Essays on

Business Cycle Dynamics:

An empirical analysis of macro, firm-level and regional data

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Contents

Preface

The business cycle is a concept of key interest for all economic actors alike. One can think of consumption and savings decisions of individual consumers, production decisions of private sector firms, and monetary and fiscal policy decisions of central bankers and the government. All can benefit from accurate forecasts of the future development of economic variables, which to a large extent depend on the business cycle. The characterization of the business cycle, and the analysis of its properties, has been the subject of innumerable studies (van Dijk et al., 2005: 147).[1]

Analysing fluctuations in economic activity or economic conditions has a long tradition in (macro)economics. The assessment of where the economy has been, where it is now and what its most likely future direction will be is of importance for economic policy. A broad range of models and methods, both theoretical and empirical in nature, have been used in policy orientated as well as academic research for investigating the sources and effects of economic fluctuations and for deriving business cycle characteristics, thus aiming to shed some light on the *dynamics of business cycles*.

In a stylised representation[2], business cycles are pervasive in nature, recurrent but not periodic, persistent, and the cyclical dynamic differs in length and severity from one to another. Business cycles represent fluctuations in aggregate economic activity, not fluctuations in a specific economic variable. The stylised pattern of "contraction – trough – expansion – peak" occurs over and over again, but does not emerge at regular predictable intervals, and declines (growth) in aggregate economic activity are usually followed by further declines (growth). The cyclical behaviour of macroeconomic variables is typically characterised by some degree of co-movement with overall economic activity. The direction, timing and volatility of the indicator with respect to aggregate dynamics are of particular relevance in business cycle analysis. In addition, especially for the real-time assessment and forecasting of economic activity a timely publication (i.e. potentially available at the end of

[1] Special issue in the *Journal of Applied Econometrics* (2005) honouring Jan Tinbergen, Nobel Prize winner in Economics in 1969.

[2] This business cycle characterisation traces back to the seminal work by Burns and Mitchell (1946) and their subsequent work at the National Bureau of Economic Research (NBER).

each month), a high frequency occurrence (i.e. on a monthly interval) as well as robust first-estimate (i.e. with a minimum of further revisions) of the business cycle indicator is desired. For the task of forecasting the future direction of economic activity, leading indicators or a composite of them have been widely used to predict peaks and troughs in the business cycle. While for the analysis of business cycle convergence between, for example, countries or regions, the focus rests on the contemporaneous relationship and its conformity. The cyclical behaviour of key economic variables is very similar in most of the industrial countries, and expansions and recessions in economic activity happen frequently to be about the same time. Thus, international aspects of the business cycle have to be taken into account. However, each economy faces its own disturbances (i.e. shocks) that are not shared with or 'imported' from other countries or regions. Moreover, business cycle conditions can vary somewhat across different parts of the economy. As such, differences between sectors or industries or variation in conditions across domestic regions may impact on the aggregated business cycle, as well. Moreover, individual firm-level specifics (i.e. heterogeneity across firms) may also contribute in shaping the dynamics of the macro business cycle, following Lucas' (1976) critique that the 'aggregated' view is seen microfounded by representative agents.

Outline of the dissertation

The outline above sketches some avenues for the applied researcher from which business cycle dynamics can be looked at. In order to contribute to the empirical business cycle literature on various dimensions, I address in this dissertation (*i*) the **macro**, (*ii*) the **firm-level**, and (*iii*) the **regional** dimension. Table 1 provides an overview of the chapters and their main structure and content. The chapters cover business cycle dynamics related to the Austrian economy as well as regions within in the European Union (EU).

Table 1: Chapter structure and contents

	Dimension	Scope	Related to	Frequency	Time period	Information set	Published as
Chapter I	Macro	Composite leading indicators Turning point detection Short-term forecasting	Austria	Monthly	1988 - 2015	Aggregated	Bierbaumer-Polly (2010)
Chapter II	Firm-level	Heterogeneity Business tendency surveys	Austria	Monthly	1996 - 2012	Individual	Bierbaumer-Polly and Hölzl (2015)
Chapter III	Regional	Synchronisation Specialisation EU-Accession	EU	Yearly	1981 - 2010	Aggregated	Bierbaumer-Polly et al. (forthcoming)

In particular, in Chapter I, following the traditional macroeconomic (i.e. aggregated) view, I focus on composite leading indicators for the Austrian economy which help in catching turning points as early as possible and in forecasting economic activity more accurately. In Chapter II, I utilise individual firm-specific data for Austrian manufacturing firms, which allow studying the (macroeconomic) consistency of business tendency survey responses and taking firm-level heterogeneity explicitly into account. Firm-level, industry- and region-specific structural characteristics permit controlling for additional microeconomic heterogeneity. Finally, in Chapter III, I examine the evolution of business cycle synchronisation and specialisation patterns between EU regions (at the NUTS-3 level), and I analyse the effect of two distinct EU-enlargement steps (i.e. Eastern enlargement in 2004 and Northern enlargement in 1995) on these measures.

In business cycle analysis, the researcher or practitioner has to take a stance on what defines 'the business cycle'. Usually and most commonly assumed in empirical work, the term refers to fluctuations of economic aggregates around their trend values[3], while there are several ways to describe the behaviour of the trend of the underlying variable. Following this approach, 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. Among them are statistical techniques in the class of 'ad-hoc' filters or structural time series models (e.g. Harvey, 1989).[4] The first class contains the most widely used de-trending approaches such as the Hodrick-Prescott (1997) filter or the Baxter-King (1999) and Christiano-Fitzgerald (2003) approximation of an ideal band-pass filter.[5] In this dissertation, I resort to the class of 'ad-hoc' filters and employ where appropriate for robustness analysis an additional filter out of the same class. The findings are not sensitive to the filtering method chosen.

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[3] This definition of business cycles is known as *deviation* cycles or *growth* cycles. Contrary, Burns and Mitchell's (1946) definition of the business cycle, i.e. expansions and contractions in the level of economic activity, is named as *classical* business 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 and applied researchers tend to favour the deviation from trend approach.

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

[5] Canova (1998), amongst others, point out that different de-trending methods may extract substantially different business cycle components from the same underlying time series which in turn effects the dating of the turning points and other business cycle characteristics. 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.

Summary and Findings

Chapter I focuses on the **macro dimension** and employs a large set of monthly business cycle indicators related to the Austrian as well as the international environment to construct a leading indicator for detecting turning points in the Austrian business cycle. In the indicator selection, I employ statistical methods from the time-series domain as well as from the frequency domain and construct the *WIFO-Frühindikator* based on the de-trended, normalised and weighted leading series. For the de-trending procedure of the component series and the final smoothing of the composite, I resort to the HP filter. The contribution to the empirical literature and business cycle analysts is twofold. First, for the Austrian economy, only few outdated studies exist, which examine the business cycle properties of a broad set of economic indicators. Second, so far the only composite leading indicator available for Austria that is designed to provide turning point signals of economic activity has been the one provided by the OECD. However, the *WIFO-Frühindikator* is based on a broader information set and published one month in advance of the OECD estimate.

The results in Chapter I demonstrate that the constructed composite leading indicator for the Austrian economy provides a useful and robust instrument for assessing the current and most likely future direction of the Austrian business cycle. Thus, it signals turning points in overall economic activity with a stable lead-time. In addition, a simple Markov regime-switching model provides a practical extension for signalling business cycle up- and downswings. However, the turning point signals are not clear-cut, especially in periods with high uncertainty. Out-of-sample evaluations of the forecasting performance show that a bivariate specification, i.e. including the references series and the composite indicator, performs superior compared to the univariate counterpart of just using the reference series. Furthermore, the results indicate that the improvements are more pronounced the longer the forecast horizon is taken. Sensitivity checks with respect to different business cycle extraction methods (BK vs. '2-sided' HP filter) and different time periods covered (1988-2008 vs. 1996-2015) provide robust results. The business cycle properties of the selected leading indicators which enter the composite remain more or less comparable. Moreover, the endpoint-bias due to the HP filter smoothing procedure is found to be not severe, i.e. the 'real-time' smoothed *WIFO-Frühindikator* does not exhibit severe phase-shifts compared to a full-sample estimate. Overall, the *WIFO-Frühindikator* is used since 2012 by the Austrian Institute of Economic Research (WIFO) for its ongoing business cycle monitoring of the Austrian economy, in particular within the institute's short-term forecasting procedures.

Chapter II focuses on the **firm-level dimension** and utilises business tendency survey (BTS) micro data for the Austrian manufacturing sector to analyse business cycle dynamics and differentials. Usually, business cycle research focuses on the macroeconomic level. Chapter II departs to some extent from the standard approach and incorporates the micro perspective, as well. BTS data have shown to contain an indispensable source of relevant business cycle information, especially in a real-time environment, and are usually used as 'balance statistics'. This implicitly assumes that firms are homogeneous entities or differences between them cancel each other out in the aggregate. But this possibly ignores important aspects of observable firm-specific heterogeneity that might be of interest. The contribution to the empirical literature is threefold. First, by analysing micro BTS data, it is possible to verify and test the (macro) consistency of the business tendency survey responses of key questions related to the business cycle dimension, such as the assessment of current production or order book levels. Second, (observable) firm-heterogeneity as well as structural characteristics of firms, industries and regions is explicitly taken into account in modelling 'aggregated' business cycle dynamics. In addition, business cycle differentials along various aspects (e.g. differences between business cycle phases: upswing vs. downswing) are tested. Third, it is the first attempt to use micro WIFO Business Cycle Survey data to investigate 'macro' business cycle dynamics from a 'micro' perspective.

The results show that firm-specific information embedded in the qualitative survey questions is relevant to understand aggregate business cycle dynamics. For example, the assessment of firms' order book levels, their current degree of capacity utilisation and their production expectations as well as obstacles in their production activities due to insufficient demand show evidence of a significant effect in explaining a firm's change in current production output. No clear results with respect to firm size are found. Also the industry affiliation of a firm or regional characteristics do not provide statistically significant results. However, heterogeneity in the behaviour of cyclical up- and downswings as well as differences between large and small firms are identified.

Chapter III deals with the **regional dimension** and focuses on NUTS-3 regions within the EU.[6] Measuring and describing the evolution of business cycle synchronisation in the EU has been a subject of high interest for empirical macro-economists in the last decades. This interest was spurred both by the policy relevance of the topic as well as by theoretical

[6] With respect to Austrian regions Bierbaumer-Polly (2012) and Bierbaumer-Polly and Mayerhofer (2013) study the development of (aggregated) business cycles in the Austrian provinces and find that the business cycle patterns differ considerably not just in an interregional comparison but also in terms of the national economy. However, during the immediate crisis years of 2008/09 business cycle dynamics are found to be rather similar among the Austrian provinces.

controversies between proponents of endogenous optimum currency area theory. On the policy side, a high level of business cycle synchronisation has been considered to be a precondition for European Monetary Union (EMU). On the theoretical side, some proponents have argued that integration should lead to higher business cycle synchronisation (e.g. Frankel and Rose, 1998). Others, however, had claimed that integration will primarily result in increased specialisation of economies on sectors of production where they have comparative advantages and this, in the face of sector specific shocks, should lead to reduced business cycle synchronisation (e.g. Krugman, 1993). Chapter III uses EU-enlargement as a testing ground for these hypotheses and analyses the impact of two very different EU-enlargement steps (i.e. Eastern and Northern enlargement) on business cycle synchronisation and sector specialisation at the regional level. The contribution to the existing literature is twofold. First, in contrast to previous research on the impact of EMU on the national level, the focus rests on the impact of EU-enlargement on the regional (NUTS-3) level. Second, Chapter III contributes to the literature on regional business cycle synchronisation and offers an ex-post evaluation of the impact of EU-enlargement on regional business cycle synchronisation and sector specialisation.

The results show that EU-accession by the 10 member states that joined the EU in May 2004 and Northern enlargement in 1995 had rather different effects on business cycle synchronisation and structural differences. Business cycles became less synchronous, and differences in sector structure increased between NUTS-3 region pairs located in different acceding countries and mixed region pairs relative to region pairs of pre-member countries in the case of Eastern enlargement. For Northern enlargement, by contrast, results are less robust. These differences suggest that the institutional as well as geographic, economic and structural differences between these two rounds of enlargement may have led to rather different patterns of adjustment.

Given the rather different results for different enlargement episodes but the rather similar distributional results, future research should thus focus on developing more differentiated hypotheses on the effects of EU-enlargement and the formation of EMU on business cycle synchronisation and sector specialisation, which take explicit consideration of starting conditions. This may be of high policy relevance given that the European Commission was negotiating on membership with six countries in 2014, which all differ widely in economic development and level of integration with the EU, whereas seven countries with equally disparate starting conditions from the Eastern enlargement rounds in 2004 and 2007 were still waiting to join EMU at that time.

References

Baxter, M. and King, R.G. (1999): 'Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series', *Review of Economics and Statistics*, MIT Press, Vol. 81(4), pp. 575-593.

Bierbaumer-Polly, J. (2010): Composite Leading Indicator for the Austrian Economy: Methodology and 'Real-time' Performance, *WIFO-Working Papers*, No. 369.

Bierbaumer-Polly, J. (2012): 'Regionale Konjunkturzyklen in Österreich', *WIFO-Monatsberichte*, Vol. 85(11), pp. 833-848.

Bierbaumer-Polly, J. and Hölzl W. (2015): Business Cycle Dynamics and Firm Heterogeneity: Evidence for Austria Using Survey Data, *WIFO Working Papers*, No. 504.

Bierbaumer-Polly, J. and Mayerhofer, P. (2013): Wiens Konjunkturentwicklung im nationalen, intra- und interregionalen Vergleich: Charakteristika, Besonderheiten, Einflussfaktoren, WIFO.

Bierbaumer-Polly, J., Huber, P. and Rozmahel, P. (forthcoming): 'Regional Business Cycle Synchronization, Sector Specialization and EU-Accession', *JCMS: Journal of Market Studies*.

Burns, A.F. and Mitchell, W.C. (1946): Measuring Business Cycles, National Bureau of Economic Research, Inc.

Canova, F. (1998): 'Detrending and business cycle facts', *Journal of Monetary Economics*, Vol. 41(3), pp. 475-512.

Christiano, L.J. and Fitzgerald, T.J. (2003): 'The Band Pass Filter', *International Economic Review*, Department of Economics, University of Pennsylvania and Osaka University Institute of Social and Economic Research Association, Vol. 44(2), pp. 435-465.

De Haan, J., Inklaar, R. and Jong-A-Pin, R. (2008): 'Will Business Cycles In The Euro Area Converge? A Critical Survey Of Empirical Research', *Journal of Economic Surveys*, Blackwell Publishing, Vol. 22(2), pp. 234-273.

Frankel, J.A. and Rose, A.K. (1998): 'The Endogeneity of the Optimum Currency Area Criteria', *The Economic Journal*, Vol. 108, pp.1009-1025.

Harding, D. and Pagan, A. (2005): 'A suggested framework for classifying the modes of cycle research', *Journal of Applied Econometrics*, Vol. 20(2), pp.151-59.

Harvey, A.C. (1989): Forecasting, Structural Time Series Models and the Kalman Filter, Cambridge, Cambridge University Press.

Hodrick R. and Prescott, J. (1997): 'Postwar U.S. Business Cycles: An Empirical Investigation', *Journal of Money, Credit, and Banking*, Blackwell Publishing, Vol. 29(1), pp. 1-16.

Krugman, P. (1993): 'Lessons of Massachusetts for EMU', in: Torres F. and Giavazzi F. (eds.), Adjustment and Growth in the European Monetary Union, Cambridge, Cambridge University Press, pp. 241-261.

Massmann, M., Mitchell, J. and Weale, M. (2003): 'Business Cycles and Turning Points: A Survey of Statistical Techniques', *National Institute Economic Review*, Vol. 183(1), pp. 90-106.

Van Dijk, D., van Dijk, H.K. and Franses, P.H. (2005): 'On the dynamics of business cycle analysis: editors' introduction', *Journal of Applied Econometrics*, Vol. 20(2), pp. 147-150.

Chapter I

Composite Leading Indicator for the Austrian Economy: Methodology and 'real-time' performance[*]

Abstract

In this paper, I construct a monthly composite leading indicator for the Austrian economy (CLI_{AT}) which shows early signals of cyclical turning points in the Austrian business cycle. First, I identify the monthly indicators which overall fare best in showing a 'steady' leading behaviour with respect to the Austrian business cycle. For this purpose, I employ statistical methods from the time-series domain as well as from the frequency domain. Thirteen series are finally classified as leading indicators. Among them, business and consumer survey data form the most prevalent group. Second, I construct the CLI_{AT} based on the de-trended, normalised and weighted leading series. For the de-trending procedure, I use the HP filter. The weights are obtained by means of principal components analysis. Furthermore, idiosyncratic elements in the CLI_{AT} are removed along with checking the endpoint-bias due to the HP filter smoothing procedure. I find that the 'real-time' smoothed CLI_{AT} does not exhibit severe phase-shifts compared to a full-sample estimate. Next, I show that the CLI_{AT} provides a useful instrument for assessing the current and likely future direction in the Austrian business cycle. Over the period 1988-2008, the CLI_{AT} indicates cyclical turns with a 'steady' lead in the majority of cases. Finally, in using an out-of-sample forecasting exercise I show that the CLI_{AT} carries important business cycle information. Its inclusion in a forecasting model can increase the projection quality of the underlying reference series.

[*] This chapter has been published as WIFO working paper: Bierbaumer-Polly, J. (2010): Composite Leading Indicator for the Austrian Economy: Methodology and 'Real-time' Performance, *WIFO-Working Papers*, No. 369.

1. Introduction

The measurement and analysis of business cycles and the prediction of turning points in the cycle has been one of the core research topics in economics throughout the past century. The foundation of economic indicator analysis was laid by Burns and Mitchell (1946) at the National Bureau of Economic Research (NBER). Work on cyclical fluctuations has traditionally been concerned with analysing the characteristics of expansions and contractions in the level of overall economic activity. This has been referred to as the 'classical' cycle concept. However, in recent decades, more and more studies follow the practice to measure the output gap as fluctuations in real output relative to its long-term trend, a concept called the growth cycle[1]. This concept emerged and gained popularity amongst business cycle analysts, as cyclical fluctuations following the classical cycle approach hardly occurred and, if so, only in modest shape from the 1970s and 80s onwards (see e.g. Tichy, 1994; Zarnowitz, 1992).

The economic indicator analysis assumes that the business cycle is characterised by simultaneous co-movements in a large number of economic variables. Economic variables and composite indices, constructed either as leading, coincident, or lagging, can be used to confirm, identify and predict movements in the business cycle (Brischetto and Voss, 2000). The leading indicator components, for example, may carry information about an early production stage or about economic expectations, be sensitive with respect to the performance of the economy, as captured for instance by stock prices, or provide other signals of pending changes in the market (Klein and Moore, 1982).

Ideally, such analysis would identify a single indicator that captures the cyclical movements in economic activity in a timely and accurate manner. Unfortunately, no single economic indicator exists which carries all the essential business cycle information. Consequently, composite indices have been developed to compensate for limitations arising with the use of single indicators. Nowadays, many composite indices exist and get published on a regular, mostly monthly, basis. Often, special attention is drawn to composites carrying lead information about impending cyclical turning points. For example, a set of leading indicators is widely used by the OECD to predict growth cycles in the economies of its member countries.

For the Austrian economy, there exist only few studies which examine the business cycle properties of a broad set of economic indicators. Breuss (1984), for example, tests pre-selected leading, coincident and lagging economic indicators with respect to their turning

[1] Using the growth cycle definition, the 'business cycle' can be defined as fluctuations in the level of economic activity around its underlying long-run trend; this is representing periods of above-trend and below-trend rates of economic growth.

points, compares their attributes with an underlying reference series and constructs a composite index for each group of indicators. Other studies focus primarily on dating the Austrian business cycle (see Hahn and Walterskirchen, 1992; Scheiblecker, 2007).

The main objectives of this paper are: (1) to provide an analysis of the business cycle properties of a large set of indicators from a variety of statistical measures; (2) to select a set of time series which provide individually early signals of turning points in the Austrian business cycle; (3) to combine the set of leading indicators into a composite leading indicator (CLI) corresponding to the Austrian economy[2]; (4) to assess the composite's performance of predicting cyclical turning points; and (5) to verify its useability in the Austrian Institute of Economic Research's (WIFO) economic forecasting procedures.

The remainder of the paper is organised as follows. Section 2 describes the data and identifies business cycle turning points for the reference series selected. Section 3 presents an outline of the selection criteria used to identify leading indicators and discusses the findings. Section 4 outlines the steps of the construction process of the CLI_{AT}. Section 5 tests the performance of various versions of the new CLI_{AT}. Section 6 conducts an out-of-sample forecast exercise. Section 7 contains some concluding remarks.

2. Data set and turning points in the reference series

The data set for the indicator analysis contains monthly time series from various key areas in the Austrian economy. It further includes data from the international economy, mostly related to the euro area as a whole or to Germany, the most important trading partner for Austria. The data set contains series on industrial production, trade, prices and wages, the labour market, international trade, financial and commodity market, and, among qualitative data, business and consumer surveys.

In the dataset at hand, most time series start in the early to mid 1980s. However, some data are only available from the mid 90s onwards. In order to get a sample period as long as possible and, most importantly, to include series which contain information on business cycles, I restrict the sample period to a range between January 1988 and December 2008, in total 252 monthly observations. With this data range, the initial dataset of more than 150 time series are cut back to 91 monthly series, where data have been available for the whole period. Table 1 gives an overview of the series included in the analysis.

[2] As from now, I label the CLI for the Austrian economy CLI_{AT}.

Table 1: Key Areas of the indicator set

	Number of series	
related to	Austria	Rest of the world
Industry production	6	-
Trade	5	-
Prices & Wages	11	-
Labour market	5	-
International trade	16	-
Financials	8	5
Commodity market	-	5
Surveys	13	13
Composite indicators	1	3
Total	65	26

Source: The series are taken from the WIFO Economic Database. http://www.wifo.ac.at/wwa/jsp/index.jsp?&language=2&fid=31412

Whenever necessary, the series are seasonally adjusted with Tramo-Seats[3]. Unit root tests show that most series are integrated of order one, i.e. I(1), except for the survey data which follow, with two exceptions, an I(0) process. A detailed list of all 91 indicators included in the final dataset, their seasonal adjustment and data transformation applied is shown in Table A1 (Appendix).

2.1 Selecting the reference series

The inspection of the business cycle properties of these indicators requires a reference series: a benchmark that is meant to reflect overall economic activity. Most commonly, real GDP or some industrial production index is used for this purpose.

Following Scheiblecker (2007), I select quarterly real gross value added excluding forestry and agriculture, denoted as Y_{exFA}^{GVA}, as the reference series[4]. Scheiblecker (2007) has argued that this series should carry and exhibit stronger cyclical variations compared to GPD and, hence, provide a better base for business cycle and indicator analysis.

2.2 Identifying turning points in the reference series

The procedure used to analyse the cyclical component in the reference series and to identify and assess the timing of peaks and troughs follows an NBER-type approach using the Bry and Boschan (1971) dating algorithm[5]. To start with, using the growth-cycle concept, the cyclical

[3] 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.

[4] The reference series was also adjusted for seasonal and working day effects using Tramo-Seats.

[5] The program BUSY (Release 4.1), a software tool developed by the European Commission (FP5), was used for business cycle analysis (Fiorentini and Planas, 2003). Source: http://eemc.jrc.ec.europa.eu/EEMCArchive/Software/BUSY.

component of the time series has to be isolated from the band of low to high frequencies. As such, a business cycle filter is required which eliminates the trend and irregular component, leaving behind the intermediate business cycle component of the underlying series. With this approach, the type of de-trending method used is very important. Different methods for trend estimation may yield different outcomes and effects in turn the analysis of co-movements and similarities in patterns between the reference series and the individual indicator.

Prominent examples in the economics literature include the Hodrick and Prescott (1980, 1997) filter and the approximate band-pass filter proposed by Baxter and King (1999). For the task at hand, I use the Baxter-King (BK) band-pass filter which allows suppression of both the low frequency trend components and the high frequency irregular components in an economic series. Baxter and King (1999) argue that the NBER definition of a business cycle requires a band-pass approach that is retaining components of the time series with periodic fluctuations between 6 and 32 quarters (1.5 to 8 years), while removing components at higher and lower frequencies. Note that this corresponds to the frequency domain interval of [π/16, π/3]. The frequency band used in this study to extract the cyclical component follows the values suggested by Baxter and King.[6]

Formally, the BK filter is derived from two consecutive low-pass[7] filters preserving the movements within the lower and upper bounds [*a*, *b*] of the implied business cycle frequency band. In its representation, the BK filter is symmetric of length *K* with filter weights given by

$$\nu_k = \frac{\sin kb - \sin ka}{k\pi} - \frac{1}{2K+1} \sum_{k=-K}^{K} \frac{\sin kb - \sin ka}{k\pi}, \tag{2-1}$$

where symmetry ($\nu_k = \nu_{-k}$) is imposed, so that the filter does not induce a phase shift. However, this means that filtered values are only obtainable for periods *K+1* to *T-K*. To overcome the lack of *K* filtered values at the series start and endpoints, different solutions, such as AR forecasts, exist.[8]

[6] 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 to use an upper bound of 10 years for European business cycles.

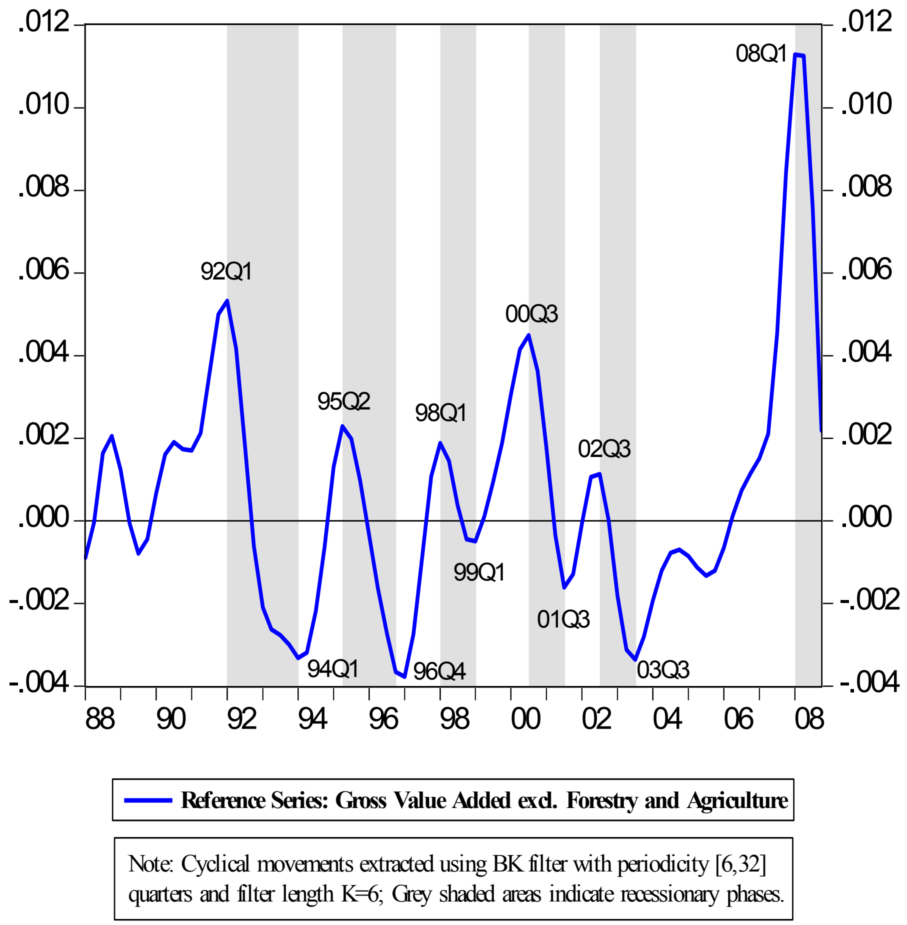
[7] In general, low-pass filters allow all frequencies below or equal to a certain threshold to pass.

[8] Note that most approaches are concerned with obtaining filtered values for the *K* end-of-sample periods. The method I chose and implemented in BUSY lies in modifying the filter for the end-of-sample values in such a way that an asymmetric approximation to the filter is worked out.

Figure 1 shows the business cycle chronology of the reference series Y_{exFA}^{GVA} with its turning points over the sample period from 1988Q1 to 2008Q4. Table 2 lists the dated turning points accordingly.

The chronology of the business cycle reveals five full cycles (peak-to-peak; P-P) in the reference series. The first cycle, starting with the peak in 92Q1, lasts 14 quarters until 95Q2 with the trough marked around the 1993/94 recession at 94Q1. The next two P-P cycles continue until the first quarter of 1998 and the third quarter of 2000, respectively. In both cases, the bottom in the cycle is reached around 5 to 7 quarters after the cyclical peak.

Figure 1: Business Cycle Chronology of the Reference Series Y_{exFA}^{GVA}



The shortest peak-to-peak cycle found in the reference series is the one ranging from 2000Q3 to 2002Q3, thus, only lasting a bit more than two years. This is caused by the trough identified in mid 2001 with a subsequent trough-to-peak duration of only 5 quarters.

The fifth cycle, which spans over 5 years and has its peak in the first quarter of 2008, represents the long period of economic prosperity before the onset of the financial crisis. The trough-to-peak duration in this cycle is as long as 19 quarters. As the BK filter is two-sided, the high estimate of the peak in 2008Q1 also reflects the sharp downturn thereafter. The estimate is still subject to some uncertainty and may be revised once more future observations become available. Finally, looking at the average duration of the cycles or phases it can be observed that the peak-cycle lasts a bit more than 3 quarters longer than the trough-cycle, and the phase period from a trough to the next peak is roughly 1 quarter longer compared to the average peak-to-trough phase. Overall, the turning point chronology derived in this work is similar to those found in other studies identifying turning points for the Austrian economy (see e.g. Scheiblecker, 2007; Artis et al., 2004).

Table 2: Turning Points of the Reference Series Y_{exFA}^{GVA}

Peak (P)	**Trough (T)**	Cycles		Phases	
		P to P	**T to T**	**P to T**	**T to P**
(1)	(2)	(3)	(4)	(5)	(6)
92Q1		-			-
	94Q1		-	9	
95Q2		14			6
	96Q4		12	7	
98Q1		12			6
	99Q1		10	5	
00Q3		11			7
	01Q3		11	5	
02Q3		9			5
	03Q3		9	5	
08Q1		23			19

Note: The turning points have been analysed between 1988Q1 and 2008Q4.
Cycle/phase length indicates number of quarters it takes to pass through.
Source: Own calculations / BUSY software.

3. Selection process[9]

The next step after selecting the reference series and dating its turning points is to analyse the cyclical behaviour of the indicator set with respect to the reference chronology. For this purpose, I use statistical methods from the time-series domain as well as from the frequency domain.[10] Since the analysis focuses on the cyclical component, the business cycle

[9] Note (as of December 2015): The business cycle components for the indicator set have been extracted identical to the reference series with the BK filter. But in the construction procedure of the CLI_{AT} (see Section 4) the HP filter is applied at some stages. “Supplement A” to this chapter adds a sensitivity analysis using the HP filter, in particular a ‘2-sided’ version of it, already in the selection process. Results are quite robust between these two filtering methods with respect to the obtained indicator properties.

[10] Most statistical results are obtained using again the software package BUSY (see Section 2.2)

information is extracted, as with the reference series, using the Baxter-King filter. Again, the frequency range is set from 6 to 32 quarters.

The descriptive bivariate statistics used are pair-wise Granger-causality tests, cross-correlations, and, in the frequency domain, coherences and mean-delay of the cross-spectra. Statistical procedures incorporating dynamic factor models (Forni et al., 2000) are also applied. In addition, salient statistics from the turning point analysis for each indicator are compared with those of the reference series to determine, for example, the median lead/lag time at peaks and troughs.[11] The publication timeliness of an indicator in combination with its revision frequency is also considered when choosing the set of indicators that finally enter the CLI for the Austrian economy.

Table 3: Selection Results – 'Leading' Indicators

x_i		Key area (1)	related to Austria (2)
x_1	ATX stock market index	Financials	No
x_2	DJ EURO STOXX 50 stock market index	Financials	No
x_3	Job vacancies, total	Labour market	Yes
x_4	Exports, total	International trade	Yes
x_5	WIFO Industry production, total without energy and construction	Industry production	Yes
x_6	WIFO Industry production expectations for the month ahead	Surveys	Yes
x_7	Consumer Confidence	Surveys	Yes
x_8	Business Confidence Climate (industry, construction and retail) 1)	Surveys	Yes
x_9	ifo Business Climate for Germany	Surveys	No
x_{10}	European Commision: Production trend observed in recent months for Germany	Surveys	No
x_{11}	European Commision: Production expectations for the months ahead for Germany	Surveys	No
x_{12}	European Commision: Production expectations for the months ahead in the Euro-Area	Surveys	No
x_{13}	OECD CLI for Germany, trend-restored	Composite Indicators	No
x_{14}	OECD CLI for the Euro-Area, trend-restored	Composite Indicators	No

1) Based on geometric average incorporating industry, construction and retail WIFO confidence survey data.
Source: Own calculation.

Table 3 starts with summarising the findings from this analysis in presenting the set of the 14 indicators that overall fare best in showing a 'steady' leading behaviour with respect to Y_{exFA}^{GVA}. This set of indicators is subsequently referred to as $\chi_t^{(14)} \equiv \chi_t = \left(x_{1,t}, x_{2,t}, \ldots, x_{n,t}\right)'$, with $n = 14$ and the individual indicator denoted as $x_{i,t}$. Section 3.1 provides a short discussion on the statistical methods used. Section 3.2 discusses the findings for $\chi_t^{(14)}$ in more detail; while the detailed results for all 91 indicators are shown in Table A2 (Appendix).

[11] To evaluate the length of the lead/lag, the median lead/lag at turning points is preferred to the mean, since the number of turning points is small and the mean measure would be affected by extreme values.

From Table 3, column (1), it can be seen that, with seven series included, business and consumer survey indicators form the predominant group in the set of $\chi_t^{(14)}$. In more detail, the set includes production expectations for the month ahead related to Austria, Germany and the euro-area as a whole, a three-sectoral business confidence climate index[12], a consumer confidence indicator, and the widely recognised ifo Business Climate index for Germany. The high proportion of survey indicators in the selected indicator set $\chi_t^{(14)}$ is not surprising, insofar as business and consumer confidence surveys exhibit in general a strong positive leading correlation with the overall state of economic activity.

Among the quantitative series, the following are identified as 'lead' indicators: job vacancies, export volumes, and the WIFO industrial production measure. Another important group of indicators is given by the OECD composite leading indicators for Germany and the euro-area. Further, out of the group of financial series, the ATX and EUROSTOXX 50 stock market indices are selected.

Overall, as displayed in column (2) of Table 3, less than half of the series directly relate to the Austrian economy, whereas the remaining series pertain solely to Germany and the euro-area.

3.1 Methods

3.1.1 Granger-causality and cross-correlations

Starting within the basic statistics from time-series domain, I inspect pair-wise Granger causality tests and cross correlations between the individual indicators $x_{i,t}$ and the reference series Y_{exFA}^{GVA}. The pair-wise Granger-causality test is used to determine whether the indicator series has explanatory power for future values in the reference series or vice versa. Depending on their order of integration, series are transformed into first- or second-difference stationary series. The order of integration is determined by the Augmented Dickey-Fuller (ADF) test[13].

The second method used in the time domain is cross-correlations, a measure of linear relationship between variables. I use it to identify leads and lags between the reference series Y_{exFA}^{GVA} and the individual indicator series $x_{i,t}$. Attention is drawn to the number of quarters lead

[12] I construct the business confidence climate (BCC) indicator as a geometric average incorporating three individual WIFO confidence survey data, namely the industry, construction and retail confidence climate series.

The precise formula is: $BCC = [(industry_{CC} + 200)\times(construction_{CC} + 200)\times(retail_{CC} + 200)]^{1/3} - 200$.

[13] 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.

or lag at which the maximum absolute cross-correlation emerges. The correlation coefficient shows the extent to which the cyclical profiles of both series resemble each other. Note that the presence of extreme values can affect the estimate of the cross-correlation coefficient.

3.1.2 Coherence and mean delay

The frequency domain[14] provides further useful measures for business cycle analysis. The statistics used therein are the pair wise coherences and mean delays among the indicators and the reference series, both being derived from the cross-spectrum. In general, coherence measures the linear relatedness, i.e. correlation, of two stationary series at a special frequency across all leads and lags of the series. The coherence measure is bounded between 0 and 1. The closer it is to 1 the stronger is the linear relationship.

One has to keep in mind though that the coherence statistic does not account for phase differences between two processes, i.e. it does not provide any information whether both series exhibit simultaneous movements or one process leads/lags the other one (Croux et al., 1999). A remedy to this situation fulfils the statistic of mean delay. It provides a measure indicating a leading or lagging property of the indicator series with respect to the reference series. The statistic is derived calculating the phase-spectrum, within the business cycle boundaries, between both series. For example, a mean delay measure of +1.0 reveals a lead of one quarter.

In this study, the coherence as well as the mean delay statistic is averaged across the business cycle frequency band of concern, i.e. in the range from 6 to 32 quarters.

3.1.3 Turning point analysis

The next group of descriptive statistics examined are derived from turning point analysis. As with the reference series, the turning point detection procedure used follows, with some modifications[15], the original Bry and Boschan (1971) routine. The turning points of each individual series are compared to the ones found in the reference series. Duration measures, such as mean or median lead/lag at cyclical peaks and troughs, are used to obtain further insights of co-movements between the series.

Note that the median lag at all turning points should not be too different from the average lead of the cyclical indicator series if the individual indicator series $x_{i,t}$ is to give reliable

[14] A Fourier-transformation is used to convert time domain statistics into their frequency domain equivalents.

[15] The original procedure developed at the NBER is tailored to non-stationary quarterly data, whereas BUSY also allows for stationary series.

information both about approaching turning points as well as the evolution of the reference series Y_{exFA}^{GVA}.

3.1.4 Dynamic factor analysis

Dynamic factor model (DFM) statistics complete the set of methods used to analyse the individual cyclical behaviour of the indicator set on hand. DFMs are based on the assumption that the dynamics of a large set of time series is driven by a set of unobservable common factors[16]. They allow for inspecting the co-movements among a set of series in a thrifty way. When constructing a composite indicator, ideally, the set of indicators used would load high on a single factor, which has the interpretation of reflecting the business cycle.

I use the DFM by Forni et al. (2000) as implemented in BUSY. This DFM version uses principal components from the frequency domain and therefore provides factor loadings that abstract from leads and lags among the series. At the same time, it provides the mean delays among the common components of series as extracted by the DFM.

As identification and selection criteria, I use the following two measures, which are commonly used: (1) the ratio of the common component variance over the indicators variance to analyse the degree of commonality or co-movement among the indicator series. A ratio close to 1 means strong commonality whereas a low value represents almost independence of the indicators, thus, not qualifying as a good cyclical indicator; and (2) the cross-correlation between the common component of each individual indicator and the common component of the reference series. This measure is used to classify the individual series as leading, coincident and lagging with respect to the reference series.

In addition, a series classification in consideration of an indicators' leading, lagging, or coincident behaviour, based on mean delay values of the first common component, is accomplished. The classification is based on the following rules: If mean delay is greater than 1 (-1), the indicator is leading (lagging) by more than one period; and if mean delay is between this threshold, the indicator is classified as coincident.

Next, the individual test results with respect to $\chi_t^{(14)}$ are discussed, and Table 4 summarises these findings.

[16] The DFM, as described by Forni et al. (2000), assumes that *N* 2[nd]-order stationary variables at time *t* share *q* orthogonal common factors. By estimating the common components the indicators are cleaned of idiosyncratic movements or short-term irregularities affecting each indicator.

3.2 Results

3.2.1 Granger-causality and cross-correlation

The results for each indicator out of $\chi_t^{(14)}$ indicate that Granger-causality runs from the indicator to the reference series, and the results are statistically significant at the 1% level for most of the series. All individual series $x_{i,t}$ exhibit maximum cross-correlations at leads, with the number of periods (t_{max}) ranging between 1 and 3 quarters. For example, indicators with t_{max} at +1Q are job vacancies or productions expectations for the month ahead. The three-sectoral business confidence climate series as well as both stock market indices have, for instance, their t_{max} at +2Q. The only indicator in the set with the maximum cross-correlation occurring at +3Q is the consumer confidence series. The cross-correlation coefficients with respect to the corresponding t_{max} vary between 0.52 and 0.76.

3.2.2 Coherence and mean delay

The coherence measure ranges from a low of 0.13, the value for the consumer confidence indicator, to 0.59, a value obtained for the series representing export volumes. However, most values oscillate around 0.25 to 0.30, indicating a somewhat weak relationship. Unfortunately, this is not in line with the results determined for the maximum cross-correlation coefficients above, where much higher linear correlations are found.

All selected indicators have a mean delay greater than zero, with most values being in the range of +0.8 to +1.2. In the upper bound, the consumer confidence indicator is located with a value over +2.0. This is the same result as for the t_{max} measure in the time domain. On the other end, mean delay statistics for the real sector indicators, i.e. job vacancies, export volumes and industry production, are all around or below +0.3.

3.2.3 Turning point analysis

The results show, for example, that all series exhibit a median lead in their turning points with respect to peaks, troughs and over the whole time span. The median lead ranges from about half a quarter to a full year, with the lead time at cyclical troughs being more pronounced. The average durations of cycles, i.e. the time-span between peak-to-peak (P-P) and trough-to-trough (T-T), and phases, i.e. between peak-to-trough (P-T) and trough-to-peak (T-P), are somewhat shorter for the individual indicator $x_{i,t}$ compared to the values obtained for the reference series Y_{exFA}^{GVA}.

Table 4: Selected 'Leading' Indicators – Statistical Results

		Time series domain					Frequency domain		Turning point analysis			Dynamic factor analysis			
		Granger-Causality [1]		**Cross-Correlation** [2]			**Coher-ence** [3]	**Mean Delay** [4]	**Median lag at..** [5]			**Var. Ratio** [6]	**CC-Corr.** [7]		**CC-Classif.** [8]
		X->Y	Y->X	r_0	r_{max}	t_{max}			Peaks	Troughs	All		r_{max}	t_{max}	
x_i		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
x_1	ATX stock market index	4.01493 ***	1.36302	0.35	0.58	+2	0.20	+1.20	-4.0	-3.5	-2.5	0.305	0.901	+1	lead
x_2	DJ EURO STOXX 50 stock market index	4.64888 ***	1.03505	0.45	0.57	+2	0.26	+0.71	-0.5	-3.5	-1.5	0.362	0.904	+1	lead
x_3	Job vacancies, total	4.44090 ***	0.43955	0.63	0.65	+1	0.43	+0.25	-1.0	-1.0	-1.0	0.513	0.954	0	co
x_4	Exports, total	6.41154 ***	1.75740	0.75	0.76	+1	0.59	+0.31	-1.0	-2.5	-1.0	0.865	0.984	0	co
x_5	WIFO Industry production, total without energy and construction	2.28353 *	1.95229	0.54	0.57	+1	0.32	+0.37	-1.0	-2.5	-1.5	0.762	0.985	0	co
x_6	WIFO Industry production expectations for the month ahead	5.67116 ***	0.42230	0.43	0.52	+1	0.23	+0.87	-0.5	-3.5	-2.0	0.803	0.863	+1	lead
x_7	Consumer Confidence	3.91389 ***	0.68783	0.14	0.68	+3	0.13	+2.16	-3.0	-3.0	-3.0	0.381	0.855	+1	lead
x_8	Business Confidence Climate (industry, construction and retail)	2.03585 *	0.51853	0.31	0.52	+2	0.16	+1.22	-2.5	-3.0	-3.0	0.726	0.872	+1	lead
x_9	ifo Business Climate for Germany	6.77403 ***	0.98422	0.50	0.69	+2	0.34	+0.95	-1.5	-3.5	-2.0	0.838	0.881	+1	lead
x_{10}	Production trend observed in recent months for Germany	8.79156 ***	1.52522	0.43	0.54	+2	0.24	+0.98	-1.5	-3.5	-2.0	0.812	0.863	+1	lead
x_{11}	Production expectations for the months ahead for Germany	12.93240 ***	0.79081	0.46	0.61	+1	0.29	+1.05	-1.0	-4.0	-1.5	0.826	0.869	+1	lead
x_{12}	Production expectations for the months ahead in the Euro-Area	11.62090 ***	0.23330	0.48	0.60	+1	0.29	+0.92	-1.0	-3.0	-1.5	0.849	0.866	+1	lead
x_{13}	OECD CLI for Germany, trend-restored	9.21444 ***	1.04648	0.54	0.70	+1	0.39	+0.95	-1.5	-3.5	-2.5	0.852	0.876	+1	lead
x_{14}	OECD CLI for the Euro-Area, trend-restored	8.11007 ***	1.31464	0.47	0.72	+2	0.34	+1.13	-1.5	-3.0	-2.5	0.811	0.879	+1	lead

1) Performed on quarterly data with lag-length of 4; F-test statistic: *** indicates statistically significance at 1%, ** indicates statistically significance at 5%; * indicates statistically significance at 10%
2) r_0… contemporaneous cross-correlation; r_{max}… maximum cross-correlation at lag (t_{max}): + (-) sign refers to a lead (lag) w.r.t. the reference series
3) Average of spectral mass over the range of business cycle frequencies (between 6 and 32 quarters); statistical measure ranges between 0 and 1
4) Cross-spectrum between indiv. series and reference series; in average over ranges of business cycle periodicity (between 6 and 32 quarters): + (-) sign refers to a lead (lag) w.r.t. the reference series
5) Median turning point behaviour of indiv. series w.r.t. reference series at cyclical peaks, troughs and over the whole cycle: + (-) denotes a lag (lead) w.r.t. the reference series
6) Ratio of the common component variance over the series variance
7) Cross-correlation between series common component and the common component of the reference series (out of the Dynamic Factor Analysis); t_{max} indicates period with maximum correlation
8) Checking mean delay of the cross-spectra between series common component and reference series common component, with the following classification rules:
lead… mean delay < -1; lag… mean delay > 1; co… -1 < mean delay < 1

Source: Own calculations / BUSY software.

3.2.4 Dynamic factor analysis

For most series, the variance ratios are at around 0.8, meaning that a high proportion of the series variance is explained by the common factor. The ATX and EUROSTOXX 50 stock market indices together with the consumer confidence indicator mark exceptions with a variance ratio between 0.3 and 0.4. Most cross-correlation coefficients show their maximum value at +1Q, signalling the highest co-movement in the common components at one quarter lead. However, the series job vacancies, export volumes and industry production have their maximum cross-correlation with the reference series at t_0.

The results for the series classification are in line with the results derived from the common component cross-correlation analysis, i.e. all series with +1Q have a calculated mean delay higher than one, hence, being classified as leading series.

3.3 Data availability, revision and comparison

As a complement to the selection criteria outlined in Section 3.1, I also consider the timeliness, i.e. of the data and their stability with regard to subsequent revisions of the initial releases. For apparent reasons, for leading composite indicators, the timely availability of reasonably reliable data is especially important. Therefore, a publication lag of zero weeks, i.e. data availability at the end of the month, would be ideal.

As shown in Table 5, column (1), this holds primarily true for the group of survey indicators and the stock market indices. Job vacancies data follow within two to three weeks. With a publication delay between five and six weeks, the OECD composite leading indicators as well as the export volumes series are available. At the top margin, with data available not until 12 weeks after the end of the month, the indicator for industrial production is found. This is by no means suitable for inclusion into a composite index. As a consequence, I eliminate this indicator series from $\chi_t^{(14)}$.

With respect to data revision, some indicators are subject to ongoing correction, but none of the revision procedures seem to provide clear reasons for exclusion. However, it is to note that, for example, estimates of Austrian foreign trade figures undergo some intense revisions. Their first and intermediate estimates are generally too low and the upward correction is quite significant (Bilek-Steindl et al., 2009).

Considering the findings derived in this section, the final set of 'leading' indicators used for construction of the CLI_{AT} is highlighted in Table 5 column (3). I refer to it in subsequent sections as $\chi_t^{(13)}$.

Table 5: Data Timeliness and Revision

x_i		Timeliness [1]	Revision	Element of CLI_{AT} [6]
		(1)	(2)	(3)
x_1	ATX stock market index	0 to 1	No	Yes
x_2	DJ EURO STOXX 50 stock market index	0 to 1	No	Yes
x_3	Job vacancies, total	2 to 3	Yes [2]	Yes
x_4	Exports, total	5 to 6	Yes [3]	Yes
x_5	WIFO Industry production, total without energy and construction	11 to 12	Yes [4]	No
x_6	WIFO Industry production expectations for the month ahead	3 to 4	No	Yes
x_7	Consumer Confidence	0	No	Yes
x_8	Business Confidence Climate (industry, construction and retail)	3 to 4	No	Yes
x_9	ifo Business Climate for Germany	0	No	Yes
x_{10}	Production trend observed in recent months for Germany	0	No	Yes
x_{11}	Production expectations for the months ahead for Germany	0	No	Yes
x_{12}	Production expectations for the months ahead in the Euro-Area	0	No	Yes
x_{13}	OECD CLI for Germany, trend-restored	5 to 6	Yes [5]	Yes
x_{14}	OECD CLI for the Euro-Area, trend-restored	5 to 6	Yes [5]	Yes

1) Number indicates publication lag in weeks.
2) Due to monthly seasonal adjustment process.
3) Ongoing, i.e. month-by-month; plus in May revision of previous year.
4) Ongoing, i.e. previous plus ongoing year.
5) Due to the monthly trend-restoring procedure.
6) Indicates whether individual indicator will be used later in the construction of the CLI for the Austrian economy.
Source: Timeliness measure and Revision indicator are derived from the WIFO Economic Database.

Before I turn to constructing a CLI_{AT} from the data set (see Section 4), I compare the latter with the composition of existing composite indices for Austria or groups of indicators that have previously been used to forecast growth of economic activity in Austria.

I choose the OECD Composite Leading Indicator[17], the OeNB Economic Indicator (OEI)[18] and the Bank Austria Business Indicator[19] for this task. The former represents an index concerning early turning point detection in the Austrian business cycle, while the latter two are used for short-term forecasts of Austrian real GDP.

Table 6 provides the list of individual indicators incorporated in each of these 'composite' indicators. Column (1) shows that about half of those indicators, though included in the data set, are not classified as 'leading' with respect to the reference series Y_{exFA}^{GVA} chosen in this study.

[17] The OECD CLI is constructed as a monthly indicator and uses industrial production as the reference series.

[18] The Austrian central bank publishes every quarter estimates of the so-called OeNB-business-cyle- indicator, an indicator which estimates the growth of GDP for the next quarter. One part of the estimation procedure is based on a state-space model composed of six indicators (Fenz et al., 2005).

[19] The Bank Austria Business Indicator for Austria attempts to assess the current economic climate in Austria up to half a year earlier before the GDP data get published.

These series are as follows: (1) information about order book levels in the manufacturing sector and the interest rate spread out of the OECD CLI for Austria; (2) volume of outstanding loans to the non-financial sector, real exchange rate USD/EUR, number of employees and total new car registrations all incorporated in the OEI state-space model; and (3) consumer confidence and the growth rate of consumer loans used in the Bank Austria Business Indicator.

Table 6: Other Composite Indices / Groups of Indicators for Austria

		Element of CLI_{AT}	Series Weights
		(1)	(2)
OECD Composite Leading Indicator [1]			
01	Production: future tendency (manufacturing; % balance)	Yes	1/6
02	Order books: level (manufacturing; % balance)	No	1/6
03	Ifo business climate indicator for Germany	Yes	1/6
04	Consumer confidence indicator	Yes	1/6
05	Unfilled job vacancies (persons)	Yes	1/6
06	Spread of interest rates (% per annum)	No	1/6
OeNB Economic Indicator (OEI) - Explanatory Variables of the State-Space Model [2]			
01	Ifo business climate indicator for Germany	Yes	- [5]
02	Outstanding loans to the domestic non financial sector	No	-
03	Number of job vacancies	Yes	-
04	Real exchange rate index USD/EUR	No	-
05	Number of employees	No	-
06	New car registrations	No	-
Bank Austria Business Indicator for Austria [3]			
01	Confidence of Austrian industry	Yes	1/10
02	Confidence of industry in the Euro Area, weighted by Austria's foreign trade	Yes	3/10
03	Confidence of Austrian consumers [4]	No	5/10
04	Growth of consumer loans	No	1/10

1) Source http://www.oecd.org/document/43/0,3343,en_2649_34349_1890603_1_1_1_1,00.html
2) Source http://www.oenb.at/de/geldp_volksw/prognosen/konjunkturindikator/oenb-konjunkturindikator.jsp
3) Source http://www.bankaustria.at/en/open.html?opencf=/en/18917.html
4) Indicator is based on the European Commission Business and Consumer Survey; whereas the consumer confidence indicator used in this study is provided by the market research institute FESSEL-GfK. Therefore, the indicator has been classified with 'No', meaning it is not included in the CLI_{AT}.
5) Weights are not applicable in the OeNB state-space model.

