period have to be taken with caution and may provide wrong signals. As such the cyclical upturn identified for these three regions at the very end of the sample should therefore be discarded.

Overall, it can be said that the business cycle chronology for the Austrian regions gives a rather unsystematic pattern in the 1990s and does not uniformly match the turning points identified in the Austrian aggregate, GVA_{AT}. However, from 2000 onwards a higher degree of turning point synchronisation can be observed. The next part of the empirical analysis is concerned with the question: Have the Austrian regional business cycles become more synchronised, i.e. are they converging or not?

4.4 Measuring Regional Business Cycle Synchronisation

With the presentation of the business cycle chronologies (see again Table 6) it was made clear that by just looking at the turning point dates derived and its composition that some kind of synchronisation took place. In order to describe the degree of comovement the following analysis is based on cross-correlation statistics out of the time-series domain, the coherence measure as its counterpart in the frequency domain, and the concordance statistic (see Section 3 for a formal description of these statistics).

But to start with I take advantage of the turning points detected and use them to derive some indicators which should give information about the symmetry in the cyclical dynamic (Fiorentini and Planas, 2003). As such the average duration of phases and cycles along with the average and median distance between turning points identified in the regions and the Austrian wide aggregate, GVA_{AT}, have been calculated. Table 7 provides an overview of the turning point statistics obtained.

Table 7: Turning Point Statistics of the Austrian Regions w.r.t. GVA_{AT} [1)]

		Average lag [2)]		Median lag [3)]		Phases and Cycles (avg. duration)				Total Nr. of Turning Points	
	Regions	▲	▼	▲	▼	[▲-▼]	[▼-▲]	[▲-▲]	[▼-▼]	▲	▼
	Austria					10.0	12.3	21.7	19.7	4	4
NUTS 2	Vienna	-0.5	+1.5	-0.5	+1.5	7.5	9.0	15.8	14.8	5	5
NUTS 2	Lower Austria	-1.5	+3.0	+0.0	+2.0	7.6	9.0	16.0	15.8	5	6
NUTS 2	Burgenland	+2.0	+5.7	-0.5	+3.0	11.7	10.3	18.0	22.7	4	4
NUTS 2	Styria	-2.5	-4.7	-2.0	-6.0	8.3	15.7	23.3	18.0	4	3
NUTS 2	Carinthia	-2.5	-2.5	-2.5	-2.5	7.8	8.8	15.8	15.7	5	4
NUTS 2	Upper Austria	-1.0	+0.3	+0.0	-2.5	9.8	10.7	21.7	20.7	4	4
NUTS 2	Salzburg	+3.7	+1.0	+2.5	+0.5	6.5	10.3	15.3	16.0	4	5
NUTS 2	Tyrol	+1.5	+1.0	+1.5	+0.0	11.5	16.0	34.0	27.0	2	3
NUTS 2	Vorarlberg	-2.8	-0.3	-2.5	+0.0	11.0	9.8	23.7	20.0	4	5
NUTS 1	Eastern Austria	-0.3	+2.3	-0.5	+1.0	20.0	12.0	32.5	31.5	3	3
NUTS 1	Southern Austria	-1.3	-2.5	-0.5	-2.5	7.3	14.7	21.3	19.5	4	3
NUTS 1	Western Austria	+0.5	+0.3	+0.0	+0.0	9.3	12.5	21.0	19.3	4	4
	Industrial Austria	-1.0	-2.0	+0.0	-2.0	7.0	9.8	16.0	13.3	5	4

[1)] Turning point statistics are based on the business cycle chronology presented in Table 6.
▲..indicates peak / downturn; ▼..indicates trough / upturn.
[2-3)] The plus (minus) sign denotes a lag (lead) duration (in quarters) with respect to the reference series GVA_{AT}.
Source: Own calculation / BUSY software.

The most interesting findings are summarised as follows. First, some regions tend to lead the Austrian business cycle at both cyclical up- and downturns. This especially holds for Southern Austria, where Styria and Carinthia have a lead time of roughly between two and four quarters. Vorarlberg, for example, leads the national aggregate at peaks but tends to coincide at troughs. Next, the industrial regions show on average a leading behaviour but, for example, Lower Austria lags behind of three quarters at a cyclical trough. This is quite surprising because it would have been expected that the manufacturing sector dominates the national business cycle. As a consequence, Länder with a high manufacturing proportion in their respective economic activity should lead the cycle in both directions. Finally, the NUTS level 1 aggregate of Western Austria exhibits an almost zero mean and median lag at both peaks and troughs. In other words, Western Austria mirrors the turning points in the reference series about one-by-one. This reinforces a previous finding that the regions of Western Austria in aggregation may be seen as a proxy for the national business cycle.

4.4.1 Cross-correlations and Coherence

For the assessment of the degree of linear comovement in the business cycle component between the Austrian regions and the national-wide aggregate, GVA_{AT}, I first look at the contemporaneous cross-correlations measure.[33] In order to obtain robust results I decided to calculate correlation coefficients based on different sample periods. In the first run, I use the full sample (1988:Q1-2009:Q4). Next, I split the sample in the middle to check the degree of change in the linear relationship from one period to another. Finally, I calculate the contemporaneous cross-correlation based on a rolling 28 quarters window to assess the degree of convergence for the Austrian Länder.