4. Construction of a CLI for the Austrian economy

With the final set of $\chi_t^{(13)}$ identified, I now turn to combining the individual series $x_{i,t}$ into a composite leading indicator (CLI_{AT}). The steps in constructing the CLI_{AT} are as follows:[20]

- first, individual series are, if needed, corrected for their long-term trend applying the Hodrick-Prescott (HP) filter (see Section 4.1);
- second, weights for the normalised component series $x_{i,t}^{z}$ are determined by means of principal component analysis (PCA) and by using these weights the series are aggregated to form the monthly CLI_{AT} (see Section 4.2); and
- third, short-term irregularities in the constructed CLI_{AT} are eliminated using once again the HP filter (see Section 4.3).

I construct three different composite leading indices, $\Omega = \{\Psi_{full}^{pca}, \Psi_{full}^{ew}, \Psi_{flash}^{pca}\}$, which differ in the numbers of single indicators $x_{i,t}$ combined and the weights assigned to each of the components. The main composite index, denoted as Ψ_{full}^{pca}, contains all series included in $\chi_t^{(13)}$, with individual weights being derived from PCA. In addition, a composite with equal weights assigned to each individual indicator is constructed as well and denominated as Ψ_{full}^{ew}. This is done to assess the role of the weighting method.

In order to account for the various publication lags at hand for individual component series, I construct a third version of the CLI_{AT} incorporating only series, where data are promptly available. I call this the 'flash' CLI_{AT}, labelled as Ψ_{flash}^{pca}, where series weights are again calculated using PCA. Nine series out of $\chi_t^{(13)}$ classify to be included in the 'flash' version: the seven business and consumer survey indicators and the two stock market indices.

4.1 De-trending with the HP filter

Some of the monthly indicators contain long-run trends, which have to be removed from the series in order to uncover the cyclical variations in the series. As already mentioned in Section 2.2, one prominent method for removing trend movements is the Hodrick-Prescott (HP) filter. Despite some criticism[21] relating to spurious cyclical behaviour using the HP method for de-

[20] At some stages of the construction process I build on technical guidelines out of the '*Handbook on Constructing Composite Indicators – Methodology and User Guide*' provided by the OECD (Nardo et al., 2005).

[21] Harvey and Jaeger (1993) have shown, for example, that in small samples the HP filter can cause apparent cyclical fluctuations between the series even when the pre-filtered series are uncorrelated.

trending (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.

I follow this stance and use the HP filter to remove the trend component from the monthly series $x_{i,t}$ where applicable. Out of the indicator set $\chi_t^{(13)}$, six series contain trend moments: ATX and EUROSTOXX 50 stock market indices, job vacancies, export volumes and both OECD CLI series. These indicators are therefore considered in their de-trended form in the construction steps which follow.

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:

$$\min_{\{\tau_t\}} \sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \tag{4-1}$$

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 residuals $y_t - \tau_t$, i.e. the deviation from trend, is then commonly referred to as the business cycle component.

The choice of λ depends on data frequency. For quarterly data λ is usually set to 1600, while for monthly data the value of λ=14,400 is most often found in the literature.[22] 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 provide a rule to obtain λ in the case the quarterly frequency of observations is altered:

$$\lambda_s = s^m \times \lambda_q \tag{4-2}$$

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; and λ_q is set to 1600, the value for quarterly data.[23] Ravn and Uhlig (1997) recommend using a power value m=4. I follow this suggestion and obtain λ_m=129,600 as the appropriate value for monthly data. This value

[22] When $\lambda=\infty$ the solution to the minimisation problem in (4-1) is a linear trend, while with λ=0 the trend component reflects the original series.

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

converts in the frequency domain perspective to a cut-off point of the high-pass filter to roughly below 120 months.[24]

4.2 Normalisation and Weighting

Before constructing the monthly CLI_{AT}, normalisation of the individual component series $x_{i,t}$ is necessary in order to reduce the influence of series with marked cyclical variance and to express all series in the same unit of measure. The normalisation method chosen are z-scores. This standardises indicators to a common scale with a mean of zero and standard deviation of one which follow a standard normal distribution. The formula is as follows

$$x_{i,t}^{z} = \frac{x_{i,t} - \mu_i}{\sigma_i} \sim N(0,1) \text{ and } \overline{\chi}_t^{(13)} = \left\{x_{1,t}^{z}, \ldots, x_{13,t}^{z}\right\} \tag{4-3}$$

where $x_{i,t}^{z}$ represents the standardised component series; μ_i and σ_i denote the mean and standard deviation of the series, respectively. The outcomes of this step are series where the cyclical movements are expressed in comparable form with cyclical amplitudes homogenised[25].

Various weighting methods may be used to combine the individual series to form the CLI_{AT}. One straightforward method is to use a simple average with the same weights for each series. This approach, for example, is used by the OECD for its composite leading indicators. However, equal weights may not reflect the optimal contribution of individual series to a business cycle indicator. In order to obtain individual series weights for the CLI_{AT}, the method of PCA is used and applied to the set of normalised series $\overline{\chi}_t^{(13)}$.

4.2.1 Principal component analysis (PCA) – Methodology

The objective of PCA is to explain the observed series $(x_1, x_2, \ldots, x_n)$ from k linear combinations (principal components) of the original data.

$$x_i^{z} = a_{i1}PC_1 + a_{i2}PC_2 + \ldots + a_{ij}PC_j + u_t \tag{4-4}$$

[24] The approximate value of 120 month is in line with the λ parameter value the OECD uses in their de-trending procedure in the construction of their leading composite indicators; OECD setting: λ=133,107.94 ≡ 120 month.

[25] Note that standardised scores for each series deals with outliers to some extent, but it still allows extreme values to influence the results because the range between the minimum and maximum z-scores will vary for each indicator, thus, it gives greater weight to an indicator in those units with extreme values (Freudenberg, 2003).

The factor loadings a_{ij} (with i=1…n, j=1…k) are chosen such that the following conditions are satisfied[26]: (1) the first principal component PC_1 explains the maximum possible proportion of the variance in the whole set of variables; (2) subsequent principal components PC_j are orthogonal and uncorrelated to the previous components $\left(PC_1,\ldots,PC_{j-1}\right)$ and explain again the maximum possible portion of the variance conditional on the previous components. The number of principal components, i.e. the set of principal components that captures the variation in the original variable set to a sufficient extent, is usually found from the cumulative explained variance and eigenvalues. The number of principal components is usually chosen from the following rule of thumb-criteria: (1) the number of eigenvalues being larger than one; the number of components that (2) contribute individually to the explanation of overall variance being higher than 10%; and (3) a cumulative explanation power of the overall variance of more than 60%.

The weights v_i of series $x_{i,t}^{z}$ in the CLI_{AT} are found from the squared factor loadings a_{ij}^2 at the principal component with the highest loading, multiplied with the portion of the explained variance explained by the respective component:[27]

$$v_i = a_{ik}^2 \times \varphi_k \qquad (4\text{-}5)$$

$$\varphi_k = \sigma_{PCk} / \left(\sum_{i=1}^{m} \sigma_{PCi} \right), \qquad (4\text{-}6)$$

where $k = \arg\max_i \left[a_{ij}{}^2 \right]$.

That is, φ_j represents the portion of the explained variance for principal component j to the cumulative sum of the explained variance of the m retained principal components; σ_{PCj} denotes the variance explained by the j-th principal component (with $i \le j \le m$); and m denotes the number of retained factors. The series weight v_i is based on the maximum value of the squared factor loading found for the series multiplied by φ_j and scaled to unity sum.

[26] Factor loadings measure the correlation between the individual series and the latent factors. The square of the factor loading indicates the proportion of variance shared by the series with the factor.

[27] The approach used to obtain individual series weights follows the technique described in Nicoletti et al. (2000); see also Nardo et al. (2005), Section 6.1. In principle, the signs of factor loadings should be considered as well, of course, but they are all positive in the present case.

4.2.2 Principal component analysis (PCA) – Results

Table 7 displays the results derived from PCA regarding CLI$_{AT}$ Ψ^{pca}_{full}. Applying the rules of thumb for determining the number of factors gives two principal components, which account for about 79% of the total variance. The squared factor loadings ($a_{i,j}^2$) have, with two exceptions, their maximum value on factor 1. The two series which have higher loadings on factor 2 are the EUROSTOXX 50 stock market index and the job vacancies series. The individual series weights v_i derived range from 4 to 10%. The group of business and consumer survey series constitute a combined weight of 60%, hence, representing the largest share in Ψ^{pca}_{full}. The OECD composite leading indicators and the stock market indices represent 20% and 10%, respectively. The remaining share is split between the series for job vacancies and export volumes, each having a weight of 6%.

Table 7: PCA Results – Individual Series Weights

	CLI$_{AT}$	**Factor 1**	**Factor 2**	Factor 3	Factor 4	Factor 5
	Eigenvalues	8.954	1.259	0.762	0.494	0.407
	Variance explained (in %)	68.90	9.70	5.87	3.80	3.13
	Cumulative variance explained (in %)		78.60	84.43	88.23	91.36
	Proportion of explained variance / cum. explained variance (φ_j)	0.88	0.12			
x_i	**Indicators**	**Loadings**		**Weights**		
		$a_{i,1}$	$a_{i,2}$	$a_{i,1}^2$	$a_{i,2}^2$	v_i
x_1	ATX stock market index	0.259	0.157	**0.07**	0.02	**0.07**
x_2	DJ EURO STOXX 50 stock market index	0.230	0.505	0.05	**0.26**	**0.04**
x_3	Job vacancies, total	0.193	0.654	0.04	**0.43**	**0.06**
x_4	Exports, total	0.238	0.154	**0.06**	0.02	**0.06**
x_5	WIFO Industry production expectations for the month ahead	0.295	-0.209	**0.09**	0.04	**0.09**
x_6	Consumer Confidence	0.250	0.098	**0.06**	0.01	**0.06**
x_7	Business Confidence Climate (industry, construction and retail)	0.266	-0.093	**0.07**	0.01	**0.07**
x_8	ifo Business Climate for Germany	0.309	-0.057	**0.10**	0.00	**0.09**
x_9	Production trend observed in recent months for Germany	0.295	-0.238	**0.09**	0.06	**0.09**
x_{10}	Production expectations for the months ahead for Germany	0.308	-0.277	**0.09**	0.08	**0.09**
x_{11}	Production expectations for the months ahead in the Euro-Area	0.296	-0.265	**0.09**	0.07	**0.09**
x_{12}	OECD CLI for Germany, trend-restored	0.315	-0.008	**0.10**	0.00	**0.10**
x_{13}	OECD CLI for the Euro-Area, trend-restored	0.318	-0.012	**0.10**	0.00	**0.10**

Source: Own calculations.

Applying the same PCA approach to the 'flash' CLI$_{AT}$ reveals that the first principal component is sufficient to describe the variance of the data, i.e. factor 1 explains more than 70% of the variation. Therefore, only this factor is used to derive the component weights. Business and consumer survey indicators then account for 84%, and the group of stock market indices form a share of 16% within the CLI$_{AT}$ Ψ^{pca}_{flash}. Additionally, I have allocated the weight $v_i = 1/13$ to each of the series contained in Ψ^{ew}_{full}. Table 8 provides on overview of the different component weights obtained.

Table 8: Individual Series Weights – Summary

		CLI$_{AT}$		
x_i		X_{full}^{PCA}	X_{full}^{EW}	X_{flash}^{PCA}
x_1	ATX stock market index	0.07	1/13	0.09
x_2	DJ EURO STOXX 50 stock market index	0.04	1/13	0.07
x_3	Job vacancies, total	0.06	1/13	-
x_4	Exports, total	0.06	1/13	-
x_5	WIFO Industry production expectations for the month ahead	0.09	1/13	0.13
x_6	Consumer Confidence	0.06	1/13	0.09
x_7	Business Confidence Climate (industry, construction and retail)	0.07	1/13	0.11
x_8	ifo Business Climate for Germany	0.09	1/13	0.13
x_9	Production trend observed in recent months for Germany	0.09	1/13	0.13
x_{10}	Production expectations for the months ahead for Germany	0.09	1/13	0.14
x_{11}	Production expectations for the months ahead in the Euro-Area	0.09	1/13	0.13
x_{12}	OECD CLI for Germany, trend-restored	0.10	1/13	-
x_{13}	OECD CLI for the Euro-Area, trend-restored	0.10	1/13	-

Source: Own calculations.

4.3 Aggregation and Smoothing

In general, the monthly CLI$_{AT}$ is obtained as the weighted average from the normalised individual indicators:

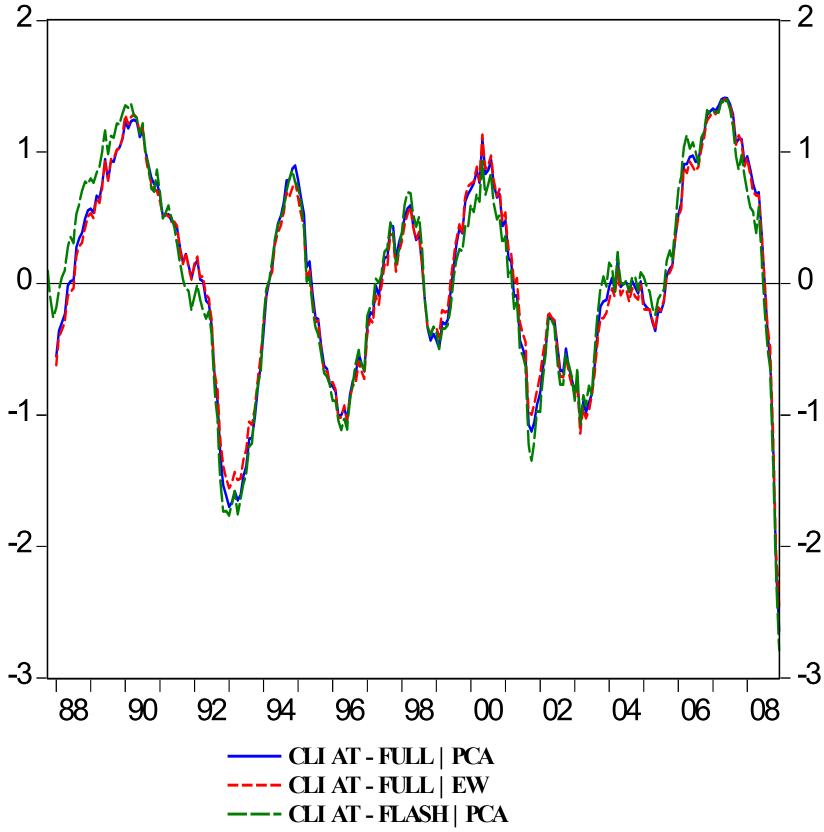
$$\psi_t = \sum_{i=1}^{k} v_i x_{i,t}^z \text{ and } \Psi\{\cdot\}|_1^T = \{\psi_1, \ldots, \psi_T\} \tag{4-7}$$

where ψ_t is the aggregated CLI$_{AT}$ value at time *t*; v_i represents the individual series weight; $x_{i,t}^z$ is the z-score value for the individual series at time *t*; and $\Psi\{\cdot\}|_1^T$ stands for the unsmoothed full period CLI$_{AT}$ irrespective of the version.

As can bee seen in Figure 2, the resulting monthly CLI$_{AT}$ contains some noise, which hampers its usefulness in real-time, e.g. as regards a timely detection of turning points. Therefore, I apply the HP filter again on $\Psi\{\cdot\}|_1^T$ in order to smooth the series, i.e. to eliminate these irregular movements and to preserve the business-cycle frequencies.[28]

[28] In doing so, I follow current practice at the OECD. Starting from December 2008, the OECD uses as well the HP filter as smoothing procedure within its CLI methodology, replacing the Month-for-Cyclical-Dominance (MCD) approach.

Figure 2: Unsmoothed Monthly CLIs for the Austrian economy



4.3.1 Determining optimal λ for HP smoothing procedure

As already discussed, selection of the smoothing parameter λ is crucial when applying the HP filter. From the gain function of the HP filter (see e.g. Harvey and Jaeger, 1993), the relationship between λ and cut-off frequency ω_c is found as

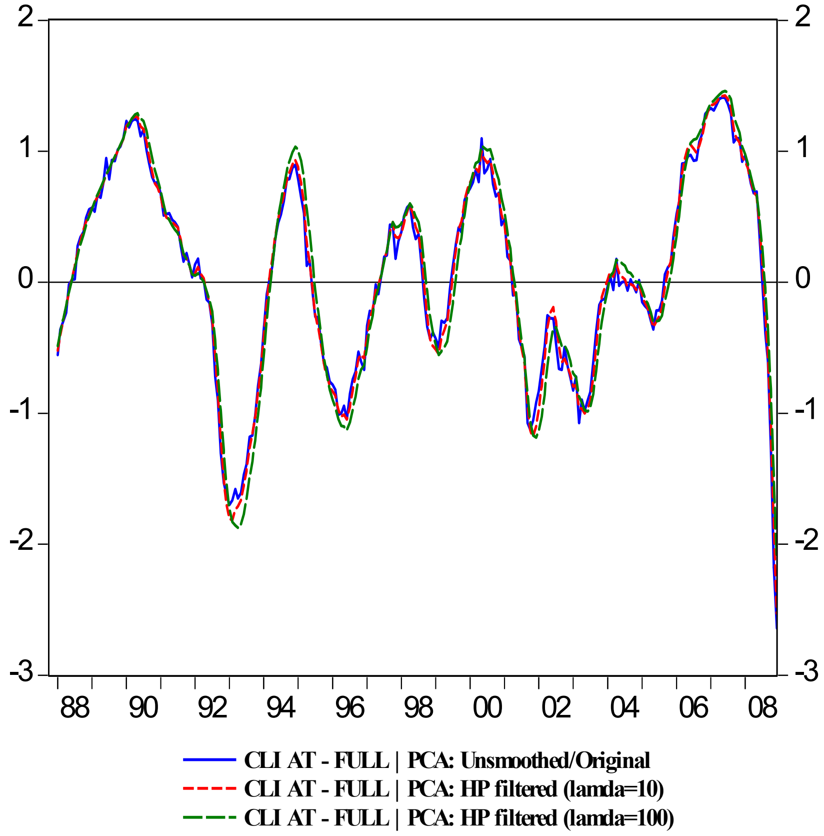
$$\lambda = \left[4 \times (1 - \cos(\omega_c))^2\right]^{-1}, \tag{4-8}$$

such that the gain for $\omega > \omega_c$ is smaller than 0.5; p denotes the number of periods it takes to complete a full cycle and $\omega_c = 2\pi / p$.

Some sensitivity analysis is conducted on an appropriate value of λ in the range between 10 and 100, where these λ-values correspond to periods roughly between 11 and 20 months, respectively. Figure 3 shows the two HP filtered CLI_{AT} series as well as the unsmoothed CLI_{AT} $\Psi_{full}^{pca}|_1^T$. It can be seen that a good part of the noise is removed in both smoothed series.[29]

[29] Note that the higher λ is set the more irregular movements will be eliminated.

Figure 3: Unsmoothed vs. HP filtered CLI_{AT}



From further visual inspection within the set of λ [10, 100] considered, the value of λ=20 appear sufficient to remove the noise in the unsmoothed CLI_{AT}; this value corresponds to p=13.2 months. It, thus, removes cyclical components in the series below this threshold.

4.3.2 HP filter endpoint problem and 'real-time' application

An important issue when dealing with filter methods is the well-known endpoint problem. While the HP filter is two-sided symmetric around the central values, it becomes one-sided at the end of the sample. As a consequence, the endpoint estimates of a HP filtered series would be subject to subsequent revisions when T gets revised or when new values become available.[30] For a thorough discussion of the endpoint problem in the HP filter see, for example, King and Rebelo (1993) or Kaiser and Maravall (1999, 2001). Besides, the one-

[30] By comparing the endpoint bias of various filter methods, Kranendonk et al. (2004) point out that the HP filter is more sensitive in this respect compared to the band-pass filters of Baxter and King (1999) and Christiano and Fitzgerald (2003).

sided HP filter gives rise to a phase shift in the filtered series, thereby possibly delaying the detection of turning points.

Another property of the HP filter and often the cause for critics is the fact that the HP filter exhibits stronger leakages at chosen cut-off frequencies ω_c, i.e. that leakage from cycles from just outside ω_c can be significant. However, this problem is not that severe in the given context of eliminating the high-frequency noise from the series. I base this reasoning on the ground that leakages from the idiosyncratic movements remaining in the HP filtered series do not constrain the usage of the CLI_{AT} in detecting turning points.

Based on this point of view, I concentrate in the remaining part of this section on the issue of the endpoint problem. Intuitively, when it comes to removing short-term noise, the endpoint sample problem becomes the more severe, the higher the value of λ. Hence, there emerges a possible trade-off between the degree of smoothness of the CLI_{AT} and possible biases in real-time application.

To inspect the endpoint bias of the HP filter, a quasi 'real-time' setting is applied. That is, instead of running the HP filter once over the whole sample period, i.e. from 1988M1 to 2008M12, for smoothing the monthly CLI_{AT}, the HP filter is repeatedly applied on a sub-sample[31]. This sub-sample is supplemented at each run with the 'latest' CLI_{AT} value available at that time. The course of action taken can be formalised as

$$\tilde{\Psi}\left\{\cdot\right\}_{t|t} = \Theta\left(\Psi\left\{\cdot\right\}|_1^t \,|\lambda = 20\right) \tag{4-9}$$

where $\tilde{\Psi}\left\{\cdot\right\}_{t|t}$ represents the HP filtered estimate of the CLI_{AT} for time t given the preliminary, i.e. unsmoothed, CLI_{AT} series $\Psi\left\{\cdot\right\}|_1^t$ with t=27…T; and Θ denotes the HP filter function for $\Psi\left\{\cdot\right\}|_1^t$ with the smoothing parameter λ set to 20.

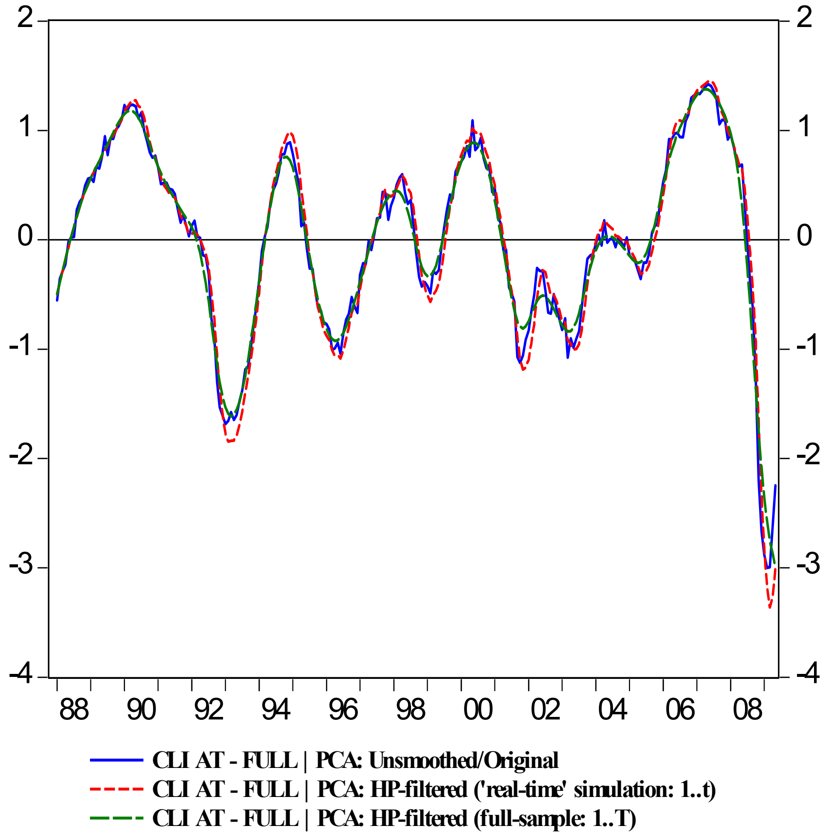
The quasi 'real-time' smoothed CLI_{AT} output series $\tilde{\Psi}\left\{\cdot\right\}|_1^t$ are therefore composed of HP filtered values representing each the most recent estimate in the sub-sample used. As a useful side product to this 'real-time' procedure, I automatically obtain a set of smoothed full-sample output series, which I denote as $\tilde{\Psi}\left\{\cdot\right\}|_1^T$. With both sets of smoothed CLIs on hand, it is now possible to check for the existence of phase-shifts between these series.

Figure 4 displays the 'real-time' and full-sample HP filtered CLI_{AT} as well as the unsmoothed version. It can be seen that most of the idiosyncratic noise contained in $\Psi_{full}^{pca}|_1^T$ is removed in

[31] The first sub-sample contains values up to 1990M3 (i.e. 27 observations), thus, providing a sufficient long data series for the first smoothing operation.

the HP filtered output series. Contrasting the CLI$_{AT}$ $\tilde{\Psi}^{pca}_{full}|^{t}_{1}$ with $\tilde{\Psi}^{pca}_{full}|^{T}_{1}$ shows the consequences of endpoint bias: the full-sample estimate is much smoother at cyclical turning points compared to the 'real-time' HP filtered version. This is due to the asymmetry of the HP filter at the endpoint of the data sample. However, no distinct phase-shifts can be observed. This is good news with respect to the timing of turning points. But some caution should be taken concerning turning points signals. In 'real-time', these signals may be exaggerated.

Figure 4: Full-sample vs. 'real-time' HP filtered CLI$_{AT}$



Overall, given that the 'real-time' HP filtered CLI$_{AT}$ $\tilde{\Psi}^{pca}_{full}|^{t}_{1}$ performs quite well and the simulation setting represents the more pragmatic use-case, I use $\tilde{\Psi}\{\cdot\}|^{t}_{1}$ as the base series for the conversion into quarterly frequency.

The conversion procedure marks the final step in the construction process of the CLI$_{AT}$. The set of monthly CLIs is transformed to quarterly frequency by simply taking the average of the monthly series.

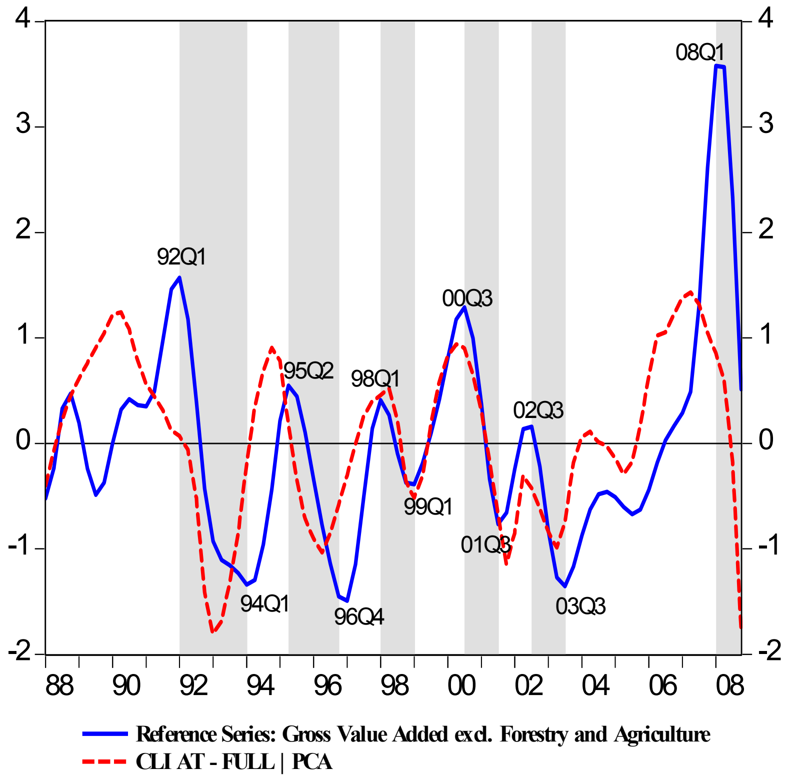
5. Performance of the CLI for the Austrian economy

The performance of the CLI_{AT} over time is a crucial determinant of the indicator's useability. There are a number of criteria upon which an indicator can be assessed. In line with the objectives of this study, the most important criterion, as outlined at the outset, is the indicator's ability to give reliable signals of turning points in the Austrian business cycle. Another criterion, which is discussed in the subsequent section, is the indicator's ability to reduce forecast errors of the underlying reference series, hence, to improve its projection quality.

This section presents the results obtained from the turning point analysis for the CLI_{AT}. More precisely, the different versions of the CLI_{AT} are analysed using the statistical methods outlined in Section 3. I include the OECD CLI for Austria as well in the analysis to compare the CLI_{AT} performance with this already existing composite leading indicator[32].

First and foremost, the CLI_{AT} should exhibit a steady leading behaviour with respect to the reference cycle in Y_{exFA}^{GVA}.

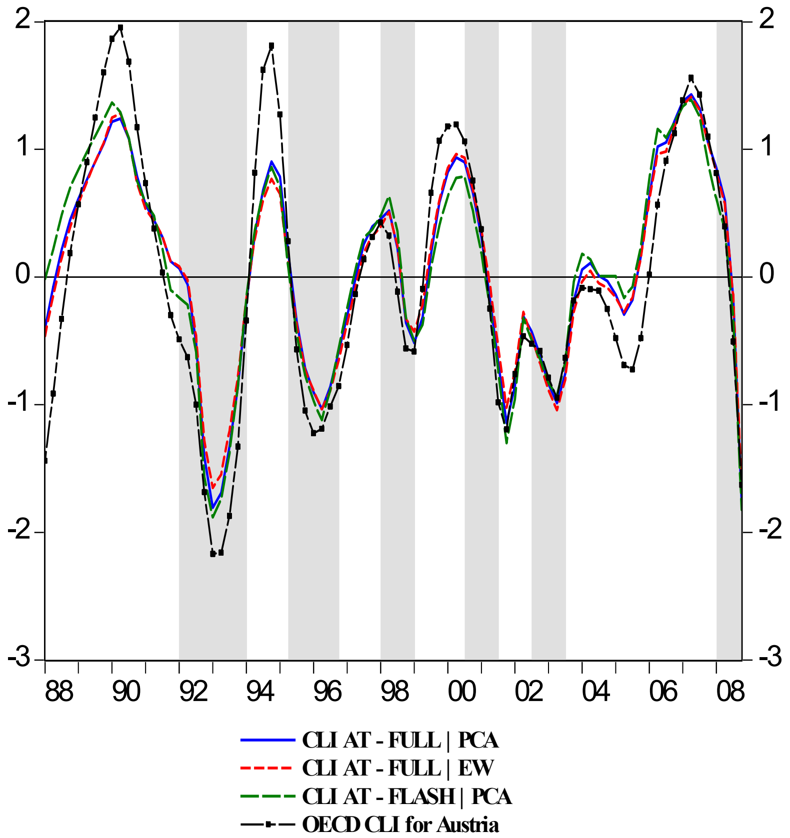
Figure 5: CLI_{AT} vs. Reference Series



[32] In this case, the amplitude adjusted version of the OECD CLI has been used. This series represents the cyclical component of the CLI. See OECD http://stats.oecd.org/wbos/Index.aspx?DatasetCode=KEI.

A visual turning point inspection of $\tilde{\Psi}_{full}^{pca}|_1^t$ (see Figure 5) reveals that the CLI_{AT} has its cyclical turning points principally prior to the underlying reference chronology, i.e. in 8 out of 11 times the CLI_{AT} turns before the reference series. Only the downswing between the peak in 1998Q1 and the following trough in 1999Q1 and the turning point in 2001Q3 mark an exemption where $\tilde{\Psi}_{full}^{pca}|_1^t$ coincides or slightly lags the cyclical turns in the reference series.

Figure 6: Comparison of different CLIs



As shown in Figure 6, differences among the various versions of the CLI_{AT} are small. This especially holds for the CLI_{AT} $\tilde{\Psi}_{full}^{pca}|_1^t$ and $\tilde{\Psi}_{full}^{ew}|_1^t$. I infer from this result that moderate differences in the weights assigned to single components in otherwise identical composite indices do not affect the outcome as much as one would expect. The OECD CLI for Austria[33] displayed shows, on average, higher cyclical amplitudes, but with regards to turning points the series is almost similar to the constructed CLIs.

[33] The OECD CLI series has been standardised as well using the z-score measure described in Section 4.2.

The results from the visual analysis allow concluding that the newly constructed CLI_{AT} is able to provide early signals of turning points in the Austrian business-cycle.

5.1 Statistical Results

As displayed in Table 9, the pair-wise Granger-causality test indicates that for all tested versions of the CLI_{AT} Granger-causality runs from the CLI_{AT} to the reference series Y_{exFA}^{GVA}. The results are all statistically significant at the 1% level. Calculating cross-correlations reveals that all composite indices have their maximum cross-correlation r_{max} at +2Q with a cross-correlation coefficient for this period around 0.60. The contemporaneous r_0 cross-correlation coefficients range between 0.34 and 0.42, thus, displaying similar magnitude.

Table 9: CLIs – Statistical Results

	Time series domain					Frequency domain		Turning point analysis		
	Granger-Causality 1)		Cross-Correlation 2)			Coherence 3)	Mean Delay 4)	Median lag at.. 5)		
	X->Y	Y->X	r_0	r_{max}	t_{max}			Peaks	Troughs	All
Indicators	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CLI_{AT} *XfullPCA*	5.54004 ***	0.90161	0.42	0.59	+2	0.25	+1.05	-2.0	-3.0	-2.0
CLI_{AT} *XfullEW*	4.98645 ***	0.79081	0.43	0.61	+2	0.26	+1.03	-2.0	-3.0	-2.0
CLI_{AT} *XflashPCA*	6.32502 ***	1.69714	0.37	0.57	+2	0.21	+1.17	-2.0	-3.0	-2.0
OECD CLI 6)	4.99981 ***	0.21309	0.34	0.58	+2	0.20	+1.28	-2.0	-3.5	-2.0

Note: The CLI_{AT} indicators listed denote the 'real-time' HP filtered version of the CLI_{AT}.

1) - 5) See notes to Table 4.

6) Amplitude adjusted version of the OECD CLI for Austria.

Source: Own calculations / BUSY software.

The coherence measure, as the counterpart to the cross-correlation statistic in the time series domain, varies from 0.20 to 0.26. These values represent merely a weak linear relationship between the CLI_{AT} and the underlying reference series. However, this result is not surprising, because the same circumstance has been identified in the analysis process for the individual leading indicators (see Section 3.2). The second statistic calculated in the frequency domain is the mean delay. Values obtained for the mean delay measure are all greater than one indicating a leading behaviour of at least one quarter within the business cycle frequency. Out of the four CLIs analysed, the OECD CLI ranks top with a mean delay of +1.28Q. This is followed by $\widetilde{\Psi}_{flash}^{pca}|_1^t$ with a value of +1.17Q. The remaining two CLIs exhibit a mean delay of +1.05 and +1.03, respectively.

Further, results from the turning point analysis with respect to the median lead time provide a consistent picture. That is, the lead time at cyclical peaks, troughs and over the whole business cycle is almost the same irrespective of the type of CLI analysed; with values between +2.0Q and +3.5Q. Obtaining the average instead of the median lead time provides similar results. This shows that the estimated turning points do not contain any real trouble-making outliners verifying a 'stable' leading nature of the CLI_{AT} with respect to the reference series.

Overall, the results from the turning point analysis show that the CLI_{AT} is able to provide signals of cyclical turns with a lead time between one and two quarters, reinforcing the outcomes derived from the merely visual inspection at the outset of this section. It is interesting to note, though, that:

(i) the performance of the equally weighted composites CLI_{AT} $\widetilde{\Psi}^{ew}_{full}|^{t}_{1}$ and OECD CLI is not remarkably different to indices where the weights are obtained using PCA;

(ii) the 'flash' CLI_{AT} performs quite similar to the full-component CLI_{AT}; and

(iii) the different versions of the CLI_{AT} show comparable results to the OECD CLI, even tough containing to a large extent different single indicators.

These findings are quite good news. First, the 'flash' CLI_{AT}, which is immediately available at the end of each period, can be used to get a first but good approximation of the direction the economy is most likely heading to. Next, this first assessment can be verified with the release of the OECD CLI for the Austrian economy about a month later. This is especially useful given the fact that the OECD CLI contains other single indicators, such as the interest rate spread, not incorporated in the CLI_{AT}. Finally, with the release of the full-component CLI_{AT} about 6 weeks later compared to the 'flash' CLI_{AT}, it is possible to refine the predication made about impending turning points in the Austrian business-cycle.

6. Out-of-sample forecasting exercise

In this section, the information contained in the CLIs for forecasting the reference series Y^{GVA}_{exFA} is examined. I conduct a recursive out-of-sample forecast exercise. Predictions made use only information available prior to the forecasting period, thus simulating a 'real-time' environment. The forecasting model I use and outlined in Section 6.1 builds on the framework proposed by Stock and Watson (1999) for forecasting U.S. inflation. It has been subsequently applied, for example, by Altimari (2001), Carstensen (2007) and Hofmann (2008) to investigate inflation predictability in the euro area.

I evaluate forecasting performance with forecasting horizons varying from one quarter to three years ahead. Forecasts of the reference series excluding any composite leading indicator serve as the benchmark case. The root mean squared error (RMSE)[34] measure is used to evaluate the forecast quality. Beside the various versions of the CLI_{AT} on hand, the OECD CLI for Austria is used, as well. Provided that a reduction in the forecast errors can be achieved by means of the CLI_{AT}, it might be of use to incorporate the CLI_{AT} in the WIFO institutes' regular forecasting routines.

Overall, the results of forecasting exercise show that the forecast quality can be improved in the majority of cases tested, i.e. yielding a smaller RMSE compared to the univariate benchmark forecasts. This is especially true the longer the forecasting horizon is taken. Section 6.2 provides detailed test results and discussion.

6.1 Methodology

The forecasts of Y_{exFA}^{GVA} are determined using the following linear bivariate model:

$$y_{t+h}^{h} - y_t = \alpha + \beta(L)\Delta y_t + \gamma(L)x_t + \varepsilon_{t+h} \qquad (6\text{-}1)$$

where y_t is the logarithm of the reference series Y_{exFA}^{GVA}; x_t is an indicator variable representing different versions of composite leading indicators; and $\beta(L)$ and $\gamma(L)$ are polynomials in the lag operator L that specify the number of lags included in the regression. In the single-equation model specified in (6-1), future values of y_t depend on current and possible past realisations of y_t and indicator x_t. Moreover, the model is expressed in first difference, because y_t follows an I(1) process, while the individual indicator x_t is assumed to follow an I(0) process.

The forecast procedure is run for different forecast horizons, with h varying from 1 to 12 quarters. I consider specifications of $\beta(L)$ and $\gamma(L)$ running from 1 through 5 lags. The number of optimal lags for both regressors is determined recursively using the Akaike's information criterion (AIC) at each run. This implies that at each step of the forecast procedure 25 different model estimates are compared and the one with the minimum AIC value is chosen. The time span in the forecast procedure ranges from 1988Q1 to 2008Q4 with the first out-of-sample forecast starting from 1995Q1-h to the end of the sample period.

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[34] The RMSE for any forecast is the square root of the arithmetic average of the squared differences between the actual and the predicted series value over the time period for which simulated forecasts are constructed.

It is calculated as: $RMSE^{h} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[y_t - E_i\left(y_{t+h}^{h}\right)\right]^2}$ where h denotes the forecasting horizon.

The forecast for 2000Q3 with h=4 provides an example. This forecast is made in 1999Q3 and is based on a forecasting regression using data up to 1999Q2. Once the forecast for a given quarter in the forecast sample has been computed, the procedure moves one quarter forward and uses one additional data point per step to estimate the forecasting regression and to construct the forecast. The procedure stops after the forecast for 2008Q4 has been constructed; that is the last period in the data sample.

I evaluate the accuracy of the reference series forecasts from a univariate model setting, where the parameter $\gamma(L) = 0$, to the bivariate specification by comparing the RMSE of these two sets of forecasts, such as:

$$U = \frac{RMSE_b}{RMSE_u} \qquad (6\text{-}2)$$

where the subscript b and u denote the bivariate and univariate model specification, respectively. This measurement is often referred to as *Theil's coefficient*. The Theil coefficient equals one if the forecast model of concern is of the same quality as the 'simple' forecast, less than one if an improvement arises and greater than one if the forecast model is not as good.

6.2 Results

In Table 10, the forecasting evaluation results for the bivariate model (6-1) over the different forecasting horizons, divided into short-, medium- and long-term, are displayed. I consider the following versions of the CLI_{AT}: all three one-sided/asymmetric HP filtered versions $\left\{\tilde{\Psi}^{pca}_{full}\big|^{t}_{1}, \tilde{\Psi}^{ew}_{full}\big|^{t}_{1}, \tilde{\Psi}^{pca}_{flash}\big|^{t}_{1}\right\}$, the unsmoothed CLI_{AT} $\Psi^{pca}_{full}\big|^{T}_{1}$ as well as the two-sided HP filtered version $\tilde{\Psi}^{pca}_{full}\big|^{T}_{1}$, and the OECD CLI for Austria.

Looking at Table 10 closely, the results show that only a few forecasts provide deterioration in the RMSE measure, i.e. they have relative RMSEs greater than unity. In particular, some of the short- to medium-term forecasts, especially those at one and five quarter horizons, perform worse than the benchmark case. In contrast, forecasts three quarter ahead perform quite well and improve the forecast quality by around 20%. Furthermore, the improvement in the predictive accuracy is more pronounced for longer forecast horizons. Forecasts for seven quarters ahead and more reduce the RMSE in several cases by as much as 25%.

Table 10: Results of the Out-of-Sample Forecasting Procedure

	Quarterly forecast horizons (h = 1..12)											
	short-term				medium-term				long-term			
	1	2	3	4	5	6	7	8	9	10	11	12
Univariate RMSE [1)]	0.0063	0.0087	0.0104	0.0119	0.0132	0.0148	0.0168	0.0187	0.0198	0.0211	0.0227	0.0243
Indicators [2)]												
$\text{CLI}_{\text{AT}} X_{full}^{PCA}$	1.02	0.93	0.83	0.90	1.00	0.93	0.86	0.81	0.77	0.77	0.80	0.82
$\text{CLI}_{\text{AT}} X_{full}^{EW}$	0.98	0.91	0.82	0.87	0.97	0.90	0.82	0.77	0.74	0.77	0.74	0.75
$\text{CLI}_{\text{AT}} X_{flash}^{PCA}$	1.02	0.98	0.94	0.98	1.01	1.03	0.96	0.94	0.91	0.89	0.90	0.88
$\text{CLI}_{\text{AT}} X_{full}^{PCA}$	0.94	0.92	0.79	0.96	0.98	0.94	0.85	0.85	0.80	0.78	0.80	0.83
$\text{CLI}_{\text{AT}} X_{full}^{PCA}$	0.90	0.84	0.82	0.84	0.86	0.81	0.84	0.80	0.75	0.76	0.74	0.77
OECD CLI [3)]	0.97	0.97	0.95	0.94	1.00	0.90	0.94	0.87	0.84	0.86	0.87	0.83

Note: The sample period for the recursive forecasting regressions ranges from 1988Q1 to 2008Q4.
The forecast evaluation sample runs from 1995Q1-*h* to 2008Q4.
The first set of CLI_{AT} indicators listed denote the 'real-time' HP filtered version of the CLI_{AT},
whilst the second block contains the unsmoothed and full-sample HP filtered version of the CLIAT, respectively.

1) Absolute forecast RMSE values for the univariate model setting.
2) Values are the ratio between the forecast RMSE of the bivariate model which uses the variable indicated and the forecast RMSE of the univariate model; numbers less (greater) than 1.0 refer to an improvement.
3) Amplitude adjusted version of the OECD CLI for Austria.

Source: Own calculations.

By contrasting the results of the various composite leading indicators tested, it can be seen that: (1) out of the one-sided HP filtered series, the CLI_{AT} $\tilde{\Psi}\left\{{}^{(\cdot)}_{full}\right\}\big|_1^t$ performs much better compared to the 'flash' version. Moreover, the equally weighted CLI_{AT} $\tilde{\Psi}^{ew}_{full}\,\big|_1^t$ shows the best RMSE results over the full range of forecast periods considered; (2) forecasts using the OECD CLI perform in general not as good as forecasts incorporating any of the CLI_{AT}; and (3) the best single indicator with regards to improvement in projection accuracy is the symmetric HP filtered CLI_{AT} $\tilde{\Psi}^{pca}_{full}\,\big|_1^T$.

7. Summary

The aim of this paper was to construct a monthly composite leading indicator for the Austrian economy, which shows early signs of cyclical turning points in the Austrian business cycle. So far, the only CLI available for Austria that is designed to provide such signals between expansions and slowdowns of economic activity has been the one provided by the OECD.

I analysed 91 monthly single indicators, spanning over the period 1988-2008, to select the series which overall fare best in showing a 'steady' leading behaviour with respect to an underlying reference series. As reference series, I made use of the time-series real gross value added, excluding forestry and agriculture. I followed the growth cycle approach and used for business cycle extraction the BK band-pass filter with a frequency range set between 6 and 32 quarters. Out of the 91 individual indicators, 13 series were finally qualified to enter the CLI for the Austrian economy.

The analysis was carried out by means of statistical methods from the time-series domain as well as from the frequency domain, whereas pair-wise Granger-causality and cross-correlations measures correspond to the former and coherence and mean-delay statistics to the latter group. Dynamic factor models and measures derived from the turning point analysis supplemented the statistical procedures used.

The study identified the following set of 'leading' indicators for the Austrian business cycle: (i) two series representing the group of financials, i.e. ATX and EUROSTOXX 50 stock market index; (ii) the real-sector indicators job vacancies and export volumes; (iii) the OECD CLI for Germany and the euro-area; and (iv) seven separate business and consumer survey indicators such as the WIFO industry production expectations for the month ahead. These findings, i.e. the types of indicators used, are basically in line with what other euro-area country specific CLIs incorporate. However, there exists one notable exception. Many CLIs also include series reflecting credit market conditions, such as outstanding loans granted or the interest rate spread. A priori, I would have expected that these series also qualify to enter the CLI_{AT}, but according to the results obtained in this study I had to exclude these kinds of individual series.

The CLI_{AT} was constructed following a multiple-step procedure. First, individual monthly series were corrected for their long-run trend. The de-trending was performed using the HP filter with a λ value set equal to 129,600, as suggested by Ravn and Uhlig (1997). Second, the component weights for the individual normalised series were obtained by means of PCA and subsequently aggregated to form the intermediate, i.e. monthly, CLI_{AT}. Finally, to make the cyclical signal in the CLI_{AT} clearer and to account for the idiosyncratic elements a HP filter smoothing operation was performed. The appropriate value for λ was derived out of a sensitivity analysis conducted in the range between 10 and 100 and found to equal 20.

At this stage, I further checked the degree to which the smoothed CLI_{AT} is exposed to the endpoint problem. In doing so, I simulated a quasi 'real-time' environment; as such, the HP filter was repeatedly applied to a sub-sample, which was supplemented at each run by one period. I demonstrated that the 'real-time' smoothed CLI_{AT} does not exhibit severe phase-shifts compared to the full-sample estimate. Consequently, I used primarily the 'real-time' estimates to evaluate the performance of the CLI_{AT}.

In examining the cyclical turning points and the leading behaviour of the CLI_{AT} with respect to the reference series, the following key findings emerge. First, the CLI_{AT} provides cyclical turns in the majority of cases prior to the reference series. Only in 2 out of 11 turning points the CLI_{AT} coincides and slightly lags in one case. Second, statistical measures confirm the leading nature of the CLI_{AT}. The maximum cross-correlations coefficient is found at two-quarter lead and, out of the frequency domain, the corresponding mean-delay value obtained is greater than one. Further, the performance between different CLIs as well as the OECD CLI was compared. The difference in the CLIs consists of the weighting method used and the number of single indicators combined. The results indicate that, overall, no significant disparity can be observed.

Finally, I provided an out-of-sample evaluation of the forecasting accuracy of the reference series by comparing results obtained from a univariate and bivariate, i.e. including the CLI_{AT}, model specification. The performance was evaluated for forecasting horizons varying from 1 up to 12 quarters. The simulation showed that the bivariate specification performs superior in most of the cases, i.e. producing a lower RMSE compared to the univariate counterpart. Furthermore, the results indicate that the improvements are more pronounced the longer the forecast horizon is taken. For the mid- to long-term horizon, I found a reduction in the RMSE by up to 25%.

In conclusion, the constructed CLI for the Austrian economy provides a useful and supplementary self-contained instrument for assessing the current and most importantly the likely future direction in the Austrian business cycle. However, it is important to recognise that the CLI_{AT} needs close monitoring in the near future in order to re-evaluate the relevance and performance in real-time and to confirm the findings from this study.

References

Agresti, A.M. and Mojon, B. (2001): Some Stylized Facts on the Euro Area Business Cycle, *ECB Working Paper Series*, No. 95.

Altimari, S.N. (2001): Does money lead inflation in the euro area?, *ECB Working Paper Series*, No. 63.

Artis, M., Marcellino, M. and Proietti, T. (2004): Characterizing the Business Cycle for Accession Countries, *CEPR Discussion Papers*, No. 4457.

Baxter, M. and King, R.G. (1999): ‘Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series’, *Review of Economics and Statistics*, MIT Press, Vol. 81(4), pp. 575-593.

Bilek-Steindl, S., Sauer, P. and Scheiblecker, M. (2009): 'Revision Analysis of Quarterly National Accounts in Austria', *WIFO-Monatsberichte* (monthly reports), Vol. 82(10), pp. 749-766.

Breuss, F. (1984): 'Konjunkturindikatoren für die österreichische Wirtschaft', *WIFO-Monatsberichte* (monthly reports), Vol. 57(8), pp. 464-492.

Brischetto, A. and Voss, G. (2000): Forecasting Australian Economic Activity Using Leading Indicators, *RBA Research Discussion Paper*, rdp2002-02.

Bry, G. and Boschan, Ch. (1971): 'Standard Business Cycle Analysis of Economic Time Series', in: National Bureau of Economic Research, Cyclical Analysis of Time Series: Selected Procedures and Computer Programs, pp. 64-150.

Burns, A.F. and Mitchell, W.C. (1946): Measuring Business Cycles, National Bureau of Economic Research, Inc.

Canova, F. (1998): 'Detrending and business cycle facts', *Journal of Monetary Economics*, Vol. 41(3), pp. 475-512.

Carstensen, K. (2007): Is Core Money Growth a Good and Stable Inflation Predictor in the Euro Area?, *Kiel Institute for the World Economy Working Paper*, No. 1318.

Christiano, L.J. and Fitzgerald, T.J. (2003): 'The Band Pass Filter', *International Economic Review*, Department of Economics, University of Pennsylvania and Osaka University Institute of Social and Economic Research Association, Vol. 44(2), pp. 435-465.

Croux, Ch., Forni, M. and Reichlin, L. (1999): A Measure of Comovement for Economic Variables: Theory and Empirics, *CEPR Discussion Papers*, No. 2339.

Fenz, G., Schneider, M. and Spitzer, M. (2005): The Economic Indicator of the OeNB: Methods and Forecasting Performance, OeNB Workshop No.5/2005.

Fiorentini, G. and Planas, Ch. (2003): User manual BUSY-Program, EC Fifth Framework Program, Joint Research Centre of the European Commission, Ispra.

Forni, M., Hallin, M., Lippi, M. and Reichlin, L. (2000): 'The Generalized Dynamic-Factor Model: Identification And Estimation', *Review of Economics and Statistics*, MIT Press, Vol. 82(4), pp. 540-554.

Freudenberg, M. (2003): Composite indicators of country performance: A critical assessment, *OECD Science, Technology and Industry Working Papers*, No. 16.

Hahn, F. and Walterskirchen, E. (1992): Stylized Facts der Konjunkturschwankungen in Österreich, Deutschland und den USA, *WIFO-Working Papers*, No. 58.

Harvey, A.C. and Jaeger, A. (1993): 'Detrending, Stylized Facts and the Business Cycle', *Journal of Applied Econometrics*, Vol. 8(3), pp. 231-247.

Hodrick R. and Prescott, J. (1980): Postwar U.S. Business Cycles: An Empirical Investigation, *Carnegie Mellon University*, Discussion Paper, No. 451.

Hodrick R. and Prescott, J. (1997): 'Postwar U.S. Business Cycles: An Empirical Investigation', *Journal of Money, Credit, and Banking*, Blackwell Publishing, Vol. 29(1), pp. 1-16.

Hofmann, B. (2008): Do Monetary Indicators Lead Euro Area Inflation?, *ECB Working Paper Series*, No. 867.

Kaiser, R. and Maravall, A. (1999): 'Estimation of the Business Cycle: A Modified Hodrick-Prescott Filter', *Spanish Economic Review*, Vol. 1(2), pp. 175-206.

Kaiser, R. and Maravall, A. (2001): Measuring Business Cycles in Economic Time Series, Lecture Notes in Statistics, Springer-Verlag New York, Vol. 154.

King, R.G. and Rebelo, S.T. (1993): 'Low Frequency Filtering and Real Business Cycles', *Journal of Economic Dynamics and Control*, Vol. 17(1-2), pp. 207-231.

Klein, Ph.A. and Moore, G.H. (1982): The Leading Indicator Approach to Economic Forecasting--Retrospect and Prospect, *NBER Working Papers*, No. 0941.

Kranendonk, H.C., Bonenkamp, J. and Verbruggen, J. (2004): A Leading Indicator for the Dutch Economy - Methodological and Empirical Revision of the CPB System, *CESifo Group Munich Working Paper Series*, No. 1200.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, St., Hoffman, A. and Giovannini, E. (2005): Handbook on Constructing Composite Indicators - Methodology and User Guide, *OECD Statistics Working Papers*, No. 3.

Nicoletti, G., Scarpetta, St. and Boylaud, O. (2000): Summary Indicators of Product Market Regulation with an Extension to Employment Protection Legislation, *OECD Economics Department Working Papers*, No. 226.

Ravn, M.O. and Uhlig, H. (1997): On adjusting the hp-filter for the frequency of observations, Tilburg University, *Center for Economic Research Discussion Paper*, No. 50.

Scheiblecker, M. (2007): 'Dating of Business Cycles in Austria', *WIFO-Monatsberichte* (monthly reports), Vol. 80(9), pp. 715-730.

Stock, J.H. and Watson, M.W. (1999): 'Forecasting Inflation', *Journal of Monetary Economics*, Vol. 44(2), pp. 293-335.

Tichy, G. (1994): Konjunktur - Stilisierte Fakten, Theorie, Prognose, Springer Verlag, Berlin, 2nd Edition.

Zarnowitz, V. (1992): Business Cycles: Theory, History, Indicators, and Forecasting, NBER, University of Chicago Press.

Chapter I

Appendix

Table A1: Overview Indicator List – Properties

		Data		
		Seasonal + working day adjustment [1]	**log Trans-form.**	**Order of Integration** [2]
		(1)	(2)	(3)
	Industry production			
01	OECD: Industry production, total, NACE classification (C, D, E), excl. construction	Yes	Yes	I(1)
02	OECD: Industry production, manufacturing	Yes	Yes	I(1)
03	OECD: Industry production, manufacturing plus intermediate goods	Yes	Yes	I(1)
04	OECD: Industry production, manufacturing plus investment goods	Yes	Yes	I(1)
05	WIFO: Industry production, total, incl. energy	Yes	Yes	I(1)
06	WIFO: Industry production, total, without energy, without construction	Yes	Yes	I(1)
	Trade			
07	Retail sales, total (excl. vehicle, petrol stations and rep. of consumer durables)	Yes	Yes	I(1)
08	New vehicle registrations, total	Yes	Yes	I(0)
09	New vehicle registrations, passenger cars (group of wage earners)	Yes	Yes	I(1)
10	New vehicle registrations, passenger cars (group of self-employed people)	Yes	Yes	I(1)
11	Overnight stays, total (incl. home and foreigners)	Yes	Yes	I(1)
	Prices & Wages			
12	Wholesale prices, total	Yes	Yes	I(1)
13	Wholesale prices, total excl. fruit, vegetables and potatoes	Yes	Yes	I(1)
14	Wholesale prices, durable products	Yes	Yes	I(1)
15	Wholesale prices, non-durable goods	Yes	Yes	I(1)
16	Wholesale prices, consumer items	Yes	Yes	I(1)
17	Wholesale prices, consumer products	Yes	Yes	I(1)
18	Wholesale prices, investment goods	Yes	Yes	I(1)
19	Wholesale prices, intermediate goods	Yes	Yes	I(1)
20	Index of minimum wages, total	Yes	Yes	I(2)
21	Index of minimum wages, blue collar workers	Yes	Yes	I(2)
22	Index of minimum wages, white collar workers	Yes	Yes	I(2)
	Labour market			
23	Unemployment rate (national definition)	Yes	No	I(1)
24	Registered unemployed persons (national definition), total	Yes	Yes	I(1)
25	Job vacancies, total	Yes	Yes	I(1)
26	Employees, total incl. persons on parental leave or in military service	Yes	Yes	I(1)
27	Employees (economically active), total	Yes	Yes	I(1)
	International trade			
28	Exports, total	Yes	Yes	I(1)
29	Exports, basic manufactures (SITC 6)	Yes	Yes	I(1)
30	Exports, machines + transport equipment (SITC 7)	Yes	Yes	I(1)
31	Exports, misc. manufactured goods (SITC 8)	Yes	Yes	I(1)
32	Exports to Germany	Yes	Yes	I(1)
33	Exports into EU15	Yes	Yes	I(1)
34	Exports into EU27	Yes	Yes	I(1)
35	Exports into EU27 minus EU15	Yes	Yes	I(1)
36	Imports, total	Yes	Yes	I(1)
37	Imports, basic manufactures (SITC 6)	Yes	Yes	I(1)
38	Imports, machines + transport equipment (SITC 7)	Yes	Yes	I(1)
39	Imports, misc. manufactured goods (SITC 8)	Yes	Yes	I(1)
40	Imports to Germany	Yes	Yes	I(1)
41	Imports from EU15	Yes	Yes	I(1)
42	Imports from EU27	Yes	Yes	I(1)
43	Imports from EU27 minus EU15	Yes	Yes	I(1)
	Financials			
44	ATX stock market index	not required	Yes	I(1)
45	Loans to euro area nonfinancial institutions, in EUR	Yes	Yes	I(1)
46	Loans to euro area households (incl. Non-profit institutions), in EUR	Yes	Yes	I(1)
47	Loans to euro area corporations (excl. financial institutions), in EUR	Yes	Yes	I(1)
48	Deposits of euro area nonfinancial institutions, in EUR	Yes	Yes	I(1)
49	EURIBOR, 3-month	not required	No	I(1)
50	Austrian federal government 10 year bond yield	not required	No	I(1)

Table A1 (cont.): Overview Indicator List – Properties

		Data		
		Seasonal + working day adjustment [1]	**log Trans-form.**	**Order of Integration**
		(1)	(2)	(3)
	Financials (cont.)			
51	Interest rate spread (long minus short)	not required	No	I(1)
52	Exchange rate USD/EUR	not required	No	I(1)
53	Exchange rate GBP/EUR	not required	No	I(1)
54	Dow Jones EURO STOXX 50 stock market index	not required	Yes	I(1)
55	S&P 500 stock market index	not required	Yes	I(1)
56	DJIA stock market index	not required	Yes	I(1)
	Commodity market			
57	HWWI Commodity Price Index, total, in EUR	Yes	Yes	I(1)
58	HWWI Commodity Price Index, total excl. energy, in EUR	Yes	Yes	I(1)
59	HWWI Commodity Price Index, crude oil, in EUR	Yes	Yes	I(1)
60	Gold USD, fine ounce	not required	No	I(1)
61	Petroleum USD, UK Brent (per barrel)	not required	No	I(1)
	Surveys			
	Source: Austrian Institute of Economic Research (WIFO)			
62	Industry: Production trend observed in recent months	not required	No	I(0)
63	Industry: Assessment of order-book levels	not required	No	I(0)
64	Industry: Assessment of export order-book levels	not required	No	I(0)
65	Industry: Assessment of stocks of finished products	not required	No	I(0)
66	Industry: Production expectations for the month ahead	not required	No	I(0)
67	Industry: Selling price expectations for the next 3 month	not required	No	I(0)
68	Construction: Selling price expectations for the next 3 month	not required	No	I(0)
69	Business Confidence, Industry	not required	No	I(0)
70	Business Confidence, Construction	not required	No	I(0)
71	Business Confidence, Retail	not required	No	I(0)
72	Consumer Confidence	not required	No	I(0)
73	Business confidence climate (industry, construction and retail)	not required	No	I(1)
	Source: European Commission			
74	AT: Economic Sentiment Indicator (ESI)	not required	No	I(0)
75	DE: Economic Sentiment Indicator (ESI)	not required	No	I(0)
76	DE: Business Confidence	not required	No	I(0)
77	DE: Production trend observed in recent months	not required	No	I(0)
78	DE: Production expectations for the months ahead	not required	No	I(0)
79	DE: Employment expectations for the months ahead	not required	No	I(0)
80	EA: Economic Sentiment Indicator (ESI)	not required	No	I(0)
81	EA: Business Confidence	not required	No	I(0)
82	EA: Production trend observed in recent months	not required	No	I(0)
83	EA: Production expectations for the months ahead	not required	No	I(0)
84	EA: Employment expectations for the months ahead	not required	No	I(0)
	Source: Ifo Institute for Economic Research, Munich			
85	DE: ifo Business Climate (Industry and Trade)	already adj.	No	I(0)
86	DE: Assessment of current business situation (Industry and Trade)	already adj.	No	I(1)
87	DE: Business expectations (Industry and Trade)	already adj.	No	I(0)
	OECD Composite Leading Indicators			
88	CLI for Austria	already adj.	No	I(1)
89	CLI for Germany	already adj.	No	I(1)
90	CLI for the Euro-Area	already adj.	No	I(1)
91	CLI for the U.S.	already adj.	No	I(1)

1) *Yes* … series seasonal + working day adjusted (where required) using Tramo/Seats;
not required ... series does not contain any seasonal effects;
already adj. ... series has been already seasonally adjusted by external data provider.
2) The test for order of integration has been determined using the Augmented Dickey-Fuller (AFD) test.

Note: Seasonal adjustment procedure and ADF-test have been performed on monthly data frequency.
Source: Own calculations / BUSY software.

Table A2: Overview Indicator List – Statistical Results

		Time series domain					Frequency domain		Turning point analysis			Dynamic factor analysis			
		Granger-Causality 1)		**Cross-Correlation** 2)			**Coherence** 3)	**Mean Delay** 4)	**Median lag at..** 5)			**Var. Ratio** 6)	**CC-Corr.** 7)		**CC-Classif.** 8)
		X->Y	Y->X	r_0	r_{max}	t_{max}			Peaks	Troughs	All		r_{max}	t_{max}	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Industry production														
01	OECD: Industry production, total, NACE classification (C, D, E), excl. construction	3.82790 ***	4.81641 ***	0.63	0.68	+1	0.45	+0.40	-1.0	-2.0	-1.5	0.778	0.983	+0	co
02	OECD: Industry production, manufacturing	3.91082 ***	3.54661 ***	0.61	0.66	+1	0.41	+0.42	-1.0	-2.5	-1.5	0.813	0.982	+0	co
03	OECD: Industry production, manufacturing plus intermediate goods	4.20186 ***	8.04796 ***	0.60	0.66	+1	0.41	+0.47	-0.5	-2.5	-1.5	0.874	0.961	+0	co
04	OECD: Industry production, manufacturing plus investment goods	1.04829	4.95619	0.51	0.57	+1	0.30	+0.46	-0.5	-3.0	-2.0	0.446	0.997	+0	co
05	WIFO: Industry production, total, incl. energy	2.19899 *	3.99730 ***	0.56	0.59	+1	0.34	+0.36	-0.5	-1.0	0.0	0.693	0.987	+0	co
06	WIFO: Industry production, total, without energy, without construction	2.28353 *	1.95229	0.54	0.57	+1	0.32	+0.37	-1.0	-2.5	-1.5	0.762	0.985	+0	co
	Trade														
07	Retail sales, total (excl. vehicle, petrol stations and rep. of consumer durables)	0.92709	0.54955	0.33	0.41	+2	0.14	+0.58	-3.5	-0.5	-2.5	0.142	0.828	+2	lead
08	New vehicle registrations, total	0.57365	1.58465	0.20	0.35	-2	0.07	-1.11	2.0	0.5	1.5	0.051	0.653	-2	lag
09	New vehicle registrations, passenger cars (group of wage earners)	0.06092	2.14000 *	-0.13	-0.22	+2	0.03	-5.95	3.0	1.0	2.5	0.086	-0.874	+1	lead
10	New vehicle registrations, passenger cars (group of self-employed people)	3.74141 ***	1.23019	0.64	0.64	+0	0.45	-0.15	1.5	0.0	1.0	0.322	0.946	+0	co
11	Overnight stays, total (incl. home and foreigners)	1.26769	1.26702	0.32	0.37	-2	0.12	-0.56	0.5	0.5	0.5	0.049	0.643	-1	lag
	Prices & Wages														
12	Wholesale prices, total	7.85256 ***	0.79952	0.63	0.63	+0	0.39	-0.16	-0.5	-0.5	-0.5	0.481	0.988	+0	co
13	Wholesale prices, total excl. fruit, vegetables and potatoes	6.54794 ***	0.59115	0.62	0.62	+0	0.38	-0.17	-1.0	-1.0	-1.0	0.482	0.989	+0	co
14	Wholesale prices, durable products	0.73355	0.85650	-0.28	-0.28	+0	0.10	+2.07	1.0	-0.5	1.5	0.054	-0.842	+3	lead
15	Wholesale prices, non-durable goods	1.56801	0.53498	-0.11	-0.46	+4	0.05	-5.66	1.5	2.5	2.0	0.105	-0.829	+2	lead
16	Wholesale prices, consumer items	3.42162 ***	0.46138	0.46	0.46	+0	0.22	-0.01	0.5	0.5	1.5	0.386	0.971	+0	co
17	Wholesale prices, consumer products	3.44888 ***	0.57003	0.42	0.42	+0	0.17	-0.05	0.5	0.5	0.5	0.384	0.956	+0	co
18	Wholesale prices, investment goods	0.69529	1.09534	-0.11	-0.14	-4	0.02	-7.20	-0.5	-0.5	1.0	0.041	-0.788	+3	lead
19	Wholesale prices, intermediate goods	6.05428 ***	0.64464	0.60	0.60	+0	0.35	-0.19	-1.0	0.5	-0.5	0.352	0.996	+0	co
20	Index of minimum wages, total	1.63035	2.14245 *	-0.15	-0.33	+4	0.04	-6.34	3.5	2.0	3.5	0.234	-0.887	+1	lead
21	Index of minimum wages, blue collar workers	1.77356	1.43078	-0.16	-0.38	+4	0.05	-6.26	3.0	-0.5	3.0	0.258	-0.886	+1	lead
22	Index of minimum wages, white collar workers	1.28197	1.57820	-0.20	-0.35	+4	0.06	-6.67	3.5	-1.0	2.0	0.259	-0.886	+1	lead
	Labour market														
23	Unemployment rate (national definition)	1.49699	2.19304 *	-0.58	-0.58	+0	0.36	+7.41	1.0	2.5	3.5	0.616	-0.971	+0	lead
24	Registered unemployed persons (national definition), total	1.32805	1.21611	-0.53	-0.53	+0	0.30	+7.39	1.0	2.5	3.5	0.576	-0.969	+0	lead
25	Job vacancies, total	4.44090 ***	0.43955	0.63	0.65	+1	0.43	+0.25	-1.0	-1.0	-1.0	0.513	0.954	+0	co
26	Employees, total incl. persons on parental leave or in military service	4.06039 ***	0.91105	0.67	0.67	+0	0.48	-0.26	1.0	-2.0	0.0	0.328	0.985	+0	co
27	Employees (economically active), total	4.33290 ***	1.07720	0.76	0.76	+0	0.61	-0.09	-0.5	-3.0	-1.5	0.421	0.993	+0	co

Table A2 (cont.): Overview Indicator List – Statistical Results

	International trade	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
28	Exports, total	6.41154 ***	1.75740	0.75	0.76	+1	0.59	+0.31	-1.0	-2.5	-1.0	0.865	0.984	+0	co
29	Exports, basic manufactures (SITC 6)	4.76960 ***	0.60977	0.70	0.70	+0	0.50	+0.15	0.0	-0.5	0.0	0.794	0.994	+0	co
30	Exports, machines +transport equipment (SITC 7)	4.27280 ***	0.87591	0.72	0.75	+1	0.56	+0.38	-1.0	-2.5	-1.0	0.769	0.975	+0	co
31	Exports, misc. manufactured goods (SITC 8)	2.00263	0.98718	0.56	0.59	+1	0.35	+0.30	-0.5	-0.5	-0.5	0.462	0.992	+0	co
32	Exports to Germany	5.63364 ***	2.36878 *	0.78	0.78	+0	0.64	+0.07	0.0	-1.0	-0.5	0.748	0.990	+0	co
33	Exports into EU15	6.35434 ***	1.05144	0.79	0.79	+0	0.64	+0.14	0.0	-1.5	-0.5	0.810	0.996	+0	co
34	Exports into EU27	5.01880 ***	1.18533	0.78	0.78	+0	0.63	+0.17	0.0	-1.5	0.0	0.828	0.995	+0	co
35	Exports into EU27 minus EU15	2.05787 *	1.37101	0.53	0.53	+0	0.30	+0.21	-0.5	-2.5	-1.0	0.410	0.968	+0	co
36	Imports, total	0.85529	0.87711	0.68	0.68	+0	0.48	+0.15	-1.0	-0.5	-1.0	0.818	0.989	+0	co
37	Imports, basic manufactures (SITC 6)	0.98201	1.65743	0.66	0.66	+1	0.48	+0.20	-1.0	-1.5	-1.0	0.680	0.983	+0	co
38	Imports, machines +transport equipment (SITC 7)	1.55205	0.30152	0.59	0.59	+0	0.38	+0.21	-0.5	-2.0	-1.0	0.808	0.989	+0	co
39	Imports, misc. manufactured goods (SITC 8)	0.55966	0.57540	0.45	0.58	+2	0.28	+0.44	-2.0	-3.0	-2.5	0.435	0.958	+0	co
40	Imports to Germany	1.96419	1.28834	0.69	0.69	+0	0.49	+0.11	0.0	-2.5	-1.0	0.693	0.996	+0	co
41	Imports from EU15	1.79791	1.22848	0.77	0.77	+0	0.62	+0.13	0.0	-2.0	-0.5	0.727	0.999	+0	co
42	Imports from EU27	1.45533	1.68372	0.76	0.76	+0	0.61	+0.07	0.0	-2.0	-0.5	0.715	0.998	+0	co
43	Imports from EU27 minus EU15	2.88779 ***	0.80926	0.61	0.61	+0	0.39	-0.31	0.5	-0.5	0.5	0.455	0.989	+0	co
	Financials														
44	ATX stock market index	4.01493 ***	1.36302	0.35	0.58	+2	0.20	+1.20	-4.0	-3.5	-2.5	0.305	0.901	+1	lead
45	Loans to euro area nonfinancial institutions, in EUR	0.58619	1.94863	0.12	0.30	-3	0.03	-1.45	2.0	3.0	3.0	0.127	-0.605	+2	lead
46	Loans to euro area households (incl. Non-profit institutions), in EUR	0.63862	0.31035	-0.11	0.33	+4	0.01	+5.10	-3.0	0.0	-0.5	0.013	-0.711	+0	lag
47	Loans to euro area corporations (excl. financial institutions), in EUR	1.12257	1.35605	0.09	0.29	-4	0.02	-1.61	1.5	1.0	2.0	0.010	-0.584	+4	lag
48	Deposits of euro area nonfinancial institutions, in EUR	0.72786	0.99861	0.02	0.22	-4	0.01	+1.66	-1.0	-2.0	-1.5	0.104	-0.885	+0	lead
49	EURIBOR, 3-month	2.22277 *	2.09443 *	0.70	0.73	-1	0.53	-0.33	1.0	-1.0	0.5	0.553	0.974	+0	co
50	Austrian federal government 10 year bond yield	0.65748	0.22273	0.43	0.48	+1	0.21	+0.50	-1.0	-1.0	-1.0	0.439	0.947	+0	co
51	Interest rate spread (long minus short)	0.37098	3.15363 ***	-0.39	-0.56	-2	0.22	+6.46	-3.0	-3.5	-2.5	0.156	-0.867	-1	lag
52	Exchange rate USD/EUR	1.55290	0.73799	0.34	0.34	+0	0.12	-0.28	0.0	0.5	0.0	0.125	0.811	-1	lag
53	Exchange rate GBP/EUR	5.61646 ***	2.18780 *	-0.33	-0.55	+2	0.18	-6.28	3.5	3.5	3.5	0.366	-0.866	+1	lead
54	Dow Jones EURO STOXX 50 stock market index	4.64888 ***	1.03505	0.45	0.57	+2	0.26	+0.71	-0.5	-3.5	-1.5	0.362	0.904	+1	lead
55	S&P 500 stock market index	7.50510 ***	0.37124	0.53	0.62	+1	0.33	+0.44	-1.0	-1.0	-1.0	0.195	0.910	+0	co
56	DJIA stock market index	5.75156 ***	0.70222	0.48	0.60	+1	0.30	+0.58	-2.5	-2.0	-2.0	0.186	0.893	+1	co
	Commodity market														
57	HWWI Commodity Price Index, total, in EUR	3.27446 ***	0.51960	0.54	0.54	+0	0.29	-0.05	-2.5	0.0	-1.0	0.291	0.964	+0	co
58	HWWI Commodity Price Index, total excl. energy, in EUR	4.91453 ***	0.95628	0.65	0.65	+0	0.43	+0.28	-0.5	-2.0	-1.5	0.691	0.971	+0	co
59	HWWI Commodity Price Index, crude oil, in EUR	2.32515 *	0.73998	0.43	0.43	+0	0.19	-0.08	0.5	0.5	0.5	0.167	0.923	+0	co
60	Gold USD, fine ounce	5.78393 ***	0.22904	0.30	0.30	+0	0.08	+0.22	-2.5	1.0	-1.5	0.039	0.688	+1	lead
61	Petroleum USD, UK Brent (per barrel)	6.37231 ***	0.91803	0.61	0.61	+0	0.38	-0.21	0.5	0.5	0.5	0.157	0.988	+0	co

Table A2 (cont.): Overview Indicator List – Statistical Results

	Surveys	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Source: Austrian Institute of Economic Research (WIFO)														
62	Industry: Production trend observed in recent months	2.27819 *	1.90166	0.37	0.46	+2	0.17	+0.88	-2.0	-3.0	-2.0	0.818	0.873	+0	co
63	Industry: Assessment of order-book levels	1.97480	1.65755	0.39	0.47	+2	0.19	+0.76	-1.5	-2.5	-2.0	0.813	0.917	+0	co
64	Industry: Assessment of export order-book levels	2.85861 **	2.36144 *	0.42	0.47	+1	0.20	+0.67	-1.0	-2.5	-1.5	0.803	0.934	+0	co
65	Industry: Assessment of stocks of finished products	1.20621	0.93630	-0.26	-0.45	+2	0.12	-6.08	3.5	3.0	3.0	0.718	-0.857	+1	lead
66	Industry: Production expectations for the month ahead	5.67116 ***	0.42230	0.43	0.52	+1	0.23	+0.87	-0.5	-3.5	-2.0	0.803	0.863	+1	lead
67	Industry: Selling price expectations for the next 3 month	3.44906 **	0.70606	0.47	0.51	+1	0.25	+0.61	-1.0	-3.0	-1.0	0.821	0.888	+0	co
68	Construction: Selling price expectations for the next 3 month	1.97268	1.32310	0.39	0.45	+1	0.19	+0.73	-3.0	-3.5	-3.5	0.600	0.857	+1	lead
69	Business Confidence, Industry	4.30830 ***	1.25438	0.39	0.49	+2	0.19	+0.89	-1.5	-3.0	-2.0	0.825	0.880	+0	co
70	Business Confidence, Construction	0.67575	0.54477	0.21	0.32	+3	0.07	+1.15	-2.0	-1.0	-2.0	0.387	0.834	+1	lead
71	Business Confidence, Retail	2.60305 **	0.99154	0.41	0.64	+2	0.26	+0.99	-2.0	-3.0	-2.0	0.391	0.900	+1	co
72	Consumer Confidence	3.91389 ***	0.68783	0.14	0.68	+3	0.13	+2.16	-3.0	-3.0	-3.0	0.381	0.855	+1	lead
73	Business confidence climate (industry, construction and retail)	2.03585 *	0.51853	0.31	0.52	+2	0.16	+1.22	-2.5	-3.0	-3.0	0.726	0.872	+1	lead
	Source: European Commission														
74	AT: Economic Sentiment Indicator (ESI)	5.62195 ***	1.92134	0.41	0.55	+2	0.23	+0.93	-1.5	-3.5	-2.0	0.820	0.872	+0	co
75	DE: Economic Sentiment Indicator (ESI)	8.91739 ***	0.58163	0.52	0.62	+1	0.33	+0.71	-1.5	-3.0	-2.5	0.842	0.926	+0	co
76	DE: Business Confidence	10.81900 ***	0.57935	0.55	0.64	+1	0.36	+0.69	-1.0	-3.0	-2.0	0.898	0.921	+0	co
77	DE: Production trend observed in recent months	8.79156 ***	1.52522	0.43	0.54	+2	0.24	+0.98	-1.5	-3.5	-2.0	0.812	0.863	+1	lead
78	DE: Production expectations for the months ahead	12.93240 ***	0.79081	0.46	0.61	+1	0.29	+1.05	-1.0	-4.0	-1.5	0.826	0.869	+1	lead
79	DE: Employment expectations for the months ahead	5.42413 ***	1.43123	0.61	0.65	+1	0.42	+0.40	-1.0	-2.0	-1.0	0.880	0.981	+0	co
80	EA: Economic Sentiment Indicator (ESI)	9.16392 ***	0.59536	0.52	0.62	+1	0.33	+0.73	-1.5	-2.5	-2.0	0.874	0.923	+0	co
81	EA: Business Confidence	9.42748 ***	0.30931	0.52	0.60	+1	0.32	+0.69	-1.0	-3.0	-1.5	0.884	0.912	+0	co
82	EA: Production trend observed in recent months	10.43400 ***	0.88507	0.51	0.57	+1	0.30	+0.67	0.0	-3.0	-1.0	0.883	0.907	+0	co
83	EA: Production expectations for the months ahead	11.62090 ***	0.23330	0.48	0.60	+1	0.29	+0.92	-1.0	-3.0	-1.5	0.849	0.866	+1	lead
84	EA: Employment expectations for the months ahead	4.92743 ***	0.45442	0.63	0.65	+1	0.43	+0.33	-1.0	-2.0	-1.0	0.875	0.986	+0	co
	Source: Ifo Institute for Economic Research, Munich														
85	DE: ifo Business Climate (Industry and Trade)	6.77403 ***	0.98422	0.50	0.69	+2	0.34	+0.95	-1.5	-3.5	-2.0	0.838	0.881	+1	lead
86	DE: Assessment of current business situation (Industry and Trade)	5.18356 ***	1.41920	0.61	0.68	+1	0.43	+0.53	-0.5	-3.0	-1.5	0.867	0.944	+0	co
87	DE: Business expectations (Industry and Trade)	8.62510 ***	1.29624	0.26	0.60	+2	0.19	+1.88	-2.0	-2.0	-2.0	0.695	0.834	+1	lead
	OECD Composite Leading Indicators														
88	CLI for Austria	5.38753 ***	0.79231	0.49	0.72	+2	0.34	+0.97	-2.0	-3.5	-2.0	0.839	0.881	+1	lead
89	CLI for Germany	9.21444 ***	1.04648	0.54	0.70	+1	0.39	+0.95	-1.5	-3.5	-2.5	0.852	0.876	+1	lead
90	CLI for the Euro-Area	8.11007 ***	1.31464	0.47	0.72	+2	0.34	+1.13	-1.5	-3.0	-2.5	0.811	0.879	+1	lead
91	CLI for the U.S.	5.46727 ***	1.40214	0.40	0.60	+2	0.24	+1.11	-2.0	-4.0	-2.0	0.383	0.846	+1	lead

1) - 8) See notes to Table 4.

Source: Own calculations / BUSY software.

Chapter I – Supplement A

Sensitivity Analysis using '2-sided' HP Filter

Preface

In the published working paper (Bierbaumer-Polly, 2010), which constitutes the first chapter of this dissertation, the indicator analysis and the subsequent leading indicator selection were performed on Baxter-King (BK) filtered data. However, in the construction step of the CLI_{AT}, I twisted methodology and removed trends in the selected series, in particular for the indicators reflecting real variables, with the Hodrick-Prescott (HP) filter. The final smoothing of the CLI_{AT} was also performed with the HP filter.

In order to harmonise, for robustness-check, the business cycle extraction methodology in the analysis as well as in the construction step, I repeated the indicator analysis and selection based on HP filtered data derived from the original data source. In particular, I determined the business cycle component to be the difference between two HP filter operations (one eliminating trend components and one cancelling out irregular movements). My findings are more or less similar to the BK filter case, especially with respect to the identified set of leading indicators.

1. An approximate band-pass ('2-sided') version of the HP filter

Initially, the HP filter as proposed in Hodrick and Prescott (1997) is a two-sided symmetric linear high-pass filter which yields the 'smoothed' trend (controlled by λ) of the underlying series. The residual term between the original series and the estimated trend term is commonly referred to as business cycle component. However, the business cycle component still contains irregular movements at the very high frequency which may obscure the 'true' business cycle signal. In contrast, band-pass business cycle filters like Baxter-King aim to isolate the fluctuations for a particular bandwidth of (business cycle) frequencies. Usually the upper frequency eliminating noise corresponds to 1.25 years, while the lower one eliminating the trend is set, for example, to 8 years (Baxter and King, 1999).

It has been recently suggested to use an approximation to the band-pass filter which is based on the difference between two HP filters (see e.g. Massmann et al., 2003; Artis et al., 2003; Proietti, 2005). As such, two cut-off frequencies [ω_L, ω_U] representing the lower and upper bound of the frequencies to be isolated have to be chosen.

The appropriate λ value corresponding to the cut-off frequencies can be obtained using $\lambda = \left[4(1-\cos(\omega_C))^2\right]^{-1}$, where ω_C is either set to ω_L or ω_U . Table SA.1 provides the results corresponding to periodicities of 6, 32 and 40 quarters, where the first two reflect the BK periodicities and the latter represents the respective time period for the λ-value proposed by Hodrick and Prescott (1997) for quarterly data. The given λ is based on the argument that a 5 percent standard deviation from the trend is moderately large as is an 1/8th of a percent change in the standard deviation of the quarterly trend growth rate: $\lambda_q = 5^2/[0.5/4]^2 = 1600$.

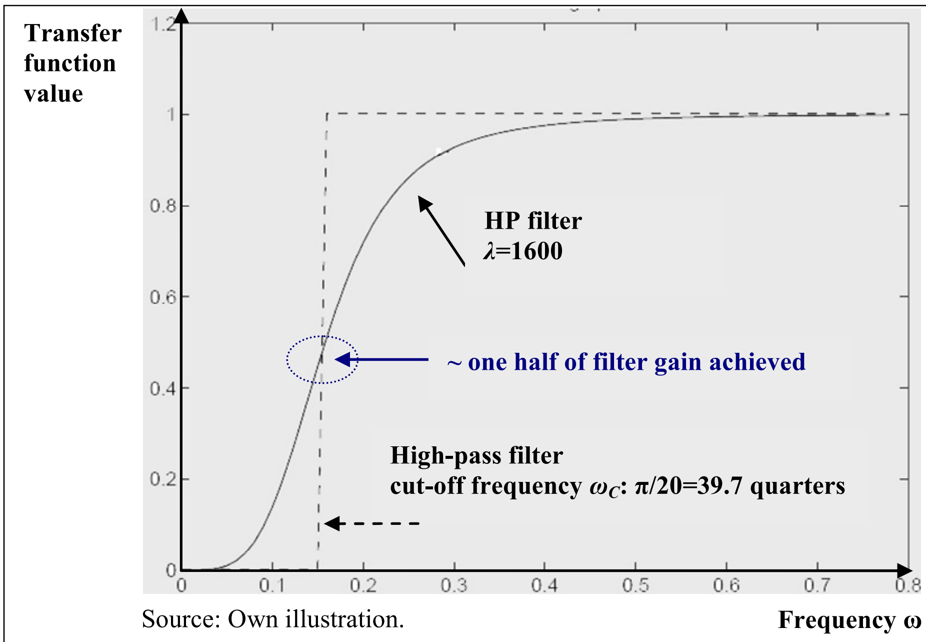
Table SA.1: Smoothing parameter λ

Frequency	Periodicity	λ-value
Lower bound: $\omega_L = 1.047$	6 Quarters $\equiv \pi/3$	1
Upper bound: $\omega_U = 0.196$	32 Quarters $\equiv \pi/16$	677
Upper bound: $\omega_U = 0.157$	40 Quarters $\equiv \pi/20$	1600

Source: Own illustration.

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 $\lambda_q = 1600$. Maravall 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 filter gain has been achieved. As such, Maravall 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 and 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 with $\lambda_q = 1600$. See Figure SA.1 for some illustration of the approach chosen by Maravall and del Rio (2001).

Figure SA.1: HP filter versus ideal high-pass filter



Source: Own illustration.

In using periodicities of [5, 32] quarters, Massmann et al. (2003), for example, notes that the cyclical estimator obtained from the 'band-pass' HP filter version is comparable to the one derived using the BK filter but having the advantage that it provides endpoint estimates, as well. However, the authors also comment that the cyclical component is slightly noisier compared to the BK filter.

For the results presented next I have used periodicities of [6, 40] quarters for approximating a 2-sided HP filter ($\widetilde{HP}_{\omega_L}^{\omega_U} \equiv \widetilde{HP}_{1}^{1600}$).

2. Results

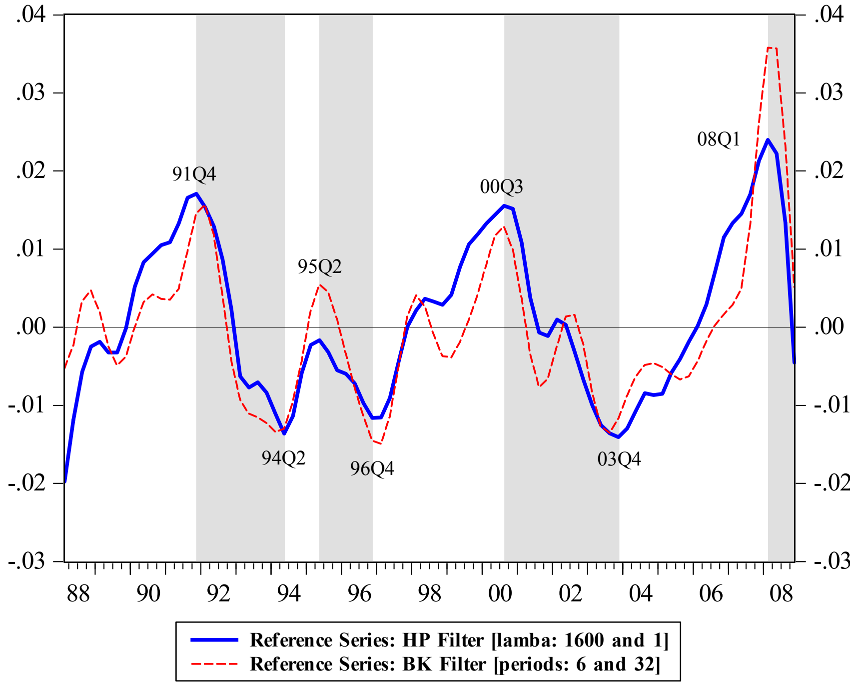
With the BK filter ($\widetilde{BK}_6^{32}$), five full business cycles (peak-to-peak) are obtained for the reference series of Y_{exFA}^{GVA}, applying the '2-sided' HP filter ($\widetilde{HP}_1^{1600}$) instead reveals three full business cycle runs. In the latter, the business cycle downturn 1998/99 and the mild recovery 2001/02 do not shown up as a 'distinct' business cycle phase (i.e. with a certain duration; minimum three quarters in this analysis) in order to be picked up by the Bry-Boschan dating routine. Although the number of identified cycles differs, the overall business cycle dynamics are quite similar (see Figure SA.2 and Table SA.2): a business cycle upswing until 1991, a downturn up to the end of 1996 with some interim recovery (mid 1994 to mid 1995), a strong expansionary phase until 2000, which stopped and turned down as far as 2003, and a following long lasting phase of the pre-crisis business cycle upswing with the sudden stop in 2008 due to outbreak of the so called 'great' recession.

Moreover, applying the $\widetilde{HP}_1^{1600}$ on the indicator set reveals very robust results with respect to the earlier findings in Bierbaumer-Polly (2010). The business cycle properties (i.e. granger-causality, cross-correlation, coherence, mean delay, turning point statistics, and dynamic factor analysis) of the whole dataset and in particular those representing the set of 'leading' indicators are very close to the $\widetilde{BK}_6^{32}$ case. Clearly, if one takes a closer look the magnitudes of some measures for some indicators are in some cases slightly higher or lower, but the overall picture does not change. See Table SA.3 ('leading' indicators) and Table SA.3 (full dataset) for the detailed results using the 2-sided HP filter ($\widetilde{HP}_1^{1600}$).

Given the robustness of the results, it can be concluded that the indicator selection in Bierbaumer-Polly (2010), even though based on BK filtered data, led to the same set of 'leading' indicators as one would have used $\widetilde{HP}_1^{1600}$ from the very first.

Nevertheless, this sensitivity analysis shows that results differ between different extraction methods (e.g. differences in the dating for the reference series, or different business cycle properties), even though these differences are in this case rather small and negligible. However, in other cases the differences might be more pronounced and, hence, would have to be taken into account before drawing major conclusions. At least, some robustness checks should be put in place.

Figure SA.2: Business Cycle Chronology of the Reference Series Y_{exFA}^{GVA}



Note: Cyclical movements extracted using "2-sided" HP filter [lamda: 1600 und 1] and BK filter with periodicity [6,32] quarters and filter length K=6; Grey shaded areas indicate recessionary phases based on the HP filtered reference series.

Table SA.2: Turning Points of the Reference Series Y_{exFA}^{GVA} [HP-filtered 1600|1]

Peak (P)	**Trough (T)**	Cycles		Phases	
		P to P	**T to T**	**P to T**	**T to P**
(1)	(2)	(3)	(4)	(5)	(6)
91Q4		-			-
	94Q2		-	11	
95Q2		15			5
	96Q4		10	7	
00Q3		22			16
	03Q4		25	14	
08Q1		31			18

Note: The turning points have been analysed between 1988Q1 and 2008Q4.
Cycle/phase length indicates number of quarters it takes to pass through.
Source: Own calculations / BUSY software.

Table SA.3: 'Leading' Indicators – Statistical Results [HP-filtered 1600|1]

		Time series domain					Frequency domain		Turning point analysis			Dynamic factor analysis			
		Granger-Causality [1]		**Cross-Correlation** [2]			**Coher-ence** [3]	**Mean Delay** [4]	**Median lag at..** [5]			**Var. Ratio** [6]	**CC-Corr.** [7]		**CC-Classif.** [8]
		X->Y	Y->X	r_0	r_{max}	t_{max}			Peaks	Troughs	All		r_{max}	t_{max}	
x_i		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
x1	ATX stock market index	4.01493 **	1.36302	0.57	0.62	+1	0.37	+0.76	-8.0	-5.0	-5.5	0.505	0.878	+0	lead
x2	DJ EURO STOXX 50 stock market index	4.64888 **	1.03505	0.70	0.71	+1	0.53	+0.32	-6.0	-4.5	-4.0	0.507	0.918	+0	co
x3	Job vacancies, total	4.44090 **	0.43955	0.79	0.79	+0	0.66	+0.07	-4.0	-2.0	-1.5	0.554	0.982	0	co
x4	Exports, total	6.41154 **	1.75740	0.77	0.77	+0	0.59	+0.30	-3.5	-2.5	-1.5	0.862	0.983	0	co
x5	WIFO Industry production, total without energy and construction	2.28353 *	1.95229	0.75	0.77	+1	0.60	+0.28	-2.5	-2.5	-2.0	0.827	0.984	0	co
x6	WIFO Industry production expectations for the month ahead	5.67116 **	0.42230	0.54	0.57	+1	0.32	+0.78	-4.5	-4.0	-3.0	0.778	0.848	+0	lead
x7	Consumer Confidence	3.91389 **	0.68783	0.42	0.65	+3	0.27	+0.99	-5.5	-3.0	-3.5	0.511	0.839	+1	lead
x8	Business Confidence Climate (industry, construction and retail)	2.03585 *	0.51853	0.35	0.58	+3	0.18	+1.21	-4.5	-5.0	-3.5	0.733	0.825	+1	lead
x9	ifo Business Climate for Germany	6.77403 **	0.98422	0.66	0.72	+1	0.49	+0.66	-2.5	-4.5	-2.5	0.870	0.885	+0	co
x10	Production trend observed in recent months for Germany	8.79156 **	1.52522	0.52	0.56	+1	0.30	+0.83	-3.0	-3.5	-2.0	0.725	0.831	+1	lead
x11	Production expectations for the months ahead for Germany	12.93240 **	0.79081	0.49	0.56	+1	0.28	+0.92	-3.0	-3.5	-2.0	0.724	0.825	+1	lead
x12	Production expectations for the months ahead in the Euro-Area	11.62090 **	0.23330	0.48	0.54	+1	0.26	+0.91	-5.0	-3.5	-2.0	0.733	0.825	+0	lead
x13	OECD CLI for Germany, trend-restored	9.21444 **	1.04648	0.67	0.71	+1	0.49	+0.64	-3.5	-4.0	-2.5	0.845	0.869	+0	lead
x14	OECD CLI for the Euro-Area, trend-restored	8.11007 **	1.31464	0.59	0.69	+1	0.42	+0.83	-4.5	-4.0	-2.5	0.822	0.841	+1	lead

1) - 8) See notes to Table 4 (Chapter 1).

Source: Own calculations / BUSY software.

Table SA.4: Overview Indicator List – Statistical Results [HP-filtered 1600|1]

		Time series domain					Frequency domain		Turning point analysis			Dynamic factor analysis			
		Granger-Causality [1]		**Cross-Correlation** [2]			**Coherence** [3]	**Mean Delay** [4]	**Median lag at..** [5]			**Var. Ratio** [6]	**CC-Corr.** [7]		**CC-Classif.** [8]
		X->Y	Y->X	r_0	r_{max}	t_{max}			Peaks	Troughs	All		r_{max}	t_{max}	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Industry production														
01	OECD: Industry production, total, NACE classification (C, D, E), excl. construction	3.82790 ***	4.81641 ***	0.78	0.78	+1	0.64	+0.21	-2.5	-3.0	-1.5	0.776	0.986	+0	co
02	OECD: Industry production, manufacturing	3.91082 ***	3.54661 ***	0.76	0.77	+1	0.61	+0.26	-2.5	-2.0	-1.0	0.830	0.982	+0	co
03	OECD: Industry production, manufacturing plus intermediate goods	4.20186 ***	8.04796 ***	0.73	0.75	+1	0.57	+0.33	-3.0	-2.5	-1.5	0.849	0.959	+0	co
04	OECD: Industry production, manufacturing plus investment goods	1.04829	4.95619	0.74	0.74	+0	0.58	+0.17	0.0	-3.0	-2.0	0.632	0.999	+0	co
05	WIFO: Industry production, total, incl. energy	2.19899 *	3.99730 ***	0.77	0.77	+1	0.63	+0.25	-2.5	-3.0	-1.5	0.786	0.988	+0	co
06	WIFO: Industry production, total, without energy, without construction	2.28353 *	1.95229	0.75	0.77	+1	0.60	+0.28	-2.5	-2.5	-2.0	0.827	0.984	+0	co
	Trade														
07	Retail sales, total (excl. vehicle, petrol stations and rep. of consumer durables)	0.92709	0.54955	0.63	0.63	+0	0.46	+0.01	-3.5	-2.0	-1.5	0.227	0.952	+0	co
08	New vehicle registrations, total	0.57365	1.58465	0.38	0.42	+1	0.19	+0.21	-1.5	-4.0	0.0	0.102	0.983	+0	co
09	New vehicle registrations, passenger cars (group of wage earners)	0.06092	2.14000 *	-0.05	0.19	+4	0.00	+1.67	-0.5	-4.0	0.5	0.005	0.501	+0	lag
10	New vehicle registrations, passenger cars (group of self-employed people)	3.74141 ***	1.23019	0.78	0.78	+0	0.65	+0.20	0.5	-4.0	-1.0	0.466	0.995	+0	co
11	Overnight stays, total (incl. home and foreigners)	1.26769	1.26702	0.36	0.48	-3	0.16	-0.69	-2.5	3.5	0.5	0.069	0.596	-1	lag
	Prices & Wages														
12	Wholesale prices, total	7.85256 ***	0.79952	0.63	0.63	+0	0.36	-0.29	-1.0	-1.5	0.0	0.408	0.958	+0	co
13	Wholesale prices, total excl. fruit, vegetables and potatoes	6.54794 ***	0.59115	0.62	0.62	+0	0.34	-0.30	-1.5	-2.0	0.0	0.396	0.963	+0	co
14	Wholesale prices, durable products	0.73355	0.85650	-0.39	-0.39	+0	0.16	+7.05	0.5	-3.5	-2.5	0.091	-0.910	+0	lead
15	Wholesale prices, non-durable goods	1.56801	0.53498	-0.48	-0.64	+3	0.29	-6.91	3.0	6.0	3.0	0.357	-0.874	+1	lead
16	Wholesale prices, consumer items	3.42162 ***	0.46138	0.47	0.47	+0	0.22	-0.31	-2.0	-1.0	-0.5	0.325	0.933	+0	co
17	Wholesale prices, consumer products	3.44888 ***	0.57003	0.34	0.34	+0	0.11	-0.62	-2.0	-1.0	-0.5	0.249	0.850	+0	co
18	Wholesale prices, investment goods	0.69529	1.09534	-0.12	-0.31	-4	0.03	+5.80	5.5	-2.0	0.0	0.013	-0.894	+0	lead
19	Wholesale prices, intermediate goods	6.05428 ***	0.64464	0.64	0.64	+0	0.36	-0.23	-4.0	1.5	-2.5	0.347	0.982	+0	co
20	Index of minimum wages, total	1.63035	2.14245 *	-0.18	-0.60	+4	0.07	-5.79	6.0	5.5	6.0	0.296	-0.848	+1	lead
21	Index of minimum wages, blue collar workers	1.77356	1.43078	-0.32	-0.52	+4	0.13	-6.32	6.5	-6.5	5.0	0.411	-0.836	+1	lead
22	Index of minimum wages, white collar workers	1.28197	1.57820	-0.36	-0.55	+4	0.16	-6.46	7.0	-6.0	6.0	0.408	-0.846	+1	lead
	Labour market														
23	Unemployment rate (national definition)	1.49699	2.19304 *	-0.65	-0.65	+0	0.42	+7.21	-5.5	-4.5	-5.5	0.501	-0.994	+0	lead
24	Registered unemployed persons (national definition), total	1.32805	1.21611	-0.61	-0.61	+0	0.37	+7.26	-5.5	-4.5	-5.5	0.501	-0.989	+0	lead
25	Job vacancies, total	4.44090 ***	0.43955	0.79	0.79	+0	0.66	+0.07	-4.0	-2.0	-1.5	0.554	0.982	+0	co
26	Employees, total incl. persons on parental leave or in military service	4.06039 ***	0.91105	0.65	0.65	-1	0.43	-0.59	-0.5	-4.0	-2.0	0.175	0.813	+0	co
27	Employees (economically active), total	4.33290 ***	1.07720	0.79	0.79	+0	0.65	-0.35	-1.5	-0.5	0.0	0.363	0.951	+0	co

Table SA.4 (cont.): Overview Indicator List – Statistical Results [HP-filtered 1600|1]

	International trade	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
28	Exports, total	6.41154 ***	1.75740	0.77	0.77	+0	0.59	+0.30	-3.5	-2.5	-1.5	0.862	0.983	+0	co
29	Exports, basic manufactures (SITC 6)	4.76960 ***	0.60977	0.70	0.70	+0	0.48	+0.32	-4.0	-2.5	-0.5	0.799	0.980	+0	co
30	Exports, machines +transport equipment (SITC 7)	4.27280 ***	0.87591	0.79	0.79	+0	0.64	+0.29	-3.0	-2.0	-2.0	0.814	0.984	+0	co
31	Exports, misc. manufactured goods (SITC 8)	2.00263	0.98718	0.70	0.70	+0	0.52	+0.06	0.0	-1.5	0.0	0.416	0.992	+0	co
32	Exports to Germany	5.63364 ***	2.36878 *	0.80	0.80	+0	0.65	+0.21	-1.5	-2.0	-1.0	0.767	0.992	+0	co
33	Exports into EU15	6.35434 ***	1.05144	0.79	0.79	+0	0.62	+0.26	-2.0	-2.0	-1.0	0.833	0.990	+0	co
34	Exports into EU27	5.01880 ***	1.18533	0.80	0.80	+0	0.64	+0.24	0.5	-1.5	-0.5	0.833	0.989	+0	co
35	Exports into EU27 minus EU15	2.05787 *	1.37101	0.60	0.60	+0	0.33	+0.01	-0.5	-2.0	-1.0	0.253	0.946	+0	co
36	Imports, total	0.85529	0.87711	0.78	0.78	+0	0.61	+0.21	-2.0	-2.0	-1.5	0.843	0.988	+0	co
37	Imports, basic manufactures (SITC 6)	0.98201	1.65743	0.81	0.81	+0	0.68	+0.19	0.0	-4.0	-2.0	0.734	0.987	+0	co
38	Imports, machines +transport equipment (SITC 7)	1.55205	0.30152	0.69	0.69	+0	0.47	+0.31	-5.0	-2.0	-1.5	0.827	0.975	+0	co
39	Imports, misc. manufactured goods (SITC 8)	0.55966	0.57540	0.72	0.72	+0	0.55	+0.07	-2.0	-4.0	-2.0	0.604	0.994	+0	co
40	Imports to Germany	1.96419	1.28834	0.71	0.71	+0	0.50	+0.32	-1.0	-3.5	-1.0	0.727	0.990	+0	co
41	Imports from EU15	1.79791	1.22848	0.75	0.75	+0	0.56	+0.30	-1.0	-3.5	-1.0	0.823	0.987	+0	co
42	Imports from EU27	1.45533	1.68372	0.75	0.75	+0	0.56	+0.26	-1.0	-3.5	-1.0	0.817	0.988	+0	co
43	Imports from EU27 minus EU15	2.88779 ***	0.80926	0.45	0.45	+0	0.17	-0.36	1.5	-4.5	1.5	0.173	0.916	+0	co
	Financials														
44	ATX stock market index	4.01493 ***	1.36302	0.57	0.62	+1	0.37	+0.76	-8.0	-5.0	-5.5	0.505	0.878	+0	lead
45	Loans to euro area nonfinancial institutions, in EUR	0.58619	1.94863	0.35	0.41	-2	0.14	-0.42	3.5	2.0	3.0	0.127	0.814	-1	lag
46	Loans to euro area households (incl. Non-profit institutions), in EUR	0.63862	0.31035	0.11	0.53	+4	0.04	+1.97	0.0	1.5	0.0	0.058	0.796	+2	lead
47	Loans to euro area corporations (excl. financial institutions), in EUR	1.12257	1.35605	0.28	0.69	-4	0.15	-1.18	4.0	1.5	3.5	0.097	0.700	-1	lag
48	Deposits of euro area nonfinancial institutions, in EUR	0.72786	0.99861	0.26	0.49	-4	0.11	-0.61	-3.0	0.5	0.5	0.034	0.759	-2	lag
49	EURIBOR, 3-month	2.22277 *	2.09443 *	0.81	0.81	+0	0.68	-0.26	0.5	-1.0	0.5	0.454	0.964	+0	co
50	Austrian federal government 10 year bond yield	0.65748	0.22273	0.42	0.42	+0	0.20	-0.20	-3.0	-2.0	-1.5	0.369	0.979	+0	co
51	Interest rate spread (long minus short)	0.37098	3.15363 ***	-0.70	-0.70	+0	0.49	+7.15	-2.5	-9.0	-5.0	0.165	-0.914	+0	lag
52	Exchange rate USD/EUR	1.55290	0.73799	0.15	-0.22	-4	0.01	+0.22	-3.0	-5.0	-0.5	0.034	0.620	-1	lead
53	Exchange rate GBP/EUR	5.61646 ***	2.18780 *	-0.62	-0.65	+1	0.43	-7.01	-1.5	1.5	1.0	0.318	-0.885	+0	lead
54	Dow Jones EURO STOXX 50 stock market index	4.64888 ***	1.03505	0.70	0.71	+1	0.53	+0.32	-6.0	-4.5	-4.0	0.507	0.918	+0	co
55	S&P 500 stock market index	7.50510 ***	0.37124	0.74	0.74	+1	0.59	+0.31	0.0	-0.5	0.0	0.388	0.944	+0	co
56	DJIA stock market index	5.75156 ***	0.70222	0.74	0.74	+0	0.59	+0.32	-1.5	-0.5	-1.0	0.407	0.951	+0	co
	Commodity market														
57	HWWI Commodity Price Index, total, in EUR	3.27446 ***	0.51960	0.59	0.59	+0	0.32	+0.05	-2.0	-4.5	-1.0	0.345	0.984	+0	co
58	HWWI Commodity Price Index, total excl. energy, in EUR	4.91453 ***	0.95628	0.48	0.48	+0	0.20	+0.58	-3.0	-5.0	-2.0	0.446	0.922	+0	co
59	HWWI Commodity Price Index, crude oil, in EUR	2.32515 *	0.73998	0.55	0.55	+0	0.29	-0.04	-2.0	-0.5	0.0	0.244	0.992	+0	co
60	Gold USD, fine ounce	5.78393 ***	0.22904	0.01	-0.48	+4	0.00	-4.95	-3.5	-0.5	1.0	0.004	0.494	+0	co
61	Petroleum USD, UK Brent (per barrel)	6.37231 ***	0.91803	0.69	0.69	+0	0.46	-0.16	-2.0	-0.5	0.0	0.264	0.974	+0	co

Table SA.4 (cont.): Overview Indicator List – Statistical Results [HP-filtered 1600|1]

	Surveys	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Source: Austrian Institute of Economic Research (WIFO)														
62	Industry: Production trend observed in recent months	2.27819 *	1.90166	0.50	0.50	+1	0.26	+0.79	-4.5	-5.5	-3.0	0.768	0.849	+0	lead
63	Industry: Assessment of order-book levels	1.97480	1.65755	0.37	0.52	+3	0.17	+1.00	-4.5	-5.5	-3.0	0.744	0.862	+0	lead
64	Industry: Assessment of export order-book levels	2.85861 **	2.36144 *	0.52	0.52	+0	0.28	+0.63	-4.0	-5.5	-3.0	0.760	0.903	+0	co
65	Industry: Assessment of stocks of finished products	1.20621	0.93630	-0.37	-0.43	+2	0.16	-6.28	4.5	-5.5	4.0	0.631	-0.818	+1	lead
66	Industry: Production expectations for the month ahead	5.67116 ***	0.42230	0.54	0.57	+1	0.32	+0.78	-4.5	-4.0	-3.0	0.778	0.848	+0	lead
67	Industry: Selling price expectations for the next 3 month	3.44906 **	0.70606	0.61	0.61	+0	0.36	+0.43	-5.0	-3.5	-2.5	0.753	0.898	+0	co
68	Construction: Selling price expectations for the next 3 month	1.97268	1.32310	0.61	0.61	+0	0.34	+0.29	-2.0	-3.5	-2.0	0.518	0.878	+0	lead
69	Business Confidence, Industry	4.30830 ***	1.25438	0.52	0.54	+1	0.29	+0.75	-4.5	-3.0	-2.0	0.789	0.862	+0	lead
70	Business Confidence, Construction	0.67575	0.54477	0.37	0.42	+4	0.15	+1.03	-4.5	-1.0	-2.0	0.505	0.814	+1	lead
71	Business Confidence, Retail	2.60305 **	0.99154	0.59	0.66	+1	0.41	+0.54	-3.5	-4.5	-2.5	0.586	0.924	+0	co
72	Consumer Confidence	3.91389 ***	0.68783	0.42	0.65	+3	0.27	+0.99	-5.5	-3.0	-3.5	0.511	0.839	+1	lead
73	Business confidence climate (industry, construction and retail)	2.03585 *	0.51853	0.35	0.58	+3	0.18	+1.21	-4.5	-5.0	-3.5	0.733	0.825	+1	lead
	Source: European Commission														
74	AT: Economic Sentiment Indicator (ESI)	5.62195 ***	1.92134	0.56	0.57	+1	0.33	+0.72	-4.5	-3.0	-2.0	0.797	0.860	+0	lead
75	DE: Economic Sentiment Indicator (ESI)	8.91739 ***	0.58163	0.62	0.65	+1	0.42	+0.62	-3.0	-4.0	-2.5	0.865	0.916	+0	co
76	DE: Business Confidence	10.81900 ***	0.57935	0.62	0.63	+1	0.41	+0.63	-2.5	-6.0	-3.0	0.859	0.911	+0	co
77	DE: Production trend observed in recent months	8.79156 ***	1.52522	0.52	0.56	+1	0.30	+0.83	-3.0	-3.5	-2.0	0.725	0.831	+1	lead
78	DE: Production expectations for the months ahead	12.93240 ***	0.79081	0.49	0.56	+1	0.28	+0.92	-3.0	-3.5	-2.0	0.724	0.825	+1	lead
79	DE: Employment expectations for the months ahead	5.42413 ***	1.43123	0.67	0.67	+0	0.46	+0.44	-3.0	-5.0	-2.5	0.861	0.964	+0	co
80	EA: Economic Sentiment Indicator (ESI)	9.16392 ***	0.59536	0.58	0.62	+1	0.37	+0.71	-4.0	-3.5	-2.0	0.837	0.895	+0	co
81	EA: Business Confidence	9.42748 ***	0.30931	0.54	0.56	+1	0.31	+0.72	-4.0	-6.0	-2.5	0.785	0.882	+0	co
82	EA: Production trend observed in recent months	10.43400 ***	0.88507	0.52	0.52	+1	0.27	+0.75	-4.5	-5.5	-3.0	0.717	0.862	+0	lead
83	EA: Production expectations for the months ahead	11.62090 ***	0.23330	0.48	0.54	+1	0.26	+0.91	-5.0	-3.5	-2.0	0.733	0.825	+0	lead
84	EA: Employment expectations for the months ahead	4.92743 ***	0.45442	0.68	0.68	+0	0.46	+0.41	-3.5	-3.0	-1.5	0.862	0.963	+0	co
	Source: Ifo Institute for Economic Research, Munich														
85	DE: ifo Business Climate (Industry and Trade)	6.77403 ***	0.98422	0.66	0.72	+1	0.49	+0.66	-2.5	-4.5	-2.5	0.870	0.885	+0	co
86	DE: Assessment of current business situation (Industry and Trade)	5.18356 ***	1.41920	0.77	0.77	+0	0.62	+0.43	-2.0	-4.5	-2.5	0.911	0.947	+0	co
87	DE: Business expectations (Industry and Trade)	8.62510 ***	1.29624	0.38	0.59	+2	0.23	+1.31	-4.5	-4.0	-3.0	0.676	0.816	+1	lead
	OECD Composite Leading Indicators														
88	CLI for Austria	5.38753 ***	0.79231	0.70	0.74	+1	0.54	+0.54	-4.0	-3.0	-2.0	0.854	0.887	+0	co
89	CLI for Germany	9.21444 ***	1.04648	0.67	0.71	+1	0.49	+0.64	-3.5	-4.0	-2.5	0.845	0.869	+0	lead
90	CLI for the Euro-Area	8.11007 ***	1.31464	0.59	0.69	+1	0.42	+0.83	-4.5	-4.0	-2.5	0.822	0.841	+1	lead
91	CLI for the U.S.	5.46727 ***	1.40214	0.52	0.56	+1	0.29	+0.77	-3.5	-3.5	-3.5	0.316	0.798	+1	lead

1) - 8) See notes to Table 4 (Chapter 1).