The detailed results are shown in Table 8. The highest correlation coefficient using the full-sample is found with 0.91 in Upper Austria. This is followed by Carinthia and Vorarlberg with each having a coefficient of 0.84. On the other side of the scale ranks Burgenland with a value of 0.65. Bearing in mind the differences identified in the business cycle chronologies it has to be assumed that the linear relationship obtained for this 20 year period overstates the 'true' one prior the year 2000 and underestimates the comovement thereafter. This is confirmed if one looks at the cross-correlation coefficients obtained for the two-subsample case. As expected, the coefficients for the period 1988-1998 are lower, most often quite significantly, compared to 1988-2009 or 1999-2009. By looking at a Länder ranking, Vienna, for example, ranks amongst the least synchronised Länder in the full-sample case but exhibits the highest linear relationship amongst the Länder concerning the years 1988-1998.

[33] Note that I have used an adjusted reference series for each pair-wise calculation of the cross-correlation coefficient between a region and the reference series, GVA_{AT}. In following Schirwitz et al. (2009c) I subtracted the value for the respective region from the reference series prior the estimation in order to avoid 'spurious' high correlation coefficients.

Table 8: Business Cycle Synchronisation Statistics for the Austrian Regions [1)]

	Regions	Cross-Correlation 1988–2009		1988–1998		1999–2009		rolling window [2)] min.		max.		Coherence Periodicity 6 to 32Q [3)]	
NUTS 2	Vienna	0.75	8	0.75	1	0.79	8	0.35	99:2	0.85	09:4	0.75	6
	Lower Austria	0.82	6	0.65	4	0.87	7	0.17	99:2	0.92	09:4	0.82	3
	Burgenland	0.65	9	0.52	8	0.71	9	0.27	03:1	0.81	09:4	0.49	9
	Styria	0.81	7	0.60	5	0.88	6	0.12	99:2	0.91	09:4	0.78	4
	Carinthia	0.84	2	0.73	3	0.89	5	0.34	99:2	0.94	07:3	0.82	2
	Upper Austria	0.91	1	0.73	2	0.96	1	0.20	99:2	0.97	09:4	0.89	1
	Salzburg	0.82	5	0.48	9	0.92	4	0.44	95:1	0.94	09:4	0.73	8
	Tyrol	0.83	4	0.55	7	0.93	2	0.30	99:4	0.95	08:3	0.75	7
	Vorarlberg	0.84	3	0.57	6	0.93	3	0.03	99:3	0.96	09:4	0.76	5
NUTS 1	Eastern Austria	0.89	2	0.86	2	0.90	3	0.62	99:2	0.94	08:4	0.94	2
	Southern Austria	0.82	3	0.68	3	0.86	4	0.20	99:2	0.89	09:4	0.83	4
	Western Austria	0.90	1	0.90	1	0.91	2	0.78	99:2	0.97	04:4	0.97	1
	Industrial Austria	0.82	4	0.50	4	0.94	1	-0.08	99:2	0.96	09:4	0.91	3

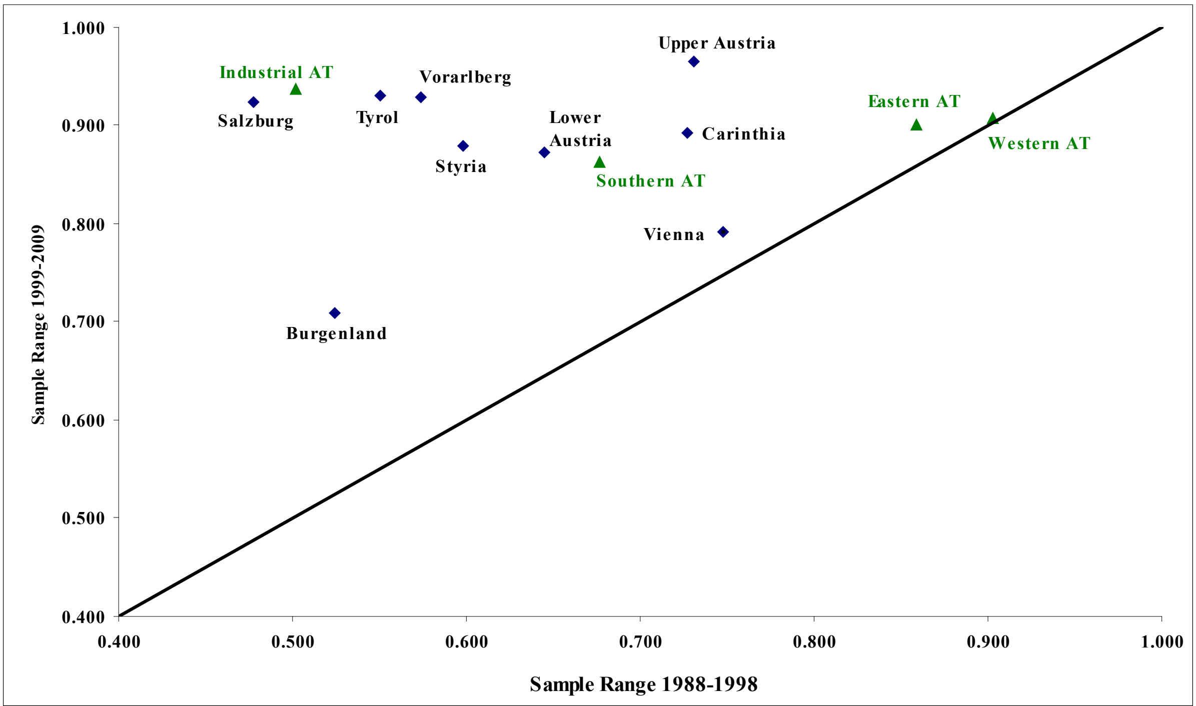
[1)] Synchronisation measures based on the regions business cycle component extracted using HP filter (lambda=1600).
The reference series, GVA_{AT}, has been adjusted for each region such that the regions value has been eliminated from GVA_{AT}.
Grey shaded columns indicate the relative position of each region within the set of regions.
[2)] A rolling window of 28 quarters is used. First value obtained for 1994:Q4.
The dates 'YY:Q' next to the min/max correlation coefficients show the quarter in which these values appear.
[3)] The coherence is averaged across the business cycle frequencies in the range between 6 to 32 quarters.
Source: Own calculation.