Source: Own calculations / BUSY software.

References

Artis, M.J., Marcellino M. and Proietti, T. (2003): Dating the Euro Area business cycle, *CEPR Discussion Paper*, No. 3696.

Baxter, M. and King, R.G. (1999): 'Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series', *Review of Economics and Statistics*, MIT Press, Vol. 81(4), pp. 575-593.

Bierbaumer-Polly, J. (2010): Composite Leading Indicator for the Austrian Economy: Methodology and 'Real-time' Performance, *WIFO-Working Papers*, No. 369.

Hodrick R. and Prescott, J. (1997): 'Postwar U.S. Business Cycles: An Empirical Investigation', *Journal of Money, Credit, and Banking*, Blackwell Publishing, Vol. 29(1), pp. 1-16.

Maravall, A. and del Rio, A. (2001): Time Aggregation and the Hodrick-Prescott Filter, *Banco de España Working Papers*, No. 0108.

Massmann, M., Mitchell J. and Weale, M. (2003): 'Business Cycles and Turning Points: A Survey of Statistical Techniques', *National Institute Economic Review*, Vol. 183(1), pp. 90-106.

Proietti, T. (2005): 'New algorithms for dating the business cycle', *Computational Statistics & Data Analysis*, Elsevier, Vol. 49(2), pp. 477-498.

Chapter I – Supplement B

Reassessment of the 'WIFO-Frühindikator'[1]

Preface

In the published working paper that constitutes chapter 1 of this dissertation (Bierbaumer-Polly, 2010), the indicator analysis and subsequent construction of the composite leading indicator CLI_{AT} covers the time period from 1988 to 2008. Since 2012, the CLI_{AT} has been used by the Austrian Institute of Economic Research (WIFO) for its ongoing business cycle monitoring of the Austrian economy. Especially within the institute's short-term forecasting procedures, the CLI_{AT} is watched closely in order to detect turning points in the overall business cycle of the economy as soon as possible.

In order to reassess, for robustness-check, the business cycle properties of the underlying indicator set and the performance of the CLI_{AT} up to the current date, I repeated the analysis based on up-to-date data that reach up to the 2nd quarter of 2015. Moreover, I added a simple Markov regime-switching model to detect turning point signals in the overall business cycle dynamics. My findings are very robust with respect to the original results (Bierbaumer-Polly, 2010) and suggest that the Markov-switching model provides a useful extension for signalling business cycle up- and downswings. However, the turning point signals are not clear-cut, especially in periods with high uncertainty.

[1] The composite leading indicator CLI_{AT} is coined *WIFO-Frühindikator* and results of the indicator are published on the WIFO business cycle webpage (konjunktur.wifo.ac.at) every first week of a month.

1. Revisiting the composite leading indicator

In the published working paper (Bierbaumer-Polly, 2010) my analysis covers the years from 1988 to 2008. Since then, business cycle dynamics have been shaped by the 'great recession' and its aftermaths. In the post-crises years following the huge drop in 2008/09 and its (modest) recovery until 2010/11, economic activity has weakened and has been characterised by a bumpy up and down without showing a clear tendency of business cycle movements and turning point signals. Episodes like the euro area debt-crisis which have further led to loss in confidence have impacted on this unusual long period of stagnate economic growth. This rather distinct business cycle pattern since 2008 may have changed the leading property of some of the selected business cycle indicators or for the CLI_{AT} as a whole with respect to the underlying reference series (i.e. overall business cycle). Similarly, business cycle indicators which were omitted in the original selection may now prove to exhibit relevant leading business cycle characteristics.

1.1 Data and reference series

In this reassessment, I restrict the indicator set to range between January 1996 and June 2015, in total 102 monthly series.[2] The starting point is predetermined by the availability of the reference series. I again employ quarterly real gross value added excluding forestry and agriculture obtained from the national accounts as the benchmark series (Y_{exFA}^{GVA}). However, since September 2014 the national accounts follow the ESA 2010 framework, and consistent quarterly data are only available from 1996 onwards. I use the Bry and Boschan (1971) algorithm for dating the business cycle peaks and troughs. For extracting the business cycle component, I resort to the '2-sided' HP filter ($\widetilde{HP}_1^{1600}$) as outlined in Supplement A to this chapter.[3]

Figure SB.1 shows the business cycle chronology of the references series with the business cycle downturns indicated by the grey shaded areas. For the period covered, the dating procedure reveals three phases of business cycle upswings and downswings. Both phases last on average about three years. However, the length of each phase differs quite substantially. The business cycle upswing prior the crisis was very persisted and continued for five years, whereas the sudden drop and recovery surrounding the financial crisis 2008/09 only lasted less than two years. Table SB.1 lists the dated turning points.

[2] A detailed list of the full indicator set, the data transformations applied and the seasonal adjustment performed is shown in Table SB.A1 in the Appendix.

[3] Figure SB.1 (Appendix) contrasts the cyclical component of the '2-sided' HP filter with the BK filter [6; 32]. Both series exhibit rather similar movements and the dates of the peaks and troughs match in most cases.

Figure SB.1: Business Cycle Chronology of the Reference Series Y_{exFA}^{GVA}

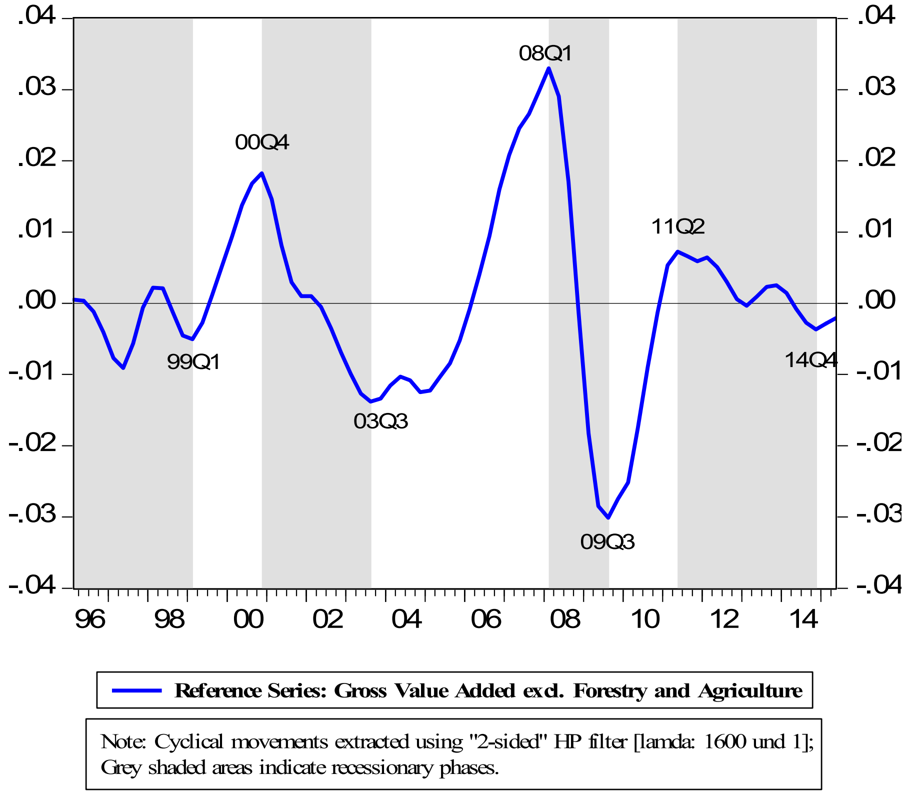


Table SB.1: Turning Points of the Reference Series Y_{exFA}^{GVA}

Peak (P)	Trough (T)	Cycles		Phases	
		P to P	T to T	P to T	T to P
(1)	(2)	(3)	(4)	(5)	(6)
	99Q1		-	-	
00Q4		-			8
	03Q3		19	12	
08Q1		30			19
	09Q3		25	7	
11Q2		14			7
	14Q4		22	15	
	Average	22	22	11.3	11.3

Note: The turning points have been analysed between 1996Q1 and 2015Q2.
Cycle/phase length indicates number of quarters it takes to pass through.
Source: Own calculations / BUSY software.

1.2 Indicator analysis

To keep consistency with the work in Bierbaumer-Polly (2010), I resort to the same set of statistical methods out of the time-series (i.e. Granger-causality and cross-correlations) and frequency domain (i.e. coherence and mean-delay) as well as on information derived from a dynamic factor model and turning point statistics in order to identify 'leading' business cycle indicators.[4] The business cycle components are extracted in line with the reference series using $\widetilde{HP}_1^{1600}$.

Besides the 'leading' characteristics of an indicator, in a real time setting the publication timeliness as well as the revision frequency of the indicator also needs to be considered when selecting the components of the CLI_{AT}. In order to take the timely availability of the indicators into account (i.e. by the end of each month), which allows to construct the CLI_{AT} on a monthly basis and provides information on the most recent months, the focus at the WIFO institute rests on the 'flash' version of the CLI_{AT} – in particular, on the variant reflecting the 'real-time' HP filter case.[5] As a result, I primarily focus in this reassessment on the ten indicators included in the published *WIFO-Frühindikator*, which basically reflects the original 'flash' version of the CLI_{AT}.[6] Besides reassessing the business cycle properties of the pre-existing 'leading' indicators for the new time-span (1996 to 2015), I also look on the remaining set of indicators to identify those series which exhibit a 'leading' behaviour as well. Table SB.2 summarises the statistical results for the selected indicators.[7] The results of the 'flash' indicators are fairly similar to the one derived in Bierbaumer-Polly (2010), even though minor differences exist in the magnitude of some of the measures employed. For example, the cross-correlation coefficient for the ATX stock market index at lead *t+2* is higher compared to the original analysis (+0.77 instead of +0.58), but on the other hand, Granger-causality is not found to run from the indicator to the reference series. Likewise, consumer confidence exhibits a higher cross-correlation measure but the maximum magnitude is found at *t+2* instead of *t+3*. Overall, however, the results confirm the lead time of the 'flash' indicators. In addition to the pre-existing 'flash' indicators, I identify a set of six additional series which may lead the overall business cycle. These are mostly survey data and include, for example, information on order-book levels, production trends in recent months, or with respect to the international environment the economic sentiment in Germany or the euro area.

[4] For a description of the methods: see Chapter 1, Section 3.1.

[5] For a discussion of the HP filter endpoint problem and a 'real-time' setting: see Chapter 1, Section 4.3.2.

[6] As of January 2013 the *WIFO-Frühindikator* had been augmented with information on the number of job vacancies due to earlier releases of the indicator from that time on. The weights of the individual series had been adjusted accordingly.

[7] See Table SB.A2 in the Appendix for results of the complete indicator list.

Table SB.2:'Flash'-Indicators – Statistical Results

			Time series domain					Frequency domain		Turning point analysis			Dynamic factor analysis			
			Granger-Causality 1)		**Cross-Correlation** 2)			**Coherence** 3)	**Mean Delay** 4)	**Median lag at..** 5)			**Var. Ratio** 6)	**CC-Corr.** 7)		**CC-Classif.** 8)
			X->Y	Y->X	r_0	r_{max}	t_{max}			Peaks	Troughs	All		r_{max}	t_{max}	
x_i	**Indicatorname**	**Area**	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Already in use (as of Jan-13)															
x1	ATX stock market index	Financials	1.45245	4.14007 ***	0.57	0.77	+2	0.40	+0.42	-6.0	-2.0	-2.0	0.552	0.886	+1	lead
x2	DJ EURO STOXX 50 stock market index	Financials	2.39840 *	1.10314	0.22	0.24	+1	0.05	+0.43	-0.5	-2.5	-2.0	0.110	0.990	+0	co
x3	Job vacancies, total	Labour market	3.22980 **	2.24080 *	0.79	0.81	+1	0.66	+0.43	-2.0	-3.0	-2.0	0.535	0.985	+0	co
x4	Industry production expectations for the month ahead	Survey / WIFO	3.35603 **	4.59008 ***	0.52	0.77	+2	0.38	+0.40	-3.0	-4.5	-3.0	0.788	0.862	+1	lead
x5	Consumer Confidence	Survey / WIFO	2.51301 *	4.62086 ***	0.58	0.84	+2	0.45	+0.41	-3.5	-1.0	-2.5	0.628	0.878	+1	lead
x6	Business Confidence Climate (industry, construction and retail)	Survey / WIFO	2.47132 *	1.90347	0.64	0.84	+2	0.50	+0.41	-2.0	-2.5	-2.0	0.436	0.876	+1	lead
x7	ifo Business Climate for Germany	Survey / ifo	3.70438 ***	1.17703	0.60	0.85	+2	0.47	+0.41	-3.0	-2.0	-2.0	0.869	0.876	+1	lead
x8	Production trend observed in recent months for Germany	Survey / EC	2.13625 *	1.73737	0.33	-0.77	-4	0.23	+0.40	-3.0	-4.0	-3.0	0.673	0.830	+1	lead
x9	Production expectations for the months ahead for Germany	Survey / EC	2.22378 *	2.05782 *	0.31	-0.76	-4	0.22	+0.39	-2.5	-4.5	-2.5	0.649	0.825	+1	lead
x10	Production expectations for the months ahead in the Euro-Area	Survey / EC	3.66756 ***	2.52696 **	0.41	-0.71	-4	0.28	+0.40	-2.5	-4.5	-2.5	0.714	0.846	+1	lead
	Additional indicators identified															
x11	Industry production trend observed in recent months	Survey / WIFO	0.57294	6.46440 ***	0.47	0.71	+2	0.31	+0.40	-3.0	-3.5	-3.0	0.763	0.854	+1	lead
x12	Industry assessment of order-book levels	Survey / WIFO	0.91560	3.31116 **	0.72	0.79	+1	0.57	+0.41	-2.0	-3.0	-2.0	0.859	0.944	+0	co
x13	Economic Sentiment Indicator (ESI) for Germany	Survey / EC	1.36113	1.71856	0.59	0.81	+2	0.43	+0.41	-2.0	-2.5	-2.5	0.835	0.871	+1	lead
x14	Economic Sentiment Indicator (ESI) for the Euro-Area	Survey / EC	3.57157 **	2.38333 *	0.55	0.81	+2	0.41	+0.41	-2.0	-2.0	-2.0	0.794	0.871	+1	lead
x15	Production trend observed in recent months in the Euro-Area	Survey / EC	2.96787 **	2.67196 **	0.49	0.73	+2	0.33	+0.40	-2.5	-4.0	-2.5	0.770	0.856	+1	lead
x16	DJIA stock market index	Financials	3.03082 **	0.89577	0.67	0.80	+2	0.51	+0.43	-2.0	-6.0	-2.0	0.487	0.929	+0	co

1) Performed on quarterly data with lag-length of 4; F-test statistic: *** indicates statistically significance at 1%, ** indicates statistically significance at 5%; * indicates statistically significance at 10%

2) r_0...contemporaneous cross-correlation; r_{max}... maximum cross-correlation at lag (t_{max}): + (-) sign refers to a lead (lag) w.r.t. the reference series

3) Average of spectral mass over the range of business cycle frequencies (between 6 and 32 quarters); statistical measure ranges between 0 and 1

4) Cross-spectrum between indiv. series and reference series; in average over ranges of business cycle periodicity (between 6 and 32 quarters): + (-) sign refers to a lead (lag) w.r.t. the reference series

5) Median turning point behaviour of indiv. series w.r.t. reference series at cyclical peaks, troughs and over the whole cycle: + (-) denotes a lag (lead) w.r.t. the reference series

6) Ratio of the common component variance over the series variance

7) Cross-correlation between series common component and the common component of the reference series (out of the Dynamic Factor Analysis); t_{max} indicates period with maximum correlation

8) Checking mean delay of the cross-spectra between series common component and reference series common component, with the following classification rules:
lead...mean delay < -1; lag...mean delay > 1; co...-1 < mean delay < 1

Source: Own calculations / BUSY software.

1.3 Comparing different versions of the 'flash' $\mathbf{CLI_{AT}}$

The original 'flash' version, $\widetilde{\Psi}^{\mathrm{ORI}}_{\mathrm{flash}}$, of the composite leading indicator is calculated at the WIFO institute on a monthly basis since 2012. The weights of this $\mathrm{CLI_{AT}}$ were determined using principal component analysis (PCA). Table SB.3 column (1) displays the respective weights. Given that the time period has changed on which the indicator analysis is based on, I redo the PCA and derive new component weights of the $\mathrm{CLI_{AT}}$ ($\widetilde{\Psi}^{\mathrm{UPD}}_{\mathrm{flash}}$). This is to take possible changes in the explanatory power of the variable set into account. As can be seen in column (2), the weights are almost identical to the $\widetilde{\Psi}^{\mathrm{ORI}}_{\mathrm{flash}}$ version. Finally, I also construct a new variant of the $\mathrm{CLI_{AT}}$ ($\widetilde{\Psi}^{\mathrm{NEW}}_{\mathrm{flash}}$), in which I include the additional 'leading' indicators identified in the selection step. This version of the $\mathrm{CLI_{AT}}$ contains 16 series, and the individual component weights range from 3% (job vacancies) to 8% (production expectations and trends in the euro-area). The proportion of the indicators related to the Austrian economy as well as related to the real sector is lower compared to the original 'flash' version.

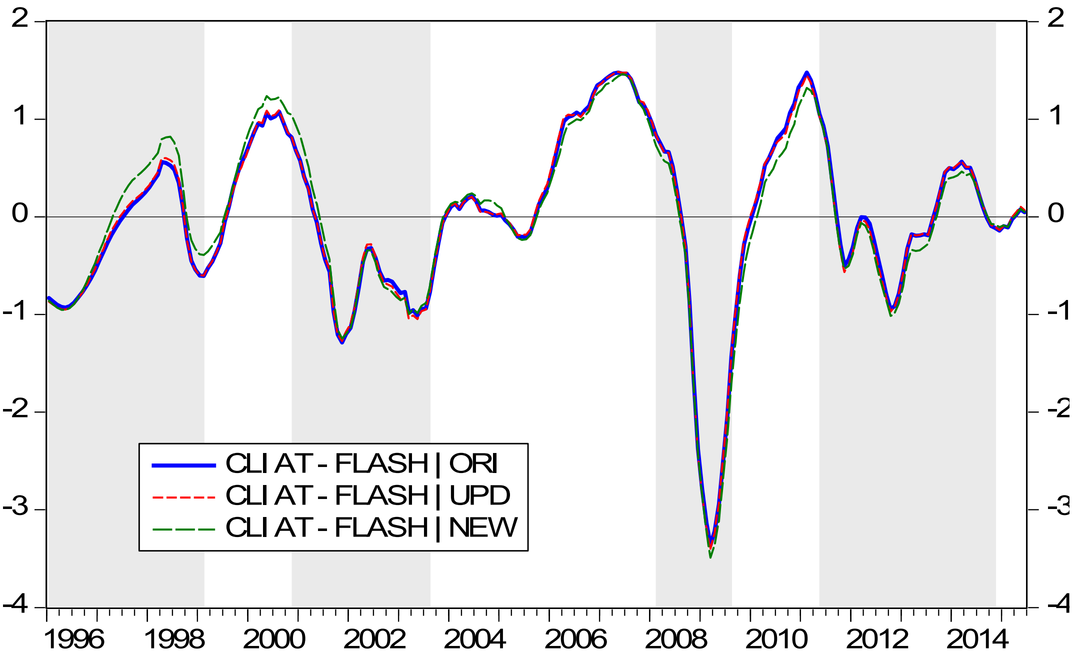
Table SB.3:'Flash'-Indicators – Weights

		FLASH $\mathrm{CLI_{AT}}$		
		ORI	UPD	NEW
x_i		(1)	(2)	(3)
x1	ATX stock market index	0.09	0.10	0.06
x2	DJ EURO STOXX 50 stock market index	0.05	0.09	0.05
x3	Job vacancies, total	0.08	0.05	0.03
x4	Industry production expectations for the month ahead	0.12	0.12	0.07
x5	Consumer Confidence	0.09	0.08	0.05
x6	Business Confidence Climate (industry, construction and retail)	0.10	0.10	0.06
x7	ifo Business Climate for Germany	0.13	0.11	0.06
x8	Production trend observed in recent months for Germany	0.12	0.12	0.07
x9	Production expectations for the months ahead for Germany	0.12	0.12	0.07
x10	Production expectations for the months ahead in the Euro-Area	0.11	0.12	0.08
x11	Industry production trend observed in recent months	-	-	0.07
x12	Industry assessment of order-book levels	-	-	0.06
x13	Economic Sentiment Indicator (ESI) for Germany	-	-	0.07
x14	Economic Sentiment Indicator (ESI) for the Euro-Area	-	-	0.07
x15	Production trend observed in recent months in the Euro-Area	-	-	0.08
x16	DJIA stock market index	-	-	0.06
	Proportion of domestic related indicators (vs. international environment)	47%	44%	40%
	Proportion of real-sector indicators (vs. survey data)	22%	23%	20%

Source: Own calculations.

Contrasting the three variants of the monthly CLI_{AT} reveals no distinct differences (Figure SB.2). For the composites $\widetilde{\Psi}_{\text{flash}}^{\text{ORI}}$ and $\widetilde{\Psi}_{\text{flash}}^{\text{UPD}}$, this result comes as no surprise given their almost identical weights. With respect to $\widetilde{\Psi}_{\text{flash}}^{\text{NEW}}$, it seems that the additional set of indicators incorporated in this variant do not add different dynamics over the course of the business cycle, in particular not at the cyclical turning points. Given the rather similar movements of the CLI_{AT}'s, I focus in the performance re-evaluation on the original 'flash' version.

Figure SB.2: 'Flash'-Indicators – Different Versions



1.4 Performance evaluation

The CLI_{AT} is designed to give reliable and timely signals of turning points in the Austrian business cycle. In addition, the composite indicator should improve the forecasting quality of the underlying reference series. From a visual inspection of the turning points (see Figure SB.3), it can be seen that the CLI_{AT} ($\widetilde{\Psi}_{\text{flash}}^{\text{ORI}}$) has its cyclical turning points predominantly prior to the underlying reference chronology. The statistical measures confirm this picture. The pair-wise Granger-causality test indicates that Granger-causality runs from the CLI_{AT} to the Y_{exFA}^{GVA}, but contrary to the findings in Bierbaumer-Polly (2010) also the other way round. The cross-correlation reveals a maximum coefficient (r_{max}) of +0.79 at two quarters lead. Also the frequency domain measures (albeit to some lesser extent) as well as the turning points statistics indicate a leading property of the CLI_{AT}. Thus, they confirm the results in the original work (Bierbaumer-Polly, 2010) that the CLI_{AT} is able to provide signals of cyclical turning points with a lead time between one to two quarters.

With respect to the out-of-sample forecasting performance of the CLI_{AT}, the results show that the bivariate specification performs better for all forecast horizons tested, i.e. producing a lower RMSE compared to the univariate case (see Table SB.4), and that the improvements increase with the forecast horizon chosen (from 25% to 50% reduction in the RMSE).

Figure SB.3: CLI_{AT} vs. Reference Series Y_{exFA}^{GVA}

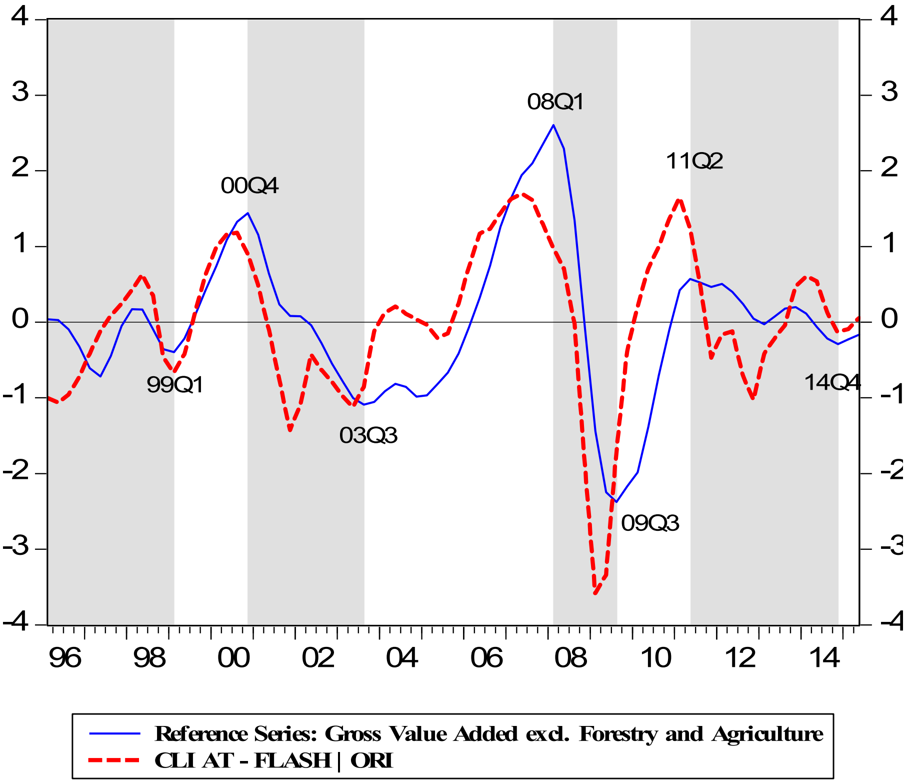


Table SB.4: 'Flash'-Indicators – Out-of-sample Forecasting Procedure

	Quarterly forecast horizons (h = 1..12)											
	short-term				medium-term				long-term			
	1	2	3	4	5	6	7	8	9	10	11	12
Univariate RMSE [1)]	0.0091	0.0137	0.0188	0.0241	0.0279	0.0316	0.0346	0.0373	0.0385	0.0397	0.0397	0.0378
FLASH CLI_{AT} [2)]												
ORI	0.79	0.74	0.62	0.58	0.52	0.50	0.52	0.49	0.46	0.47	0.44	0.48
UPD	0.78	0.73	0.62	0.59	0.53	0.51	0.53	0.50	0.50	0.49	0.45	0.49
NEW	0.77	0.75	0.65	0.61	0.55	0.54	0.57	0.59	0.61	0.61	0.58	0.61

Note: The sample period for the recursive forecasting regressions ranges from 1996Q1 to 2015Q2. The forecast evaluation sample runs from 2003Q1-*h* to 2015Q2.

1) Absolute forecast RMSE values for the univariate model setting.

2) Values are the ratio between the forecast RMSE of the bivariate model which uses the variable indicated and the forecast RMSE of the univariate model; numbers less (greater) than 1.0 refer to an improvement.

Source: Own calculations.

1.5 Variability of the CLI_{AT}

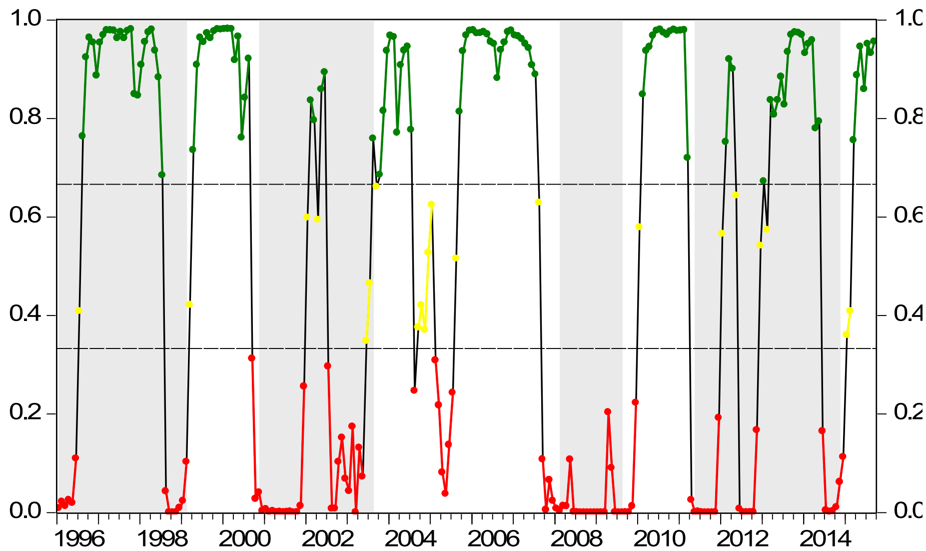
The individual series of the CLI_{AT} enter the composite (if required) in seasonal and trend adjusted form. The cyclical signals as well as the irregular movements remain in the indicator itself and subsequently in the CLI_{AT}. To eliminate part of the 'noise', the CLI_{AT} is finally smoothed by means of the HP filter (see Chapter 1, Section 4.3). One objective of a business cycle indicator or a composite thereof like the CLI_{AT} is that the (trend-)cyclical component should dominate over the irregular signal (Abberger and Nierhaus, 2009). If the latter dominates the dynamics in the series, the business cycle signal may become ambiguous. Nevertheless, at cyclical turning points the 'noise' may provide useful information given that the trend-cycle information is typically very persistent. In order to assess the variability of the CLI_{AT}, I employ two measures commonly found in the empirical literature: (*i*) the IC-ratio, and proximate (*ii*) the MCD-measure (Nardo et al., 2005). The IC-ratio presents the average amplitudes of the irregular to the cyclical component, where a value greater than one shows that the month-to-month change in the indicator is, on average, more influenced by irregular movements. To calculate the IC-ratio I derive the irregular component of the CLI_{AT} by subtracting the smoothed CLI_{AT} ($\widetilde{\Psi}_{\text{flash}}^{\text{ORI}}$) from the unsmoothed version ($\Psi_{\text{flash}}^{\text{ORI}}$). The value of the IC-ratio is 0.66. Given that it is less than one, the result for the MCD-measure also equals one. It only takes one month (i.e. the minimum duration possible) that the cyclical factor dominates the 'noise' without regard of the sign of both components.

1.6 Turning point signals based on a Markov regime-switching-model

In addition to the already used ad-hoc non-parametric model of Bry and Boschan (1971), I include a parametric model for turning point detection. In particular, I resort to the widely used Markov regime-switching autoregressive (MS-AR) time series model class which has become increasingly popular since Hamilton's (1989) application of this procedure to date the U.S. business cycle. The estimation of such a MS-AR is performed in practise with an extension of the Kalman filter in combination with Maximum-Likelihood estimators.

In a baseline Markov regime-switching model, the economy is allowed to 'switch' between a contractive and an expansionary regime. The probability of being in either state of the cycle, i.e. being in recession or expansion, depends on a Markov chain which contains the probabilities for switching from one regime to the other. The threshold-probability for either state has to be defined because it is a priori not clear at which magnitude of the obtained probabilities one can speak of an expansion or contraction in overall economic activity. A fairly simple rule is 50:50, meaning that the business cycle is in an upswing once the probability for the state ‘upswing’ is greater or equal to 50%. However, this classification might be rather too strict. Abberger and Nierhaus (2010) propose an alternative classification, the so-called ‘ifo traffic light’: A business cycle upswing (downswing) is prevailing, once the respective regime probability is greater than 2/3. For probabilities in between no clear business cycle phase can be detected. I follow the classification scheme ‘red-yellow-green’ in Abberger and Nierhaus (2010) and Glocker and Hölzl (2015) and estimate a univariate Markov regime-switching model on the smoothed $\mathrm{CLI_{AT}}$ ($\tilde{\Psi}^{\mathrm{ORI}}_{\mathrm{flash}}$). Results for the filtered probabilities are shown in Figure SB.4.[8] The area with the green dots (above the $^2/_3$ line) represents business cycle expansion, the red dots (below the $^1/_3$ line) mark downswings, and the yellow dots in between show an area of indifference. According to this classification, in 51% of the time the business cycle is in an upswing, in 41% in a downswing, and in 8% indifferent. The low proportion of time in the middle range of the probability distribution shows that there exists most of the time a rather clear distinction between the two business cycle phases of expansion and contraction.

Figure SB.4: Regime-switching probabilities (filtered) of the CLI_{AT}



Contrasting the regime-switching probabilities with the dating of the reference series (Y^{GVA}_{exFA}) it can be seen that the indicated regimes derived from the $\mathrm{CLI_{AT}}$ lead the overall business cycle turning points, in particular at peaks in the cycle. This means that changes from ‘green’

[8] The regime-switching probabilities can be obtained either using the full information set of the underlying variable(s) for any time period *t*, or using only the information available up to the respective time period *t*. In the first case the probabilities are referred to as being ‘smoothed’, in the latter as being ‘filtered’. Given that the latter is the more realistic case in a real-time environment, I resort in the discussion of the results on filtered regime-switching probabilities.

to ‘red’ occur some months earlier compared to the cyclical turning point in Y_{exFA}^{GVA}, and the probability changes its magnitude quite fast from high to low, indicating a rather clear turning point signal. For business cycle expansions the signals are not that clear-cut. For example, in 2003 or 2009 the regime-switching probabilities turn ‘green’ only some months after the turning points identified for the reference series. Moreover, the long lasting business cycle expansionary period prior to the financial crisis in 2008/09 provides mixed evidence. For most of the time the probabilities are above 0.8 pointing to a strong and robust expansion. But in 2004/05 the signal is rather noisy, showing some interim cooling down of economic activity and uncertainty in business and consumer sentiment prevailing at that time. Also in the most recent years the regime-switching probabilities switch several times from ‘green’ to ‘red’ and vice versa, substantiate the rather bumpy business cycle dynamics observed.

Overall, the Markov-switching model provides a useful extension for signalling business cycle up- and downswings. However, the turning point signals are not clear-cut, especially in periods with high uncertainty.

References

Abberger, K. and Nierhaus, W. (2009): ‘Months for Cyclical Dominance und ifo Geschäftsklima’, *ifo Schnelldienst*, Vol. 62(7), pp. 11-19.

Abberger, K. and Nierhaus, W. (2010): ‘Markov-Switching and the IFO Business Climate: the IFO Business Cycle Traffic Lights’, OECD Journal: *Journal of Business Cycle Measurement and Analysis*, Vol. 2010(2), pp. 1-13.

Bry, G. and Boschan, Ch. (1971): ‘Standard Business Cycle Analysis of Economic Time Series’, in: National Bureau of Economic Research, Cyclical Analysis of Time Series: Selected Procedures and Computer Programs, pp. 64-150.

Glocker, Ch. and Hölzl, W. (2015): ‘Bestimmung einer Konjunkturampel für Österreich auf Basis des WIFO-Konjunkturtests’, *WIFO-Monatsberichte*, Vol. 88(3), pp. 175-183.

Hamilton, J.D. (1989): ‘A new approach to the analysis of nonstationary time series and the business cycle’, *Econometrica*, Vol. 57, pp. 357-84.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, St., Hoffman, A. and Giovannini, E. (2005): Handbook on Constructing Composite Indicators - Methodology and User Guide, OECD Statistics Working Papers, No. 3.

Chapter I – Supplement B

Appendix

Table SB.A1: Overview Indicator List – Properties

		Data				
		Freq.	**Conv. to Quarter**	**log Trans-form.**	**Ord. of Integr.** [1]	**SA** [2]
		(1)	(2)	(3)	(4)	(5)
	Industry production					
01	OECD: Industry production, total, NACE classification (C, D, E), excl. construction	M	Avg	Yes	I(1)	Yes
02	OECD: Industry production, manufacturing	M	Avg	Yes	I(1)	Yes
03	OECD: Industry production, manufacturing plus intermediate goods	M	Avg	Yes	I(1)	Yes
04	OECD: Industry production, manufacturing plus investment goods	M	Avg	Yes	I(0)	Yes
05	WIFO: Industry production, total, incl. energy	M	Avg	Yes	I(1)	Yes
06	WIFO: Industry production, total, without energy, without construction	M	Avg	Yes	I(1)	Yes
07	OECD: Industry production, manufacturing, durable goods	M	Avg	Yes	I(1)	Yes
08	OECD: Industry production, manufacturing, none-durable goods	M	Avg	Yes	I(0)	Yes
	Trade					
09	Retail sales, total (excl. vehicle, petrol stations and rep. of consumer durables)	M	Avg	Yes	I(0)	Yes
10	New vehicle registrations, total	M	Sum	Yes	I(1)	Yes
11	New vehicle registrations, passenger cars (group of wage earners)	M	Sum	Yes	I(1)	Yes
12	New vehicle registrations, passenger cars (group of self-employed people)	M	Sum	Yes	I(1)	Yes
13	Overnight stays, total (incl. home and foreigners)	M	Sum	Yes	I(1)	Yes
	Prices & Wages					
14	Wholesale prices, total	M	Avg	Yes	I(1)	Yes
15	Wholesale prices, total excl. fruit, vegetables and potatoes	M	Avg	Yes	I(1)	Yes
16	Wholesale prices, durable products	M	Avg	Yes	I(1)	Yes
17	Wholesale prices, non-durable goods	M	Avg	Yes	I(1)	Yes
18	Wholesale prices, consumer items	M	Avg	Yes	I(1)	Yes
19	Wholesale prices, consumer products	M	Avg	Yes	I(1)	Yes
20	Wholesale prices, investment goods	M	Avg	Yes	I(1)	Yes
21	Wholesale prices, intermediate goods	M	Avg	Yes	I(1)	Yes
22	Index of minimum wages, total	M	Avg	Yes	I(1)	Yes
23	Index of minimum wages, blue collar workers	M	Avg	Yes	I(2)	Yes
24	Index of minimum wages, white collar workers	M	Avg	Yes	I(1)	Yes
	Labour market					
25	Unemployment rate (national definition)	M	Avg	No	I(0)	Yes
26	Registered unemployed persons (national definition), total	M	Avg	Yes	I(1)	Yes
27	Job vacancies, total	M	Avg	Yes	I(0)	Yes
28	Employees, total incl. persons on parental leave or in military service	M	Avg	Yes	I(1)	Yes
29	Employees (economically active), total	M	Avg	Yes	I(2)	Yes
	International trade					
30	Exports, total	M	Sum	Yes	I(1)	Yes
31	Exports, basic manufactures (SITC 6)	M	Sum	Yes	I(1)	Yes
32	Exports, machines +transport equipment (SITC 7)	M	Sum	Yes	I(1)	Yes
33	Exports, misc. manufactured goods (SITC 8)	M	Sum	Yes	I(1)	Yes
34	Exports to Germany	M	Sum	Yes	I(1)	Yes
35	Exports into EU15	M	Sum	Yes	I(1)	Yes
36	Exports into EU28	M	Sum	Yes	I(1)	Yes
37	Exports into EU28 minus EU15	M	Sum	Yes	I(1)	Yes
38	Imports, total	M	Sum	Yes	I(1)	Yes
39	Imports, basic manufactures (SITC 6)	M	Sum	Yes	I(1)	Yes
40	Imports, machines +transport equipment (SITC 7)	M	Sum	Yes	I(1)	Yes
41	Imports, misc. manufactured goods (SITC 8)	M	Sum	Yes	I(1)	Yes
42	Imports to Germany	M	Sum	Yes	I(1)	Yes
43	Imports from EU15	M	Sum	Yes	I(1)	Yes
44	Imports from EU28	M	Sum	Yes	I(1)	Yes
45	Imports from EU28 minus EU15	M	Sum	Yes	I(1)	Yes
	Financials					
46	ATX stock market index	M	Avg	Yes	I(1)	not requ.
47	Loans to euro area nonfinancial institutions, in EUR	Q	Month3	Yes	I(1)	Yes
48	Loans to euro area households (incl. Non-profit institutions), in EUR	Q	Month3	Yes	I(1)	Yes
49	Loans to euro area corporations (excl. financial institutions), in EUR	Q	Month3	Yes	I(1)	Yes
50	Deposits of euro area nonfinancial institutions, in EUR	Q	Month3	Yes	I(1)	Yes
51	Loans to domestic nonfinancial institutions, in EUR	Q	Month3	Yes	I(0)	Yes
52	Loans to domestic households (incl. Non-profit institutions), in EUR	Q	Month3	Yes	I(0)	Yes
53	Loans to domestic corporations (excl. financial institutions), in EUR	Q	Month3	Yes	I(1)	Yes
54	M1 money supply - Euro Area	Q	Avg	Yes	I(1)	Yes
55	M2 money supply - Euro Area	Q	Avg	Yes	I(1)	Yes
56	M3 money supply - Euro Area	Q	Avg	Yes	I(1)	Yes

Table SB.A1 (cont.): Overview Indicator List – Properties

		Data				
		Freq.	**Conv. to Quarter**	**log Trans-form.**	**Ord. of Integr.** 1)	**SA** 2)
		(1)	(2)	(3)	(4)	(5)
	Financials (cont.)					
57	EURIBOR, 3-month	M	Avg	No	I(1)	not requ.
58	Austrian federal government 10 year bond yield	M	Avg	No	I(1)	not requ.
59	Interest rate spread (long minus short)	M	Avg	No	I(0)	not requ.
60	Exchange rate USD/EUR	M	Avg	No	I(1)	not requ.
61	Exchange rate GBP/EUR	M	Avg	No	I(1)	not requ.
62	Dow Jones EURO STOXX 50 stock market index	M	Avg	Yes	I(0)	not requ.
63	S&P 500 stock market index	M	Avg	Yes	I(1)	not requ.
64	DJIA stock market index	M	Avg	Yes	I(1)	not requ.
	Commodity market					
65	HWWI Commodity Price Index, total, in EUR	M	Avg	Yes	I(1)	Yes
66	HWWI Commodity Price Index, total excl. energy, in EUR	M	Avg	Yes	I(1)	Yes
67	HWWI Commodity Price Index, crude oil, in EUR	M	Avg	Yes	I(1)	Yes
68	Gold USD, fine ounce	M	Avg	No	I(1)	not requ.
69	Petroleum USD, UK Brent (per barrel)	M	Avg	No	I(1)	not requ.
	Surveys					
	Source: Austrian Institute of Economic Research (WIFO)					
70	Industry: Production trend observed in recent months	M	Avg	No	I(0)	already adj.
71	Industry: Assessment of order-book levels	M	Avg	No	I(0)	already adj.
72	Industry: Assessment of export order-book levels	M	Avg	No	I(0)	already adj.
73	Industry: Assessment of stocks of finished products	M	Avg	No	I(0)	already adj.
74	Industry: Production expectations for the month ahead	M	Avg	No	I(0)	already adj.
75	Industry: Selling price expectations for the next 3 month	M	Avg	No	I(0)	already adj.
76	Construction: Selling price expectations for the next 3 month	M	Avg	No	I(0)	already adj.
77	Business Confidence, Industry	M	Avg	No	I(0)	already adj.
78	Business Confidence, Construction	M	Avg	No	I(0)	already adj.
79	Business Confidence, Retail	M	Avg	No	I(0)	already adj.
80	Consumer Confidence	M	Avg	No	I(1)	already adj.
81	Business confidence climate (industry, construction and retail)	M	Avg	No	I(0)	already adj.
82	Construction: Assessment of order-book levels	M	Avg	No	I(1)	already adj.
83	Construction: Employment expectations	M	Avg	No	I(0)	already adj.
84	Construction: Building activity in recent months	M	Avg	No	I(0)	already adj.
	Source: European Commission					
85	AT: Economic Sentiment Indicator (ESI)	M	Avg	No	I(0)	already adj.
86	DE: Economic Sentiment Indicator (ESI)	M	Avg	No	I(0)	already adj.
87	DE: Business Confidence	M	Avg	No	I(0)	already adj.
88	DE: Production trend observed in recent months	M	Avg	No	I(0)	already adj.
89	DE: Production expectations for the months ahead	M	Avg	No	I(0)	already adj.
90	DE: Employment expectations for the months ahead	M	Avg	No	I(0)	already adj.
91	EA: Economic Sentiment Indicator (ESI)	M	Avg	No	I(0)	already adj.
92	EA: Business Confidence	M	Avg	No	I(0)	already adj.
93	EA: Production trend observed in recent months	M	Avg	No	I(0)	already adj.
94	EA: Production expectations for the months ahead	M	Avg	No	I(0)	already adj.
95	EA: Employment expectations for the months ahead	M	Avg	No	I(0)	already adj.
	Source: Ifo Institute for Economic Research, Munich					
96	DE: ifo Business Climate (Industry and Trade)	M	Avg	No	I(0)	already adj.
97	DE: Assessment of current business situation (Industry and Trade)	M	Avg	No	I(0)	already adj.
98	DE: Business expectations (Industry and Trade)	M	Avg	No	I(0)	already adj.
	OECD Composite Leading Indicators 3)					
99	CLI for Austria	M	Avg	No	I(0)	already adj.
100	CLI for Germany	M	Avg	No	I(0)	already adj.
101	CLI for the Euro-Area	M	Avg	No	I(0)	already adj.
102	CLI for the U.S.	M	Avg	No	I(0)	already adj.

1) The test for order of integration has been determined using the Augmented Dickey-Fuller (ADF) test.
2) *Yes* …series seasonal + working day adjusted (where required) using Tramo/Seats;
not requ. ... series does not contain any seasonal effects;
already adj. ... series has been already seasonally adjusted by external data provider.
3) Amplitude and seasonal adjusted version of the OECD CLIs.

Note: Seasonal adjustment procedure and ADF-test have been performed on monthly data frequency, except for the financial indicators of loans, money supply and deposits which enter in quarterly frequency.
Source: Own calculations / BUSY software.