The correlation coefficients for both subsamples are sown as well in Figure 8**.** Points lying above the 45-degree line indicate an increase in the comovement from on period to the other. As can be seen, the increase in the linear relationship is quite substantial for most regions. For example, all four Western regions have a cross-correlation coefficient in the 1999-2009 period of more than 0.90. Remarkable, Salzburg changed its coefficient from 0.48 to 0.92. The least linear relationship can be obtained for Burgenland, but it still increased its coefficient from 0.52 to 0.71.

Not much of a change in the linear relationship can be observed at the NUTS 1 level for Eastern and Western Austria. Both aggregates remain with their cross-correlation coefficient at around 0.90, hence, representing a high degree of comovement in both subsamples. Contrary, the 'industrial' aggregate showed a weak synchronised pattern during the first 10 years but changed its coefficient to as high as 0.94.

The cross-correlation results based on the 7-year moving average window show that the linear relationship changes quite significantly over the sample period as indicated by the minimum and maximum values for each region. The values obtained range from close to unity down to zero. In other words, the business cycle components of the reference series and its regions equivalent move in some periods almost identical but in other period of times no linear relationship can be observed at all. The data in Table 8 also displays the quarter in which the minimum and maximum cross-correlation coefficient appears. Most regions have their minimum value around the second quarter in 1999. This means that in the period from 1992/93 to 1999 the least co-movement occurred. On the other side, the maximum value is most often found for the end of the sample period, i.e. 2009:Q4, reinforcing the finding that the Austrian regions get more synchronised with the national aggregate over the sample period. Appendix D provides a graphical representation of the pair-wise rolling cross-correlation coefficients and depicts as described the V-shaped curve in the 90s.

Figure 8: Two-Period Comparison of Regional Correlation with GVA_{AT}



The coherence measure calculated in the frequency domain supports the results obtained from the cross-correlation analysis.[34] On the Länder scale, Upper Austria marks with 0.89 the highest coherence value indicating the strongest comovement amongst all regions with the reference series. All other regions, except Burgenland, follow with a value above 0.70. Burgenland ranks last with a coherence statistic of 0.49, i.e. only 49 per-cent of the variability observed between 6 and 32 quarters can be explained by the co-moving variability.

[34] Remember, the coherence (bounded between 0 and 1) measures the proportion of the variance explained by the Länder series to the frequencies given by the reference series (GVA_{AT}). The frequencies of the cycle used range between 6 and 32 quarters. A high value means that the Länder series contains information which is strongly linked to the cyclical behaviour of the reference series.

Within the NUTS 1 aggregates, Western Austria shows the largest coherence value. Its co-moving relationship with the reference series is almost unity.

4.4.2 Concordance

The last measure I want to employ for analysing the pattern of comovement is the concordance index based on Harding and Pagan (2002).[35] The same as with the cross-correlation statistics, the concordance measure has been calculated over the full-sample period, for 2 subsamples and finally over a rolling window of again 28 quarters. The results (see Table 9 and Figure 9) can be summarised as follows. Considering the full 20 year sample period, all Austrian Länder, except Burgenland, are roughly between 70-80% of the time in the same state as the Austrian business cycle. The highest proportion can be found for Vorarlberg (84%) and the lowest for Burgenland (59%). Note that Western Austria shares the same cyclical phase with the national aggregate in 97% of the time, this increases to 100% for the subsample 1999-2009.

Comparing the two subsamples on the Länder scale confirms earlier findings that the first period, i.e. from 1988-1998, shows lower synchronisation with the reference series compared to the year 1999 and onwards. However, there exit some Länder for which the concordance index increases only marginally and in the case of Salzburg it actually slightly decreases by two per-cent points. Länder which exhibit a relative low concordance index, i.e. around 0.5, in the period 1988-1998 are Lower Austria, Burgenland, Styria and Upper Austria. This is interestingly, given that most of these Länder are belonging to the group of "Industriebundesländer". The industrial aggregate correctly captures this circumstance showing a value of 0.50. But considering the period 1999-2009 these industrial Länder provide a concordance measure of 80% and more.

Concordance results using the rolling window basically show again that there exist periods where the synchronisation with the reference series is rather weak, i.e. less than 40%. However, this does not hold for all Länder. Vienna, for example, reports a minimum concordance measure of 71%. According to this, Vienna remains at least 71% of the time in the same state as the national aggregate, thus, providing, besides Vorarlberg, the most constant concordance index of all Austrian Länder.[36]

[35] Remember, the concordance index (bounded between 0 and 1) measures the proportion of time two data series remain in the same cyclical phase, i.e. being together either above or below trend.
[36] See Appendix D for a graphical representation of the rolling concordance measure for each region.

Table 9: Business Cycle Concordance Statistics for the Austrian Regions [1)]

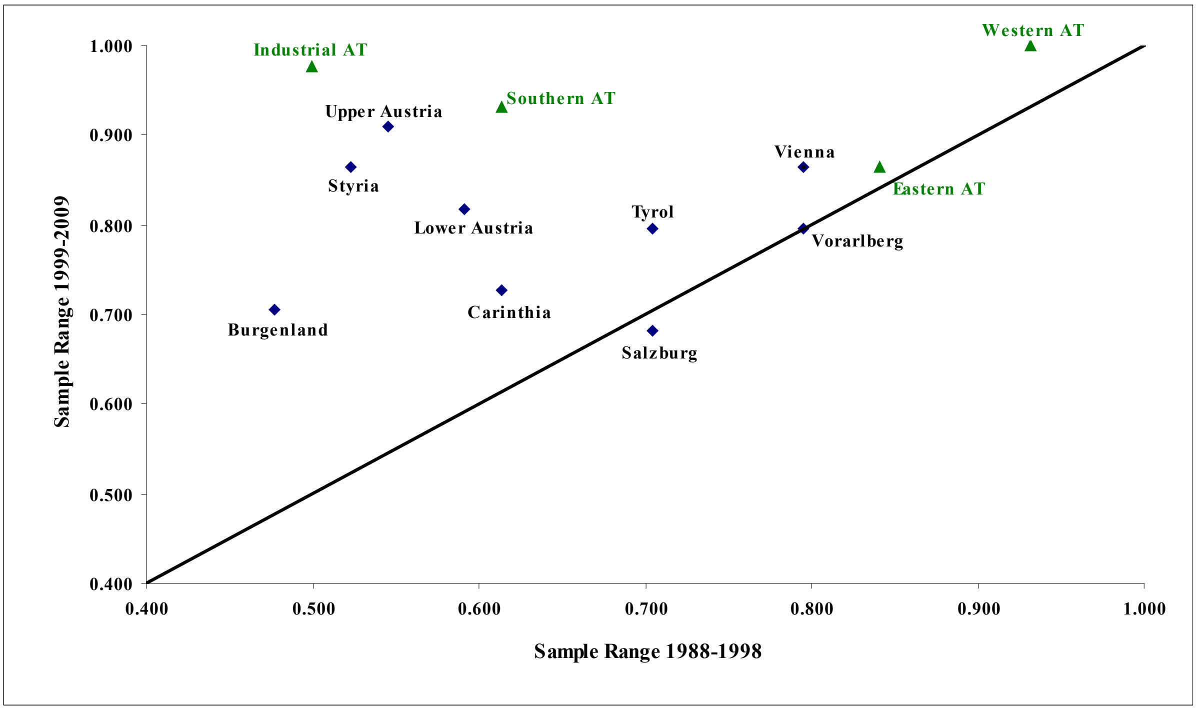
	Regions	1988–2009		1988–1998		1999–2009		rolling window [2)] min.	rolling window [2)] max.
NUTS 2	Vienna	0.830	2	0.795	1	0.864	3	0.714	0.964
	Lower Austria	0.705	5	0.591	6	0.818	5	0.321	0.821
	Burgenland	0.591	9	0.477	9	0.705	8	0.286	0.786
	Styria	0.693	6	0.523	8	0.864	3	0.393	0.821
	Carinthia	0.670	8	0.614	5	0.727	7	0.393	0.786
	Upper Austria	0.727	4	0.545	7	0.909	1	0.393	0.929
	Salzburg	0.693	6	0.705	3	0.682	9	0.536	0.857
	Tyrol	0.750	3	0.705	3	0.795	6	0.643	0.893
	Vorarlberg	0.841	1	0.795	1	0.886	2	0.679	1.000
NUTS 1	Eastern Austria	0.852	2	0.841	2	0.864	4	0.786	1.000
	Southern Austria	0.773	3	0.614	3	0.932	3	0.500	0.929
	Western Austria	0.966	1	0.932	1	1.000	1	0.893	1.000
	Industrial Austria	0.739	4	0.500	4	0.977	2	0.286	1.000

[1)] Turning point statistics are based on the business cycle chronology presented in Table 6. Grey shaded columns indicate the relative position of each region within the set of regions.

[2)] A rolling window of 28 quarters is used. First value obtained for 1994:Q4.

Source: Own calculation.

Figure 9: Two-Period Comparison of Regional Concordance with GVA_{AT}



5 SUMMARY AND CONCLUSION

The aim of this paper was to analyse regional business cycles in the Austrian economy, to highlight the differences between the Länder cycles with respect to the national wide aggregate and to assess the degree of comovement between the business cycles.

The approach taken in this study was as follows. In the theoretical part, I first highlighted the differences between the *classical* and *deviation* business cycle approach in order to demonstrate that depending on the definition chosen cyclical turning points occur at different point in times. Next, I outlined different business cycle dating procedures (primarily non-parametric methods) for detecting turning points in the cycle. The most popular and widely used Bry-Boschan (1971) dating algorithm and has been discussed along with amendments proposed by Harding and Pagan (2001, 2002) for quarterly data.