Table SB.A2: Overview Indicator List – Statistical Results

		Time series domain					Frequency domain		Turning point analysis			Dynamic factor analysis			
		Granger-Causality 1)		**Cross-Correlation** 2)			**Coherence** 3)	**Mean Delay** 4)	**Median lag at..** 5)			**Var. Ratio** 6)	**CC-Corr.** 7)		**CC-Classif.** 8)
		X->Y	Y->X	r_0	r_{max}	t_{max}			Peaks	Troughs	All		r_{max}	t_{max}	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Industry production														
01	OECD: Industry production, total, NACE classification (C, D, E), excl. construction	1.31847	4.81524 ***	0.96	0.96	+0	0.96	+0.05	0.0	-0.5	0.0	0.868	0.999	+0	co
02	OECD: Industry production, manufacturing	1.45163	4.74457 ***	0.96	0.96	+0	0.95	+0.08	0.0	-0.5	0.0	0.902	0.997	+0	co
03	OECD: Industry production, manufacturing plus intermediate goods	2.40559 *	4.41994 ***	0.92	0.94	+1	0.89	+0.21	0.0	-0.5	0.0	0.954	0.983	+0	co
04	OECD: Industry production, manufacturing plus investment goods	2.35722 *	3.24200 **	0.92	0.92	+0	0.88	-0.10	0.5	-0.5	0.0	0.751	0.995	+0	co
05	WIFO: Industry production, total, incl. energy	0.37159	3.51449 **	0.93	0.93	+0	0.90	+0.00	0.0	0.0	0.0	0.850	0.999	+0	co
06	WIFO: Industry production, total, without energy, without construction	0.37391	2.07366 *	0.93	0.93	+0	0.89	+0.06	0.0	0.0	0.0	0.908	0.997	+0	co
07	OECD: Industry production, manufacturing, durable goods	2.10208 *	2.41932 *	0.62	0.63	-1	0.44	-0.13	0.5	0.0	0.5	0.320	0.981	+0	co
08	OECD: Industry production, manufacturing, none-durable goods	3.56080 **	1.79150	0.75	0.77	+1	0.62	+0.19	-1.5	-3.5	-1.0	0.407	0.983	+0	co
	Trade														
09	Retail sales, total (excl. vehicle, petrol stations and rep. of consumer durables)	2.08452 *	3.37577 **	0.25	0.52	+3	0.11	+1.15	-4.5	-3.0	-3.5	0.121	0.875	+2	lead
10	New vehicle registrations, total	1.65765	0.58049	-0.01	-0.53	-4	0.05	+4.03	-9.5	-4.0	-5.5	0.123	0.834	+2	lead
11	New vehicle registrations, passenger cars (group of wage earners)	1.12037	2.86832 **	-0.44	-0.55	-2	0.24	+6.82	-1.5	-5.0	-5.0	0.163	-0.840	+0	lag
12	New vehicle registrations, passenger cars (group of self-employed people)	2.17177 *	0.75087	0.58	0.68	+1	0.38	+0.67	-0.5	-3.5	-1.5	0.636	0.923	+0	co
13	Overnight stays, total (incl. home and foreigners)	0.73787	0.64913	0.17	0.44	-4	0.07	-1.58	-3.0	-4.0	-4.0	0.091	-0.677	+2	lead
	Prices & Wages														
14	Wholesale prices, total	2.78128 **	2.12577 *	0.72	0.74	-1	0.53	+0.40	0.5	0.0	0.5	0.594	0.976	+0	co
15	Wholesale prices, total excl. fruit, vegetables and potatoes	2.81437 **	2.19930 *	0.72	0.74	-1	0.54	+0.40	0.5	0.0	0.5	0.600	0.978	+0	co
16	Wholesale prices, durable products	0.43508	0.63796	-0.44	-0.63	-3	0.25	+0.41	-7.5	-0.5	-4.0	0.131	-0.745	-1	lag
17	Wholesale prices, non-durable goods	2.58352 **	1.12037	-0.15	-0.59	+4	0.08	+0.42	-6.0	3.5	3.5	0.158	-0.842	+2	lead
18	Wholesale prices, consumer items	0.99811	1.44907	0.50	0.56	-1	0.28	+0.40	1.0	2.5	2.5	0.300	0.926	+0	co
19	Wholesale prices, consumer products	1.02756	1.42911	0.42	0.48	-1	0.20	+0.40	1.5	2.5	2.0	0.231	0.895	+0	co
20	Wholesale prices, investment goods	0.58929	1.10054	-0.28	-0.62	-4	0.13	+0.41	-10.5	2.5	-6.0	0.115	0.584	+3	lag
21	Wholesale prices, intermediate goods	2.59643 **	2.66704 **	0.78	0.79	-1	0.63	+0.40	0.0	0.0	0.0	0.685	0.985	+0	co
22	Index of minimum wages, total	4.68055 ***	7.61875 ***	-0.44	0.62	-4	0.25	+0.41	5.0	2.0	5.5	0.654	-0.870	+0	lead
23	Index of minimum wages, blue collar workers	4.35008 ***	5.80388 ***	-0.38	0.63	-4	0.21	+0.42	5.5	5.5	5.5	0.568	-0.868	+1	lead
24	Index of minimum wages, white collar workers	5.43848 ***	7.56035 ***	-0.42	0.64	-4	0.24	+0.42	5.5	6.0	5.5	0.609	-0.867	+1	lead
	Labour market														
25	Unemployment rate (national definition)	1.69122	0.79722	-0.71	-0.72	-1	0.65	+0.34	-8.5	-7.0	-7.5	0.425	-0.995	+0	lag
26	Registered unemployed persons (national definition), total	1.52363	0.52733	-0.81	-0.81	-1	0.68	+0.42	-1.5	1.0	0.5	0.535	-0.994	+0	lag
27	Job vacancies, total	3.22980 **	2.24080 *	0.79	0.81	+1	0.66	+0.43	-2.0	-3.0	-2.0	0.535	0.985	+0	co
28	Employees, total incl. persons on parental leave or in military service	1.53826	2.51864 **	0.86	0.94	-1	0.79	+0.43	-0.5	-2.5	-1.0	0.541	0.940	+0	co
29	Employees (economically active), total	1.70777	2.76330 **	0.87	0.95	-1	0.81	+0.43	1.0	0.5	1.0	0.548	0.937	+0	co

Table SB.A2 (cont.): Overview Indicator List – Statistical Results

	International trade	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
30	Exports, total	2.98581 **	2.16356 *	0.89	0.89	+0	0.83	+0.41	0.0	0.0	0.0	0.907	0.993	+0	co
31	Exports, basic manufactures (SITC 6)	3.74639 ***	1.99343	0.90	0.90	+0	0.84	+0.41	0.0	0.5	0.0	0.876	0.996	+0	co
32	Exports, machines +transport equipment (SITC 7)	1.27701	1.65146	0.88	0.89	+1	0.80	+0.41	0.0	-0.5	0.0	0.892	0.986	+0	co
33	Exports, misc. manufactured goods (SITC 8)	0.39163	2.22264 *	0.82	0.82	+0	0.71	+0.40	0.5	0.0	0.0	0.699	0.998	+0	co
34	Exports to Germany	1.49369	3.60998 **	0.81	0.84	+1	0.69	+0.41	0.0	-0.5	0.0	0.908	0.976	+0	co
35	Exports into EU15	1.52621	4.15811 ***	0.88	0.89	+1	0.80	+0.41	0.0	-1.0	0.0	0.923	0.985	+0	co
36	Exports into EU28	2.49846 *	4.06293 ***	0.89	0.89	+0	0.82	+0.41	0.0	-0.5	0.0	0.913	0.992	+0	co
37	Exports into EU28 minus EU15	2.07678 *	2.39649 *	0.81	0.81	+0	0.69	+0.40	-0.5	0.0	0.0	0.705	0.998	+0	co
38	Imports, total	1.68013	5.45404 ***	0.87	0.87	+0	0.78	+0.41	0.0	0.0	0.0	0.898	0.995	+0	co
39	Imports, basic manufactures (SITC 6)	2.62396 **	2.67698 **	0.89	0.89	+0	0.82	+0.41	-1.5	0.0	0.0	0.915	0.991	+0	co
40	Imports, machines +transport equipment (SITC 7)	0.96109	4.50957 ***	0.86	0.86	+0	0.76	+0.41	-0.5	-2.0	-0.5	0.875	0.991	+0	co
41	Imports, misc. manufactured goods (SITC 8)	0.85351	4.98696 ***	0.88	0.88	+0	0.82	+0.42	-1.0	-1.0	-1.0	0.809	0.998	+0	co
42	Imports to Germany	3.52154 **	4.07434 ***	0.84	0.84	+0	0.72	+0.42	0.0	-0.5	0.0	0.882	0.990	+0	co
43	Imports from EU15	2.00844	6.74266 ***	0.86	0.86	+0	0.77	+0.42	0.0	-0.5	0.0	0.915	0.992	+0	co
44	Imports from EU28	2.01361	5.96234 ***	0.85	0.85	+0	0.74	+0.41	0.0	-0.5	0.0	0.910	0.991	+0	co
45	Imports from EU28 minus EU15	0.70487	3.75544 ***	0.71	0.71	+0	0.51	+0.40	0.0	-3.0	0.0	0.760	0.986	+0	co
	Financials														
46	ATX stock market index	1.45245	4.14007 ***	0.57	0.77	+2	0.40	+0.42	-6.0	-2.0	-2.0	0.552	0.886	+1	lead
47	Loans to euro area nonfinancial institutions, in EUR	0.15797	1.91025	0.25	0.63	-4	0.11	+0.43	3.0	3.5	3.5	0.128	0.654	-2	lag
48	Loans to euro area households (incl. Non-profit institutions), in EUR	1.36296	0.49315	0.33	0.55	+4	0.14	+0.43	-5.0	0.0	-0.5	0.196	0.921	+0	co
49	Loans to euro area corporations (excl. financial institutions), in EUR	0.78916	1.43251	0.07	0.57	-4	0.06	+0.43	4.0	2.5	4.0	0.150	-0.798	+2	lead
50	Deposits of euro area nonfinancial institutions, in EUR	0.36296	2.85346 **	0.19	0.66	-4	0.08	+0.42	-1.5	0.5	0.0	0.114	-0.615	+2	lead
51	Loans to domestic nonfinancial institutions, in EUR	1.44701	2.52738 **	0.32	0.59	-3	0.15	+0.43	2.5	1.0	1.5	0.142	0.703	-2	lag
52	Loans to domestic households (incl. Non-profit institutions), in EUR	1.57330	1.61495	0.61	0.61	+0	0.40	+0.42	-4.5	0.5	-0.5	0.298	0.998	+0	co
53	Loans to domestic corporations (excl. financial institutions), in EUR	1.07038	2.34776 *	0.20	0.68	-4	0.12	+0.43	2.5	2.5	3.5	0.203	-0.696	+3	lead
54	M1 money supply - Euro Area	5.16234 ***	1.02312	-0.04	0.78	+4	0.11	+0.40	-6.0	-4.5	-4.5	0.234	0.749	+3	lead
55	M2 money supply - Euro Area	0.07542	2.59668 **	0.03	0.69	-4	0.07	+0.43	3.5	1.5	3.5	0.204	-0.779	+2	lead
56	M3 money supply - Euro Area	0.05705	3.48189 **	0.04	0.77	-4	0.10	+0.43	4.5	6.0	6.0	0.261	-0.787	+2	lead
57	EURIBOR, 3-month	1.40874	8.47848 ***	0.84	0.93	-1	0.76	+0.42	0.5	1.0	1.0	0.540	0.932	+0	co
58	Austrian federal government 10 year bond yield	0.41749	1.13323	0.39	0.48	-2	0.18	+0.40	0.0	-4.5	-1.5	0.091	0.778	+0	co
59	Interest rate spread (long minus short)	1.18264	3.42827 **	-0.80	-0.87	-1	0.71	+0.41	1.0	-3.5	-3.0	0.551	-0.950	+0	lag
60	Exchange rate USD/EUR	0.88418	2.54237 **	0.01	-0.24	+4	0.00	+0.39	-3.5	-7.5	-6.0	0.010	0.647	+0	co
61	Exchange rate GBP/EUR	3.86639 ***	1.63550	-0.63	-0.76	+2	0.48	+0.40	-1.0	-9.0	-8.0	0.498	-0.943	+0	lead
62	Dow Jones EURO STOXX 50 stock market index	2.39840 *	1.10314	0.22	0.24	+1	0.05	+0.43	-0.5	-2.5	-2.0	0.110	0.990	+0	co
63	S&P 500 stock market index	1.38841	3.34350 **	0.66	0.66	+0	0.48	+0.37	0.0	-1.0	0.0	0.472	0.995	+0	co
64	DJIA stock market index	3.03082 **	0.89577	0.67	0.80	+2	0.51	+0.43	-2.0	-6.0	-2.0	0.487	0.929	+0	co
	Commodity market														
65	HWWI Commodity Price Index, total, in EUR	0.87932	2.21185 *	0.64	0.64	+0	0.44	+0.38	-0.5	-3.5	-1.0	0.515	0.977	+0	co
66	HWWI Commodity Price Index, total excl. energy, in EUR	1.10942	1.41231	0.66	0.73	+1	0.48	+0.40	-1.0	-3.5	-0.5	0.774	0.931	+0	co
67	HWWI Commodity Price Index, crude oil, in EUR	0.58582	1.89964	0.57	0.57	+0	0.35	+0.39	-4.5	-4.5	-4.5	0.377	0.977	+0	co
68	Gold USD, fine ounce	2.39840 *	1.10314	0.22	0.24	+1	0.05	+0.43	-0.5	-2.5	-2.0	0.110	0.990	+0	co
69	Petroleum USD, UK Brent (per barrel)	1.38841	3.34350 **	0.66	0.66	+0	0.48	+0.37	0.0	-1.0	0.0	0.472	0.995	+0	co

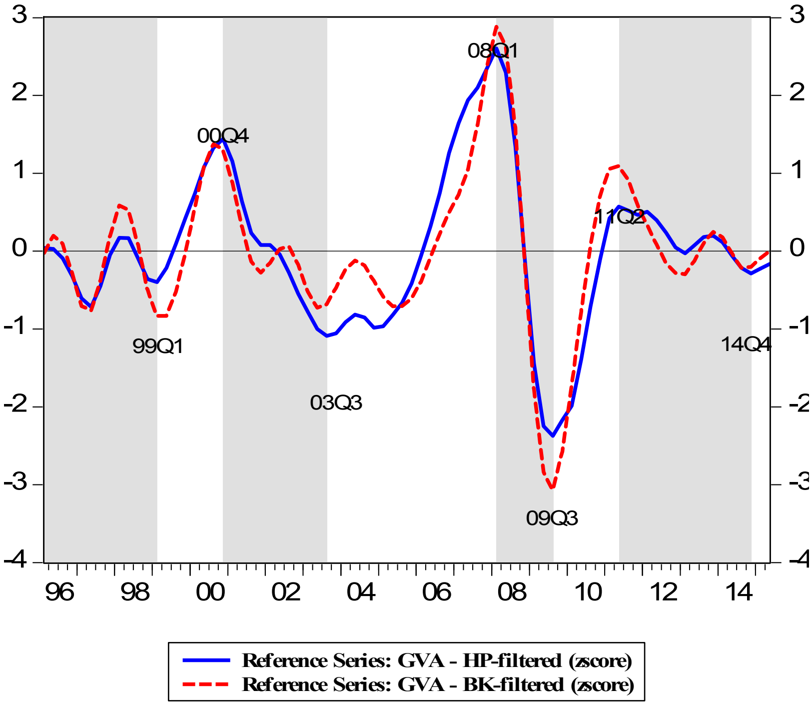
Table SB.A2 (cont.): Overview Indicator List – Statistical Results

	Surveys	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Source: Austrian Institute of Economic Research (WIFO)														
70	Industry: Production trend observed in recent months	0.57294	6.46440 ***	0.47	0.71	+2	0.31	+0.40	-3.0	-3.5	-3.0	0.763	0.854	+1	lead
71	Industry: Assessment of order-book levels	0.91560	3.31116 **	0.72	0.79	+1	0.57	+0.41	-2.0	-3.0	-2.0	0.859	0.944	+0	co
72	Industry: Assessment of export order-book levels	1.40007	2.59757 **	0.74	0.79	+1	0.59	+0.41	-1.5	-3.0	-2.0	0.854	0.957	+0	co
73	Industry: Assessment of stocks of finished products	2.08920 *	4.41950 ***	-0.42	-0.70	+3	0.27	+0.40	5.5	0.5	4.5	0.683	-0.857	+1	lead
74	Industry: Production expectations for the month ahead	3.35603 **	4.59008 ***	0.52	0.77	+2	0.38	+0.40	-3.0	-4.5	-3.0	0.788	0.862	+1	lead
75	Industry: Selling price expectations for the next 3 month	1.88349	4.07382 ***	0.65	0.72	+1	0.46	+0.40	-2.5	-4.0	-2.5	0.827	0.915	+0	co
76	Construction: Selling price expectations for the next 3 month	2.39076 *	3.29663 **	0.65	0.65	+0	0.46	+0.39	-1.0	0.0	0.0	0.494	0.990	+0	co
77	Business Confidence, Industry	2.48941 *	2.60757 **	0.63	0.78	+2	0.47	+0.41	-2.5	-3.5	-2.5	0.848	0.881	+0	co
78	Business Confidence, Construction	1.28670	1.67677	0.65	0.70	+1	0.46	+0.41	-1.5	-2.5	-2.5	0.523	0.953	+0	co
79	Business Confidence, Retail	1.78078	0.45986	0.18	0.62	+3	0.15	+0.39	-3.0	-5.0	-3.0	0.377	0.801	+2	lead
80	Consumer Confidence	2.51301 *	4.62086 ***	0.58	0.84	+2	0.45	+0.41	-3.5	-1.0	-2.5	0.628	0.878	+1	lead
81	Business confidence climate (industry, construction and retail)	2.47132 *	1.90347	0.64	0.84	+2	0.50	+0.41	-2.0	-2.5	-2.0	0.436	0.876	+1	lead
82	Construction: Assessment of order-book levels	0.54531	3.66398 ***	0.62	0.69	+2	0.43	+0.41	-4.0	-2.0	-2.5	0.869	0.938	+0	co
83	Construction: Employment expectations	1.82605	1.23636	0.62	0.65	+1	0.42	+0.41	-2.0	-2.0	-0.5	0.942	0.965	+0	co
84	Construction: Building activity in recent months	2.44536 *	2.05416 *	0.55	0.64	+2	0.37	+0.38	-3.0	-4.5	-2.0	0.586	0.916	+0	co
	Source: European Commission														
85	AT: Economic Sentiment Indicator (ESI)	2.69487 **	4.17927 ***	0.57	0.81	+2	0.43	+0.41	-2.5	-4.0	-2.5	0.837	0.867	+1	lead
86	DE: Economic Sentiment Indicator (ESI)	1.36113	1.71856	0.59	0.81	+2	0.43	+0.41	-2.0	-2.5	-2.5	0.835	0.871	+1	lead
87	DE: Business Confidence	2.26956 *	1.85616	0.61	0.77	+2	0.44	+0.41	-2.5	-4.0	-2.5	0.857	0.867	+0	co
88	DE: Production trend observed in recent months	2.13625 *	1.73737	0.33	-0.77	-4	0.23	+0.40	-3.0	-4.0	-3.0	0.673	0.830	+1	lead
89	DE: Production expectations for the months ahead	2.22378 *	2.05782 *	0.31	-0.76	-4	0.22	+0.39	-2.5	-4.5	-2.5	0.649	0.825	+1	lead
90	DE: Employment expectations for the months ahead	2.46219 *	2.75726 **	0.73	0.82	+1	0.58	+0.41	-1.0	-3.0	-1.5	0.899	0.938	+0	co
91	EA: Economic Sentiment Indicator (ESI)	3.57157 **	2.38333 *	0.55	0.81	+2	0.41	+0.41	-2.0	-2.0	-2.0	0.794	0.871	+1	lead
92	EA: Business Confidence	2.90096 **	1.95654	0.62	0.80	+2	0.47	+0.41	-2.0	-4.0	-2.0	0.864	0.865	+1	lead
93	EA: Production trend observed in recent months	2.96787 **	2.67196 **	0.49	0.73	+2	0.33	+0.40	-2.5	-4.0	-2.5	0.770	0.856	+1	lead
94	EA: Production expectations for the months ahead	3.66756 ***	2.52696 **	0.41	-0.71	-4	0.28	+0.40	-2.5	-4.5	-2.5	0.714	0.846	+1	lead
95	EA: Employment expectations for the months ahead	2.86233 **	2.38568 *	0.76	0.85	+1	0.63	+0.41	-1.5	-3.5	-1.5	0.915	0.936	+0	co
	Source: Ifo Institute for Economic Research, Munich														
96	DE: ifo Business Climate (Industry and Trade)	3.70438 ***	1.17703	0.60	0.85	+2	0.47	+0.41	-3.0	-2.0	-2.0	0.869	0.876	+1	lead
97	DE: Assessment of current business situation (Industry and Trade)	3.22099 **	1.00760	0.78	0.88	+1	0.67	+0.42	-2.5	-2.5	-2.5	0.942	0.942	+0	co
98	DE: Business expectations (Industry and Trade)	3.20860 **	0.97829	0.19	-0.79	-4	0.20	+0.39	-3.0	-1.0	-2.5	0.586	0.778	+2	lead
	OECD Composite Leading Indicators														
99	CLI for Austria	8.12532 ***	0.42187	0.51	0.81	+2	0.38	+0.41	-2.5	-4.5	-2.5	0.797	0.867	+1	lead
100	CLI for Germany	12.91400 ***	0.51871	0.38	-0.74	-4	0.27	+0.40	-2.5	-4.5	-2.5	0.709	0.841	+1	lead
101	CLI for the Euro-Area	11.70690 ***	0.66394	0.55	0.83	+2	0.42	+0.41	-2.5	-1.5	-2.0	0.787	0.872	+1	lead
102	CLI for the U.S.	7.74084 ***	0.96067	0.51	0.80	+2	0.37	+0.40	-2.5	-5.5	-2.0	0.717	0.878	+1	lead

1) - 8) See notes to Table 4 (Chapter 1).

Source: Own calculations / BUSY software.

Figure SB.A1: Business Cycle Chronology: HP filter vs. BK filter



Chapter II

Business Cycle Dynamics and Firm Heterogeneity: Evidence for Austria Using Survey Data*

Abstract

In this paper, we study the (macroeconomic) consistency of individual firm-level business tendency survey responses and take firm-level heterogeneity explicitly into account. Adding firm-level, industry- and region-specific structural characteristics allows controlling for additional microeconomic heterogeneity. The dataset we use are the business tendency survey micro data for Austrian manufacturing covering the time period 1996 to 2012. Our results show that firm-specific information embedded in the qualitative survey questions is relevant to understand aggregate business cycle dynamics. For example, the assessment of firms' order book levels, their current degree of capacity utilisation and their production expectations as well as obstacles in their production activities due to insufficient demand show evidence of a significant effect in explaining a firms' change in current production output, hence, it also affects the behaviour of the aggregate business cycle. However, we do not find clear results with respect to firm size nor do we find explanatory power of the industry affiliation of a firm and with respect to regional characteristics. We are able to identify heterogeneity in behaviour for cyclical up- and downswings as well as between large and small firms.

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1. Introduction

Business cycle research usually focuses on the macroeconomic level. Most of the theoretical and empirical business cycle literature deals with this 'aggregated' view, even though it is microfounded by representative agents. In our analysis of business cycle dynamics and differentials, we depart to some extent from the standard approach and incorporate the micro perspective as well.[1] This allows us on the one hand to verify the consistency of common business cycle characteristics with individual firm-level survey responses. On the other hand, our approach permits us to incorporate firm-heterogeneity, though often neglected in the analysis of 'aggregated' business cycle movements, and to check whether heterogeneity plays a significant role in shaping the overall business cycle.

In the macroeconomic context, the aggregated measure usually represents some quantitative indicator of economic activity with its scope for an economy as a whole (e.g. GDP), for a particular sector or industry (e.g. industrial production) or for demand components like consumption. These measures are typically derived from official statistics. The assessment of the current economic environment such as a countries' stance in the business cycle requires timely and up-to-date information for decision-makers (e.g. policy makers) and for policy-orientated research. But official quantitative data are not only available with a significant time delay and on a low-frequency basis but are also subject to subsequent revisions. This 'information gap' leaves room for uncertainty, not just for the future path of the economy but also with respect to its current state. Qualitative indicators, such as information derived from business tendency surveys (BTS), can help to mitigate the problem and close the gap of missing readily available 'hard' (i.e. quantitative) data. As a consequence, 'soft' (i.e. survey)

[1] In the field of business cycle research, in particular at the theoretical side, 'micro-foundation' of the models started to gain attention, for example, in Kydland and Prescott's (1982) real business cycle (RBC) model. This was following Lucas' (1976) critique of econometric policy evaluation with the missing notion of rational expectations. A further development (and structurally related to the RBC models) are the so-called dynamic stochastic general-equilibrium (DSGE) models (see e.g. Smets and Wouters, 2003; Christiano et al., 2005).

indicators are widely used to assess current economic developments and/or base short-term economic forecasts on it. Prominent examples of BTS sourced indicators are the Ifo business climate index or the economic sentiment indicators (ESI) provided by the European commission.

It is common to translate the individual survey responses into quantitative measures in form of 'balance statistics'.[2] These indicators reflect an 'aggregated' view (i.e. cross-sectional average) of economic agents' judgment of their current economic environment and their expectations. The latter play a crucial part in the decision making process of an agent (e.g. firm) and may affect the immediate and future course of their business activity (Erkel-Rousse and Minodier, 2009). Typically, questions in business surveys refer (a) to firm-specific characteristics such as production, sales, inventories, demand conditions, prices and employment, and, (b) to the general macroeconomic environment. Both dimensions are key elements reflecting business conditions and economic activity.

Moreover, the qualitative data should represent a reasonable proxy for the underlying quantitative, but not yet available, business cycle indicators from official statistics. But as Graff and Etter (2004) point out, there exists a trade-off between timeliness and precision of such indicators. BTS data reveal the required information *as early* as possible (usually by the end of the month), whereas official business cycle indicators are supposed to reflect the realisation of the underlying economic process *as close* as possible. The informational content of the survey questions asked aims to cover the broad range of business activities and different phases of a firm's production process. Following the stylised representation in Oppenländer (1996: 26ff), a firm's economic processes may be linked on a 'time-dimension'

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[2] Anderson (1951) proposed the use of a balance statistic to convert qualitative survey data into quantitative measures of respondents' assessments and expectations. The balance is usually calculated as the difference between (weighted) percentages of positive and negative answers to the respective question of interest. A huge literature is devoted to survey response quantification. Nardo (2003) or Mitchell et al. (2004) provide, among others, an overview of quantification techniques and discuss issues of them.

around its actual production activity: Expectations about future business conditions (e.g. with respect to earnings or production capacity) in accordance with actual demand conditions (e.g. degree of incoming orders, change in the level of inventory) lead production and sales of a firm. The degree of a firm's capacity utilisation, for example, usually runs in-line with output, whereas firms react in adjusting their employment-levels most often past current production decisions. These stylized business cycle regularities with respect to the timing (lead/lag/co-movement) should be evident in the data, irrespective of using quantitative or qualitative business cycle indicators.

Moreover, the indicators should be statistically correlated if both sources (BTS data and official statistics) measure and relate to the same empirical process (for example industrial production). A number of empirical studies have analysed business cycle properties of survey data, its theoretical foundations or its practical use in the analysis of current economic conditions as well as its short-term forecasting ability of economic activity.[3] In a nutshell, BTS data have shown to contain an indispensable source of relevant business cycle information. Though most of these studies resort on 'balance statistics' in their analysis, implicitly assuming that firms are homogeneous entities or difference between them cancel each other out in the aggregate. But this possibly ignores important aspects of observable firm-specific heterogeneity that might be of interest. The cross-sectional behaviour and characteristics of individual firms can help in understanding the behaviour of aggregates (Higson et al., 2002). In a recent study on business cycle dynamics, Müller and Köberl (2015) argue in line with Caballero and Engel (2003) and Clower (1998) that results obtained on the

[3] For example: Hölzl and Schwarz (2014) provide an overview of the methodology and assess the business cycle properties and forecast characteristics of 'aggregated' (i.e. balanced) BTS data for the Austrian economy. Cesaroni (2011) investigates the cyclical behavior of survey indicators such as the degree of plant utilisation, inventories, order book levels, and confidence indices with respect to the Italian business cycle and confirms the predictive ability of these qualitative indicators in forecasting short-term GDP growth. Knetsch (2005) focuses in the case for Germany on inventory fluctuations and the co-movement between the 'aggregated' survey responses and official inventory investment.

micro level (e.g. individual firms) might differ in the interpretation of the same aggregate phenomena and that firm behaviour has to be taken into account before drawing conclusions on the macro level.

In macroeconomics, shocks are generally interpreted as evidence of a common aggregate disturbance which have originated *inter alia* from monetary policy, or technology changes and spread out into the national economy, their regions and industrial sectors (Park and Hewings, 2003). However, shocks specific to a region or industry sector may also influence other regions and industries, for example, through supply-chain or FDI linkages. Therefore, differentials in business cycles at a disaggregated dimension can, among other things, be related to (inter)national, region-specific and/or industry-specific shocks and these cycles may not necessarily coincide with and share the same properties of the aggregated business cycle.

Empirical studies focusing on the regional (i.e. sub-national) or sectoral (i.e. sub-industry) dimension usually assess whether similarity of the industrial mix lead to business cycle synchronisation or whether industry-specific shocks increase business cycle differentials for regions with a high degree of specialisation.[4] But as Basile et al. (2014) have shown, adding the firm-level dimension to the analysis of business cycle dynamics, thus allowing for firm heterogeneity, may change results. Their analysis uses BTS micro data for the Italian economy, and they distinguish between firm-, sectoral-, and regional-specific factors. They find evidence that the industry mix does not provide an explanation for the (regional, i.e. in their case North versus South) business cycles differentials. However, differences in terms of

[4] Fatás (1997), Forni and Reichlin (1997), Clark and van Wincoop (2001) and Barrios et al. (2003) were among the first to highlight and stress the potential importance of the regional dimension. For studies analysing sources of business cycle co-movements and fluctuations on a disaggregated regional and/or sectoral level see e.g. Clark and Shin (1998); Park and Hewings (2003); Reis (2005); Belke and Heine (2006); Afonso and Furceri (2007); Norman and Walker (2007); Holly and Petrella (2008) or Gadea et al. (2011). With respect to Austrian regions see Bierbaumer-Polly (2012) or Bierbaumer-Polly and Mayerhofer (2013). The authors studied the development of (aggregated) business cycles in the Austrian provinces and found that the business cycle patterns differ considerably not just in an interregional comparison but also in terms of the national economy.

enterprise composition (i.e. firm-specific variables such as firm size or export propensity) do account for large parts of these differentials over different phases of the Italian business cycle. The results in Basile et al. (2014) affirm theoretical indications that firm-specific information might help explaining 'aggregated' business cycle dynamics and acting, *inter alia*, as mechanism for transmission of shocks.

Other empirical studies using qualitative survey data at an individual firm-level and related to the domain of business cycle analysis are, among others, Kaiser and Spitz (2000); Ehrmann (2005); Nieuwstad (2005); Müller and Köberl (2007, 2008) and Bachmann et al. (2012).

Kaiser and Spitz (2000), for example, show that the inclusion of firm-specific variables such as regional and sectoral affiliation or firm size may substantially reduce the inaccuracy of the standard error of the outcome variable of interest (e.g. sales growth). Ehrmann (2005) has used business survey data to investigate the link between firm size and the monetary transmission mechanism. He finds that business conditions of small firms deteriorate relatively more compared to large ones after a monetary tightening. Nieuwstad (2005) compares the fit of production information (recent output and expectations) derived from manufacturing business sentiment surveys in the Netherlands to official turnover statistics for the respective company. He shows in the case for individual data that about one third of all survey respondents give coherent and unbiased answers to the questions relating to recent production, but also a high share of companies (roughly 20 per-cent) answer completely illogical. At the industry level the fit between the balance statistics and production data increases to more than 50 percent. Accounting for seasonality leads in addition to an increased fit between survey and official data, and, in general, firms are better at assessing the recent past than predicting the near future.

By using micro data from the BTS in the Swiss manufacturing industry, Müller and Köberl (2007) investigate the adjustment process of a firm to a demand shock, where the authors interpret a firms' judgment about its technical capacities in line with the effective change in capacity utilisation from one period to another as a positive, negative, or no demand shock. The results indicate that companies react asymmetrically to the respective shock-type. Adjustments to positive shocks occur in sum about a half year faster than adjustments to negative shocks. In their subsequent study, Müller and Köberl (2008) use their identification scheme of shocks in order to derive a business cycle indicator. Using this measure, the authors show in a nowcasting exercise the good forecasting performance of this indicator for one quarter ahead forecasts of the Swiss real GDP growth. Bachmann et al. (2012) construct monthly uncertainty indices from German and U.S. business survey data in order to analyse the dynamic relationship between uncertainty and economic activity. To measure uncertainty the authors resort on the one hand to ex-ante forecast disagreement. This is based on the cross-sectional (weighted) standard deviation of the survey responses. On the other hand, the cross-sectional standard deviation of ex-post forecast errors, where forecast errors are built on the difference between current production changes and production change expectations in the previous period, is used as another proxy for uncertainty. The results in Bachmann et al. (2012) point to a "wait and see" effect[5] of uncertainty on economic activity, tough smaller in magnitude in the case for Germany compared to the U.S.

In light of the above, our objective and contribution to the empirical literature is threefold: First, by analysing micro BTS data, we are in a position to verify and test the (macro) consistency of the business tendency survey responses of key questions related to the *business cycle dimension*, such as the assessment of current production or order book levels. In doing so, we adhere to economic processes of a firm as sketched out in Oppenländer (1996: 26ff). Second, we take advantage of the micro dataset and take (observable) firm-heterogeneity

[5] The literature (see e.g. Bloom, 2009) describes the "wait and see effect" as a cautious firm behaviour related to an interaction between uncertainty and frictions related to adjustment costs for labor and capital (at least) in the short-run.

explicitly into account in modelling ‘aggregated’ business cycle dynamics. Besides the business cycle dimension (Objective 2), where firm-heterogeneity is implicitly considered due to the use of the individual survey responses, we focus on the *structural dimension* as well. Following Basile et al. (2014), we control for additional heterogeneity by adding firm-level, industry-specific and regional ‘structural’ characteristics to the model. In addition, we test for business cycle differentials along various aspects (e.g. differences between business cycle phases: upswing vs. downswing). Finally, to best of our knowledge, no empirical analysis along the individual firm-level dimension for the Austrian economy has been conducted to investigate ‘macro’ business cycle dynamics from a ‘micro’ perspective.[6] The use of the micro WIFO Business Cycle Survey (Konjunkturtest – KT) data represents a novelty in this respect. The econometric estimations are based on a Correlated Random Effects Ordered Probit Model.

The remainder of this paper is organised as follows. Section 2 describes the micro dataset, outlines the utilised covariates and discusses briefly their expected effects. Section 3 explains the model and sets out our estimation strategy. Section 4 discusses results. The paper ends in concluding remarks.

2. Data and measurements

Our dataset contains individual firm-level survey data as well as industry and regional information. The firm-level dimension is our main data source. We utilise micro data from the monthly WIFO KT, which is a representative monthly business tendency survey (BTS). The time period we cover ranges from the beginning of 1996 up to the end of 2012 (T_m=204 months). The unbalanced panel dataset contains n_m=2,772 firms and in total i_m=115,055

[6] There exist, though, quite a few studies analysing the aggregated Austrian business cycle. Among them are Breuss (1984), Hahn and Walterskirchen (1992), Artis et al. (2004a, 2004b), Scheiblecker (2007) and Bierbaumer-Polly (2010).

observations. Given the month-by-month survey interval, our initial database is based on monthly observations. However, some relevant questions in the survey, like the degree of capacity utilisation, are only asked on a quarterly basis and some firms answer only the quarterly questionnaire.[7] As the quarterly-type indicators may encompass relevant business cycle information and we want to use information on a large number of firms, we constrain our panel data sample to the quarterly frequency (T_q=68 quarters, n_q=2,563 firms, i_q=55,250 observations)[8]. With respect to our industry- and regional-level data we resort to annual employment data taken from the Austrian Social Security Database (ASSD), which is an administrative register and provides data on a highly disaggregated level (e.g. NACE-5-digit on the sectoral level or on municipalities in the regional context).

2.1 A proxy for the 'aggregated' business cycle

First and foremost, we need some proxy measure for the 'aggregated' business cycle derived from the individual firm-level data. The questions asked in the WIFO KT are either related to the current business situation or refer to the respective expectations about the coming development.[9] Out of this set of questions the assessment of a firms' production output, in particular the change in the output level, provides a natural candidate for depicting business cycle information. Similar to Basile et al. (2014), we use the question on "*Our production has been ... in the last 3 months? (a) increased, (b) remained the same, or (c) decreased*" as our

[7] Until 1996 the WIFO KT was a quarterly survey. In 1996 the frequency changed to a monthly survey. Many of the firms in the survey panel opted to continue to answer the survey on a quarterly basis.

[8] Quarterly questions are contained in the January, April, July and October survey. Given that a high proportion of respondents predominantly participate only in the 'comprehensive' survey, thus every three months, the coverage of firms is by far highest in the first month of a quarter. Therefore, limiting the analysis only to the quarterly frequency should not raise a major concern. It is to note, though, that this approach results in losing information for firms participating on a month-by-month basis. Responses, for example, for February get skipped.

[9] See Appendix Table A1 for an overview of the WIFO KT questionnaire.

dependent variable (y_{it}).[10] We assume that the response to this question captures the current state of a firms' position in the business cycle. Our outcome variable is coded as 1='has increased', 2='remained the same', and 3='has declined'. The informational content of the qualitative assessment of a firm's production output is widely used among business cycle analysts due to its timely availability compared to official quantitative data and its forecasting capability of business cycle movements of some underlying economic activity measure like GDP or industrial production.

Usually, 'balance statistics' (i.e. share of positive answers [$y_{it} = 1$] minus share of negative answers [$y_{it} = 3$]) are derived from the individual firm responses to quantify the informational content embedded in the question asked.[11] A positive value means that the overall tendency of the production output has been increasing. This points to an expansion of economic activity, hence, to an upswing in the business cycle. Contrary, a negative balance value, i.e. relatively more firms indicate decreasing production levels, may be an indication of a business cycle downturn. Given that the export orientated manufacturing sector plays a crucial role for the small and open Austrian economy, it is reasonable to assume, though qualitative in nature, that the assessment of the change in production output provides a good proxy for the national business cycle.[12]

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[10] There exists a slight difference in the question asked related to current production in the Italian survey. The question is read as "*Do you consider the level of production of your company in the current month as high, normal or low?*" and is more related to the judgement of the 'stock', whereas in Austria the question focuses more on the 'flow' (i.e. the change from one period to another). With respect to the business cycle, the former is more concerned with the level of economic activity (boom vs. recession) whereas the later relates to changes in the cycle (expansion vs. contraction). See, for example, Asako et al. (2007) for a discussion on differences among firms concerning their perception of the business cycle.

[11] Usual assumptions of the balance method are that the cut-points between the different possible answer categories are equally spaced (i.e. symmetric around zero) and that the cut-points are equal across respondents as well as across time (Henzel and Wollmershäuser, 2005).

[12] For balances, Hölzl and Schwarz (2014) have demonstrated that aggregated indices of the WIFO KT provide a reliable tool for monitoring the current economic situation. In particular, the authors show a high correlation of sector-wide balance indices (i.e. including manufacturing, construction and services) with overall economic activity. The contemporaneous cross-correlation coefficient for the period 1997-2013 for the balance indicator reflecting current economic conditions (including the assessment of current production levels) is greater than +0.6, with its highest value (>+0.7) reaching at about one quarter lead.

There have been numerous studies on the quantification of qualitative survey data, i.e. the way in which survey responses are linked to and anticipate official data (see, for example, Geil and Zimmermann, 1996; Nardo, 2003; or Vermeulen, 2014, for a discussion). Prominent quantification techniques found are the Carlson and Parkin (1975) 'probability approach' and the Pesaran (1984) 'regression approach'. In following Cunningham et al. (1998) who give a micro-foundation to the Carlson-Parkin method, our empirical firm-level model (as outlined in Section 3) is in the spirit of the 'probability approach'.[13]

2.2 Firm-level covariates/controls

The WIFO KT micro database contains the full set of individual firm responses of the questions asked in the BTS, as well as some structural firm characteristics. We assume that the first depicting a broad range of economic processes and business activities of a firm and, as such, containing appropriate firm-level covariates to analyse and verify 'aggregated' business cycle dynamics. The latter, on the other hand, can be used to control for structural elements of the surveyed firms, allowing for additional firm-heterogeneity in the analysis.

Our selection of the firm-level covariates as explanatory determinants for the current production activity of a firm and, in the aggregate, of the economy as a whole, is guided by economic processes of a firm and its temporal link to the business cycle (Oppenländer, 1996: 26ff). Covering current business cycle dynamics we use information on (*i*) order book levels, (*ii*) main factors limiting production[14], (*iii*) stock of finished products, (*iv*) selling prices, and (*v*) degree of capacity utilisation. For the set of forward looking questions, i.e. related to

[13] Note, though, that the balance statistic approach is just a special case (i.e. with time invariant parameters) of the Carlson-Parkin method.

[14] In the question related to factors limiting the current production, the respondents are asked to choose between six categories (none, insufficient demand, shortage of labour force, shortage of material and/or equipment, financial constraints, others).

expected changes in the coming months, we resort to expectations on (*vi*) production output, (*vii*) selling prices, and (*viii*) employment along with firms' (*ix*) overall business sentiment.

Table 1 provides an overview of the list of explanatory variables along its classification of the economic process and its business cycle timing with respect to a firm's current production output. Further, the expected sign of the correlation between the qualitative indicator and production output (irrespective if measured with survey data or official statistics) is shown.

Table 1: Firm-level covariates (business cycle dimension)

Question	Economic Process 1)	Timing 2)	Correlation 3)
Production (change), next 3 months	Expectations	lead	+
Selling prices (change), next 3 months	Expectations	lead	+
Firm's employment (change), next months	Expectations	lead	+
Firm's business sentiment (level), next 6 months	Sentiment	lead	+
Total order books (level), current	Demand	lead	+
Factors limiting productions 4)	Demand/Supply/Finance	lead/co	-
Stocks of finished products (level), current	Demand/Production	co	-
Selling prices (change), past 3 months	Demand/Production	co	+
Capacity utilisation (level)	Production	co	+

Notes: 1) Classification according to Oppenländer (1996: 27). 2) The timing notation indicates the expected temporal pattern with respect to the current production activity of a firm: lead=leading; co=contemporaneously. 3) The "+" and "-" sign indicates the expected change of current production output based on an increase of the respective survey indicator. Its also an indication of the pro-/countercyclicality of the indicator. 4) We test for two (out of six) categories: insufficient demand and financial constraints.

As has been verified in numerous empirical studies and used in applied business cycle analysis, firms' expectations on their short-term economic prospects (e.g. with respect to production, employment, or their selling prices) provide leading information for the assessment of current economic activity. To take advantage of this leading behaviour we utilise the firm-level covariates related to expectations one period lagged (i.e. expectations at time t_{q-1} are used in explaining change in current production at time t_q). Similarly, we lag the survey responses related to order book levels also by one quarter, given that changes in demand conditions do not immediately soak up in changing production levels.

With respect to the structural characteristics of the surveyed firms, we resort on the one hand to the natural logarithm of firm size (number of employees) and its squared term. On the other hand, we utilise industry classification of a firm. The role of firm size has been emphasised in the literature related to monetary policy and credit markets. Firm size is widely considered a proxy, though far away from perfect, for capital market access (Carreira and Silva, 2010). Results show that small firms with little collateral and lower value of assets should be more affected by a monetary tightening than large ones and the strength of (small) firms' reaction to a monetary shock depends on the stance of the business cycle (see e.g. Gertler and Gilchrist, 1994; Perez-Quiros and Timmermann, 2000; or Ehrmann, 2005). With respect to regional business cycle differentials Basile et al. (2014) find that firm size has a positive and significant effect on the probability of having a high level of production in the North vs. South and that this effect is greater in business cycle upswings. To test the effect of small vs. large, we add a dummy large and set its value equal one for firms with an employment threshold of greater or equal to 100 employees.

In contrast to the firm size effect, and against existing empirical evidence, Basile et al. (2014) do not find a significant effect of the industry mix in explaining differences in regional business cycle dynamics. To employ industry information in our analysis we extract the NACE-2-digit code and create industry-sector dummies for each of the sectors available. Using the NACE classification, we further supplement the firm-level data with an industry classification based on main industrial groupings (MIGs; i.e. intermediate goods, capital goods, and consumer goods)[15].

[15] See http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Main_industrial_grouping_(MIG).

2.3 Industry covariates/controls

Industry covariates and controls are used to take industry-specifics into account. First, we employ a measure of mobility barriers and follow Hölzl (2013) by using an indicator of excess labour turnover. Excess labour turnover is defined as

$$EXLT_g = \frac{JC_t + JD_t - |JC_t - JD_t|}{0.5 \times (E_t + E_{t-1})} \tag{2-1}$$

where JC_t and JD_t denote job creation and destruction in two-digit industry g (with $g = 1, \ldots, G$) during time *t* and *t-1*, respectively, and E represents employment levels in this sector. $EXLT_g$ measures excessive employment turnover that is not related to changes in the level of employment and, thus, does not account for the variability of employment growth but for the volatility of job generation and job destruction. As such, it is a proxy for mobility barriers like sunk costs, especially for mobility barriers that relate to firm specific human capital and firm specific organizational capital. Industries with a low value of $EXLT_g$ exhibit a high degree of labour hoarding and can be thought as industries that face higher (implicit) labour adjustment costs, as labour hoarding is closely associated with organisational and firm-specific capital embedded in a firm's workforce (Oi, 1962). Over the course of the business cycle firms in industries that exhibit low values of $EXLT_g$ will not adjust their workforce and production capacity as much as firms in sectors where labour hoarding is less prevalent. Thus, labour hoarding may affect the probability of firms' indicating increased production output from one period to another.

Furthermore, we add to our set of industry data the average employment growth in the period between 1996 and 2012 as well as the number of employees (taken as median averaged across the years 1996 to 2012) in each industry. This is done to control for differences in growth rates across industries. Firms in growing industries are expected to be more likely to indicate an expansion of their production levels than firms in declining industries.

2.4 Regional covariates/controls

For the regional aspects we augment the dataset with a sector concentration index. Depending on the type of (macro-)economic shock, the degree of specialisation of a region, among other things, can impact on a firms' production output during the business cycle. Firms in regions characterised by a high concentration of only few sectors might react differently compared to firms operating in regions which are broadly diversified with respect to the industry structure. Frenken et al. (2007) state that portfolio theory, with its claim that variety reduces risk, might help in investigating the effect of a region's sectoral composition on the firms' business cycle movement, which in turn feeds back to the aggregated output.

We calculate a related variety (RV) measure for each NUTS-3 region based on annual employment data. Regions with a sectoral composition of related industries are more prone to aggregated demand shocks; however, knowledge spillovers (Jacobs externalities) between firms within the regions are more likely among related sectors. In following Frenken et al. (2007), we derive a specialisation indicator as the weighted sum of entropy statistics at the 4-digit level within each 2-digit industrial sector. It is given by

$$P_g = \sum_{i \in S_g} p_i \tag{2-2}$$

$$H_g = \sum_{i \in S_g} \frac{p_i}{P_g} log_2 \left(\frac{1}{p_i / P_g} \right) \tag{2-3}$$

$$RV = \sum_{g=1}^{G} P_g H_g \tag{2-4}$$

where all the NACE-4-digit sectors i are assigned to a particular 2-digit sector S_g (with $g = 1, \ldots, G$), the 2-digit sector shares P_g are the sum of all 4-digit shares p_i, and H_g represents the weighted entropy within each of the 2-digit sectors. We test the related variety measure either based on all sectors (RV_{all}) or restricted to only manufacturing sectors (RV_{manuf}).

Besides the RV measure, we also control for employment concentration (EC) in a region at the NACE 4-digit level by deriving a Herfindahl-Hirschman Index (HHI). It is formally defined as

$$EC^{HHI} = \sum_{g=1}^{G} p_i^2 \qquad (2\text{-}5)$$

where p_i is the employment share of a 4-digit sector on total industry employment, with $i \in S_g$. We again calculate one version for all industrial sectors (EC_{all}^{HHI}) and one for the manufacturing sectors (EC_{manuf}^{HHI}) only.

Basile et al. (2014) argue that local characteristics such as the local judicial system (i.e. the institutional environment in which firms operate), financial development of the region (i.e. the degree of credit market development), or production decision of neighbouring firms (i.e. local demand externalities) may represent regional unobserved structural factors which impact on a firm's production output over the course of the business cycle. Similar to Basile et al. (2014), we construct a local externality measure, $locEXT_{rt}$, for each NUTS-3 region which should capture local technological and demand externalities. We proxy local externality by

$$locEXT_{rt} = BAL_{rt}^{y_{it}} \times EMPD_{rt} \qquad (2\text{-}6)$$

where $BAL_{rt}^{y_{it}}$ indicates the balance statistic of the question related to the change in production output and $EMPD_{rt}$ represents employment density in the region derived as total employment divided by the size (i.e. square kilometre) of the respective region. In our analysis, we take the average of $locEXT_{rt}$ between 1996 and 1998 to proxy for local externalities.

In order to identify differences in business cycle dynamics between urban and rural geographical areas, we add a respective dummy. Our classification is based on a typology set out by Eurostat which defines regions within the European Union as either 'predominantly urban', 'intermediate, close to a city' or 'predominantly rural' according to some population densities criteria. Based on the zip-code of a firm, we take the respective NUTS-3 code assigned to the zip-code and map the NUTS-3 region to the urban/rural typology accordingly. Our dummy variable 'urban' takes on the value one for the first two types of regions, zero otherwise.

Summary statistics of the firm-level variables are reported in Table 2.[16] The median size of a firm in our sample is 85 and 47% of the firms are 'large' ones (according to our threshold). Half of the firms are classified as belonging to industries mainly producing intermediate goods, and nearly 60% of the firms are located in 'urban' regions. With respect to the business cycle related categorical covariates, the descriptive shows that the middle category is by far the most chosen one. Moreover, large firms tend to indicate a positive change in production output more often compared to small firms, and, similarly they exhibit a higher degree of capacity utilisation. Large firms are also more optimistic in their production and employment expectations and suffer not as often from insufficient demand as small firms do (16% vs. 22%). The degree of capacity utilisation is higher in industries specialising in investment goods and lower for consumer goods industries. Out of the responses to factors limiting current production, two thirds of the firms indicate no production obstacles, almost 20% face insufficient demand and only less than 1% are confronted with financial constraints (mostly small firms).

3. Empirical model

Our outcome variable of interest, hence our proxy for the 'aggregated' business cycle, is represented by firms' assessments of their most recent changes in production output. We denote this variable, which is limited and ordinal in nature, as y_{it}. The observed outcome in y_{it} represents an underlying latent value of the change in the production level of the surveyed firm (y_{it}^*).

[16] Table A2 and A3 (Appendix) provide an overview of the sectoral and regional specific control variables in conjunction with its NACE-2-digit and NUTS-3 breakdown, respectively.

Table 2: Descriptive statistics – Firm-level covariates/controls

Distribution - Continuous covariates	No. of obs.	Min	Q (25%)	Median	Q (75%)	Q (90%)	Max	Mean	SD	Skewness
Time-varying (x_{it})										
Firm size	55,250	1	30	85	230	520	10,000	231.5	557.8	8.9
Capacity utilisation [1)]	55,250	30	75	85	95	100	100	81.8	15.1	-1.1

Percentage of firms - Categorial covariates / controls		Total	Modalities								
			Firm size		*MIG-classification*			*Regional*		*Business Cycle Phase*	
			large	small	interm.	investment	consumer	urban	rural	up	down
Time-varying (x_{it} | Current)											
Current level of production	+	27.1	30.3	24.2	27.1	28.5	25.7	27.4	26.8	29.9	23.6
	=	55.1	54.5	55.6	54.9	54.8	55.8	55.0	55.2	54.6	55.8
	–	17.8	15.2	20.2	18.0	16.7	18.5	17.6	18.0	15.5	20.6
Order book levels [2)]	>	27.1	30.2	24.4	26.6	30.2	25.5	27.0	27.3	28.9	25.0
	=	50.9	50.5	51.2	51.0	47.4	53.9	50.8	50.9	50.3	51.6
	<	22.0	19.3	24.4	22.4	22.4	20.7	22.1	21.8	20.8	23.4
Factors limiting production	none	65.2	68.5	63.3	65.5	61.0	68.1	65.0	65.5	65.0	65.4
	insufficient demand	19.1	15.9	21.8	19.5	16.9	19.9	19.2	18.9	18.4	19.9
	shortage of labour force	5.8	5.1	6.4	5.0	6.5	4.2	6.2	5.3	5.7	6.0
	shortage of material and/or equipment	5.2	6.5	4.1	5.2	7.8	2.9	5.1	5.3	6.0	4.2
	financial constraints	0.9	0.3	1.4	0.6	1.5	1.0	0.9	0.9	0.9	0.9
	others	3.9	3.8	3.9	4.1	3.3	3.9	3.6	4.2	4.0	3.7
Stock finished products	>	18.5	19.0	18.0	21.0	15.9	15.4	17.7	19.4	17.6	19.5
	=	75.9	75.5	76.3	72.8	78.5	80.1	76.6	75.1	76.0	75.8
	<	5.6	5.4	5.8	6.2	5.6	4.5	5.7	5.5	6.3	4.8
Selling prices	+	12.1	13.0	11.3	13.5	9.5	11.3	11.3	13.1	12.4	11.7
	=	69.9	67.9	71.7	65.2	75.6	74.9	69.7	70.2	69.6	70.3
	–	18.0	19.1	17.1	21.3	14.8	13.8	19.0	16.7	18.0	18.0
Capacity utilisation	up to 50%	6.9	2.7	10.6	6.8	4.8	9.1	6.5	7.5	6.5	7.4
	50-75%	23.8	20.2	26.9	23.3	19.5	28.6	24.4	22.9	23.0	24.8
	75-90%	43.1	44.6	41.7	43.4	41.8	43.4	43.5	42.5	43.6	42.4
	90-100%	26.2	32.6	20.7	26.5	34.0	18.9	25.6	27.1	27.0	25.4
Time-varying (x_{it} | Expectations)											
Production expectations [2)]	+	20.5	23.1	18.2	20.1	21.6	20.2	20.4	20.6	20.8	20.1
	=	66.8	65.7	67.9	67.5	64.6	67.4	67.1	66.4	67.2	66.3
	–	12.7	11.2	14.0	12.4	13.8	12.4	12.5	13.0	11.9	13.6

Table 2 (cont.): Descriptive statistics – Firm-level covariates/controls

Percentage of firms - Categorial covariates / controls		Total	Modalities								
			Firm size		*MIG-classification*			*Regional*		*Business Cycle Phase*	
			large	**small**	**interm.**	**investment**	**consumer**	**urban**	**rural**	**up**	**down**
Time-varying ($x_{it} \mid$ Expectations) cont.											
Selling price expectations [2)]	+	12.9	13.4	12.4	14.0	10.6	12.5	12.7	13.1	12.5	13.3
	=	75.3	73.2	77.2	72.3	78.8	78.6	75.0	75.7	75.4	75.1
	–	11.8	13.5	10.4	13.7	10.7	8.9	12.3	11.2	12.1	11.6
Employment expectations [2)]	+	10.8	13.1	8.8	9.6	16.1	8.7	10.8	10.9	10.8	10.9
	=	72.8	69.8	75.5	74.2	67.1	75.0	72.6	73.1	72.8	72.9
	–	16.4	17.0	15.8	16.2	16.8	16.3	16.7	16.0	16.4	16.3
Business sentiment [2)]	>	12.8	13.0	12.5	12.6	14.4	11.7	12.9	12.6	13.3	12.1
	=	71.0	72.8	69.3	69.9	71.1	73.1	70.8	71.2	71.2	70.7
	<	16.3	14.1	18.2	17.5	14.5	15.2	16.3	16.2	15.5	17.2
Time-constant (x_i)											
MIG-classification	intermediate	52.8	53.4	52.3	-	-	-	50.3	56.2	-	-
	investment	22.1	24.3	20.2	-	-	-	23.7	20.0	-	-
	consumer	25.1	22.3	27.5	-	-	-	26.0	23.8	-	-
Province-classification	Vienna	10.5	9.9	10.9	9.0	9.3	14.6	18.2	0.1	-	-
	Lower-Austria	21.5	21.5	21.6	23.3	22.4	17.2	21.0	22.3	-	-
	Burgenland	22.7	24.4	21.2	21.3	26.5	22.1	23.1	22.1	-	-
	Styria	6.6	4.4	8.5	5.9	7.7	7.0	7.3	5.6	-	-
	Carinthia	6.8	6.7	6.8	6.5	4.7	9.3	4.1	10.4	-	-
	Upper Austria	7.3	6.9	7.6	5.7	7.6	10.3	9.7	3.9	-	-
	Salzburg	8.2	7.2	9.1	9.1	7.5	7.0	6.2	10.9	-	-
	Tyrol	13.5	16.3	11.1	16.8	12.4	7.6	9.9	18.5	-	-
	Vorarlberg	3.0	2.6	3.3	2.5	1.9	4.9	0.5	6.3	-	-
Modalities											
Firm size	small	52.6	-	-	-	-	-	-	-	-	-
	large	47.4	-	-	-	-	-	-	-	-	-
MIG-classification	intermediate	52.8	-	-	-	-	-	-	-	-	-
	investment	22.1	-	-	-	-	-	-	-	-	-
	consumer	25.1	-	-	-	-	-	-	-	-	-
Urban/rural-classification	urban	57.4	-	-	-	-	-	-	-	-	-
	rural	42.6	-	-	-	-	-	-	-	-	-
Business Cycle Phase	up	49.6	-	-	-	-	-	-	-	-	-
	down	50.4	-	-	-	-	-	-	-	-	-

Source: Own calculations.
Notes: 1) The indicator of "Capacity utilisation" is actually a censored categorial variable (ranging from 30 up to 100 per-cent, on a 10 per-cent scale). But it is treated like a continuous variable in the analysis. 2) Covariates are used in the analysis as one period lagged (t-1).