Given that the deviation from trend, i.e. growth, cycle approach requires some method of de-trending, I discussed next in depth various statistical techniques found in the literature for decomposing a series into its trend and cycle plus 'noise' components. In my discussion of these methods I primarily focused on non-parametric (ad-hoc) filtering techniques. This was done following the practical decision I made to base my empirical analysis on such simple and easy-to-use ad-hoc methods. The Hodrick-Prescott (1980, 1997) filter and the band-pass filters of Baxter-King (1999) and Christiano-Fitzgerald (2003) have been outlined. In the case of the HP filter, I tried to show with a detailed discussion on the appropriate value for the smoothing parameter λ how sensitive such ad-hoc methods are with respect to the parameter choice made. One has to bear in mind this general characteristic of ad-hoc filters especially when applying these filters in practise.

In providing an outline of different synchronisation measures such *cross-correlations*, *coherence* and *concordance* which are all designed to examine the comovement between economic variables I finished off the theoretical part of this study and turned subsequently to the empirical investigation of regional business cycles in the Austrian economy.

In the empirical part of this study I started with a description of the dataset at hand. In brief, I based my analysis on quarterly data of real gross value added available for all nine Austrian Länder and three NUTS 1 level aggregates spanning over the period 1988-2009. Given the importance of the manufacturing sector in the Austrian economy I decided to construct an 'industrial' aggregate based on the Länder data of Lower Austria, Upper Austria, Styria and

Vorarlberg. A detailed analysis of the sectoral shares (e.g. manufacturing, construction etc.) on the regions gross value added measure has revealed that all of these four Länder contribute with their manufacturing sector with more than 25 per-cents to their regional economic activity.

Next, I turned to the analysis of the chosen reference series, which is the Austrian wide aggregate of real gross value added, in order to determine a reference business cycle chronology. To this end I employed different non-parametric dating procedures each related either to the classical or deviation cycle approach. This was done to highlight the differences in the turning points identified following each approach and method. As expected I found far less turning points when using the classical approach. But differences also exist when de-trended data have been used as input into the dating routine, i.e. the turning point dates and the total number of cyclical turns identified varied quite significantly. As a consequence, I decided to base the detailed analysis of the Länder cycles and the subsequent investigation of business cycle conformity between the Länder and the national aggregate on HP-filtered data. The decision for the HP-filter was mostly driven by the fact that after reading the literature it appears that most studies still employ the HP-filter when extracting the business cycle component.

In the empirical analysis on the regional level I followed basically two steps: (1) I derived the business cycle chronology for each region, i.e. for the Länder and the NUTS 1 aggregates, and (2) used the outcome of the turning point sequences to investigate the degree of synchronisation with the Austrian business cycle by calculating cross-correlation, coherence and concordance statistics.

The main empirical facts established in this paper for the Austrian Länder business cycles from 1988-2009 can be described succinctly. First, in almost any given period, there are some Länder which exhibit a positive period-on-period growth but there are also some regions where economic activity is declining. In other words, there exists a group of regions which follows closely the Austrian business cycle in one period of time, i.e. being either in a contractionary or expansionary phase, but this does not hold for all Länder simultaneously.

Second, the business cycle chronology for the Länder and NUST 1 aggregates revealed, before even applying some synchronisation measures to the data, that there exists a difference in the business cycle characteristics in the 90s compared to the years following 2000. The turning points identified in the first half of the sample, i.e. from 1988 to 1998, are far more diverse with respect to the national business cycle but also within the regions. Interestingly,

an almost uniform cyclical peak across the regions could be detected in 1991/92 and 2000 but in between no clear pattern was evident. However, from 2000 onwards, a high degree of conformity between the Austrian regions and the reference cycle has been found.
Finally, the results obtained allow the following concluding ranking. On a Länder scale, Vorarlberg and Upper Austria show the most consistent synchronised movement with the Austrian business cycle. Burgenland, in contrast, exhibits the least conformity. In between these top and bottom ranks it is hard to find a clear pattern across the statistical measures obtained. Probably, Vienna combined with Lower Austria and Carinthia ranks next to the most synchronised Länder followed by Tyrol, Salzburg and Styria. On a more aggregated level, i.e. on NUTS level 1, the ranking is much clearer. The business cycle of Western Austria actually matches the Austrian cycle close to unity, i.e. shows the highest degree of comovement amongst all analysed regions. This holds even in the 'shaky' period of the 90s. Eastern and Southern Austria follow with some distance and the business cycle of the 'industrial' aggregate shows, contrary to expectation and quite surprisingly, not such high degree of conformity with the Austrian business cycle.

This study should be seen just as a point of departure for an in-depth analysis of regional business cycles in the Austrian economy. A lot of open questions remain. Further studies may investigate what have been the driving forces behind the enormous increase in convergence (disconvergence) identified in the Austrian Länder post (pre) the year 2000? Or how does business cycle convergence look like on an intraregional Länder dimension? Or how does conformity look like in the Austrian Länder when using other measures such as employment? Or how have the Austrian Länder business cycles been influenced by their foreign neighbouring regions?

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APPENDIX A: Sectoral Proportions on Regional Gross Value Added (GVA_{REG})

		Mean Y96-09					ΔMean between Y96-97 and Y08-09														
		Secondary sector		Tertiary Sector			Secondary sector						Tertiary Sector								
	Regions	**Manu-facturing**	**Constr. & Energy**	**Retail**	**Other market orient. services**	**Non-market orient. services**	**Manufacturing**			**Construction & Energy**			**Retail**			**Other market orient. services**			**Non-market orient. services**		
	Austria	20.4	9.7	13.1	34.5	22.2	19.6	21.6	+2.0	10.2	9.3	-0.9	13.3	12.2	-1.1	32.5	35.8	+3.4	24.4	21.0	-3.4
NUTS 2	Vienna	10.0	7.2	15.3	42.1	25.4	11.0	10.0	-1.0	7.8	6.7	-1.1	15.9	13.8	-2.2	38.2	44.6	+6.5	27.1	24.8	-2.2
NUTS 2	Lower Austria	24.4	10.9	14.1	28.7	21.9	23.9	25.3	+1.3	11.8	10.6	-1.2	14.3	13.7	-0.6	26.4	29.9	+3.5	23.6	20.5	-3.1
NUTS 2	Burgenland	18.2	13.0	11.7	28.9	28.1	17.7	17.3	-0.5	13.2	13.0	-0.2	10.9	11.8	+0.9	25.4	31.6	+6.2	32.7	26.3	-6.5
NUTS 2	Styria	26.2	10.0	10.9	30.0	23.0	23.9	27.7	+3.8	9.9	9.8	-0.0	11.1	10.1	-1.0	29.1	30.9	+1.8	26.0	21.4	-4.6
NUTS 2	Carinthia	20.8	11.8	11.1	31.9	24.3	19.2	21.7	+2.5	12.7	11.8	-1.0	11.1	10.4	-0.7	30.1	33.3	+3.2	26.9	22.9	-4.0
NUTS 2	Upper Austria	30.5	10.6	11.6	28.4	18.8	29.2	32.1	+2.9	11.4	10.0	-1.5	11.7	10.8	-0.9	26.4	29.4	+3.0	21.2	17.6	-3.6
NUTS 2	Salzburg	17.6	9.6	16.0	37.4	19.5	15.9	19.2	+3.2	10.3	9.2	-1.1	15.2	15.6	+0.4	36.9	38.2	+1.3	21.7	17.9	-3.9
NUTS 2	Tyrol	18.7	10.4	11.0	39.9	20.0	17.1	20.7	+3.6	10.8	10.1	-0.7	11.0	10.3	-0.8	39.6	39.8	+0.2	21.5	19.2	-2.4
NUTS 2	Vorarlberg	27.8	11.3	10.9	32.6	17.4	26.4	30.4	+4.0	11.4	11.1	-0.3	11.0	9.8	-1.2	31.2	32.9	+1.7	20.0	15.8	-4.2
NUTS 1	Eastern Austria	15.2	8.7	14.7	36.9	24.4	15.5	15.6	+0.1	9.4	8.4	-1.0	15.2	13.7	-1.5	33.7	38.9	+5.2	26.2	23.4	-2.8
NUTS 1	Southern Austria	24.5	10.6	11.0	30.6	23.4	22.4	25.8	+3.4	10.8	10.4	-0.3	11.1	10.2	-0.9	29.4	31.7	+2.2	26.3	21.9	-4.4
NUTS 1	Western Austria	24.8	10.4	12.2	33.5	19.0	23.3	26.7	+3.4	11.0	10.0	-1.0	12.1	11.5	-0.7	32.3	34.1	+1.7	21.2	17.8	-3.4
	Industrial Austria	27.2	10.6	12.2	29.3	20.7	25.9	28.7	+2.8	11.1	10.2	-0.9	12.3	11.5	-0.8	27.6	30.3	+2.7	23.1	19.3	-3.8

Note: Numbers shown represent the percentage share of the individual sector (manufacturing, ..) w.r.t. to total Gross Value Added (GVA) for the respective region.
"Manufacturing" aggregate is based on ÖNACE D classification; it also contains data for mining and quarrying (ÖNACE C).
"Construction and Energy" aggregate is based on data according to ÖNACE F and E, respectively.
"Retail" aggregate refers to ÖNACE G, i.e. wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods.
"Other market orientated services" excluding data for Retail is based on ÖNACE H-K: hotels and restaurants; transport, storage and communication; financial intermediation; and real estate and business activities.
"Non-market orientated services" aggregate is based on ÖNACE L-P: public administration and defence; education; health and social work; other community/social/personal services; and activities of households.

Source: WIFO Database. Own calculations based on original level data prior seasonal adjustment procedure.

APPENDIX B: Unit Root Test results for Regional Gross Value Added (GVA_{REG})