In a baseline setting, the cumulative probabilities of the discrete outcome y_i are related to a set of exogenous variables x:[17]

$$\Pr(y_i \leq j|x) = F(\kappa_j - x'\beta)\; j = 1, \dots, J \tag{3-1}$$

The κ_j are the unknown threshold parameters which split the range of the latent variable into J categories, the β are the unknown coefficients and the function F represents, in our application, a cumulative standard normal distribution, $\phi(\bullet)$. The assumption of normality provides the path for the class of an ordered probit model. To ensure well-defined probabilities, it is required that $\kappa_j > \kappa_{j-1}$, $\kappa_J = \infty$ and $\kappa_0 = -\infty$.

Considering the underlying latent variable y_i^*, which is linearly related to observable and unobservable factors, it can be written as

$$y_i = j \text{ if and only if } \kappa_{j-1} \leq y_i^* = x'\beta + u < \kappa_j \tag{3-2}$$

For the unobservable factors, a zero mean and constant variance (i.e. $\sigma^2 = 1$) assumption is necessary for identification purpose. In addition, the baseline model assumes that the thresholds are the same for all individuals. As such, an increase in any of the x will shift the cumulated distribution to the right or left but with no change in the slope of the distribution.

The conditional cell probabilities that a firm reports a particular outcome j can be expressed as:

$$\Pr(y_i = j|x) = F(\kappa_j - x'\beta) - F(\kappa_{j-1} - x'\beta) \tag{3-3}$$

In our three-categories setting ($J = 3$) this is read as:

$$\Pr(y_i = 1|x_{it}) = F(-x_i'\beta_1) \tag{3-4}$$

$$\Pr(y_i = 2|x_{it}) = F(-x_i'\beta_2) - F(-x_i'\beta_1) \tag{3-5}$$

$$\Pr(y_i = 3|x_{it}) = 1 - F(-x_i'\beta_2) \tag{3-6}$$

[17] Formal exposition following Boes and Winkelmann (2006) and Pfarr et al. (2011).

A wide range of estimators exists if the model is linear. However, in the non-linear case, like estimating a model for ordered categorical variables (as we do), no straightforward method exists. In business cycle analysis or in micro-econometrics the (panel) probit model has been widely used in regressions for qualitative data.

The baseline model is read as[18]

$$y_{it}^{*} = \eta_t + \beta' x_{it} + c_i + u_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \tag{3-7}$$

$$Var(v_{it}) = \sigma_c^2 + \sigma_u^2 = \sigma_c^2 + 1$$

$$Corr(v_{it}, v_{st}) = \rho = \frac{\sigma_c^2}{\sigma_c^2 + 1}$$

where c_i is an unobserved effect representing individual (i.e. firm) heterogeneity; x_{it} are either time-constant or time-varying observed individual characteristics; the $\{u_{it}: t = 1, \dots, T\}$ are idiosyncratic errors and the composite error at time t is $v_{it} = c_i + u_{it}$, which is usually serially correlated and could also be heteroskedastic; the η_t represents separate period intercepts and are handled with time-dummies. The covariates and the idiosyncratic errors are assumed to exhibit strict exogeneity, i.e. $Cov(x_{is}, u_{it}) = 0$ with $s, t = 1, \dots, T$.

With respect to the unobserved individual heterogeneity, $Cov(x_{it}, c_i) = 0$ with $t = 1, \dots, T$ is imposed, which represents a 'random effects' type of assumption. In the random effects estimation the composite error v_{it} is assumed to be uncorrelated not only with x_{it} but also with x_i. However, an endogeneity problem may arise if the 'random effects' type of assumption (i.e. no correlation between the explanatory variables, x_{it}, and the individual-specific effects c_i) is violated. The estimation of the model will lead to inconsistent.

To relax this issue we estimate a so-called correlated random effects (CRE) model by including averages of the time-varying variables as additional explanatory variables

[18] In the estimation we correct (i.e. cluster) the standard errors for correlations across the multiple observations we have for each firm.

(Wooldridge, 2002). The CRE model allows modeling the c_i in the following way: $c_i = \omega + \bar{x}_i\xi + a_i$, with conditional normality $a_i|x_i \sim Normal(0, \sigma_a^2)$. Allowing for correlation between c_i and x_{it} by adding time averages of the time-varying variables refers to a Mundlak-Chamberlain type transformation (see Mundlak, 1978; and Chamberlain, 1982). The main benefits of the CRE estimator are that it controls for unobserved time-constant heterogeneity as with fixed effects, and by including time-averages we can measure the effects of time-constant covariates.

Estimation procedures for ordered categories usually assume that the estimated coefficients of the explanatory variables do not vary between the categories (Long, 1997), thus, having the same thresholds across individuals (i.e. firms). This is commonly known as the parallel-trend assumption. In our estimation we stick to this rather strong assumption.[19]

The estimation of the CRE ordered probit model is done using maximum likelihood.[20] The likelihood for each unit is approximated by Gauss-Hermite quadrature (Butler and Moffitt, 1982). The quantities of interest in the estimation are marginal effects given that the size of the estimated coefficients[21] of the covariates does not have any direct interpretation per se – despite the fact that the sign of the β_js and the marginal effects are the same. The marginal (or partial) effect at a particular point ($\tilde{x}_j$) of a continuous covariate x_j is given by[22]

$$\left.\frac{\partial E[y|x,c]}{\partial x_j}\right|_{x_j=\tilde{x}_j} = \left.\frac{\partial F[x\beta+c]}{\partial x_j}\right|_{x_j=\tilde{x}_j} = f(\tilde{x}\beta + c)\beta \tag{3-8}$$

---

[19] An alternative is the class of generalised ordered probit models which relax this assumption and let the coefficients of the variables to vary across categories allowing for heterogeneous effects of some explaining factors (Boes, 2007; Boes and Winkelmann, 2006). Basile et al. (2014) have applied a variant of the generalised specification to check for robustness of their results, but found no significant differences to the results based on the restricted model (i.e. with homogeneous and exogenous thresholds).

[20] Various approaches have been suggested in the literature to estimate ordinal discrete choice panel-data models. The most widely used ones are the maximum likelihood (ML) estimation or the generalised method of moments (GMM) technique. See, for example, Greene (2004) or Bertschek and Lechner (1998) for some discussion of the ML and GMM approach with respect to panel probit models.

[21] The estimated coefficients represent $\beta/_{\sigma}$, so their magnitudes are in units of the standard-deviation of the errors.

[22] Note that the relative marginal effects do not depend on the covariates, i.e. $\frac{\partial F[x\beta+c]}{\partial x_j} / \frac{\partial F[x\beta+c]}{\partial x_k} = \frac{f(x\beta+c)\beta_j}{f(x\beta+c)\beta_k} = \frac{\beta_j}{\beta_k}$.

where f represents a $\phi(\bullet)$ standard normal probability distribution function (pdf). If we assume for the unobserved individual heterogeneity c_i that $E(c_i) = \mu_c$, the partial effect at the average (PEA) is $PEA_{x_j}(x) = \theta_j(x, \mu_c) = \frac{\partial F(x,\mu_c)}{\partial x_j} = \beta_j \phi(x\beta)$.[23] As conventionally done, the $\widetilde{x_j}$ is set to the mean value ($\overline{x_j}$) of the respective covariate. For assessing and comparing the goodness-of-fit of our models, we resort similar to Basile et al. (2014) to the widely used McFadden (1973) Pseudo-R^2, AIC, BIC as well as on R^2 measures proposed by Aldrich and Nelson (1984) and Maddala (1983).[24]

4. Estimation procedure and results

4.1 Deriving a proxy for the 'aggregated' business cycle

In a first step, we specify our baseline CRE ordered probit model with only quarterly time-dummies, which correspond to quarterly fixed effects (equation (4-1)). For each period a time-dummy (η_t) is used and the marginal effects on these dummies indicate for each of the three possible responses (i.e. 1=increased, 2=remained unchanged, 3=decreased) the probability that production output has changed accordingly. The term $c_i + u_{it}$ represents the composite error as outlined in equation (3-7).

$$y_{it}^* = \eta_t + c_i + u_{it}, \quad \text{with } i = 1, \dots, N; \ t = 1, \dots, T \qquad (4\text{-}1)$$

The marginal effects[25] of the η_t for $y_{it} = 1$ are shown in Figure 1.

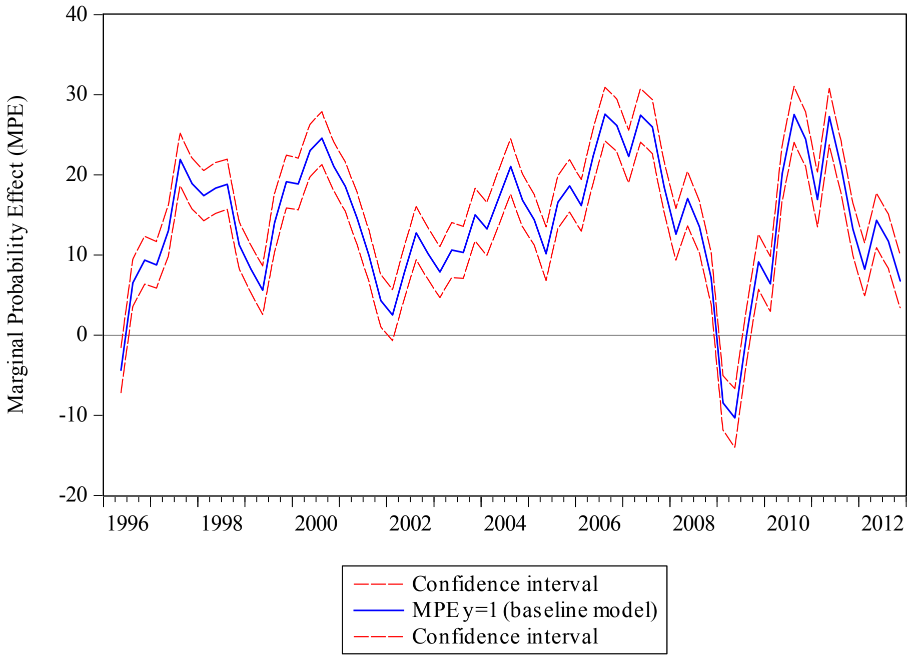
---

[23] Besides the PEA we can also obtain the average partial effect (APE) which is derived by averaging across the distribution of the unobserved heterogeneity c_i, i.e. $APE_{x_j}(x) = E_{c_i}[\theta_j(x, c_i)]$. Note that both partial effects are different quantities and can produce different estimates. The PEA is an estimate of the marginal effect for a particular entity (e.g. person, firm) at chosen covariate values (e.g. at their means), whereas the APE is an estimate of a population-averaged marginal effect.

[24] Table D1 in the Annex provides an overview of the model comparison results for the various nested model variants. In the main text we refer to the Pseudo-R^2 measure proposed by McFadden (1973).

[25] The estimated marginal probability effects at time t for a particular covariate for the possible outcomes ($y_{it} \in \{1,2,3\}$) sum up to 0. If a firm is more likely to report outcome $y_{it} = 1$, the likelihood of indicating one of the other outcomes has to decrease. As such, the marginal effects have to balance each other out. Figure B1 in the Appendix provides the respective figure.

Figure 1: Marginal probability effects of time-dummies



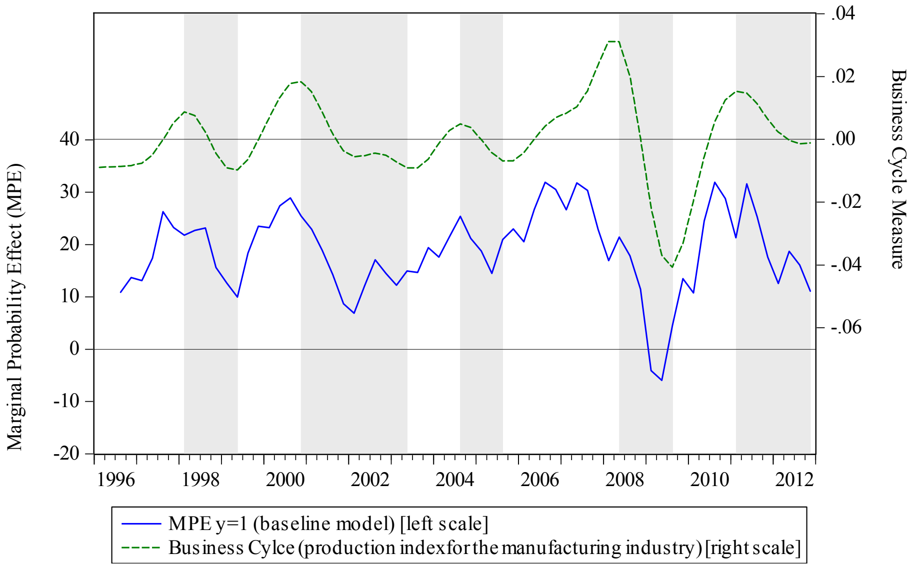
Source: Own calculations.

The estimates, plotted along the time-dimension, show expected business cycle dynamics with its characteristic pattern of up- and downswings in time.[26] In the period we cover (1996 to 2012), a firm's probability of having an increasing level of production ($y_{it} = 1$) goes up during the period from 1996 to mid 1997, followed by a downward trend until mid 1999 and then changes to an increasing trend up to the 2nd quarter of 2000. After 2000 the probability of a firm expanding its production level has been decreasing again until the beginning of 2002, when it switched again into an upward trend until early of 2007, with an exception from the end of 2004 until the beginning of 2005. During the years of the financial crisis 2008/09 a sharp decline in the marginal effect can be observed. The lowest probability is recorded for the 2nd quarter of 2009. From there on, the probability that a firm indicates an increase in its

[26] The estimation of equation (4-1) has been performed on the dataset constrained to the quarterly interval (i_q=55,250 obs.). For robustness we also compared these estimates to the one obtained using the monthly interval (i_m=115,055 obs.). The results for the marginal effects on the quarterly time-dummies are very similar. Figure B2 in the Appendix provides the respective figure.

production level went up again up to the first half of 2011 and switched again into a decreasing trend until the end of our sample period.

Figure 2: Marginal probability effects of time-dummies vs. manufacturing business cycle



Source: Own calculations.

Contrasting the time-pattern of the marginal probability effects of the $\eta_t|y_{it} = 1$ with some aggregated measure of economic activity in the manufacturing sector such as an overall production index or value added measure, it can be seen, that the temporal dynamics (i.e. business cycle movements) are rather similar (Figure 2). For instance, the business cycle component[27] of the quarterly (seasonal adjusted) production index for the Austrian industrial sector has a contemporaneous correlation with the 'time-series' of the marginal effects ($\eta_t|y_{it} = 1$) of +0.67.[28] However, the highest correlation is found at one quarter lead of the marginal probability effects series with a value of +0.79, indicating a leading behaviour over

[27] The business cycle component has been extracted using the Baxter-King band-pass filter (Baxter and King, 1999) with parameter settings: business cycle frequency between 6 and 32 quarters and filter length of 5 quarters.

[28] Using as reference series the business cycle component of the quarterly value added measure in the manufacturing industry, the correlation reduces marginally to +0.64.

the course of the (manufacturing) business cycle.[29] This result is in line with findings in Hölzl and Schwarz (2014) where the authors employ balances of the BTS data in their analysis of business cycle dynamics. Figure 2 also displays the dating of the business cycle phases (i.e. expansions and recessions).[30] We will use the dating of the cycle later on to investigate business cycle differentials of firms' responses taking into account cyclical asymmetries commonly found in the empirical literature (see e.g. Clements and Krolzig, 2003; Coakley and Fuertes, 2006; Anas et al., 2008).

The estimation of the model with only time-fixed effects controls for time-specific unobserved heterogeneity. However, it leaves a lot of unobservables in the error term. In order to explicitly control for observables and get our estimates of the marginal probability effects more robust, we augment the specification of the model along various dimensions. In detail, we split our estimation procedure in three steps. First of all, representing the core-dimension, we analyse the marginal effects using our set of firm-level covariates/controls. Next, we add the industry as well as regional aspect to the empirical model and attain our full model specification. Finally, we analyse business cycle differences taking business cycle phases (up- vs. downswing), firm size (large vs. small), and firm location (urban vs. rural) into account.

[29] The lead comes as no surprise, given that the BK-filtered business cycle component reflects levels whereas the underlying qualitative outcome variable of current production refers more or less to period-on-period changes. The latter can be seen as 'first difference filter' of the data and as such are prone to substantial shifts in the timing relationships of variables (Baxter and King, 1999).

[30] For dating the business cycle phases we resort to the widely used non-parametric Bry and Boschan (1971) algorithm. According to our dating procedure the business cycle in the manufacturing industry is characterized in the years from 1996 to 2012 by the following phases: 1996:Q1-1998:Q1 (up), 1998:Q2-1999:Q2 (down), 1999:Q3-2000:Q4 (up), 2001:Q1-2003:Q2 (down), 2003:Q3-2004:Q3 (up), 2004:Q4-2005:Q3 (down), 2005:Q4-2008:Q2 (up), 2008:Q3-2009:Q3 (down), 2009:Q4-2011:Q1 (up), and 2011:Q2-2012:Q4 (down).

4.2 Firm-level extension

As shown in Basile et al. (2014), firm specific characteristics play an important role in explaining business cycle differentials. Utilising survey data allows incorporating such information in the model, though constrained due to the particular questions asked. As outlined in the data description section, our set of individual firm-level data contains explanatory variables which are either related to the business cycle dimension (as listed in Table 1) or reflecting structural characteristics (i.e. firm size and industry affiliation). We augment our baseline model specification such that

$$y_{it}^{*} = \eta_t + \delta_s + \Psi_{it}'\beta + \overline{\Psi_i'}\gamma + c_i + u_{it} \qquad (4\text{-}2)$$

with $i = 1, \dots, N;\ t = 1, \dots, T;$

where Ψ_{it} denotes the set of time-varying firm-level covariates, $\overline{\Psi}_i$ their respective means according to the Mundlak-Chamberlain CRE approach. As noted in Basile et al. (2014), the marginal effects on the firm-specific covariate represent a 'shock'-effect (i.e. deviations from the individual averages), whereas the calculated individual averages a 'level'-effect (i.e. differences between individuals).[31] δ_s represents dummies for the industry affiliation of the firm and is used to control for time-invariant industry fixed effects; these dummies are either coded with respect to the NACE-2-digit breakdown (22 in total; δ_s^{NACE}), or representing one of the three main industrial groupings (δ_s^{MIG}).

Business cycle dimension

The estimation results of the firm-level model with respect to the business cycle covariates (Table 3, top panel) read as follows: All the 'shock' estimates of the marginal probability

[31] The estimates of the 'shock'-effect can be used in the interpretation as kind of performance (short-run) measure, whereas the 'level'-effect provides more of a structural (long-run) meaning.

effects (mpe) of the firm-level covariates are statistically significant and show apart from one variable (selling price expectations) the expected sign. In the discussion of the results, we focus primarily on the estimates related to increased production output ($y_{it} = 1$).

The mpe on the lagged **order book levels** indicate a strong link between a firms' change in production output and their assessment of their order books, evaluated one quarter in advance.[32] Firms which indicated a more than sufficient backlog of orders tend to have on average a 12% higher probability of having an increasing level of production in the next quarter compared to firms which judged their order book levels in the quarter before as rather low.[33] Moreover, firms which tend to have above average levels of order backlogs with respect to other firms have a 49% higher likelihood of reporting increased production levels. The magnitude of both estimates provides, as expected, a strong indication of firm-specific demand-side effects on the production activities of a firm.

With respect to firms' limiting factors to current production, in particular, related to **shortage of demand**, the mpe displays the expected negative sign.[34] Firms confronted with lack of demand exhibit a probability of increasing their production output, which is 15% lower compared to firms with basically no production obstacles. Interestingly, the 'level' effect exhibits a positive sign with a magnitude of 0.03 (but not statistically significant in this model variant), meaning that firms which on average are more often constrained by shortage of

[32] Note that incorporating some variables one-period lagged results in loosing data for the first quarter in our sample. The number of observations reduces from i_q=55,250 to i_{q*}=44,683.

[33] Using contemporaneous information on the order book levels provides an even stronger effect of more than sufficient backlogs of order on the probability of a firm having an increasing level of production. The marginal effect on this covariate for $y_{it} = 1$ is 0.56, indicating a more than 50% higher probability of a high level of production (see Table B1 in the Annex for results). There exists a high correlation of a firms' assessment of their change in current production output and their order book levels ($corr_{t0}$=+0.96, $corr_{t-1}$=+0.80). Figure B3 in the Appendix provides the respective figure. Note that the magnitudes of the marginal effects on the other firm-level covariates reduce, but are still predominantly statistically significant.

[34] We have also tested the explanatory power of the WIFO KT question on the limiting factor due to 'financial constraints'. But the results turned out to be not statistically significant; neither could the goodness-of-fit of the overall model be improved. As such we decided to take out this variant from the firm-level model specification and focus in this respect on the answer option 'shortage of demand'.

demand still have a higher probability of increasing current production levels. If the structural effect would be interpreted as indicating ‘firm quality’, a negative sign of this ‘structural’ marginal effect would be more plausible. However, if firms report shortage of demand as a limiting factor when the business cycle is down, the structural effect is not related to ‘firm quality’. It is then an indicator of whether the firm’s demand strongly moves in line with the business cycle.

A firm’s assessment of its current inventory level is according to our findings countercyclical related to changes in production output of the firm. The mpe on the covariate **stocks of finished products** is statistically significant and has a negative sign on the response category related to ‘too large’. This means, in the short run, firms exhibiting too large inventory levels most likely respond, *ceteris paribus*, to favourable demand-conditions with a cut-back in their current production output and satisfy demand from their stocks. The probability of increasing production output is about 10% lower compared to firms which exhibit a rather low stock of finished products. However, in the long run, firms which tend to assess their inventory level most of the time as too high (compared to other firms) have a 13% higher likelihood of reporting increased production levels. On the one hand, this may indicate that these firms are predominantly faced with high demand for their products and expecting that this will continue in the near future, as such continuing to increase production output may be a rational choice of the firm. But the positive mpe of this structural effect may also be seen as a sign of an ‘insufficient’ inventory management in place where these firms are not able to adjust their stocks of finished products to an optimal level. However, favouring our first reasoning, empirical evidence shows that inventory management (as part of good business practices) has improved over the last decades, contributing to reduced output volatility (Ahmed et al., 2004; McCarthy and Zakrajsek, 2007).

Table 3: Marginal probability effects: Firm-level

Covariates / controls	y=1 MPE	y=1 SE	y=2 MPE	y=2 SE	y=3 MPE	y=3 SE
Business cycle dimension						
Firm-level (Current)						
t-1.Order books.>	0.1153***	(0.007141)	-0.0455***	(0.003375)	-0.0699***	(0.004594)
t-1.Order books.=	0.0371***	(0.004922)	-0.0082***	(0.001060)	-0.0290***	(0.004125)
t-1.Order books.> [bar]	0.4876***	(0.026212)	-0.1827***	(0.012141)	-0.3049***	(0.017014)
t-1.Order books.= [bar]	0.2182***	(0.020442)	-0.0818***	(0.008211)	-0.1364***	(0.013038)
Limit.Factor: Insufficient demand	-0.1455***	(0.006760)	0.0545***	(0.003267)	0.0910***	(0.004493)
Limit.Factor: Insufficient demand [bar]	0.0282	(0.018081)	-0.0106	(0.006804)	-0.0176	(0.011293)
Stock finished products.>	-0.0975***	(0.012950)	0.0389***	(0.006729)	0.0586***	(0.006809)
Stock finished products.=	-0.0524***	(0.011534)	0.0259***	(0.006570)	0.0265***	(0.005027)
Stock finished products.> [bar]	0.1260***	(0.030779)	-0.0472***	(0.011634)	-0.0788***	(0.019328)
Stock finished products.= [bar]	0.0744***	(0.028318)	-0.0279***	(0.010638)	-0.0465***	(0.017750)
Selling prices.+	0.1046***	(0.009271)	-0.0353***	(0.004074)	-0.0693***	(0.006182)
Selling prices.=	0.0629***	(0.005831)	-0.0152***	(0.001285)	-0.0477***	(0.005169)
Selling prices.+ [bar]	-0.0078	(0.034235)	0.0029	(0.012818)	0.0049	(0.021418)
Selling prices.= [bar]	-0.0182	(0.021402)	0.0068	(0.008010)	0.0114	(0.013397)
Capacity utilisation	0.0109***	(0.000327)	-0.0041***	(0.000202)	-0.0068***	(0.000227)
Capacity utilisation [bar]	-0.0090***	(0.000445)	0.0034***	(0.000225)	0.0056***	(0.000273)
Firm-level (Expectations)						
t-1.Production expectations.+	0.2206***	(0.008567)	-0.0734***	(0.005123)	-0.1472***	(0.007485)
t-1.Production expectations.=	0.0893***	(0.005244)	-0.0011	(0.002499)	-0.0883***	(0.006892)
t-1.Production expectations.+ [bar]	0.0528*	(0.031588)	-0.0198*	(0.011860)	-0.0330*	(0.019759)
t-1.Production expectations.= [bar]	-0.0321	(0.024679)	0.0120	(0.009259)	0.0201	(0.015435)
t-1.Selling price expectations.+	-0.0347***	(0.009143)	0.0138***	(0.003780)	0.0209***	(0.005470)
t-1.Selling price expectations.=	-0.0244***	(0.007329)	0.0102***	(0.003349)	0.0142***	(0.004005)
t-1.Selling price expectations.+ [bar]	-0.0540	(0.034160)	0.0203	(0.012890)	0.0338	(0.021300)
t-1.Selling price expectations.= [bar]	-0.0330	(0.027485)	0.0124	(0.010339)	0.0206	(0.017160)
t-1.Employment expectations.+	0.0563***	(0.009428)	-0.0241***	(0.004313)	-0.0322***	(0.005333)
t-1.Employment expectations.=	0.0112*	(0.006066)	-0.0038*	(0.001935)	-0.0075*	(0.004140)
t-1.Employment expectations.+ [bar]	0.0342	(0.027488)	-0.0128	(0.010344)	-0.0214	(0.017159)
t-1.Employment expectations.= [bar]	0.0453**	(0.018429)	-0.0170**	(0.006980)	-0.0283**	(0.011488)
t-1.Business sentiment.>	0.0494***	(0.008907)	-0.0198***	(0.003803)	-0.0296***	(0.005287)
t-1.Business sentiment.=	0.0163***	(0.005710)	-0.0054***	(0.001752)	-0.0109***	(0.003980)
t-1.Business sentiment.> [bar]	-0.0447	(0.028139)	0.0167	(0.010565)	0.0279	(0.017599)
t-1.Business sentiment.= [bar]	-0.0235	(0.020681)	0.0088	(0.007762)	0.0147	(0.012929)
Structural dimension						
Firm-level						
Firmsize	-0.0449***	(0.009204)	0.0168***	(0.003536)	0.0281***	(0.005744)
Firmsize^2	-	-	-	-	-	-
Firmsize [bar]	0.0481***	(0.009508)	-0.0180***	(0.003679)	-0.0301***	(0.005914)
Firmsize^2 [bar]	-	-	-	-	-	-
Nace08-Sector.14	-0.0452**	(0.019415)	0.0170**	(0.007247)	0.0283**	(0.012205)
Nace08-Sector.15	-0.0342*	(0.020417)	0.0128*	(0.007660)	0.0214*	(0.012778)
Nace08-Sector.17	-0.0252*	(0.013268)	0.0094*	(0.004974)	0.0157*	(0.008311)
Nace08-Sector.20	-0.0242*	(0.012915)	0.0091*	(0.004856)	0.0151*	(0.008075)
Nace08-Sector.28	-0.0259**	(0.011234)	0.0097**	(0.004234)	0.0162**	(0.007021)
Nace08-Sector.31	-0.0236*	(0.013041)	0.0088*	(0.004898)	0.0147*	(0.008157)
N	44,683					
Pseudo R^2	0.215					
cut1	-3.3791***	(0.160257)				
cut2	-1.3277***	(0.158918)				

Source: Own calculations.
Notes: *** indicates statistically significance at 1%, ** indicates statistically significance at 5%; * indicates statistically significance at 10% level. MPE referts to the marginal probability effect. SD (in parentheses) represents clustered standard errors. Cut1 and cut2 are the estimated thresholds marking the delimination between the different answer categories in our 3-point categorial outcome variable. The MPE of the variables with a [bar] denote 'level' (long-run) effects, while the other variables listed refer to the 'shock' (short-run) effects. Time-dummies as well as none-significant industry-dummies have been omitted in the output table. The squared term on "Firm size" is used in the model estimation, but we preclude the calculation of the MPE for the squared term given its dependency on the linear term

Our results for **selling prices** (current quarter) and **selling price expectations** (lagged one quarter), though both statistically significant for the 'shock' effect, provide mixed evidence with respect to its link to firms' production output. On the one hand, firms indicating an upward tendency in their most recent selling prices have an about 10% higher probability of an increased production output compared to firms which are confronted with stagnating or even decreasing prices of their products. Firms in a position of charging higher prices are most likely confronted with more favourable demand for their products and, in turn, this higher demand may materialise in higher production. Similar reasoning may be assumed for price expectations, i.e. firms which have expected higher product prices in the coming month should be those firms which, on average, keep up and expand their production output. However, according to our results the sign of the mpe related to price expectations (lagged one quarter) is negative and points to the contrary. The probability that a firm expanding its output in the face of positive price expectations is 3% lower compared to firms which have expected a reduction in their product selling prices. One rationale behind this finding can be found in the firm innovation literature. Harrison et al. (2014) point out that the productivity effect of process innovation let firms to produce the same or even an increased amount of output with fewer inputs, thus, leading to lower unit costs. Over shorter time periods fixed capacity costs could lead to such an effect if firms expect that increased production leads via a fixed cost channel to lower unit costs. In turn, this kind of cost reduction allows the (innovative) firm to lower its product selling price, resulting in higher production, sales and higher employment.[35] By and large, our findings on price expectations and their impact on a firm's current production decisions are far from clear-cut, as it is not clear whether the demand channel (higher demand leads to higher prices) or a supply channel (capacity costs

[35] Note that the magnitude of the reduced 'cost/price effect' depends on various factors, such as the size of the reduction, the price elasticity of demand or the degree of competition among the firms (Peters et al., 2014).

and innovation lead to changes in the supply and to lower prices) applies. In the BTS firms are asked "*How do you expect your selling prices to change over the next 3 months?*", but there is no information about the 'channel' (e.g. either demand-/supply-side) that guides the price-setting expectations set of the firms.

The estimate for **capacity utilisation** signifies that if a firm enhances its operating grade by one unit (e.g. from 80 to 81 per-cent), the probability that output raises as well increases by 1%. But firms which operate most of the time above average capacity utilisation, i.e. near or on their full production capacity, have as expected a reduced possibility (by minus one percent) to increase their production levels compared to firms confronted with sparse capacity utilisation.

Moreover, firms' **production expectation** derived one quarter in the past provides an early and robust signal of changes in the production output in the next quarter to come. The estimates of the mpe are both positive and statistically significant. The 'shock' effect indicates that if a firm expects an increase in its production level in the coming months, the probability that the production output one-quarter ahead will go up is 22% higher compared to firms expecting their future production output to decline. The structural estimate (i.e. the 'level' effect) of the marginal effect provides a positive magnitude of 9%. Firms which are in general optimistic with respect to their future production possibilities tend to assess their current production activities higher than less optimistic firms. This suggests that these firms are not only more optimistic but also that they have higher growth rates than firms that are less optimistic about their production over the next months.

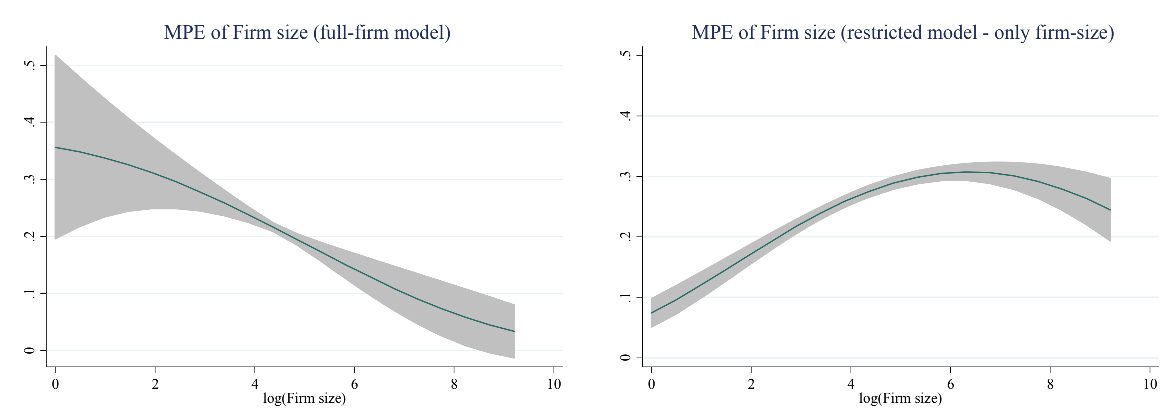
Next, the estimate for **employment expectations** lagged one-quarter shows that firms planning to increase their employment levels in the near future are also those with a higher probability of positive changes in their immediate production output (by about 6% compared to firms which expect to reduce their workforce). Thus, confirming the leading property of this firm-level labour market related BTS question. However, we do not find a statistically significant structural effect. That is to say that firms which on average are more optimistic with respect to their demand for labour do not exhibit a higher probability of increasing current production levels.

Finally, the estimation results for the business cycle covariate reflecting firms **overall business sentiment**, which can be seen as a proxy of future demand or business conditions and, thus, exhibiting the most forward looking and broad measure in the context of the BTS (Nerlove, 1983; Oppenländer, 1996: 307), reveal for the 'shock' effect a positive and statistically significant coefficient. This indicates that if a firm expecting favourable business conditions in the next two quarters to come, the probability that production output increases in the next quarter as well is 5% higher compared to more pessimistic firms.

<u>Structural dimension</u>

The results with respect to the 'structural' covariates in the firm-level model can be summarised as follows (see Table 4 – bottom panel): The marginal probability of the 'shock' effect on the **firm-size** covariate exhibits a negative sign with 0.05 in magnitude, i.e. as (log) firm size increases by one unit the predicted probability of increasing production output reduces by about 5%. We would have expected the opposite sign, given for example the arguments and empirical evidence found in the literature on the transmission of monetary shocks (Dedola and Lippi, 2005). Firm size has been identified as a determinant for different reactions, and, in particular, larger firms tend to be more prone to these shocks. Larger firms should also face lower borrowing constraints (Basile et al., 2014). As such it is assumed that large firms are in a better position to smooth production activities and change their output. The positive firm size effect should diminish and turn negative at some point, indicating an inverted U-shaped relationship. We have modelled this potential none-linearity by including the squared term of firm size in the estimation. But we do not calculate the marginal effect for the none-linear term, given the interdependency between both terms. Instead, we obtain the predictions for the marginal effect of firm size not just for the mean value, but also evaluated over a broad range of values. Figure 3 (left graph) provides the respective distribution of the mpe for the full firm-level model. The downward sloping shape confirms the negative sign of the mpe (calculated at the mean). However, an estimation of a restricted model variant with just using the firm-specific structural variables besides the quarterly dummies reveals a distribution of the marginal firm size effects which has the expected shape (Figure 3 – right graph). Moreover the point estimate for firm size has in this case the expected positive sign (though not statistically significant).

Figure 3: Marginal probability effects of (log) firm size: Full model vs. restricted



Source: Own calculations.

It seems that some of the business cycle related covariates in the full model carry firm size correlated information and pick-up parts of the firm size effect. Descriptive statistics support this argument. We have seen that there are distinct differences in the responses modalities between large and small firms (e.g. large firms tend to be more optimistic or face stronger demand).

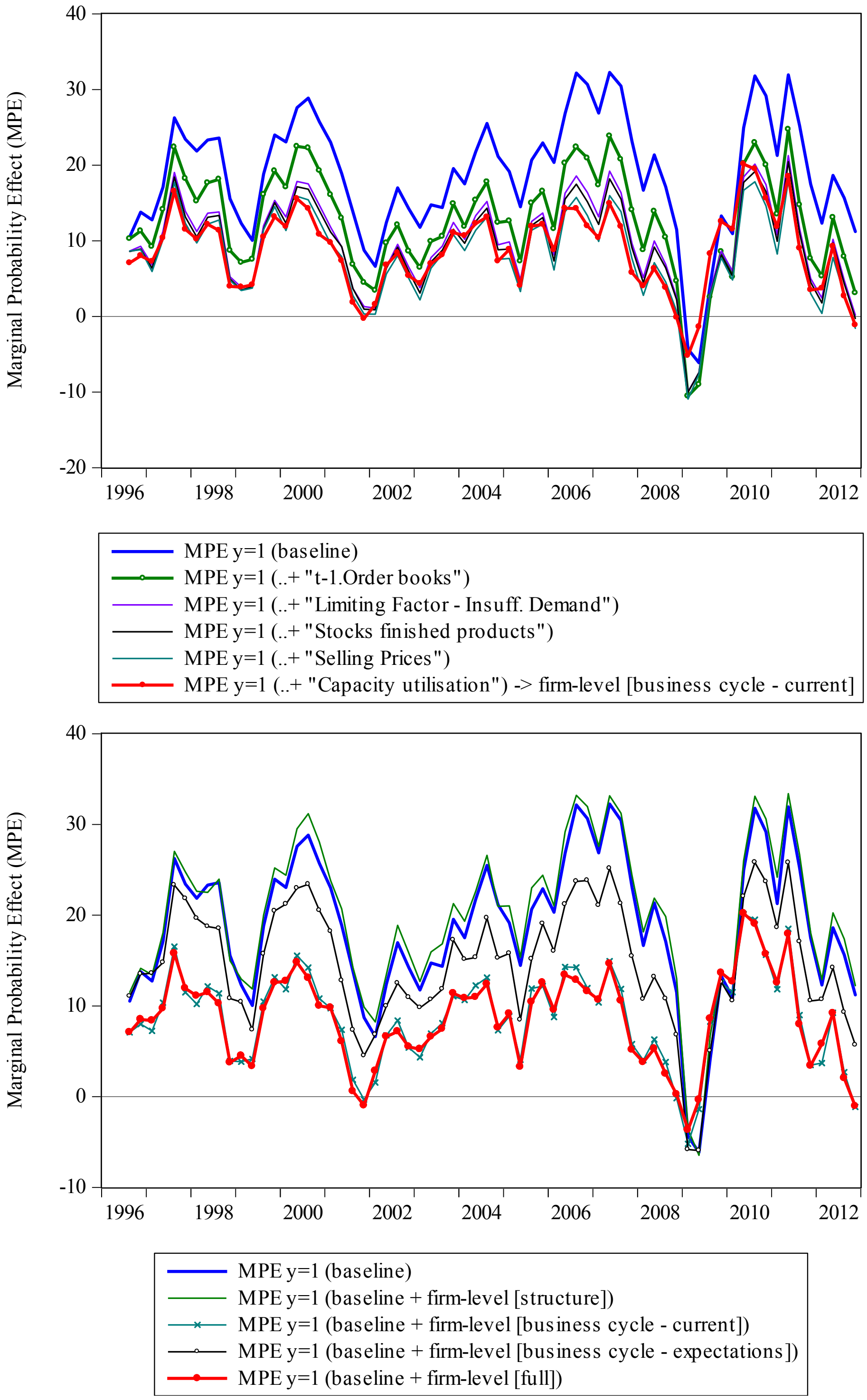
The marginal effect of the firm-size variable averaged across each firm exhibits also a statistically significant coefficient (mpe=0.05), but contrary to the 'shock' effect, with a positive sign. Larger firms (on average) tend to have a 5% higher probability of expanding their production output compared to (on average) smaller firms. This indicates also that smaller firms have a persistently lower propensity to assess their production level as increasing, and, at the aggregate level, we should observe a level difference in the business cycle assessment between small and large firms.

Finally, the estimates for the controls related to the **industry affiliation** of a firm (irrespective if we model it with δ_s^{NACE} or δ_s^{MIG}) show predominantly statistically insignificant results. This rather low explanatory power of the industry mix is in line with findings in Basile et al. (2014) and suggests that firm heterogeneity dominates industry heterogeneity when it comes to the variance of firm-level answers in business tendency surveys.

Explanatory power of the firm-level covariates

Our results so far indicate that the demand-side covariates (current order book levels and limited demand conditions), the degree of capacity utilisation as well as the expected direction of future production levels have the highest explanatory power with respect to a firm's current production output. The full 'firm-level' model also exhibits the highest goodness-of-fit value in the Pseudo-R^2 measure (0.215). The biggest improvement is achieved once the model is augmented with the information on the order book levels (lagged on period). This is also confirmed by looking on the respective changes in the quarterly time-dummies η_t (see Figure 4 – top panel).

Figure 4: Marginal probability effects: Model variants and full 'firm-level' model



Source: Own calculations.

Adding order book level information and the covariate on limiting factors due to shortage of demand to the model takes out some of the unobserved factors impacting on our 'proxy' for the overall business cycle. The estimates of η_t are reduced considerably. The inclusion of the other business cycle related variables reflect the 'current' environment impact on η_t only to some lesser extent.

Furthermore, contrasting the estimates of the quarterly time-dummies in the full 'firm-level' model specification with some interim model specifications (see Figure 4 – lower panel), we see that only controlling for firm size and sector affiliation (i.e. for the 'structural' element) does not reduce the marginal probability effects of the quarterly time-dummies ($\eta_t | y_{it} = 1$) obtained from the baseline model. Adding the set of business cycle covariates related to 'expectations' picks up some of the unobserved factors, but not as much as in the case of the covariates reflecting 'current' business activities. For the latter, the magnitudes of the temporal dynamics over the course of the business cycle are almost identical to the results obtained from the full 'firm-level' model. Hence, business cycle information embedded in this type of questions exhibits the highest explanatory power in our model setup.

4.3 Industry-/Regional-level extension

Having controlled for observable firm-specific heterogeneity, we finally augment our model with our available industry and regional variables. Our full model specification is outlined as follows:

$$y_{it}^* = \eta_t + \delta_s^{MIG} + \varphi_s + \vartheta_r + \Psi_{it}'\beta + \overline{\Psi_i'}\gamma + c_i + u_{it} \quad (4\text{-}3)$$

with $i = 1, \dots, N;\ t = 1, \dots, T;$

where φ_s denotes the additional set of industry-specific covariates (at the NACE-2-digit breakdown) and ϑ_r represents our region-specific characteristics (at the NUTS-3 level). The estimation results of our complete model are shown in Table 4.

Table 4: Marginal probability effects: Full model specification

Covariates / controls	y=1 MPE	y=1 SE	y=2 MPE	y=2 SE	y=3 MPE	y=3 SE
Business cycle dimension						
Firm-level (Current)						
t-1.Order books.>	0.1152***	(0.007122)	-0.0450***	(0.003331)	-0.0702***	(0.004606)
t-1.Order books.=	0.0371***	(0.004909)	-0.0080***	(0.001033)	-0.0291***	(0.004137)
t-1.Order books.> [bar]	0.4898***	(0.025908)	-0.1817***	(0.011875)	-0.3081***	(0.016963)
t-1.Order books.= [bar]	0.2226***	(0.019892)	-0.0826***	(0.007929)	-0.1400***	(0.012803)
Limit.Factor: Insufficient demand	-0.1449***	(0.006763)	0.0537***	(0.003209)	0.0911***	(0.004524)
Limit.Factor: Insufficient demand [bar]	0.0293*	(0.017589)	-0.0109*	(0.006548)	-0.0185*	(0.011059)
Stock finished products.>	-0.0970***	(0.012935)	0.0383***	(0.006668)	0.0586***	(0.006852)
Stock finished products.=	-0.0520***	(0.011520)	0.0255***	(0.006520)	0.0265***	(0.005060)
Stock finished products.> [bar]	0.1269***	(0.030272)	-0.0471***	(0.011332)	-0.0798***	(0.019124)
Stock finished products.= [bar]	0.0773***	(0.027764)	-0.0287***	(0.010328)	-0.0486***	(0.017510)
Selling prices.+	0.1042***	(0.009248)	-0.0347***	(0.004024)	-0.0694***	(0.006199)
Selling prices.=	0.0627***	(0.005814)	-0.0149***	(0.001249)	-0.0477***	(0.005179)
Selling prices.+ [bar]	-0.0100	(0.033550)	0.0037	(0.012431)	0.0063	(0.021120)
Selling prices.= [bar]	-0.0241	(0.020949)	0.0090	(0.007755)	0.0152	(0.013204)
Capacity utilisation	0.0109***	(0.000326)	-0.0040***	(0.000199)	-0.0068***	(0.000226)
Capacity utilisation [bar]	-0.0090***	(0.000428)	0.0033***	(0.000217)	0.0056***	(0.000265)
Firm-level (Expectations)						
t-1.Production expectations.+	0.2202***	(0.008546)	-0.0725***	(0.005074)	-0.1477***	(0.007494)
t-1.Production expectations.=	0.0890***	(0.005224)	-0.0006	(0.002489)	-0.0885***	(0.006904)
t-1.Production expectations.+ [bar]	0.0545*	(0.031410)	-0.0202*	(0.011679)	-0.0343*	(0.019764)
t-1.Production expectations.= [bar]	-0.0319	(0.024364)	0.0118	(0.009054)	0.0201	(0.015325)
t-1.Selling price expectations.+	-0.0346***	(0.009123)	0.0136***	(0.003730)	0.0210***	(0.005499)
t-1.Selling price expectations.=	-0.0243***	(0.007310)	0.0101***	(0.003311)	0.0142***	(0.004023)
t-1.Selling price expectations.+ [bar]	-0.0661**	(0.033670)	0.0245*	(0.012622)	0.0416**	(0.021092)
t-1.Selling price expectations.= [bar]	-0.0364	(0.026979)	0.0135	(0.010052)	0.0229	(0.016944)
t-1.Employment expectations.+	0.0561***	(0.009404)	-0.0238***	(0.004266)	-0.0323***	(0.005352)
t-1.Employment expectations.=	0.0112*	(0.006051)	-0.0037*	(0.001907)	-0.0075*	(0.004153)
t-1.Employment expectations.+ [bar]	0.0311	(0.027606)	-0.0116	(0.010276)	-0.0196	(0.017342)
t-1.Employment expectations.= [bar]	0.0450**	(0.018123)	-0.0167**	(0.006790)	-0.0283**	(0.011371)
t-1.Business sentiment.>	0.0493***	(0.008889)	-0.0196***	(0.003763)	-0.0297***	(0.005311)
t-1.Business sentiment.=	0.0163***	(0.005697)	-0.0053***	(0.001721)	-0.0110***	(0.003999)
t-1.Business sentiment.> [bar]	-0.0474*	(0.028097)	0.0176*	(0.010450)	0.0298*	(0.017675)
t-1.Business sentiment.= [bar]	-0.0232	(0.020406)	0.0086	(0.007577)	0.0146	(0.012838)
Structural dimension						
Firm-level						
Firmsize	-0.0445***	(0.009206)	0.0165***	(0.003503)	0.0280***	(0.005777)
Firmsize^2	-	-	-	-	-	-
Firmsize [bar]	0.0475***	(0.009501)	-0.0176***	(0.003639)	-0.0299***	(0.005942)
Firmsize^2 [bar]	-	-	-	-	-	-
Industry-level						
Excess labour turnover	0.0063***	(0.002401)	-0.0023***	(0.000893)	-0.0040***	(0.001513)
Employment growth (avg. 96-12)	0.0040**	(0.001851)	-0.0015**	(0.000686)	-0.0025**	(0.001168)
No. of employees (median, avg. 96-12)	0.0006	(0.000737)	-0.0002	(0.000274)	-0.0004	(0.000463)
Regional-level						
Employment concentration	0.0214	(0.456232)	-0.0079	(0.169203)	-0.0135	(0.287029)
Employment concentration [bar]	0.0429	(0.486822)	-0.0159	(0.180612)	-0.0270	(0.306212)
Sector concentration	-0.0030	(0.048996)	0.0011	(0.018175)	0.0019	(0.030822)
Sector concentration [bar]	-0.0053	(0.049990)	0.0020	(0.018540)	0.0033	(0.031451)
Local externalities	0.0002	(0.000292)	-0.0001	(0.000108)	-0.0001	(0.000184)
N	44,683					
Pseudo R^2	0.215					
cut1	-3.4745***	(0.189084)				
cut2	-1.4239***	(0.187732)				

Source: Own calculations.