	Test for unit root in:	Level		1st-Difference		Order of Integration
	Include in Test equation:	Const.	Const. + Trend	Const.	Const. + Trend	
	Test critical values at 1%	-3.51	-4.06	-3.51	-4.06	
	5%	-2.89	-3.46	-2.89	-3.46	
	10%	-2.58	-3.15	-2.58	-3.15	
		(1)	(2)	(3)	(4)	(5)
	Austria	-1.61	-2.77	-5.56 ***	-5.73 ***	I(1)
NUTS 2	Vienna	-2.32	-1.41	-5.63 ***	-6.13 ***	I(1)
NUTS 2	Lower Austria	-1.87	-1.63	-8.15 ***	-8.34 ***	I(1)
NUTS 2	Burgenland	-3.56 ***	-0.52	-8.09 ***	-9.11 ***	I(1)
NUTS 2	Styria	-2.19	-1.19	-7.89 ***	-8.19 ***	I(1)
NUTS 2	Carinthia	-3.00 **	-2.99	-8.03 ***	-8.39 ***	I(1)
NUTS 2	Upper Austria	-1.23	-2.37	-8.69 ***	-8.70 ***	I(1)
NUTS 2	Salzburg	-1.50	-3.37 *	-6.61 ***	-6.72 ***	I(1)
NUTS 2	Tyrol	-0.87	-2.27	-8.66 ***	-8.62 ***	I(1)
NUTS 2	Vorarlberg	-1.42	-2.67	-8.33 ***	-8.37 ***	I(1)
NUTS 1	Eastern Austria	-2.40	-1.43	-6.43 ***	-6.95 ***	I(1)
NUTS 1	Southern Austria	-2.66 *	-1.37	-7.82 ***	-8.24 ***	I(1)
NUTS 1	Western Austria	-1.11	-3.00	-6.61 ***	-6.63 ***	I(1)
	Industrial Austria	-1.48	-2.62	-7.05 ***	-7.17 ***	I(1)

Note: The test for order of integration has been determined using the Augmented Dickey-Fuller (AFD) test.
ADF-tests have been performed on seasonal adjusted quarterly data (in logarithm form).
Statistically significance at the 1%, 5% or 10% level is indicated by ***, ** or *.
MacKinnon (1996) one-sided t-statistic shown in column (1)-(4).

Source: Own calculations.

APPENDIX C: Outline of the Bry-Boschan (1971) routine implemented in BUSY[37]

►Input De-trended time series of interest.

Step 1 Apply a symmetric 2x7 moving average, called a Spencer curve, with weights given as:

t±7	t±6	t±5	t±4	t±3	t±2	t±1	t
-0.0094	-0.0188	-0.0156	0.0094	0.0656	0.1438	0.2094	0.2323

Step 2 Extend the data points on either end of the series in order to compensate for the loss of seven data points due to the 2x7 moving average (from Step I). It is assumed that the growth of the first and last four observations remains constant in the previous (next) seven periods.

Step 3 Use the smoothed series for replacing outliers detected in the original series. Outliers are identified by imposing that its standard deviation is a certain threshold (default is 3.5) outside of the series total standard deviation.

Step 4 Replace outliers by their equivalent on the Spencer curve and repeat Step I.

Step 5 Apply a 2x4 centred Moving Average (MA) on the outlier-corrected series.

Step 6 Scan for turning points in the output generated by the 2x4 MA and the one generated by the Spencer curve. A turning point is characterised by local minima or maxima in the interval $t_{\pm n}$ (default: n=5, i.e. representing a minimum length of the cycle of 5 quarters).

Step 7 Impose a minimum phase length (default: l=2), the minimum periods it is allowed to take from a peak (trough) to a trough (peak).

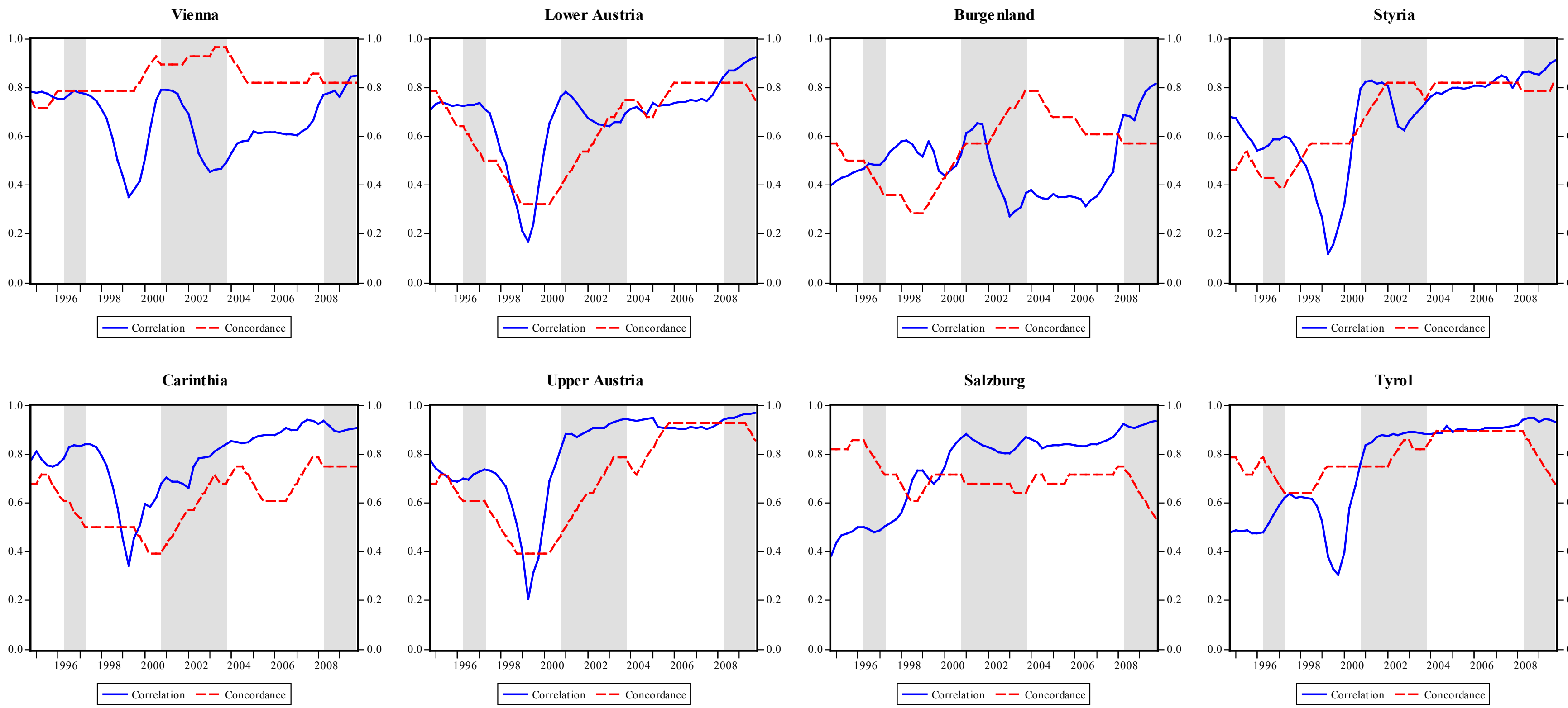
Step 8 Impose an alternation of the signs of the turning points [P→T; T→P].

Step 9 Compute the Quarters of Cyclical Dominance (QCD) and apply a MA of length QCD on the outlier-corrected series. Identify turning points and drop those found in the last or first two observations.

◄Output Business cycle chronology of the de-trended time series of interest.

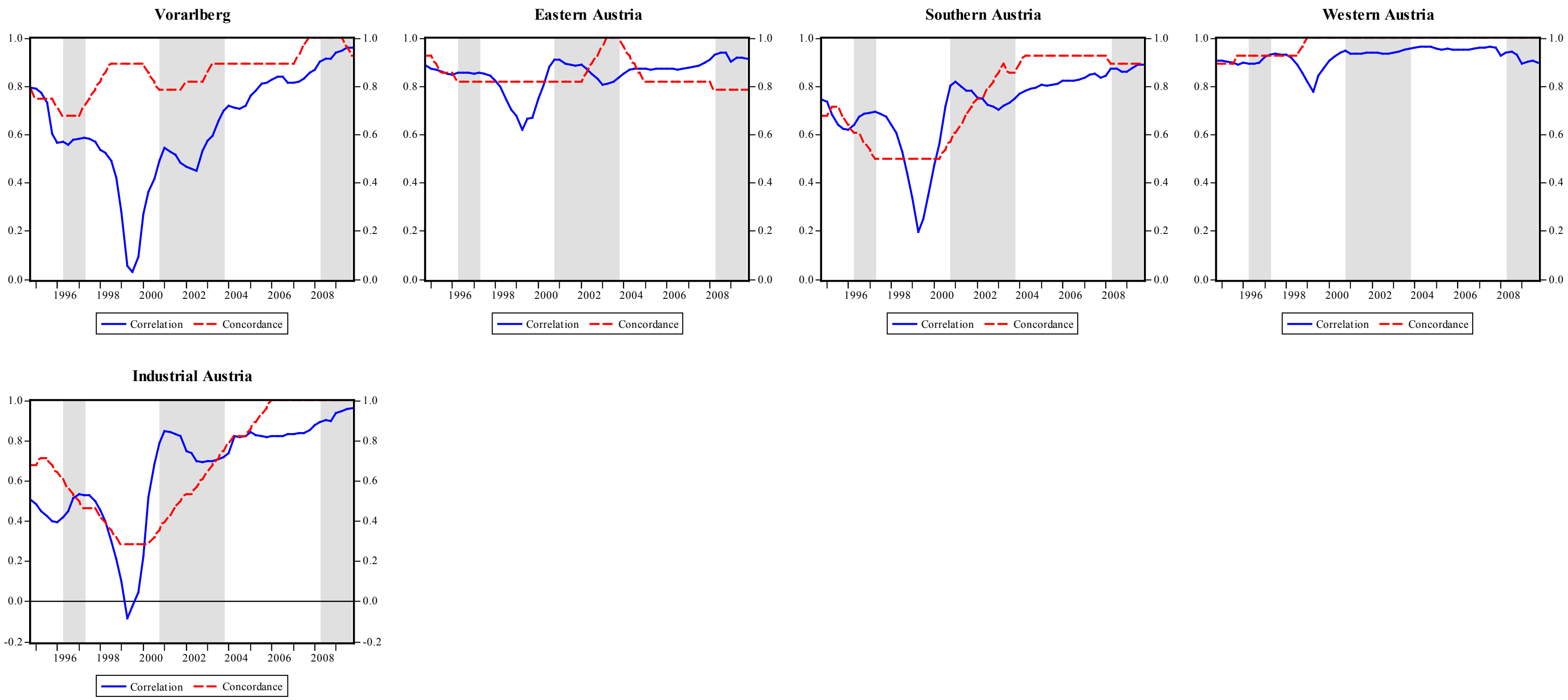
[37] Description based on Fiorentini and Planas (2003).

APPENDIX D: Overview of Regions Correlation and Concordance Statistics



Note: Grey shaded area indicate recessionary phase in the Austrian business cycle. Business cycle component has been extracted using HP filter (lambda=1600). See Section 4.2 for details.

APPENDIX D: Overview of Regions Correlation and Concordance Statistics (cont.)



Note: Grey shaded area indicate recessionary phase in the Austrian business cycle. Business cycle component has been extracted using HP filter (lambda=1600). See Section 4.2 for details.