Notes: *** indicates statistically significance at 1%, ** indicates statistically significance at 5%; * indicates statistically significance at 10% level. MPE referts to the marginal probability effect. SD (in parentheses) represents clustered standard errors. Cut1 and cut2 are the estimated thresholds marking the delimination between the different answer categories in our 3-point categorial outcome variable. The MPE of the variables with a [bar] denote 'level' (long-run) effects, while the other variables listed refer to the 'shock' (short-run) effects. Time-dummies have been omitted in the output table. Industry dummies have been dropped from the estimation due to the inclusion of the industry-level variables (otherwise colliniarty is present). The squared term on "Firmsize" is used in the model estimation, but we preclude the calculation of the MPE for the squared term given its dependency on the linear term

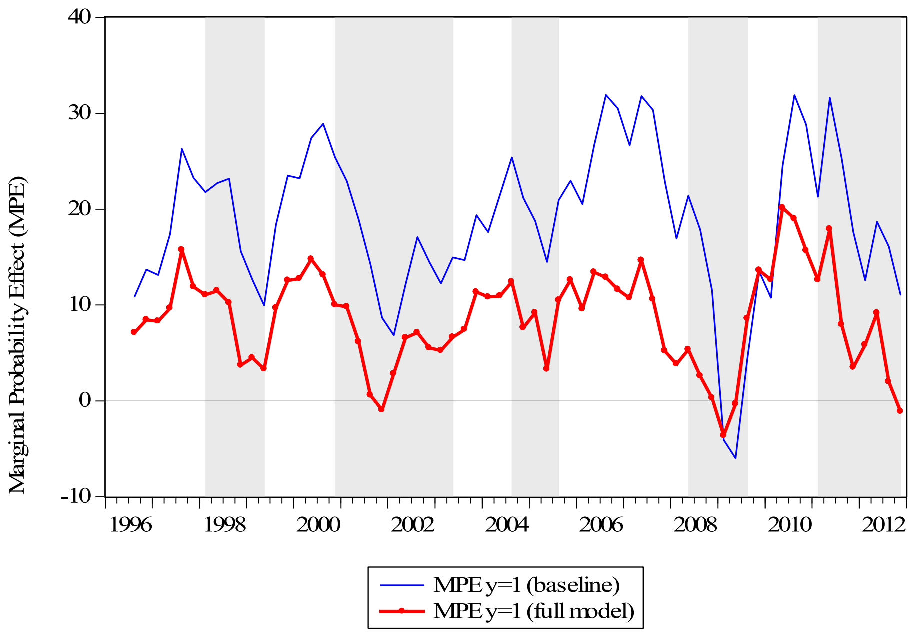
Including our industry as well as regional variables leaves the sign, magnitude and statistically significance of the firm-level covariates basically unchanged. With respect to the industry-level, our variable for sunk costs (proxied by the indicator of **excess labour turnover**) turns out to be statistically significant with a positive marginal probability effect of 0.01. This says that firms operating in an industry which is characterised by a high degree of labour turnover have a higher likelihood of increasing production (around 1%) compared to firms in where labour hoarding is dominating. The marginal effect of **employment growth** is also statistically significant (at the 5%-level) and positive but small in magnitude. Firms in high growth industries (measured by means of employment growth) have on average a higher probability of increasing production output as firms in low growth industries.

Controlling for regional aspects does not help improving the fit of the model, nor does it provide statistically significant marginal probability effects on our NUTS-3 related measures of specialisation (as measured with **related variety**), **employment concentration** and **local externalities**. With regard to business cycles Austrian regions do not have an impact on firm's assessment of their production levels. This stands quite in contrast to the findings by Basile et al. (2014) for Italian manufacturing, who find significant marginal effects on regional characteristics like local externalities or local financial backwardness in explaining North-South differences in the business cycle.

In our analysis, the inclusion of industry and regional information in the model only increased marginally the Pseudo-R^2 measure, and the estimates of the quarterly time-dummies η_t are nearly identical to the results obtained from the 'firm-level' model.

Figure 5 plots the estimates of η_t from the baseline specification (equation (4-1)) as well as from the full model specification (equation (4-3)). The full set of covariates controls for a large part of the unobserved factors embedded in the baseline specification. The estimated marginal probability effects of η_t are on average approximately half the size in the full model specification compared to the baseline. Adding firm-level, industry- and region-specific information allows controlling for additional microeconomic heterogeneity, whilst keeping the overall business cycle dynamics rather similar (contemporaneous correlation between both η_t 'time-series' is +0.75).[36]

Figure 5: Marginal probability effects: Baseline vs. full model specification



Source: Own calculations.

Interestingly, the differences between both estimates are widening up in the business cycle boom years prior the outbreak of the financial crisis and becoming negligibly small in the immediate year of the crisis and half way through the business cycle upswing in the years thereafter. It indicates that the global macroeconomic shock of the financial crisis has hit all firms in a quite similar way and that firm-level heterogeneity has not played a major role in shaping the overall business cycle during the crisis. However, in the years prior the crisis and after the crisis the evidence suggests that firm-level heterogeneity and shocks matter for shaping aggregate business cycle dynamics.

[36] The correlation with respect to the overall business cycle measure of industrial production is to some extent lower in the case of the full model specification. However, the highest correlation is found at two quarters lead (+0.6) compared to one quarter (+0.79) in the baseline setting.

4.4 Extension: firm heterogeneity and business cycle differentials

Our results so far indicate that mainly firm-level business cycle elements as well as to some degree industry-level specifics provide statistically significant marginal probability effects with the expected sign. In a final step, we analyse the effect of the introduced firm heterogeneity in our model on (i) differences along the business cycle (upswing vs. downswing), (ii) differences between large and small firms[37], and (iii) differences between geographical areas (urban vs. rural). In doing so we interact each time-varying firm-level covariate with the respective dummy (either D_{it}^{up}, D_{it}^{large}, or D_{it}^{urban}). Tables C1 to C3 in the Annex provide detailed results.

With respect to the **business cycle phases** we obtain statistically significant marginal effects on the interaction term ($D_{it}^{up} \times \Psi_{\mathrm{it}}$) for production and selling price expectations as well as for capacity utilisation. For example, in upswings of the business cycle firms are more optimistic in terms of their production expectations for the coming months. The probability of an increase in their output level is 3% higher as compared to downturns in the business cycle. Similar results with respect to production expectations are derived for differences between **large and small firms** ($D_{it}^{large} \times \Psi_{\mathrm{it}}$). For large firms expecting an increase in their production level in the coming months, the probability that the increase in the production output will materialise is 7% higher compared to small firms. Moreover, large firms tend to be more negatively affected by demand shocks (mpe is minus 3%) and exhibit a lower probability (mpe is minus 5%) of raising their selling prices in phases where the firm increases its production output ($y_{it} = 1$).

[37] We classify an observation as 'large' firm if the stated number of employees in the respective question is greater or equal to 100. According to our chosen threshold, about 47% of the observations represent large firms.

Using the regional classification of **urban vs. rural** for analysing differences in the business cycle dynamics, we find no clear indication of statistical significant marginal effects on the interaction terms ($D_{it}^{urban} \times \Psi_{\mathrm{it}}$). This confirms our results for the regional controls, ϑ_r, in the full model specification, where these controls have all been found to be not statistically significant. This leads us to conclude that the regional dimension does not help in explaining differences in business cycle dynamics across firms in Austria.

5. Conclusions

In macroeconomics the business cycle is usually analysed from an 'aggregated' point of view, either using broad measures of economic activity obtained from official statistics or utilising timely available qualitative data from business tendency surveys (or a combination of both) at a fairly aggregated level. The latter are typically used as 'balance statistics', reflecting cross-sectional averages of economic agents' judgement of their current business conditions and their expectations. The set of survey questions asked aims to cover a broad range of economic activities and expectations at the firm level that are related to the actual (production) activity of the firm. Thus business tendency survey data contains also firm-specific information that is usually ignored in business cycle research. Aggregating survey responses to balances leads to robust aggregate indicators but masks potentially aspects of individual firm behaviour, which may help to understand better the behaviour of aggregate indicators. The research presented in this paper is a first step into this direction. We used business tendency survey micro data to study the (macro) consistency of firm-level answers with regard to current assessments and expectations as well as the impact of structural characteristics and persistent firm heterogeneity on the answering patterns. As dependent variable we used the assessment of the change in production during the past three months, a variable that is very closely correlated to indicators of industrial production or value added and, thus, of special interest in business cycle analysis for forecasting.

Our results show that the answers by firms to different questions within the business tendency survey are largely consistent at the microeconomic level. This is especially visible for the assessment for order book levels, their current degree of capacity utilisation and their production expectations. Strict ccontemporaneous consistency has been verified for the stock of finished products, capacity utilisation and assessments of limiting factors of production (as well as for current order book levels, a result not reported here). Even more important for business cycle research is our result of temporal consistency covering successive (quarterly) waves of the survey, as this provides evidence for the usefulness of asking for short-term expectations. Order books as well as production expectations measured one quarter ahead show a very high association with the current assessment of production changes and provide explanatory power. This result strongly suggests that part of business cycle developments unfolds over time. Looking at these results over time also allows differentiating between unexpected and expected business cycle movements. The findings show that during the immediate years of the financial crisis in 2008/09 firm-level heterogeneity did not add much to the explanation of the business cycle shock, suggesting that this crisis was largely unexpected by Austrian manufacturing firms. But overall our econometric results show that firm-level covariates have explanatory power to help to predict changes in firms' production output. Heterogeneity across firms plays an important role and both short-run and long-run effects can be identified in the data. However, in contrast to the firm-level assessments and expectations, structural characteristics related to the firm (firm size), the industry the firm is operating in or the region it is located do not play a crucial role in shaping the answers. These variables do not affect our results, although we can observe important differences between small and large firms that industry-specifics affects the behaviour of firms. With respect to persistent firm-level differences we find that firms which exhibit a long-run above average to the questions regarding order book levels, the stock of finished products and to a lesser extend also to employment expectations have in general also a higher probability to assess the change in production levels above average. These results confirm that the findings on persistent heterogeneity in the microeconomic literature on productivity (e.g. Syverson, 2011) carry also over to business tendency surveys. Thus our analysis of business cycle dynamics from a 'micro' perspective not only provides explanatory power in the short-run but also looked in the long-run.

Overall, our findings show that using business tendency survey micro data, in particular the information set reflecting business cycle conditions (current and expectations), allows to study overall business cycle dynamics in a consistent way and that the answers to business tendency surveys – also at the firm-level – capture primarily the business cycle phenomenon and are not driven primarily by structural characteristics. At the same time we observe important firm-level heterogeneity. Taking firm-level heterogeneity into account could be fruitful for forecasting, as it could be one avenue to get clearer grip on the 'balanced' results of business tendency surveys. Moreover, further research is needed to provide tools for business cycle analysis whether there is the possibility to construct indices on subsets of firms reflecting (observable) heterogeneity at the firm-, industry- and regional-level.

References

Afonso, A. and Furceri, D. (2007): Sectoral Business Cycle Synchronization in the European Union, *ISEG-UTL Economics Working Paper*, No. 02.

Ahmed, S., Levin, A.T. and Wilson, B.A. (2004): ‘Recent U.S. Macroeconomic Stability: Good Policy, Good Practices, or Good Luck?’, *Review of Economics and Statistics*, Vol. 86, pp. 824–32.

Aldrich, J.H. and Nelson, F.D. (1984): Linear Probability, Logit, and probit Models, Sage University Press, Beverly Hills.

Anas, J., Billio, M., Ferrara, L. and Mazzi, G.L. (2008): ‘A System for Dating and Detecting Turning Points in the Euro Area’, *The Manchester School*, Vol. 76, pp. 549–577.

Anderson, O. (1951): ‘Konjunkturtest und Statistik. Möglichkeiten und Grenzen einer Quantifizierung von Testergebnissen’, *Allgemeines Statistisches Archiv*, Vol. 35, pp. 209-220.

Artis, M. J., Krolzig, H.-M. and Toro, J. (2004a): ‘The European business cycle, Oxford Economic Papers’, *Oxford University Press*, Vol. 56(1), pp. 1-44.

Artis, M.J., Marcellino, M. and Proietti, T. (2004b): Characterizing the Business Cycle for Accession Countries, *CEPR Discussion Papers*, No. 4457.

Asako, K., Ando, K. and Matsumoto, K. (2007): ‘Firms’ Perceptions of the Business Cycle and Their Managerial and Financial Conditions’, *Public Policy Review*, Vol. 3(1), pp. 1–26.

Bachmann, R., Elstner St. and Sims, E.R. (2012): ‘Uncertainty and Economic Activity: Evidence from Business Survey Data’, *American Economic Journal, Macroeconomics*, Vol. 5(2), pp. 217-49.

Barrios, S., Brülhart, M., Elliott, R.J.R. and Sensier, M. (2003): ‘A Tale of Two Cycles: Co-Fluctuations Between UK Regions and the Euro Zone’, *The Manchester School*, Vol. 71(3), pp. 265-292.

Basile, R., de Nardis, S. and Pappalardo, C. (2014): ‘Firm heterogeneity and regional business cycle differentials’, *Journal of Economic Geography*, Vol. 14(6), pp. 1087–1115.

Baxter, M. and King, R.G. (1999): ‘Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series’, *Review of Economics and Statistics*, MIT Press, Vol. 81(4), pp. 575-593.

Belke, A. and Heine, J.M. (2006): ‘Specialisation patterns and the synchronicity of regional employment cycles in Europe’, *International Economics and Economic Policy*, Vol. 3(2), pp. 91-104.

Bertschek, I. and Lechner, M. (1998): ‘Convenient Estimators for the Panel Probit Model’, *Journal of Econometrics*, Vol. 87(2), pp. 329-372.

Bierbaumer-Polly, J. (2010): Composite Leading Indicator for the Austrian Economy: Methodology and ‘Real-time’ Performance, *WIFO-Working Papers*, No. 369.

Bierbaumer-Polly, J. (2012): ‘Regionale Konjunkturzyklen in Österreich’, *WIFO-Monatsberichte*, Vol. 85(11), pp. 833-848.

Bierbaumer-Polly, J. and Mayerhofer, P. (2013): Wiens Konjunkturentwicklung im nationalen, intra- und interregionalen Vergleich: Charakteristika, Besonderheiten, Einflussfaktoren, WIFO.

Bloom, N. (2009): ‘The Impact of Uncertainty Shocks’, *Econometrica*, Vol. 77(3), pp. 623-685.

Boes, S. (2007): Three Essays on the Econometric Analysis of Discrete Dependent Variables, Universität Zürich, Zürich.

Boes, S. and Winkelmann, R. (2006): ‘Ordered Response Models’, *Allgemeines Statistisches Archiv*, Vol. 90, pp. 167-181.

Breuss, F. (1984): ‘Konjunkturindikatoren für die österreichische Wirtschaft’, *WIFO-Monatsberichte*, Vol. 57(8), pp. 464-492.

Bry, G. and Boschan, Ch. (1971): ‘Cyclical Analysis of Economic Time Series: Selected Procedures and Computer Programs Ch., in: National Bureau of Economic Research, Cyclical Analysis of Time Series: Selected Procedures and Computer Programs, pp. 64-150.

Butler, J.S. and Moffitt, R. (1982): ‘A computationally efficient quadrature procedure for the one-factor multinomial probit model’, *Econometrica*, Vol. 50, pp. 761-764.

Caballero, R.J. and Engel, E.M. (2003): Adjustment is much slower than you think, *Cowles Foundation*, Discussion Paper, No. 1430.

Carlson, J. and Parkin, M. (1975): ‘Inflation Expectations’, *Economics*, Vol. 42, pp. 123-138.

Carreira, C. and Silva, F. (2010): ‘No Deep Pockets: Some stylized results on firms' financial constraints’, *Journal of Economic Surveys*, Vol. 24, pp. 731-753.

Cesaroni, T. (2011): ‘The cyclical behavior of the Italian business survey data’, *Empirical Economics*, Vol. 41, pp. 747–768.

Chamberlain, G. (1982): ‘Multivariate regression models for panel data’, *Journal of Econometrics*, Vol. 18, pp. 5-46.

Christiano, L.J., Eichenbaum, M. and Evans, C.L. (2005): ‘Nominal rigidities and the dynamic effect of a shock to monetary policy’, *Journal of Political Economy*, Vol. 113(1), pp. 1-45.

Clark, T. and van Wincoop, E. (2001): ‘Borders and business cycles’, *Journal of International Economics*, Vol. 55(1), pp. 59-85.

Clark, T.E. and Shin, K. (1998): The Sources of Fluctuations Within and Across Countries, *FRB Kansas City Research*, Working Paper, No. 98-04.

Clements, M.P. and Krolzig, H.-M. (2003): ‘Business Cycle Asymmetries’, *Journal of Business and Economic Statistics*, Vol. 21(1), pp. 196-211.

Clower, R.W. (1998): ‘Three Centuries of Demand and Supply’, *Journal of the History of Economic Thought*, Vol. 20(4), pp. 397-410.

Coakley, J. and Fuertes, A.-M. (2006): ‘Testing for sign and amplitude asymmetries using threshold autoregressions’, *Journal of Economic Dynamics and Control*, Vol. 30(4), pp. 623-654.

Cunningham, A., Smith, R.J. and Weale, M. R. (1998): ‘Measurement Errors and Data Estimation: the Quantification of Survey Data’, in: Begg, I.G. and Henry, S.G.B. (eds.), Applied Economics and Public Policy, CUP.

Dedola, L. and Lippi, F. (2005): ‘The monetary transmission mechanism: evidence from the industries of 5 OECD countries’, *European Economic Review*, Vol. 49, pp. 1543–1569.

Ehrmann, M. (2005): ‘Firm Size and Monetary Policy Transmission - Evidence from German Business Survey Data’, in: Ifo Survey Data in Business Cycle and Monetary Policy Analysis, pp. 145-172.

Erkel-Rousse, H. and Minodier, D. (2009): Do business tendency surveys in industry and services help in forecasting GDP growth? A real-time analysis on French data, Documents de Travail de la DESE-Working Papers of the DESE, INSEE.

Fatás, A. (1997): ‘EMU: Countries or regions? Lessons from the EMS Experience’, *European Economic Review*, Vol. 41, pp. 743-751.

Forni, M. and Reichlin, L. (1997): National Policies and Local Economies: Europe and the United States, *CEPR Discussion Papers*, No. 1632.

Frenken, K., van Oort, F. and Verburg, T. (2007): ‘Related Variety, Unrelated Variety and Regional Economic Growth’, *Regional studies*, Vol. 41(5), pp. 685-697.

Gadea, M.D., Gomez-Loscos, A. and Montañes, A. (2011): Cycles inside cycles: Spanish regional aggregation, *WIFO-Working Papers*, No. 390.

Geil, P. and Zimmermann, K. (1996): ‘Quantifizierung qualitativer Daten’, in: Oppenländer, K.H. (Hrsg.), Konjunkturindikatoren: Fakten, Analysen, Verwendung, Oldenbourg, München, pp. 108-130.

Gertler, M. and Gilchrist, S. (1994): ‘Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms’, *The Quarterly Journal of Economics*, Vol. 109(2), pp. 309-340.

Graff, M. and Etter, R. (2004): ‘Coincident and leading indicators of manufacturing industry: Sales, production, orders and inventories in Switzerland’, *Journal of Business Cycle Measurement and Analysis*, Vol. 1(1), pp. 109-131.

Greene, W. (2004): ‘Convenient estimators for the panel probit model: Further results’, *Empirical Economics*, Springer, Vol. 29(1), pp. 21-47.

Hahn, F. and Walterskirchen, E. (1992): Stylized Facts der Konjunkturschwankungen in Österreich, Deutschland und den USA, *WIFO-Working Papers*, No. 58.

Harrison, R., Jaumandreu, J., Mairesse, J. and Peters, B. (2014): ‘Does Innovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro-Data from Four European Countries’, *International Journal of Industrial Organization*, Vol. 35, pp. 29-43.

Henzel, S. and Wollmershäuser, T. (2005): ‘Quantifying Inflation Expectations with the Carlson-Parkin Method: A Survey-based Determination of the Just Noticeable Difference’, *Journal of Business Cycle Measurement and Analysis*, Vol. 2, pp. 321-352.

Higson, C., Holly, S. and Kattuman, P. (2002): ‘The cross-sectional dynamics of the US business cycle: 1950–1999’, *Journal of Economic Dynamics and Control*, Vol. 26(9), pp. 1539-1555.

Holly, S. and Petrella, I. (2008): Factor demand linkages and the business cycle: interpreting aggregate fluctuations as sectoral fluctuations, Cambridge Working Papers in Economics.

Hölzl, W. (2013): ‘Persistence, survival, and growth: a closer look at 20 years of fast-growing firms in Austria’, *Industrial and Corporate Change*, Vol. 23(1), pp. 199-231.

Hölzl, W. and Schwarz, G. (2014): ‘Der WIFO-Konjunkturtest - Methodik und Prognoseeigenschaften’, *WIFO-Monatsberichte*, Vol. 87(12), pp. 835-850.

Kaiser, U. and Spitz, A. (2000): Quantification of Qualitative Data Using Ordered Probit Models with an Application to a Business Survey in the German Service Sector, *ZEW Discussion Paper*, No. 00-58.

Knetsch, Th. (2005): ‘Evaluating the German Inventory Cycle Using Data from the Ifo Business Survey’, in: Ifo Survey Data in Business Cycle and Monetary Policy Analysis, pp. 61-92.

Kydland, F.E. and Prescott, E.C. (1982): ‘Time to build and aggregate fluctuations’, *Econometrica: Journal of the Econometric Society*, Vol. 50(6), pp. 1345-1370.

Long, J.S. (1997): Regression Models for Categorical and Limited Dependent Variables, Advanced Quantitative Techniques in the Social Sciences Number 7, Sage Publications: Thousand Oaks, CA.

Lucas, R.E. (1976): ‘Econometric policy evaluation: A critique’, *Carnegie-Rochester Conference Series on Public Policy*, Vol. (1), pp. 19-46.

Maddala, G.S. (1983): Limited-Dependent and Qualitative Variables in Econometrics, Cambridge, MA: Cambridge University Press.

McCarthy, J. and Zakrajsek, E. (2007): ‘Inventory Dynamics and Business Cycles: What Has Changed?’, *Journal of Money, Credit and Banking*, Vol. 39(2–3), pp. 591–613.

McFadden, D. (1973): ‘Conditional Logit Analysis of Qualitative Choice Behavior’, in: Zarembka, P. (ed.), Frontiers in Econometrics, Academic Press, New York, pp.105-142.

Mitchell, J., Smith, R.J. and Weale, M.R. (2004): The Impact of Survey Aggregation Methods on the Quality of Business Survey Indicators, Report to the European Commission, ECFIN/2003/A3-04, 78 pages.

Müller, C. and Köberl, E. (2007): The speed of adjustment to demand shocks: A Markov-chain measurement using micro panel data, *KOF Swiss Economic Institute at the Swiss Federal Institute of Technology Zurich*, Working Paper, No. 170.

Müller, C. and Köberl, E. (2008): Business cycle measurement with semantic filtering: A micro data approach, *KOF Swiss Economic Institute at the Swiss Federal Institute of Technology Zurich*, Working Paper, No. 212.

Müller, Ch. and Köberl, E. (2015): 'Business cycle dynamics: A bottom-up approach with Markov-chain measurement', *OECD Journal: Journal of Business Cycle Measurement and Analysis*, Vol. (1).

Mundlak, Y. (1978): 'On the Pooling of Time Series and Cross Section Data', *Econometrica*, Vol. 46(1), pp. 69-85.

Nardo, M. (2003): 'The quantification of qualitative survey data: A critical assessment', *Journal of Economic Surveys*, Vol. 17, pp. 645-668.

Nerlove, M. (1983): 'Expectations, Plans, and Realizations in Theory and Practice. Econometrica', Vol. 51(5), pp. 1251–1279.

Nieuwstad, C.H. (2005): A comparison on the company level of Manufacturing Business Sentiment Survey data and Realized Turnover, *Statistics Netherland*, Discussion Paper, No. 05007.

Norman, D. and Walker, T. (2007): 'Co-Movement of Australian State Business Cycles', *Australian Economic Papers*, Vol. 46(4), pp. 360-374.

Oi, W.Y. (1962): 'Labour as a Quasi-Fixed Factor of Production', *Journal of Political Economy*, Vol. 70, pp. 538-555.

Oppenländer, K.H. (1996): 'Eigenschaften und Einteilung von Konjunkturindikatoren', in: Oppenländer, K.H. (Hrsg.), Konjunkturindikatoren: Fakten, Analysen, Verwendung, Oldenbourg, München, pp. 23-30.

Park, Y. and Hewings, G.J.D. (2003): Does Industry Mix Matter in Regional Business Cycles?, *REAL Discussion Papers*, No. 03-T-29.

Perez-Quiros, G. and Timmermann, A. (2000): 'Firm Size and Cyclical Variations in Stock Returns', *The Journal of Finance*, Vol. 55, pp. 1229-1262.

Pesaran, M.H. (1984): 'Expectations Formation in Macroeconometric Modelling', in: Malgrange, P. and Muet P.-A. (eds.), Contemporary Macroeconomic Modelling, Basil Blackwell, Oxford.

Peters, B., Dachs, B., Dünser, M., Hud, M., Köhler, C. and Rammer, C. (2014): Firm Growth, Innovation and the Business Cycle. Background Report for the 2014 Competitiveness Report, European Commission, Enterprise and Industry Directorate-General, Mannheim.

Pfarr, Ch., Schmid, A. and Schneider, U. (2011): 'Estimating Ordered Categorical Variables Using Panel Data: a Generalized Ordered Probit Model with an Autofit Procedure', *Journal of Economics and Econometrics*, Vol. 54(1), pp. 7-23.

Reis, H. (2005): Business Cycle at a sectoral level: the Portuguese case, *Banco de Portugal*, Economic Research Department, Working Paper, No. 9-05.

Scheiblecker, M. (2007): 'Dating of Business Cycles in Austria', *WIFO-Monatsberichte*, Vol. 80(9), pp. 715-730.

Smets, F. and Wouters, R. (2003): 'An estimated dynamic stochastic general equilibrium model of the Euro area', *Journal of the European Economic Association*, Vol. (1), pp. 1123-1175.

Syverson, Ch. (2011): 'What determines productivity? ', *Journal of Economic Literature*, Vol. 49(2), pp. 326-365.

Vermeulen, O. (2014): 'An evaluation of business survey indices for short-term forecasting: Balance method versus Carlson-Parkin method', *International Journal of Forecasting*, Vol. 30, pp. 882-897.

Wooldridge, J.M. (2002): Econometric Analysis of Cross Section and Panel Data, The MIT Press, Cambridge, Massachusetts.

Chapter II

Appendix

Table A1: Questionnaire of the monthly WIFO KT (manufacturing sector)

Question [1]	**Interval** [2]	**Categories** [3]
According to harmonised questionnaire		
Production, past 3 months	monthly	+ / = / -
Production, next 3 months	monthly	+ / = / -
Total order books, current	monthly	> / = / <
Export order books, current	monthly	> / = / <
Stocks of finished products	monthly	> / = / <
Selling prices, next 3 months	monthly	+ / = / -
Firm's employment, next months	monthly	+ / = / -
Factors limiting productions	quarterly	4)
Production capacity, current	quarterly	> / = / <
Months of production secured	quarterly	5)
Order books, past 3 months	quarterly	+ / = / -
Export order books, next 3 months	quarterly	+ / = / -
Capacity utilisation	quarterly	6)
Competitive position, domestic market	quarterly	+ / = / -
Competitive position, EU markets	quarterly	+ / = / -
Competitive position, extra-EU markets	quarterly	+ / = / -
Supplementary questions by WIFO		
Selling prices, past 3 months	quarterly	+ / = / -
Firm's business sentiment, current	quarterly	> / = / <
Firm's business sentiment, next 6 months	quarterly	> / = / <
Firm's assessment of their business conditions, coming months	quarterly	7)
Overall economic sentiment, current	quarterly	> / = / <
Overall economic sentiment, next 6 months	quarterly	> / = / <
Firm's total employment	quarterly	8)

Source: based on DG-ECFIN (2007) and WIFO BTS questionnaire.
Notes: 1) Firms are asked in their response to abstract from seasonal variations. 2) Quarterly questions are contained in the January, April, July and October survey. 3) "+ / = / -" relate to change: increased, remain unchanged, decreased; "> / = / <" relate to level: above normal, normal, below normal. 4) Respondents are requested to select one out of the following factors: none, insufficient demand, shortage of labour force, shortage of material and/or equipment, financial constraints, or other factors. 5) Quantitative question in number of months. 6) Quantitative question in percentage of full capacity; ranging from 30 up to 100 per-cent, on a 10 per-cent scale. 7) Categories: reasonable assessable, hardly assessable, to some degree uncertain, or uncertain as never before. 8) Quantitative question in number of employees.

Table A2: Descriptive statistics – Industry dimension (NACE-2-digit breakdown)

Section	Description	MIG-classification [2)]	No. of obs. freq.	%		Covariates / controls [3)] excess labour turnover	employment growth in % (avg. 96-12)	median no. of employees (avg. 96-12)
10	Manufacture of food products	intermediate / consumer	3,418	6.2		0.0734	-0.3	5.2
11	Manufacture of beverages	consumer	1,576	2.9		0.0532	-1.2	3.9
12	Manufacture of tobacco products [1)]	consumer	-	-				
13	Manufacture of textiles	intermediate / consumer	2,352	4.3		0.0553	-4.0	3.1
14	Manufacture of wearing apparel	consumer	1,269	2.3		0.0488	-6.2	2.0
15	Manufacture of leather and related products	consumer	694	1.3		0.0587	-2.1	2.5
16	Manufacture of wood and of products of wood/cork, except furniture; manuf. of articles of straw / plaiting materials	intermediate	4,738	8.6		0.0719	-0.2	3.9
17	Manufacture of paper and paper products	intermediate	2,645	4.8		0.0374	-0.7	9.6
18	Printing and reproduction of recorded media	consumer	1,466	2.7		0.0678	-2.3	5.1
19	Manufacture of coke and refined petroleum products [1)]	-	-	-				
20	Manufacture of chemicals and chemical products	intermediate	2,714	4.9		0.0480	-0.3	4.6
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	consumer	644	1.2		0.0333	2.9	4.1
22	Manufacture of rubber and plastic products	intermediate	3,304	6.0		0.0556	0.8	8.1
23	Manufacture of other non-metallic mineral products	intermediate	3,982	7.2		0.0616	0.1	4.1
24	Manufacture of basic metals	intermediate	3,099	5.6		0.0362	0.1	22.0
25	Manufacture of fabricated metal products, except machinery and equipment	intermediate / capital	6,614	12.0		0.0682	1.2	4.9
26	Manufacture of computer, electronic and optical products	intermediate / capital / consumer	1,702	3.1		0.0694	-0.5	4.5
27	Manufacture of electrical equipment	intermediate	2,705	4.9		0.0602	0.8	6.8
28	Manufacture of machinery and equipment n.e.c.	capital	6,687	12.1		0.0511	1.7	7.1
29	Manufacture of motor vehicles, trailers and semi-trailers	capital	1,206	2.2		0.0480	0.9	8.1
30	Manufacture of other transport equipment	capital / consumer	296	0.5		0.0318	0.6	6.7
31	Manufacture of furniture	consumer	2,371	4.3		0.0728	-2.3	4.1
32	Other manufacturing	capital / consumer	1,350	2.4		0.0720	-1.5	3.0
33	Repair and installation of machinery and equipment	capital	418	0.8		0.0674	6.6	3.6
		Total	55,250	100.0	*Min*	0.0318	-6.2	2.0
					Max	0.0734	6.6	22.0
					Mean	0.0565	-0.3	5.8
					SD	0.0134	2.5	4.1

Source: Own calculations.
Notes: 1) Section 12 and 19 have been omitted in the analysis due to missing firms allocated to that section. 2) MIG-classification based on NACE-3-digit breakdown. 3) See Section 2 for detailed data description.

Table A3: Descriptive statistics – Regional dimension (NUTS-3 breakdown)

Code	Regionname	Province	Urban/Rural [1)]	No. of obs.			Covariates / controls [2)]				
							specialisation		employment concentration		local externalities
				freq.	%		manuf.	all industries	manuf.	all industries	
AT111	Mittelburgenland	Burgenland	rural	272	0.5		1.046	1.337	0.109	0.026	2.736
AT112	Nordburgenland	Burgenland	rural	828	1.5		1.543	1.771	0.034	0.020	2.786
AT113	Südburgenland	Burgenland	rural	504	0.9		1.025	1.517	0.060	0.019	1.832
AT121	Mostviertel-Eisenwurzen	Lower Austria	rural	1,920	3.5		1.820	1.882	0.033	0.014	1.413
AT122	Niederösterreich-Süd	Lower Austria	urban	2,687	4.9		2.050	1.864	0.022	0.014	1.207
AT123	Sankt Pölten	Lower Austria	rural	1,298	2.4		1.699	1.624	0.034	0.058	2.234
AT124	Waldviertel	Lower Austria	rural	1,642	3.0		1.486	1.627	0.049	0.016	1.802
AT125	Weinviertel	Lower Austria	rural	375	0.7		1.401	1.525	0.061	0.028	0.474
AT126	Wiener Umland/Nordteil	Lower Austria	urban	1,409	2.6		1.922	2.004	0.033	0.014	-0.087
AT127	Wiener Umland/Südteil	Lower Austria	urban	2,481	4.5		1.830	1.895	0.027	0.014	8.622
AT130	Wien	Vienna	urban	5,987	10.8		1.834	1.769	0.032	0.022	-37.339
AT211	Klagenfurt-Villach	Carinthia	urban	1,976	3.6		1.677	1.808	0.040	0.027	-3.420
AT212	Oberkärnten	Carinthia	rural	870	1.6		1.235	1.357	0.062	0.028	0.458
AT213	Unterkärnten	Carinthia	rural	1,710	3.1		1.645	1.654	0.037	0.015	2.306
AT221	Graz	Styria	urban	1,792	3.2		1.243	1.457	0.085	0.037	1.682
AT222	Liezen	Styria	rural	584	1.1		1.113	1.213	0.080	0.031	-0.263
AT223	Östliche Obersteiermark	Styria	urban	1,306	2.4		1.493	1.441	0.077	0.027	2.472
AT224	Oststeiermark	Styria	rural	1,371	2.5		1.496	1.463	0.046	0.023	2.731
AT225	West- und Südsteiermark	Styria	rural	1,208	2.2		1.434	1.582	0.047	0.018	-1.526
AT226	Westliche Obersteiermark	Styria	rural	1,096	2.0		1.284	1.334	0.046	0.020	2.888
AT311	Innviertel	Upper Austria	rural	2,950	5.3		1.734	1.704	0.031	0.014	1.089
AT312	Linz-Wels	Upper Austria	urban	4,751	8.6		1.921	1.744	0.032	0.022	11.821
AT313	Mühlviertel	Upper Austria	rural	964	1.7		1.270	1.385	0.067	0.023	1.132
AT314	Steyr-Kirchdorf	Upper Austria	rural	1,390	2.5		1.389	1.517	0.097	0.029	7.747
AT315	Traunviertel	Upper Austria	urban	2,716	4.9		1.666	1.674	0.034	0.015	-2.349
AT321	Lungau	Salzburg	rural	196	0.4		0.597	1.003	0.096	0.047	-0.257
AT322	Pinzgau-Pongau	Salzburg	rural	987	1.8		1.114	1.201	0.047	0.060	-0.754
AT323	Salzburg und Umgebung	Salzburg	urban	2,320	4.2		1.839	1.945	0.025	0.016	3.164
AT331	Außerfern	Tyrol	rural	215	0.4		0.263	0.662	0.220	0.068	1.889
AT332	Innsbruck	Tyrol	urban	1,273	2.3		1.336	1.615	0.089	0.026	-0.154
AT333	Osttirol	Tyrol	rural	192	0.4		0.742	1.103	0.230	0.047	1.267
AT334	Tiroler Oberland	Tyrol	rural	277	0.5		0.988	1.015	0.077	0.082	-0.074
AT335	Tiroler Unterland	Tyrol	rural	1,782	3.2		1.471	1.355	0.050	0.039	3.647
AT341	Bludenz-Bregenzer Wald	Vorarlberg	rural	895	1.6		1.192	1.035	0.078	0.054	-0.128
AT342	Rheintal-Bodenseegebiet	Vorarlberg	urban	3,026	5.5		1.867	1.607	0.041	0.025	14.179
			Total	55,250	100.0	*Min*	0.263	0.662	0.022	0.014	-37.339
						Max	2.050	2.004	0.230	0.082	14.179
						Mean	1.419	1.505	0.064	0.030	1.006
						SD	0.401	0.306	0.047	0.017	7.565

Source: Own calculations.

Notes: 1) Urban/rural-classification based on a typology set out by Eurostat. 2) See Section 2 for detailed data description.

Table B1: Marginal probability effects: full 'firm-level' model (Order book level not lagged!)

Covariates / controls	y=1		y=2		y=3	
	MPE	SE	MPE	SE	MPE	SE
Business cycle dimension						
Firm-level (Current)						
Order books.>	0.5607***	(0.009762)	-0.1939***	(0.010081)	-0.3668***	(0.009719)
Order books.=	0.1264***	(0.003248)	0.1636***	(0.009877)	-0.2901***	(0.009840)
Order books.> [bar]	0.2114***	(0.029017)	-0.1040***	(0.014545)	-0.1074***	(0.015126)
Order books.= [bar]	0.0836***	(0.022096)	-0.0411***	(0.010886)	-0.0425***	(0.011345)
Limit.Factor: Insufficient demand	-0.0806***	(0.006021)	0.0397***	(0.003240)	0.0410***	(0.003227)
Limit.Factor: Insufficient demand [bar]	-0.0152	(0.017006)	0.0075	(0.008362)	0.0077	(0.008650)
Stock finished products.>	-0.0385***	(0.011737)	0.0189***	(0.006358)	0.0196***	(0.005519)
Stock finished products.=	-0.0165	(0.010283)	0.0090	(0.005918)	0.0075*	(0.004375)
Stock finished products.> [bar]	0.0503*	(0.029451)	-0.0248*	(0.014502)	-0.0256*	(0.014986)
Stock finished products.= [bar]	0.0298	(0.027592)	-0.0146	(0.013575)	-0.0151	(0.014031)
Selling prices.+	0.0460***	(0.008227)	-0.0214***	(0.004092)	-0.0246***	(0.004375)
Selling prices.=	0.0307***	(0.005372)	-0.0131***	(0.002053)	-0.0176***	(0.003427)
Selling prices.+ [bar]	0.0167	(0.032841)	-0.0082	(0.016195)	-0.0085	(0.016649)
Selling prices.= [bar]	-0.0028	(0.020482)	0.0014	(0.010072)	0.0014	(0.010410)
Capacity utilisation	0.0067***	(0.000272)	-0.0033***	(0.000176)	-0.0034***	(0.000160)
Capacity utilisation [bar]	-0.0048***	(0.000393)	0.0023***	(0.000218)	0.0024***	(0.000198)
Firm-level (Expectations)						
t-1.Production expectations.+	0.1657***	(0.008314)	-0.0741***	(0.005009)	-0.0916***	(0.006133)
t-1.Production expectations.=	0.0689***	(0.004795)	-0.0122***	(0.001872)	-0.0567***	(0.005437)
t-1.Production expectations.+ [bar]	0.0651**	(0.030341)	-0.0320**	(0.014980)	-0.0331**	(0.015421)
t-1.Production expectations.= [bar]	-0.0229	(0.023221)	0.0112	(0.011423)	0.0116	(0.011807)
t-1.Selling price expectations.+	-0.0135	(0.008435)	0.0069	(0.004338)	0.0066	(0.004118)
t-1.Selling price expectations.=	-0.0116*	(0.006645)	0.0060*	(0.003556)	0.0056*	(0.003097)
t-1.Selling price expectations.+ [bar]	-0.0359	(0.033222)	0.0177	(0.016416)	0.0182	(0.016822)
t-1.Selling price expectations.= [bar]	-0.0225	(0.026860)	0.0111	(0.013247)	0.0114	(0.013622)
t-1.Employment expectations.+	0.0861***	(0.009063)	-0.0460***	(0.005536)	-0.0401***	(0.004137)
t-1.Employment expectations.=	0.0295***	(0.005043)	-0.0119***	(0.001808)	-0.0176***	(0.003347)
t-1.Employment expectations.+ [bar]	0.0063	(0.026654)	-0.0031	(0.013118)	-0.0032	(0.013536)
t-1.Employment expectations.= [bar]	0.0198	(0.017561)	-0.0097	(0.008665)	-0.0101	(0.008906)
t-1.Business sentiment.>	-0.0132*	(0.007834)	0.0064*	(0.003756)	0.0068*	(0.004098)
t-1.Business sentiment.=	-0.0042	(0.005527)	0.0021	(0.002826)	0.0021	(0.002702)
t-1.Business sentiment.> [bar]	-0.0277	(0.026616)	0.0136	(0.013109)	0.0141	(0.013519)
t-1.Business sentiment.= [bar]	-0.0189	(0.019873)	0.0093	(0.009783)	0.0096	(0.010098)
Structural dimension						
Firm-level						
Firm size	-0.0171**	(0.008406)	0.0084**	(0.004159)	0.0087**	(0.004262)
Firm size^2						
Firm size [bar]	0.0184**	(0.008728)	-0.0090**	(0.004328)	-0.0093**	(0.004416)
Firm size^2 [bar]						
N	44,683					
Pseudo R^2	0.349					
cut1	-3.9626***	(0.174704)				
cut2	-1.4933***	(0.171215)				

Source: Own calculations.

Notes: *** indicates statistically significance at 1%, ** indicates statistically significance at 5%; * indicates statistically significance at 10% level. MPE referts to the marginal probability effect. SD (in parentheses) represents clustered standard errors. Cut1 and cut2 are the estimated thresholds marking the delimination between the different answer categories in our 3-point categorial outcome variable. The MPE of the variables with a [bar] denote 'level' effects. Time-dummies as well as the industry-dummies have been omitted in the output table.

Table C1: Marginal probability effects on the interaction-term: up vs. down business cycle phase

Covariates / controls	y=1		y=2		y=3	
	MPE	SE	MPE	SE	MPE	SE
Business cycle dimension						
Firm-level (Current)						
UP * t-1.Order books.>	0.0032	(0.011354)	-0.0012	(0.004233)	-0.0020	(0.007121)
UP * t-1.Order books.=	0.0141	(0.009775)	-0.0052	(0.003648)	-0.0088	(0.006131)
UP * t-1.Order books.> [bar]	-0.0085	(0.036812)	0.0032	(0.013724)	0.0053	(0.023088)
UP * t-1.Order books.= [bar]	-0.0986***	(0.030470)	0.0368***	(0.011411)	0.0618***	(0.019124)
UP * Limit.Factor: Insufficient demand	0.0075	(0.010275)	-0.0028	(0.003831)	-0.0047	(0.006445)
UP * Limit.Factor: Insufficient demand [bar]	-0.0049	(0.027129)	0.0018	(0.010114)	0.0031	(0.017015)
UP * Stock finished products.>	-0.0065	(0.019192)	0.0024	(0.007156)	0.0041	(0.012037)
UP * Stock finished products.=	0.0040	(0.017011)	-0.0015	(0.006342)	-0.0025	(0.010669)
UP * Stock finished products.> [bar]	0.0151	(0.042466)	-0.0056	(0.015833)	-0.0095	(0.026634)
UP * Stock finished products.= [bar]	0.0020	(0.039583)	-0.0007	(0.014757)	-0.0012	(0.024826)
UP * Selling prices.+	0.0104	(0.014968)	-0.0039	(0.005582)	-0.0065	(0.009387)
UP * Selling prices.=	0.0222**	(0.010778)	-0.0083**	(0.004027)	-0.0139**	(0.006761)
UP * Selling prices.+ [bar]	-0.0387	(0.048697)	0.0144	(0.018161)	0.0243	(0.030542)
UP * Selling prices.= [bar]	-0.0125	(0.031452)	0.0047	(0.011727)	0.0078	(0.019726)
UP * Capacity utilisation	-0.0012***	(0.000368)	0.0005***	(0.000138)	0.0008***	(0.000231)
UP * Capacity utilisation [bar]	0.0019***	(0.000534)	-0.0007***	(0.000200)	-0.0012***	(0.000335)
Firm-level (Expectations)						
UP * t-1.Production expectations.+	0.0322**	(0.014819)	-0.0120**	(0.005539)	-0.0202**	(0.009295)
UP * t-1.Production expectations.=	0.0284**	(0.012308)	-0.0106**	(0.004601)	-0.0178**	(0.007720)
UP * t-1.Production expectations.+ [bar]	-0.0189	(0.045868)	0.0070	(0.017102)	0.0118	(0.028768)
UP * t-1.Production expectations.= [bar]	0.0504	(0.037958)	-0.0188	(0.014162)	-0.0316	(0.023809)
UP * t-1.Selling price expectations.+	-0.0349**	(0.016547)	0.0130**	(0.006181)	0.0219**	(0.010381)
UP * t-1.Selling price expectations.=	-0.0346***	(0.012824)	0.0129***	(0.004797)	0.0217***	(0.008046)
UP * t-1.Selling price expectations.+ [bar]	0.0391	(0.049921)	-0.0146	(0.018616)	-0.0245	(0.031311)
UP * t-1.Selling price expectations.= [bar]	0.0174	(0.038338)	-0.0065	(0.014294)	-0.0109	(0.024046)
UP * t-1.Employment expectations.+	0.0084	(0.016538)	-0.0031	(0.006166)	-0.0053	(0.010373)
UP * t-1.Employment expectations.=	0.0032	(0.011149)	-0.0012	(0.004157)	-0.0020	(0.006992)
UP * t-1.Employment expectations.+ [bar]	-0.0039	(0.041759)	0.0014	(0.015568)	0.0024	(0.026191)
UP * t-1.Employment expectations.= [bar]	-0.0228	(0.028371)	0.0085	(0.010580)	0.0143	(0.017794)
UP * t-1.Business sentiment.>	-0.0013	(0.015403)	0.0005	(0.005742)	0.0008	(0.009661)
UP * t-1.Business sentiment.=	-0.0108	(0.011254)	0.0040	(0.004198)	0.0067	(0.007059)
UP * t-1.Business sentiment.> [bar]	0.0308	(0.040882)	-0.0115	(0.015245)	-0.0193	(0.025642)
UP * t-1.Business sentiment.= [bar]	0.0299	(0.031237)	-0.0111	(0.011650)	-0.0187	(0.019593)
Structural dimension						
Firm-level						
UP * Firm size	0.0075	(0.013336)	-0.0028	(0.004973)	-0.0047	(0.008364)
UP * Firm size [bar]	-0.0026	(0.013604)	0.0010	(0.005072)	0.0016	(0.008532)
N	44,683					
Pseudo R^2	0.215					
cut1	-3.5129***	(0.132638)				
cut2	-1.4613***	(0.131821)				

Source: Own calculations.
Notes: Only results for the interaction term are shown, the other covariates have been dropped from the output (the sign and magnitude of these marginal effects have not changed compared to the results presented in Table 3). "UP *" denotes the interaction term reflecting the difference in the marginal effect compared to the baseline (i.e. business cycle phase of downswing). For general notes see Table 3.

Table C2: Marginal probability effects on the interaction-term: large vs. small firms

Covariates / controls	y=1		y=2		y=3	
	MPE	SE	MPE	SE	MPE	SE
Business cycle dimension						
Firm-level (Current)						
LARGE * t-1.Order books.>	0.0214*	(0.011371)	-0.0080*	(0.004295)	-0.0134*	(0.007103)
LARGE * t-1.Order books.=	0.0133	(0.009840)	-0.0050	(0.003706)	-0.0083	(0.006146)
LARGE * t-1.Order books.> [bar]	-0.0797**	(0.037586)	0.0299**	(0.014205)	0.0498**	(0.023498)
LARGE * t-1.Order books.= [bar]	-0.0220	(0.031313)	0.0083	(0.011768)	0.0137	(0.019556)
LARGE * Limit.Factor: Insuff. demand	-0.0324***	(0.010405)	0.0122***	(0.003965)	0.0203***	(0.006510)
LARGE * Limit.Factor: Insuff. demand [bar]	0.0123	(0.028039)	-0.0046	(0.010524)	-0.0077	(0.017519)
LARGE * Stock finished products.>	-0.0258	(0.018966)	0.0097	(0.007145)	0.0161	(0.011846)
LARGE * Stock finished products.=	-0.0233	(0.016739)	0.0088	(0.006307)	0.0146	(0.010454)
LARGE * Stock finished products.> [bar]	-0.0494	(0.044806)	0.0186	(0.016854)	0.0309	(0.027990)
LARGE * Stock finished products.= [bar]	-0.0581	(0.041726)	0.0218	(0.015691)	0.0363	(0.026091)
LARGE * Selling prices.+	-0.0486***	(0.014946)	0.0183***	(0.005711)	0.0304***	(0.009343)
LARGE * Selling prices.=	-0.0285***	(0.010779)	0.0107***	(0.004095)	0.0178***	(0.006736)
LARGE * Selling prices.+ [bar]	-0.0219	(0.049347)	0.0082	(0.018534)	0.0137	(0.030819)
LARGE * Selling prices.= [bar]	0.0371	(0.031797)	-0.0139	(0.011953)	-0.0232	(0.019873)
LARGE * Capacity utilisation	0.0001	(0.000381)	-0.0000	(0.000143)	-0.0001	(0.000238)
LARGE * Capacity utilisation [bar]	-0.0007	(0.000565)	0.0003	(0.000213)	0.0004	(0.000353)
Firm-level (Expectations)						
LARGE * t-1.Production expectations.+	0.0673***	(0.014871)	-0.0253***	(0.005770)	-0.0421***	(0.009309)
LARGE * t-1.Production expectations.=	0.0198	(0.012361)	-0.0074	(0.004661)	-0.0124	(0.007722)
LARGE * t-1.Production expect.+ [bar]	0.0897*	(0.046713)	-0.0337*	(0.017650)	-0.0561*	(0.029183)
LARGE * t-1.Production expect.= [bar]	0.0112	(0.039005)	-0.0042	(0.014649)	-0.0070	(0.024358)
LARGE * t-1.Selling price expectations.+	-0.0276*	(0.016578)	0.0104*	(0.006254)	0.0172*	(0.010356)
LARGE * t-1.Selling price expectations.=	-0.0432***	(0.012851)	0.0162***	(0.004915)	0.0270***	(0.008035)
LARGE * t-1.Selling price expect.+ [bar]	0.0614	(0.050761)	-0.0231	(0.019117)	-0.0384	(0.031696)
LARGE * t-1.Selling price expect.= [bar]	0.0135	(0.038572)	-0.0051	(0.014491)	-0.0084	(0.024083)
LARGE * t-1.Employment expectations.+	-0.0115	(0.016581)	0.0043	(0.006230)	0.0072	(0.010357)
LARGE * t-1.Employment expectations.=	-0.0112	(0.011114)	0.0042	(0.004179)	0.0070	(0.006943)
LARGE * t-1.Employment expect.+ [bar]	-0.0524	(0.042118)	0.0197	(0.015855)	0.0327	(0.026307)
LARGE * t-1.Employment expect.= [bar]	-0.0373	(0.028681)	0.0140	(0.010797)	0.0233	(0.017917)
LARGE * t-1.Business sentiment.>	0.0027	(0.015401)	-0.0010	(0.005783)	-0.0017	(0.009618)
LARGE * t-1.Business sentiment.=	0.0056	(0.011293)	-0.0021	(0.004242)	-0.0035	(0.007053)
LARGE * t-1.Business sentiment.> [bar]	-0.1125***	(0.041733)	0.0422***	(0.015881)	0.0702***	(0.026059)
LARGE * t-1.Business sentiment.= [bar]	-0.0250	(0.032252)	0.0094	(0.012130)	0.0156	(0.020135)
Structural dimension						
Firm-level						
LARGE * Firm size	0.0287	(0.023340)	-0.0108	(0.008955)	-0.0179	(0.014406)
LARGE * Firm size [bar]	-0.0280	(0.021427)	0.0105	(0.008022)	0.0175	(0.013431)
N	44,683					
Pseudo R^2	0.217					
cut1	-3.6374***	(0.135007)				
cut2	-1.5803***	(0.134228)				

Source: Own calculations.
Notes: Only results for the interaction term are shown, the other covariates have been dropped from the output (the sign and magnitude of these marginal effects have not changed compared to the results presented in Table 3). "LARGE *" denotes the interaction term reflecting the difference in the marginal effect compared to the baseline (i.e. small firms). For general notes see Table 3.

Table C3: Marginal probability effects on the interaction-term: urban vs. rural regions

Covariates / controls	y=1		y=2		y=3	
	MPE	**SE**	**MPE**	**SE**	**MPE**	**SE**
Business cycle dimension						
Firm-level (Current)						
URBAN * t-1.Order books.>	-0.0180	(0.011451)	0.0067	(0.004276)	0.0113	(0.007181)
URBAN * t-1.Order books.=	-0.0088	(0.009876)	0.0033	(0.003685)	0.0055	(0.006193)
URBAN * t-1.Order books.> [bar]	-0.0265	(0.037583)	0.0099	(0.014023)	0.0166	(0.023564)
URBAN * t-1.Order books.= [bar]	0.0130	(0.031223)	-0.0048	(0.011646)	-0.0081	(0.019578)
URBAN * Limit.Fact.: Insuff. demand	0.0067	(0.010369)	-0.0025	(0.003868)	-0.0042	(0.006502)
URBAN * Limit.Fact.: Insuff. demand [bar]	-0.0143	(0.028280)	0.0053	(0.010548)	0.0090	(0.017734)
URBAN * Stock finished products.>	0.0243	(0.019125)	-0.0091	(0.007139)	-0.0153	(0.011993)
URBAN * Stock finished products.=	0.0412**	(0.016906)	-0.0154**	(0.006324)	-0.0258**	(0.010603)
URBAN * Stock finished products.> [bar]	0.0087	(0.044432)	-0.0033	(0.016570)	-0.0055	(0.027863)
URBAN * Stock finished products.= [bar]	-0.0066	(0.041568)	0.0025	(0.015505)	0.0041	(0.026063)
URBAN * Selling prices.+	-0.0055	(0.015051)	0.0020	(0.005614)	0.0034	(0.009438)
URBAN * Selling prices.=	0.0010	(0.010939)	-0.0004	(0.004080)	-0.0006	(0.006859)
URBAN * Selling prices.+ [bar]	0.0112	(0.050127)	-0.0042	(0.018699)	-0.0070	(0.031429)
URBAN * Selling prices.= [bar]	-0.0002	(0.032594)	0.0001	(0.012157)	0.0001	(0.020437)
URBAN * Capacity utilisation	0.0004	(0.000371)	-0.0001	(0.000138)	-0.0002	(0.000232)
URBAN * Capacity utilisation [bar]	-0.0005	(0.000537)	0.0002	(0.000201)	0.0003	(0.000337)
Firm-level (Expectations)						
URBAN * t-1.Production expectations.+	0.0240	(0.014922)	-0.0090	(0.005572)	-0.0151	(0.009357)
URBAN * t-1.Production expectations.=	0.0162	(0.012401)	-0.0060	(0.004629)	-0.0102	(0.007776)
URBAN * t-1.Production expect.+ [bar]	0.1185**	(0.047310)	-0.0442**	(0.017673)	-0.0743**	(0.029699)
URBAN * t-1.Production expect.= [bar]	0.0987**	(0.039258)	-0.0368**	(0.014679)	-0.0619**	(0.024630)
URBAN * t-1.Selling price expectations.+	0.0030	(0.016686)	-0.0011	(0.006224)	-0.0019	(0.010462)
URBAN * t-1.Selling price expectations.=	-0.0017	(0.012938)	0.0006	(0.004826)	0.0011	(0.008112)
URBAN * t-1.Selling price expect.+ [bar]	-0.0267	(0.051270)	0.0100	(0.019128)	0.0168	(0.032145)
URBAN * t-1.Selling price expect.= [bar]	-0.0046	(0.039521)	0.0017	(0.014742)	0.0029	(0.024780)
URBAN * t-1.Employment expectations.+	0.0252	(0.016647)	-0.0094	(0.006216)	-0.0158	(0.010439)
URBAN * t-1.Employment expectations.=	0.0082	(0.011244)	-0.0030	(0.004195)	-0.0051	(0.007050)
URBAN * t-1.Employment expect.+ [bar]	-0.0187	(0.043414)	0.0070	(0.016195)	0.0117	(0.027220)
URBAN * t-1.Employment expect.= [bar]	-0.0511*	(0.029564)	0.0191*	(0.011042)	0.0320*	(0.018540)
URBAN * t-1.Business sentiment.>	0.0124	(0.015542)	-0.0046	(0.005799)	-0.0078	(0.009745)
URBAN * t-1.Business sentiment.=	-0.0037	(0.011379)	0.0014	(0.004244)	0.0023	(0.007135)
URBAN * t-1.Business sentiment.> [bar]	-0.0764*	(0.041652)	0.0285*	(0.015542)	0.0479*	(0.026139)
URBAN * t-1.Business sentiment.= [bar]	-0.0346	(0.031968)	0.0129	(0.011924)	0.0217	(0.020052)
Structural dimension						
Firm-level						
URBAN * Firm size	0.0110	(0.013557)	-0.0041	(0.005059)	-0.0069	(0.008500)
URBAN * Firm size [bar]	-0.0079	(0.013839)	0.0029	(0.005162)	0.0049	(0.008678)
N	44,683					
Pseudo R^2	0.216					
cut1	-3.2491***	(0.169137)				
cut2	-1.1962***	(0.168552)				

Source: Own calculations.
Notes: Only results for the interaction term are shown, the other covariates have been dropped from the output (the sign and magnitude of these marginal effects have not changed compared to the results presented in Table 3). "URBAN *" denotes the interaction term reflecting the difference in the marginal effect compared to the baseline (i.e. rural regions). For general notes see Table 3.

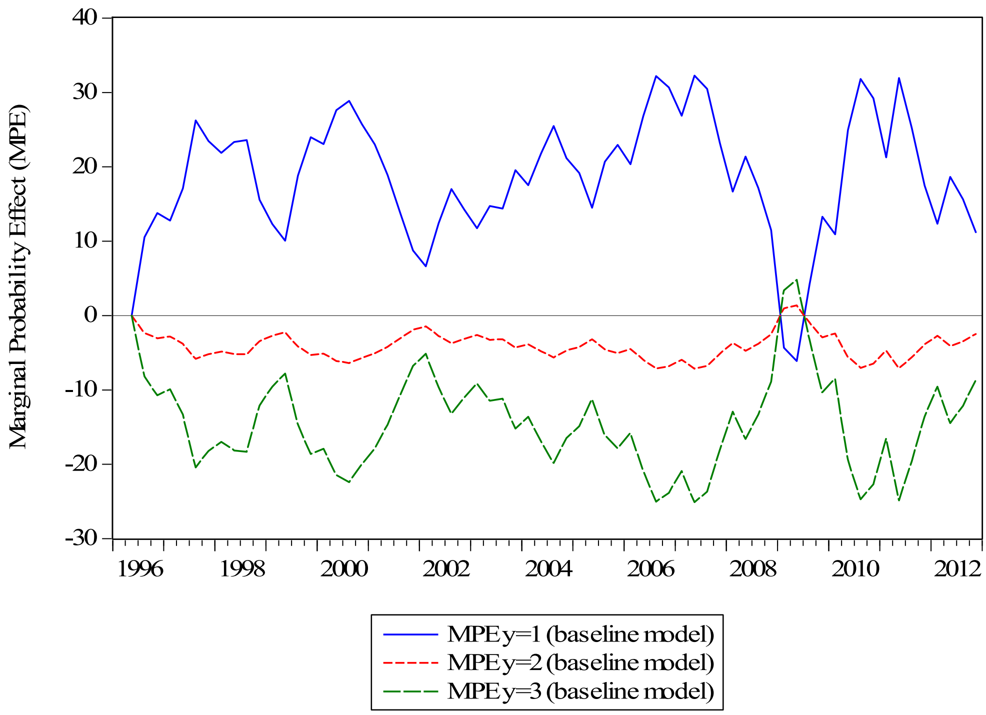
Table D1: Model evaluation – "goodness-of-fit" results

Model (i_{q*}=44,683 no. of. obs.)	R^2_{McF}	R^2_{AN}	R^2_{M}	AIC	BIC
q-dummies [baseline]	0.025	0.030	0.031	86,012	86,604
q + firm-level [structure]	0.033	0.033	0.034	85,314	85,958
q + firm-level [business cycle - current]	0.192	0.119	0.126	71,338	72,070
q + firm-level [business cycle - expectations]	0.104	0.085	0.088	79,076	79,807
q + firm-level	**0.215**	**0.163**	**0.177**	**69,359**	**70,447**
q + firm-level [structure] + industry controls	0.034	0.035	0.035	85,171	85,842
q + firm-level [structure] + regional controls	0.033	0.034	0.035	85,302	85,990
full model: firm-level + industry + regional	**0.215**	**0.161**	**0.175**	**69,362**	**70,355**
firm-level + UP*	0.215	0.298	0.346	69,381	70,618
firm-level + LARGE*	0.216	0.299	0.347	69,309	70,545
firm-level + URBAN*	0.215	0.298	0.345	69,403	70,640

Source: Own calculations.

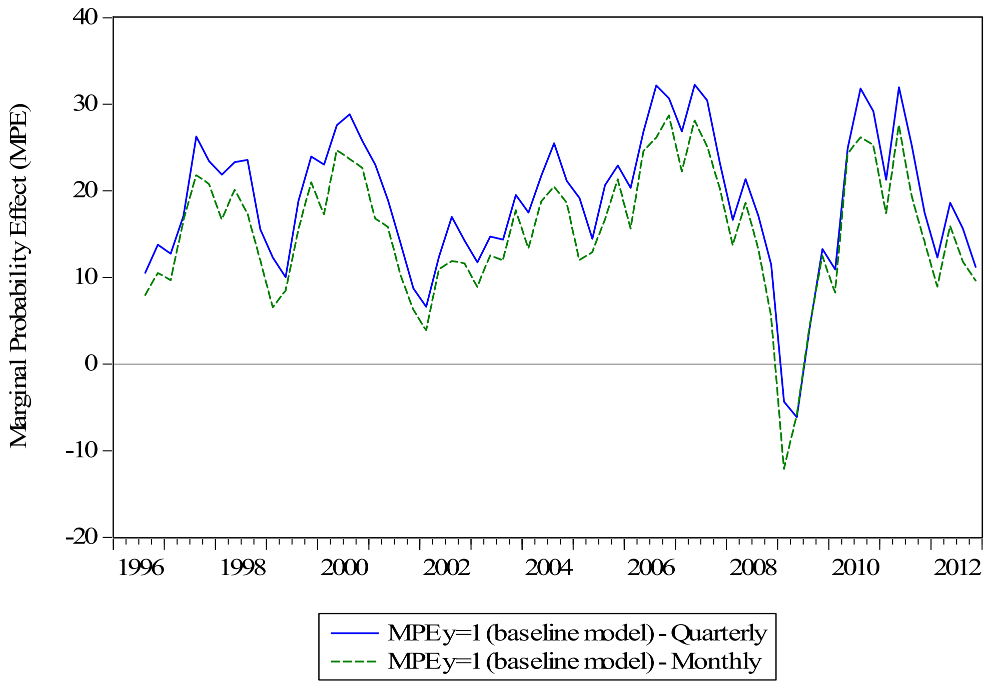
Notes: Pseudo-R^2 measures: McF.. McFadden, AN..Aldrich-Nelson, M..Maddala; Variable notation: q..q-dummies; UP*..interaction with "business cycle upswing" dummy; LARGE*..interaction with "large firm" dummy; URBAN*..interaction with "urban location" dummy.

Figure B1: Marginal probability effects of time-dummies ($y_{it} \in \{1,2,3\}$)



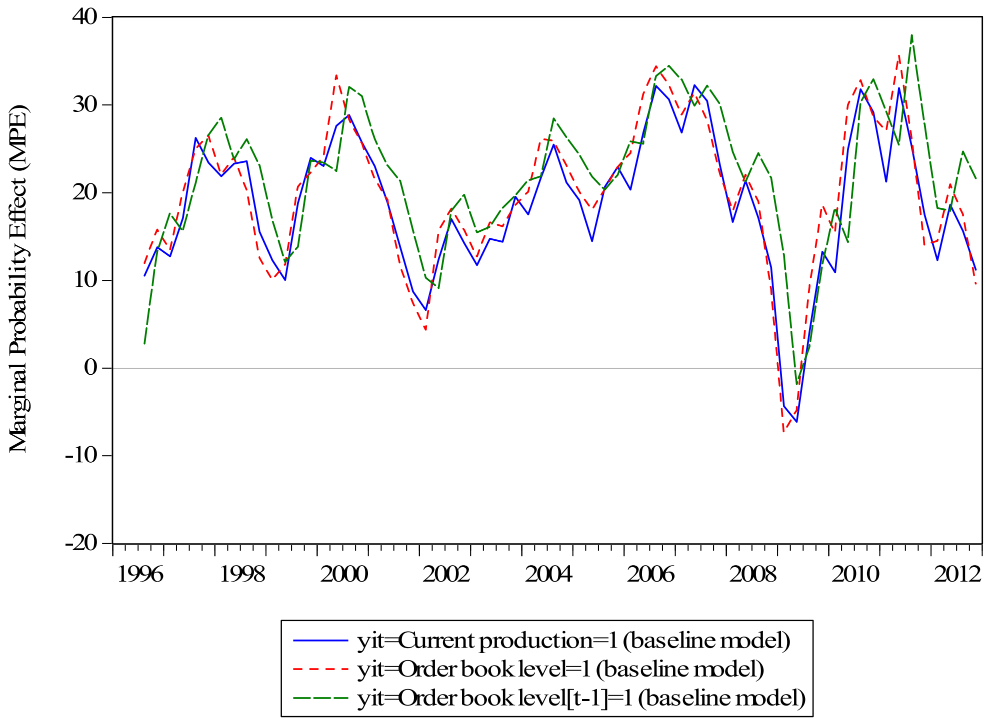
Source: Own calculations.

Figure B2: Marginal probability effects of time-dummies – quarterly vs. monthly interval



Source: Own calculations.

Figure B3: Marginal probability effects of time-dummies – y_{it} vs. order book levels



Source: Own calculations.

Chapter III

Regional Business Cycle Synchronisation, Sector Specialisation and EU-Accession*

Abstract

In this paper, we examine the effects of Eastern and Northern enlargement of the EU on regional business cycle synchronisation and sector specialisation. Difference-in-difference estimates show that cyclical synchronicity decreased and differences in sector structure increased in acceding region pairs after Eastern enlargement. For Northern enlargement results are more ambiguous. Moreover, in both enlargement episodes region pairs with highly synchronous business cycles before accession experienced weaker cyclical and structural convergence than region pairs with less synchronous cycles. Likewise, region pairs with more similar sector structures before accession experienced stronger divergence (or weaker convergence) of structural similarity and business cycle synchronicity after the enlargement. We argue that these results call for developing more differentiated hypotheses on the effect of EU-enlargement on business cycle synchronisation and sector specialisation.

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1. Introduction

Measuring and describing the evolution of business cycle synchronisation in the European Union (EU) has been a subject of high interest for empirical macro-economists in the last decades. This interest was spurred both by the policy relevance of the topic as well as by theoretical controversies between proponents of endogenous optimum currency area theory. On the policy side ever since Mundell (1961) the similarity in countries' reactions to macro-economic shocks is considered one of the most important criteria for successful monetary unions. A high level of business cycle synchronisation was therefore considered to be a precondition for European Monetary Union (EMU). On the theoretical side some proponents of endogenous business cycle theory (Frankel and Rose, 1997, 1998; EC, 1990) argued that integration, by reducing transaction costs, leads to increased trade. In the face of predominantly country specific macro-economic shocks this should lead to higher business cycle synchronisation. Others (e.g. Krugman, 1993; Bayumi and Eichengreen, 1993; Clark and van Wincoop, 2001; Kalemli-Ozcan et al., 2001), however, argued that integration will primarily result in increased specialisation of economies on sectors of production where they have comparative advantages. This, in the face of sector specific shocks, should lead to reduced business cycle synchronisation.

This paper uses EU-enlargement as a testing ground for these hypotheses. It analyzes the impact of two very different EU-enlargement steps on business cycle synchronisation and sector specialisation at the regional level. We look at "Eastern enlargement" by the 10 member states (EU-10: Czech Republic, Cyprus, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia and Slovenia) that joined the EU in May 2004 and on "Northern enlargement" by Sweden, Finland and Austria in 1995. Our contribution to existing literature is twofold. First, in contrast to previous research on the impact of EMU on the national level (Goncales et al., 2009; Christodoulopoulou, 2014), we focus on the impact of EU-enlargement on the smallest regional (NUTS-3) level for which consistent EU-wide data are available. Second, we contribute to the literature on regional business cycle synchronisation. This has so far mostly focused on identifying factors explaining differences in business cycle synchronisation among regions (Fatas, 1997; Belke and Heine, 2006; Siedschlag and Tondl, 2011; Park and Hewings, 2012; Chung and Hewings, 2015) or on regional business cycle synchronisation in periods predating EU-enlargements (Barrios et al., 2003; Barrios and de Lucio, 2003; Artis et al., 2004; Montoya and de Haan, 2008).We, in contrast, offer an ex-post evaluation of the impact of EU-enlargement on regional business cycle synchronisation and sector specialisation.

Our focus on small regions allows for an easier identification of the impact of EU-accession on sector specialisation. This is because small regions differ more pronouncedly in comparative advantages than nation states. They are also more likely to be affected by changes in comparative advantages. This enables us to apply the difference-in-difference (DiD) approach followed in previous research using national data (Goncales et al., 2009; Christodoulopoulou, 2014) to more disaggregated (i.e. regional) data. This rich dataset provides for a large number of natural comparison groups for robustness tests. It also allows for an explicit assessment of the potential heterogeneity of the impact of EU-enlargement on regional business cycle synchronisation and sector specialisation.

2. Data

We use data on annual regional gross value added (GVA) as well as its sector composition[1] at the NUTS-3 level from the Cambridge econometrics database. For the analysis of Eastern enlargement in 2004, we take 1,227 NUTS-3 regions located in the countries of the EU-25 and use data covering the years 1993 to 2010. To analyze the effects of Northern enlargement in 1995 we restrict the sample to the EU-15 countries (i.e. 979 NUTS-3 regions) and on the

[1] This differentiates between agriculture, manufacturing, construction, distributive services, financial services, real estate and non-market services.

time period 1981 to 2001.[2] To measure business cycle synchronisation between region pairs we first extract the business cycle component from each NUTS-3 region's GVA time series by the Corbae-Ouliaris (Corbae and Ouliaris, 2006) filter.[3] From this cyclical component we calculate bilateral (i.e. region-by-region) seven-year rolling window correlations. Moreover, using the sector composition of GVA for each region we derive a Krugman type index (Krugman, 1991) of structural differences between region pairs. This is given as half of the sum of absolute differences in sector shares across regions and takes a value of between zero, indicating equivalent sector shares in both regions, and one, indicating the maximum possible difference in sector composition.[4] We augment this data with the log difference in annual GVA per capita levels between region pairs (to measure differences in economic well-being and living standards between regions) and the geographic distance (in kilometers) between the capital cities of region pairs. Overall, we calculate annual bilateral business cycle correlations, indices of structural difference and the respective controls (GVA per capita differences and distances) for 752,151 NUTS-3 region pairs in the case for Eastern enlargement and 478,731 NUTS-3 region pairs for the analysis of Northern enlargement.

2.1 Descriptive Statistics

Table 1 shows descriptive statistics for these data for the last pre- and post-accession years in both enlargement rounds for a number of different region pair types. In the first two columns both regions are either located in the same country (labeled "Internal") or in different pre-existing member countries (labeled "Pre-Member"). For these region pairs institutional conditions for cross-border exchange did not change on account of EU-enlargement. They

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[2] The starting periods are dictated by data availability as time series for EU-10 regions are unavailable or unreliable before 1993 and changes in regional classification preclude an analysis before 1981. Data endpoints are chosen to incorporate one full rolling window business cycle correlation after enlargement in our baseline setting. See Table B1 in the Appendix for a list of the numbers of NUTS-3 regions for each country included in the analysis.

[3] This filter is used as it avoids loss of information at the data endpoints and has 'better' leakage properties at desired business cycle frequencies than some alternatives (Corbae et al., 2002). To check for robustness, alternative business cycle correlation measures, filtering methods and lengths of rolling windows are, however, considered below.

[4] This is defined as $SD_{ij,t} \equiv \frac{1}{2}\sum_{k=1}^{K}\left|s_{ik,t} - s_{jk,t}\right|$, with $s_{s_{ik,t}}$ and $s_{jk,t}$ the GVA-share in sector k at time t in regions i and j.

will therefore be used as an unaffected reference (control) group in the analysis. The columns labeled "Mixed" and "Acceding" correspond to region pairs where either one region or both regions belong to an acceding country. For these region pair types institutional preconditions for cross-border exchange changed on account of EU-enlargement, although potentially in different ways. They are therefore considered as affected region pairs.

The table highlights the substantial differences between the two enlargement episodes analyzed. These apply to institutional regulations after accession and to economic, geographic and structural differences among regions. Institutionally the EU joined by the three countries of Northern enlargement in 1995 differed substantially from that at the time of Eastern enlargement in 2004. This applies particularly to the introduction of EMU in 1999. Also the conditions for accession differed between these two episodes. In Northern enlargement only few derogation periods applied after accession. In the case of Eastern enlargement derogation periods applied amongst others to such important parts of the aqcuis communautaire as freedom of movement of labor.

In addition, comparing the two columns reporting descriptive statistics for "Mixed" region pairs in Table 1, acceding regions on average had higher GVA per capita than regions from pre-member countries (by 17% in the unweighted average) in Northern enlargement, but much lower GVA per capita in Eastern enlargement. Furthermore, business cycle correlations between acceding and incumbent regions were higher in Northern than in Eastern enlargement in the year preceding accession (0.28 in the former case, but 0.14 in the later) and structural differences were smaller (0.18 versus 0.21). This is probably due to a longer history of economic integration with the EU of the EFTA countries acceding in 1995 than of the mostly former COMECON countries acceding in 2004. Average geographic distances between acceding and incumbent regions were, however, larger in Northern than in Eastern enlargement on account of the remote location of some Finnish and Swedish regions.

Table 1: Descriptive statistics

Integration Step	Eastern Enlargement					Northern Enlargement				
Region pairs	Internal i,j=within-country	Pre-Member i=EU-15 j=EU-15	Mixed i= EU-10 j=EU-15	Acceding i=EU-10 j=EU-10	Full-set i=EU-25 j=EU-25	Internal i,j=within-country	Pre-Member i=EU-12 j=EU-12	Mixed i= EU-3 j=EU-12	Acceding i=EU-3 j=EU-3	Full-set i=EU-15 j=EU-15
Year	2003					1994				
Correlation [rw7|co]	0.18	0.19	0.14	0.23	0.18	0.48	0.23	0.28	0.18	0.27
	(0.48)	(0.46)	(0.45)	(0.44)	(0.46)	(0.42)	(0.45)	(0.46)	(0.52)	(0.45)
Structural difference	0.17	0.20	0.21	0.17	0.20	0.16	0.20	0.18	0.15	0.19
	(0.08)	(0.09)	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)	(0.08)	(0.06)	(0.09)
log GVA p.c. difference	-0.06	0.45	-0.62	0.10	0.14	-0.03	0.41	0.17	-0.40	0.30
	(0.95)	(1.25)	(1.12)	(1.03)	(1.25)	(0.99)	(1.26)	(1.21)	(1.12)	(1.23)
Distance (in km)	320.90	1,158.60	1,161.00	684.59	1,021.07	312.25	1,122.48	1,380.55	1,366.14	1,028.21
	(190.42)	(640.89)	(597.59)	(419.84)	(657.75)	(210.03)	(627.10)	(750.82)	(495.03)	(684.22)
Year	2010					2001				
Correlation [rw7|co]	0.61	0.52	0.50	0.54	0.53	0.19	0.05	0.10	0.03	0.08
	(0.32)	(0.36)	(0.34)	(0.31)	(0.35)	(0.47)	(0.48)	(0.47)	(0.43)	(0.48)
Structural difference	0.17	0.19	0.24	0.20	0.20	0.16	0.21	0.19	0.15	0.20
	(0.08)	(0.09)	(0.10)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.07)	(0.09)
log GVA p.c. difference	-0.07	0.47	-0.61	0.09	0.16	-0.03	0.40	0.19	-0.38	0.30
	(0.96)	(1.28)	(1.24)	(1.05)	(1.24)	(0.99)	(1.26)	(1.19)	(1.12)	(1.22)
Distance (in km)	320.90	1,158.60	1,161.00	684.59	1,021.07	312.25	1,122.48	1,380.55	1,366.14	1,028.21
	(190.42)	(640.89)	(597.59)	(419.84)	(657.75)	(210.03)	(627.10)	(750.82)	(495.03)	(684.22)
ΔYear	2010 minus 2003					2001 minus 1994				
Correlation [rw7|co]	0.43	0.33	0.36	0.31	0.35	-0.29	-0.18	-0.18	-0.15	-0.20
Structural difference	0.00	-0.01	0.03	0.03	0.00	0.00	0.01	0.01	0.00	0.01
GVA p.c. difference	-0.01	0.02	0.02	-0.02	0.02	0.00	-0.01	0.02	0.02	0.00

Source: Cambridge Econometrics, own calculations.

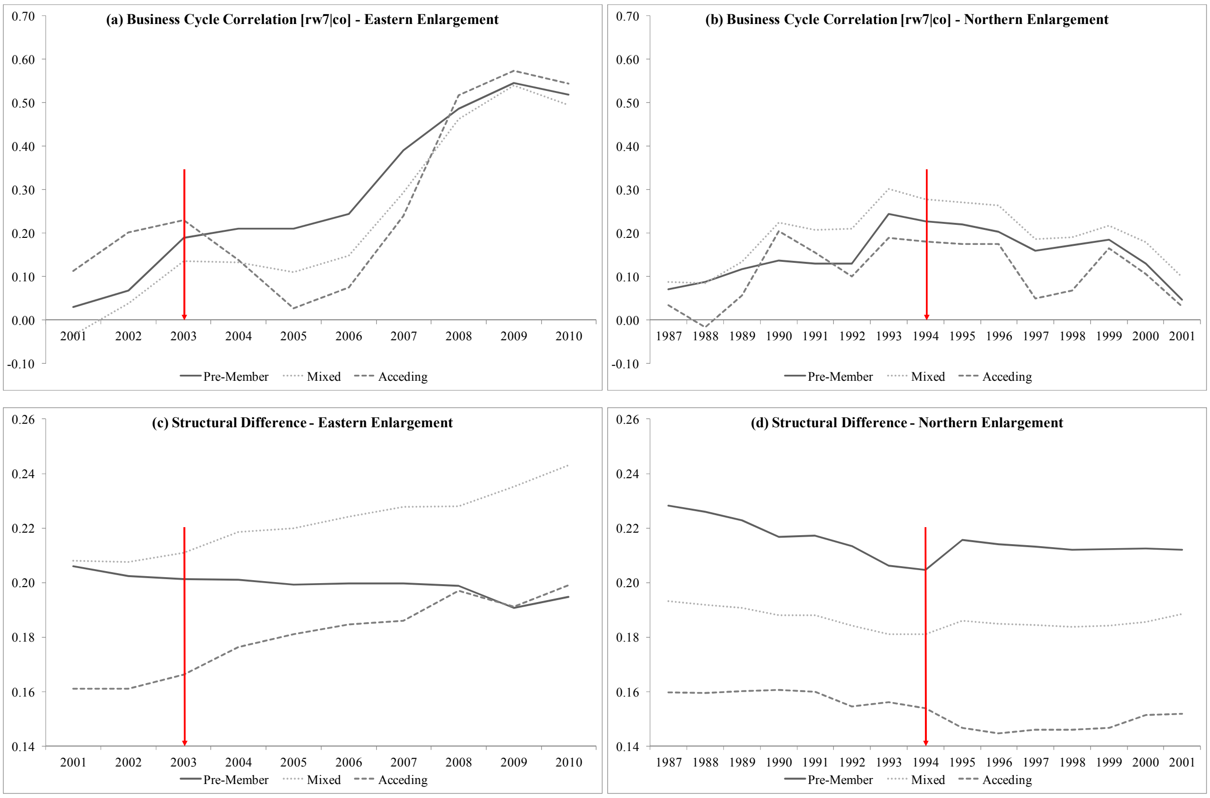
Notes: Values in brackets are standard deviations, "Internal" region pairs = region pairs located in the same country, "Pre-Member" region pairs = region pairs located in different incumbent countries, "Mixed" region pairs = region pairs in which one region is located in an acceding country and the other in an incumbent country, "Acceding" region pairs = region pairs located in different acceding countries. The business cycle correlation measure is based on a seven-year rolling window of Corbae-Ouliaris filtered data (denoted as [rw7|co]).

Similarly, due to the low level of economic integration of the Austrian with the Swedish and Finnish economy, region pairs located in different acceding regions had lower business cycle correlations, but also slightly lower structural differences among themselves in Northern than in Eastern enlargement. The heterogeneity of acceding regions in terms of GVA per capita was, however, larger (with a standard deviation of 1.12) in Northern than in Eastern enlargement (standard deviation 1.03), as were distances between acceding region pairs.

2.2 Development of indicators

A first assessment of the effect of EU-enlargements on business cycle synchronisation and sector specialisation consists of comparing the development of these variables across different region pair types. If our target indicators increase (decrease) to a similar extent for all region pair types, this would indicate that the changes observed are due to a general trend impacting on all region pairs. If, however, the change is more (less) pronounced in acceding and mixed region pairs compared to internal and/or pre-member region pairs, EU-accession might have had an additional positive (negative) impact in regions of accession countries.

Figure 1: Business cycle correlation and structural difference



Source: Cambridge Econometrics, own calculations.

Notes: "Pre-Member" region pairs = region pairs located in different incumbent countries, "Mixed" region pairs = region pairs in which one region is located in an acceding country and the other in an incumbent country, "Acceding" region pairs = region pairs located in different acceding countries. Vertical line = year before accession. The business cycle correlation measure is based on a seven-year rolling window of Corbae-Ouliaris filtered data (denoted as [rw7|co]).

Figure 1 (top panel) reports cross-section averages of business cycle correlations for the two affected region pair types as well as for region pairs of pre-existing member countries.[5] Figure 1a shows that the synchronisation of business cycles increased for all types of region pairs in Eastern enlargement. In 2001, average business cycle correlations were below 0.1 in all region pair types, while at the end of the sample period they ranged between 0.5 and 0.6. This suggests an overall tendency towards regional business cycle convergence in the period from 2001 to 2010. Business cycle correlations also moved more or less in parallel for all region

[5] This reference group – similarly to our two affected groups – focuses on cross-border relationships.

pairs before 2003 (i.e. the last year before Eastern enlargement). After this bilateral correlations decreased among acceding region pairs up to 2005 and developed more slowly among mixed than pre-member region pairs up to 2006 but picked up again thereafter. As a consequence the increase of cyclical synchronisation from 2003 to 2010 among pre-member region pairs was higher than in acceding region pairs, but lower than in mixed region pairs.

Similarly, for Northern enlargement (Figure 1b) business cycle correlations start at levels of between 0.05 and 0.10 in 1987, with a peak in 1993 and then fall again until 2001 in all region pair types. The decline from 1994 to 2001 was comparable in pre-existing region pairs and mixed region pairs (-0.18 each) but smaller in acceding region pairs (-0.15). This suggests that both after Eastern and Northern enlargement mixed region pairs experienced a larger or at least similar change in bilateral business cycle synchronisation than pre-member region pairs. The evidence for acceding region pairs is less conclusive.

The bottom panel of Figure 1 displays the development of the cross-section average of the structural difference indicator. In the case of Eastern enlargement (Figure 1c) both affected region pair types became increasingly dissimilar, while pre-member region pairs became more similar after EU-10 integration. This is in line with Krugman's (1993) hypothesis that regional specialisation increases after integration. The evidence for Northern enlargement is less clear (Figure 1d). Over the period 1987 to 1994 structural differences between all region pair types decreased. This trend continued in acceding region pairs and reversed in 1999. In pre-member and in mixed region pairs, by contrast, structural differences increased strongly in 1995 and thereafter reduced in pre-member region pairs, but increased (at least as of 1999) in mixed region pairs. Hence, relative to 1994 the increase in the index of structural difference was higher in pre-member region pairs as compared to both mixed as well as acceding region pairs. Northern and Eastern enlargement thus potentially impacted rather differently on regional business cycle synchronisation and sector specialisation between regions.

3. Method

Additional empirical evidence on these effects can be obtained by using a difference-in-difference approach. This consists of dividing the data into a subset of region pairs affected by the enlargement, and another subset unaffected as well as grouping time periods (t) into a pre-accession and a post-accession period (with τ being the year of accession). Denoting the subsets of affected and unaffected region pairs by R_n where $n = 1$ represents the unaffected and $n \in \{2, 3\}$ the affected region pairs (with $n = 2$ indicating mixed region pairs and $n = 3$ acceding region pairs) the impact of EU-accession on business cycle synchronisation and structural differences can be estimated by the regression:

$$y_{ji,t} = \alpha_t D_t + \beta_j D_{ji} + \sum_{n=2}^{3} \delta_n D_{t \geq \tau} D_{j \in R_n} + \xi_{ji,t} \qquad (3\text{-}1)$$

where $y_{ji,t}$ represents either the measure of business cycle correlation or the index of structural difference between regions (i) and (j) at time (t), and $\xi_{ji,t}$ is an i.i.d. error term. D_t is a set of dummy variables for each time period. This measures changes in the dependent variable over time that are common to all region pairs. D_{ji} is a set of dummy variables for each region pair. This controls for all region pair specific but time invariant influences on the dependent variable such as common language and distance, or whether one or both regions are border regions or separated by the sea. α_t and β_j are parameters to be estimated.

The central parameters of interest in equation (1) are the δ_n. These measure the average change in $y_{ji,t}$ in the affected (i.e. mixed or acceding) region pairs relative to the unaffected region pairs after enlargement. This is because $D_{t \geq \tau}$ indicates post-accession time periods (i.e. equals one for $t \geq \tau$ and zero otherwise), while the $D_{j \in R_n}$ are dummy variables measuring whether the considered region pair type is affected by EU-accession. A statistically significant positive (negative) value of the δ_n implies that the variable of interest increased (decreased) in affected region pairs relative to unaffected region pairs after enlargement.

Equation (1) may, however, be overly restrictive on account of the substantial persistence of business cycle correlations (particularly in the case of rolling windows) as well as structural differences. Gächter and Riedl (2013) find that modeling this persistence may substantially change results of DiD tests for the effect of EMU on national business cycle synchronisation. Furthermore, Bertrand et al. (2004) show that DiD estimates as in equation (1) may result in overly high rejection rates of the no effects hypothesis in the case of auto-correlated errors. We therefore follow a suggestion by Bertrand et al. (2004) and estimate all parameters using clustered standard errors, as this reduces over-rejection. In addition, we also collapse the data by taking means of the pre-and post-accession values of the dependent variables and estimate equation (1) with only two periods. Third, we augment equation (3-1) by the lagged endogenous variable as an additional explanatory variable and, thus, estimate the following specification:

$$y_{ji,t} = \rho y_{ji,t-1} + \alpha_t D_t + \beta_j D_{ji} + \sum_{n=2}^{3} \delta_n D_{t \geq \tau} D_{j \in R_n} + \xi_{ji,t} \quad (3\text{-}2)$$

Angrist and Pischke (2009: 246ff) show that equations (3-1) and (3-2) provide a bracketing property: If equation (3-2) is the "true" model and equation (3-1) is estimated, δ_n is overestimated. If equation (3-1) is "true" but equation (3-2) is estimated, δ_n is underestimated. In absence of knowing the correct model, the estimates of equation (3-1) and (3-2), therefore, provide upper and lower bounds to the "true" effect.

The interpretation of the parameters δ_n in equations (3-1) and (3-2), however, rests on the assumption that both affected and unaffected region pairs would have followed the same trends in business cycle correlations and structural difference in the absence of EU-accession. One way to increase the plausibility of this assumption would be to include additional variables to control for systematic deviations from the common trend assumption. Their inclusion, however, creates new issues. Correct identification of δ_n requires that none of the control variables are influenced by the treatment. This is questionable for most of the time varying variables previously found to be important drivers of regional business cycle synchronisation in the literature such as trade, foreign direct investments and structural differences. Theory suggests that all of these are themselves affected by integration. We therefore estimate versions of equations (3-1) and (3-2) without controls as well as with them.

A further assumption of DiD estimates is that unaffected region pairs are not indirectly affected by EU-accession for example through third country effects. As this cannot be tested, we use a number of alternative reference groups to assess the robustness of results (see Christodoulopoulou, 2014, for a similar approach). In the baseline specification, we use pre-member region pairs as a reference group.

We, however, also estimate equations (3-1) and (3-2) using internal region pairs as reference group. Further, for Eastern enlargement, we explore whether Euro introduction in 1999 impacts on results, by excluding all countries joining the Euro in 1999 from the sample and constraining the reference group to regions belonging to Sweden, the UK and Denmark.[6] For Northern enlargement to see whether the fact that Sweden did not join the EMU in 1999 affects results, we also check for the robustness of findings by comparing only regions joining the Euro in 1999 (i.e. Austrian and Finnish regions to all EU-12 countries except Denmark and the UK).

4. Results for Eastern Enlargement

Table 2 shows baseline regression results for equation (3-1) for seven-year rolling window business cycle correlations based on the Corbae-Ouliaris filter (in the top panel) and indices of structural differences (in the bottom panel). Columns headed "Full-Panel" report results when estimating equation (3-1) for the full set of observations. Columns headed "2-Years-Panel" use the collapsed (two periods only) version of the data. Columns headed "Dynamic-Panel" present results for the specification in equation (3-2). For each of these versions,

[6] Throughout this analysis we consider Greece to be an EMU country. Additional robustness tests show that this country does not drive the results.

results of regressions using different reference groups are reported. The first of these considers pre-existing region pairs (labeled "EU-15") as a reference group. The second uses within-country region pairs. The third omits all countries joining the Euro in 1999 (labeled "EU-15 none EMU"). Furthermore, for each model version and reference group columns headed (1) report results of models excluding controls, while columns headed (2) show results for models including time varying controls.[7]

The findings are rather insensitive to the model specification, the reference group and time dimension considered and are consistent with Krugman's hypothesis. They suggest, on the one hand, less synchronised business cycles after Eastern enlargement for both acceding and mixed region pairs relative to the reference group. The only exception to this are results for mixed regions pairs when using "EU-15" as a reference group. This may be due to the distortions arising from the EMU introduction in 12 out of the EU-15 countries just before the Eastern enlargement. On the other hand, the findings even more strongly point to an increase in structural difference among the region pairs of interest in all specifications. Business cycle correlations reduced by up to -0.17 for mixed and acceding region pairs after Eastern enlargement relative to unaffected pairs; differences in sector shares on average increased by 0.01 to 0.04. Also the coefficients of the lagged dependent variable in the dynamic panel specification are between zero and one and differ significantly from these values, as would be expected from a stable dynamic process. Furthermore, the results for the structural difference variable in models assessing business cycle correlations indicate lower business cycle correlations among region pairs with larger structural differences. The coefficients of the GVA per capita differences are positive and significant in most specifications. After controlling for structural differences, regions with higher GVA per capita differences had higher business cycle synchronisation in Eastern enlargement.

[7] In the assessment of business cycle correlations these controls are the index of structural differences and GVA per capita differences, while for the index of structural differences we resort only to GVA per capita differences.

Table 2: Baseline regression results for Eastern enlargement

Time Dimension (t)	Full-Panel						2-Years-Panel						Dynamic-Panel					
Reference Group (i,j)	EU-15		Within-country		EU-15 none EMU		EU-15		Within-country		EU-15 none EMU		EU-15		Within-country		EU-15 but none	
Model Specification	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Business Cycle Correlation [rw7|co]																		
Mixed (i,j)	-0.011***	-0.0028**	-0.029***	-0.023***	-0.14***	-0.13***	0.031***	0.053***	-0.065***	-0.052***	-0.17***	-0.16***	0.0075***	0.015***	-0.040***	-0.035***	-0.073***	-0.070***
	(0.0011)	(0.0011)	(0.0014)	(0.0014)	(0.0052)	(0.0052)	(0.0015)	(0.0015)	(0.0019)	(0.0019)	(0.0068)	(0.0068)	(0.0007)	(0.0007)	(0.0009)	(0.0010)	(0.0041)	(0.0041)
Acceding (i,j)	-0.16***	-0.15***	-0.17***	-0.17***	-0.17***	-0.17***	-0.014***	-0.0011	-0.11***	-0.10***	-0.093***	-0.096***	-0.031***	-0.029***	-0.091***	-0.088***	-0.077***	-0.081***
	(0.0045)	(0.0045)	(0.0046)	(0.0046)	(0.0064)	(0.0064)	(0.0054)	(0.0054)	(0.0056)	(0.0056)	(0.0081)	(0.0081)	(0.0027)	(0.0027)	(0.0029)	(0.0029)	(0.0047)	(0.0047)
ln(Struct. Diff.)		-0.0046***		-0.047***		-0.014***		-0.058***		-0.090***		-0.075***		-0.003***		-0.050***		0.00077
		(0.0013)		(0.0018)		(0.0045)		(0.0019)		(0.0027)		(0.0074)		(0.0006)		(0.0010)		(0.0029)
ln(GVA p.c. Diff.)		0.42***		0.32***		0.62***		0.59***		0.40***		0.45***		0.48***		0.41***		0.50***
		(0.0083)		(0.0130)		(0.0360)		(0.0093)		(0.0140)		(0.0380)		(0.0039)		(0.0068)		(0.0190)
Lagged Dep. Var.													0.40***	0.40***	0.32***	0.32***	0.32***	0.31***
													(0.0006)	(0.0006)	(0.0010)	(0.0010)	(0.0029)	(0.0029)
N	6,325,770	6,325,770	2,832,310	2,832,310	359,520	359,520	1,265,154	1,265,154	566,462	566,462	71,904	71,904	5,060,616	5,060,616	2,265,848	2,265,848	287,616	287,616
R-sq	0.288	0.289	0.325	0.326	0.258	0.261	0.306	0.312	0.386	0.390	0.265	0.271	0.68	0.17	0.62	0.23	0.59	0.18
Structural Difference																		
Mixed (i,j)	0.025***	0.025***	0.020***	0.020***	0.020***	0.020***	0.039***	0.039***	0.033***	0.033***	0.022***	0.021***	0.0070***	0.0071***	0.0058***	0.0058***	0.0070***	0.0069***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0006)	(0.0006)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0009)	(0.0009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0004)
Acceding (i,j)	0.031***	0.031***	0.025***	0.025***	0.017***	0.017***	0.039***	0.039***	0.033***	0.033***	0.011***	0.012***	0.0072***	0.0073***	0.0061***	0.0061***	0.0046***	0.0047***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0011)	(0.0011)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)	(0.0005)
ln(GVA p.c. Diff.)		0.021***		0.012***		-0.033***		0.030***		0.0079***		-0.051***		0.0075***		0.0025***		-0.019***
		(0.0010)		(0.0016)		(0.0045)		(0.0011)		(0.0019)		(0.0050)		(0.0004)		(0.0006)		(0.0019)
Lagged Dep. Var.													0.69***	0.69***	0.69***	0.69***	0.63***	0.63***
													(0.0005)	(0.0005)	(0.0009)	(0.0009)	(0.0028)	(0.0028)
N	6,325,770	6,325,770	2,832,310	2,832,310	359,520	359,520	1,265,154	1,265,154	566,462	566,462	71,904	71,904	5,060,616	5,060,616	2,265,848	2,265,848	287,616	287,616
R-sq	0.032	0.033	0.066	0.066	0.183	0.184	0.073	0.074	0.134	0.134	0.282	0.285	0.94	0.93	0.93	0.93	0.91	0.86

Source: Cambridge Econometrics, own calculations.

Notes: Table reports coefficients for regressions as in equations (3-1) and (3-2) using three different reference groups: (a) pre-member region pairs (in columns labeled "EU-15") = region pairs located in different EU-15 countries, (b) internal region pairs (in columns labeled "Within-country") = region pairs located in the same country, (c) pre-member region pairs in none-EMU countries (columns labeled "EU-15 none EMU") = region pairs located in different EU-15 countries that did not join EMU in 1999. Values in brackets are clustering corrected (by region pair) standard errors of the estimate. ***, (**), (*) signify significance at the 1% (5%) (10%) level, respectively. Region pair and time fixed effects are not reported. R-sq is the within R^2 value of the regression, N is the number of observations. The business cycle correlation measure is based on a seven-year rolling window of Corbae-Ouliaris filtered data (denoted as [rw7|co]).

Table 3: Baseline regression results for Northern enlargement

Time Dimension (t)	Full-Panel						2-Years-Panel						Dynamic-Panel					
Reference Group (i,j)	EU-12		Within-country		EU-12 but only EMU		EU-12		Within-country		EU-12 but only EMU		EU-12		Within-country		EU-12 but only EMU	
Model Specification	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Business Cycle Correlation [rw7|co]																		
Mixed (i,j)	-0.0063***	-0.0042**	0.11***	0.11***	-0.011***	-0.0072***	0.0013	0.0028	0.11***	0.11***	0.11***	0.12***	-0.014***	-0.013***	0.047***	0.046***	0.0065***	0.0076***
	(0.0017)	(0.0017)	(0.0020)	(0.0020)	(0.0021)	(0.0021)	(0.0026)	(0.0026)	(0.0032)	(0.0032)	(0.0033)	(0.0033)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Acceding (i,j)	-0.019**	-0.014	0.095***	0.096***	0.063***	0.069***	0.032**	0.033**	0.14***	0.14***	0.45***	0.45***	-0.017***	-0.015***	0.045***	0.046***	0.10***	0.11***
	(0.0097)	(0.0097)	(0.0097)	(0.0098)	(0.0140)	(0.0140)	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0240)	(0.0240)	(0.0031)	(0.0031)	(0.0029)	(0.0029)	(0.0049)	(0.0049)
ln(Struct. Diff.)		0.029***		0.031***		0.021***		-0.027***		0.015***		-0.090***		-0.0061***		0.014***		0.00069
		(0.0015)		(0.0023)		(0.0020)		(0.0030)		(0.0045)		(0.0038)		(0.0006)		(0.0008)		(0.0007)
ln(GVA p.c. Diff.)		-0.19***		-0.10***		-0.25***		-0.23***		-0.31***		-0.27***		-0.10***		-0.075***		-0.10***
		(0.0084)		(0.0160)		(0.0099)		(0.0160)		(0.0290)		(0.0190)		(0.0033)		(0.0057)		(0.0038)
Lagged Dep. Var.													0.58***	0.58***	0.64***	0.64***	0.60***	0.60***
													(0.0005)	-(0.0005)	(0.0008)	-(0.0008)	(0.0006)	-(0.0006)
N	6,009,240	6,009,240	2,228,950	2,228,950	3,927,300	3,927,300	801,232	801,232	297,194	297,194	523,640	523,640	5,208,008	5,208,008	1,931,754	1,931,754	3,403,660	3,403,660
R-sq	0.031	0.031	0.068	0.068	0.055	0.056	0.081	0.081	0.135	0.136	0.127	0.130	0.71	0.65	0.75	0.73	0.69	0.63
Structural Difference																		
Mixed (i,j)	0.0018***	0.0015***	0.0052***	0.0053***	-0.0030***	-0.0031***	-0.00029	-0.00042*	0.0061***	0.0061***	-0.0026***	-0.0026***	-0.0015***	-0.0015***	0.00052***	0.00052***	-0.0019***	-0.0019***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Acceding (i,j)	-0.0066***	-0.0071***	-0.0032***	-0.0033***	-0.0079***	-0.0082***	-0.0095***	-0.0097***	-0.0030***	-0.0031***	0.0024	0.0024	-0.0049***	-0.0050***	-0.0028***	-0.0028***	-0.0021***	-0.0021***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0016)	(0.0016)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0018)	(0.0018)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0004)
ln(GVA p.c. Diff.)		0.027***		0.018***		0.010***		0.019***		0.0088***		0.0014		0.0036***		0.00085*		-0.00060**
		(0.0011)		(0.0019)		(0.0013)		(0.0015)		(0.0025)		(0.0018)		(0.0003)		(0.0005)		(0.0003)
													0.83***	0.83***	0.84***	0.84***	0.85***	0.85***
													(0.0003)	-(0.0003)	(0.0006)	-(0.0006)	(0.0004)	-(0.0004)
N	6,009,240	6,009,240	2,228,962	2,228,962	3,927,300	3,927,300	801,232	801,232	297,196	297,196	523,640	523,640	5,208,008	5,208,008	1,931,766	1,931,766	3,403,660	3,403,660
R-sq	0.027	0.028	0.025	0.025	0.016	0.016	0.017	0.018	0.009	0.009	0.012	0.012	0.95	0.95	0.95	0.95	0.96	0.96

Source: Cambridge Econometrics, own calculations.

Notes: Table reports coefficients for a regression as in equation (3-1) and (3-2) using three different reference groups: (a) pre-member region pairs (in columns labeled "EU-12") = region pairs located in different EU-12 countries, (b) internal region pairs (in columns labeled "Within-country") = region pairs located in the same country, (c) pre-member region pairs in only EMU countries (columns labeled "EU-12 but only EMU") = region pairs located in different EU-12 countries that joined EMU in 1999. Values in brackets are clustering corrected (by region pair) standard errors of the estimate. ***, (**), (*) signify significance at the 1% (5%) (10%) level, respectively. Region pair and time fixed effects are not reported. R-sq is the within R^2 value of the regression, N is the number of observations. The business cycle correlation measure is based on a seven-year rolling window of Corbae-Ouliaris filtered data (denoted as [rw7|co]).

5. Results for Northern Enlargement

Table 3 presents the findings for Northern enlargement. The model specifications are identical to the analysis of Eastern enlargement. Using "EU-12" as reference group, business cycle correlations tend to have on average slightly decreased in the affected region pairs relative to the unaffected ones. This, however, holds only when the full time dimension is utilized. In the 2-years version of the estimates, the coefficients point in the other direction, but are less statistically significant respectively insignificant. Moreover, in the case for "EU-12 but only EMU" countries, business cycle correlations increased in the dynamic specification and in the 2-years variant in both mixed and acceding region pairs. The opposite applies in the full panel specification. The only case which provides similar results in all model versions is when considering within-country region pairs as a reference group. This delivers statistically significant positive coefficients for both mixed and acceding region pairs that range between 0.05 and 0.15. It thus signals an increase in business cycle synchronisation. Overall, thus, most results indicate an increase in business cycle synchronisation for acceding and mixed region pairs after Northern enlargement. Findings, however, are less clear-cut and robust across different specifications than in the case of Eastern enlargement.

The results with respect to structural differences between regions (bottom panel of Table 3) robustly indicate a reduction of structural differences between acceding region pairs after Northern enlargement. The coefficients for this variable are statistically significant and negative in all specifications except for the "EU-12 but only EMU" case in the 2-years panel. In cases where the coefficients are significant, region pairs located in different acceding countries became structurally more similar (by between 0.2 to 1.0 percentage points) to each other. This contradicts Krugman's (1993) hypothesis.

For structural differences between mixed region pairs, by contrast, results depend heavily on the specification and reference group chosen. When using "EU-12" region pairs as a reference group, the estimates are significantly positive in the case of the full static panel specification, negative when considering the full dynamic panel specification and insignificant in the case of the 2-years panel. Moreover, coefficients are statistically significant and positive in all specifications when using within-country region pairs as a reference group, but negative in all specifications taking "EU-12 but only EMU".

Finally, structural differences impact positively on business cycle correlations in most of the model specifications. By contrast, differences in GVA per capita mostly have a positive impact on structural differences, but a significantly negative one on business cycle synchronisation. The lagged endogenous variable in the dynamic specification is in the interval from zero to one in all specifications and highly statistically significantly different from these values.

6. Robustness

These results are confirmed by a number of robustness tests assessing their sensitivity with respect to different measures of business cycle correlation, other business cycle filtering methods and different lengths of the rolling window (Table A1 in the Appendix). In this sensitivity analysis, we repeated estimation of equation (3-1) using an 'unbounded' variant of the Cerqueira-Martins (Cerqueira and Martins, 2009) measure of business cycle synchronisation.[8] This measure has the advantage that it does not take averages over a particular time period like in the case of rolling window correlations and, therefore, distinguishes temporary correlation due to some shocks in a particular period. Next, we also applied the Hodrick-Prescott (HP) filter (using $\lambda = 6.25$ as suggested by Ravn and Uhlig, 2002) for extracting the business cycle components and changed the length of the rolling window from seven to eight years. These changes do not affect the findings that business cycles became less synchronous between acceding and mixed region pairs after Eastern

[8] We follow Artis and Okubo (2011) and Cerqueira (2013) and use an infinite sample approximation of the original Cerqueira-Martins index as T goes to infinity. This augmented index is bounded between $\pm\infty$ and is defined as:

$\rho_{ij,t}^{cm^*} \equiv \frac{1}{2}\log\left(1/(1-\rho_{ij,t}^{cm})\right)$ where $\rho_{ij,t}^{cm} \equiv 1 - \frac{1}{2}\left[(d_{j,t} - \bar{d}_j)/\sqrt{\frac{\sum_{t=1}^{T}(d_{j,t}-\bar{d}_j)^2}{T}} - (d_{i,t} - \bar{d}_i)/\sqrt{\frac{\sum_{t=1}^{T}(d_{i,t}-\bar{d}_i)^2}{T}}\right]^2$.

enlargement as almost all robustness tests indicate a lower business cycle synchronisation relative to unaffected region pairs after Eastern enlargement.[9]

With respect to Northern enlargement, the results from our robustness tests provide further support to a potentially increased business cycle synchronisation of acceding and mixed region pairs relative to unaffected region pairs, as the majority of coefficients are positively significant. This applies to all variants of the specification except when (a) focusing on the eight-years rolling window correlation and not using internal regions as a reference group, (b) using the seven-years rolling window correlation based on the HP-filter and "EU-12" or "EU-12 but only EMU" as a reference group in the full static panel specification, and (c) using internal region pairs as a reference group in the 2-years panel specification for the Cerqueira-Martins business cycle correlation measure.

7. Heterogeneous effects

Enlargements could, however, also impact differently on different regions. For instance, region pairs that are more distant to each other may be less strongly affected by integration than region pairs located closer to each other. Alternatively, region pairs that already had high business cycle correlations before EU-accession may have experienced a lower increase (or larger decrease) in bilateral business cycle synchronisation. These regions may also have differed in their reaction in terms of the changes in sector specialisation. Likewise, region pairs which already were structurally closer to each other before EU-accession, on account of having rather similar comparative advantages, may have experienced weaker tendencies to

[9] The exceptions are when region pairs from "EU-15" are used as a reference group (both for the HP-filtered data and the eight-year rolling window correlation). This may again be due to EMU introduction. The 2-years panel along with the Cerqueira-Martins business cycle correlation measure and the "EU-15 none EMU" reference group also point to an increase in business cycle synchronisation.

specialise. Following Krugman's hypothesis this would also lead to lower increases (larger decreases) in business cycle synchronisation among such region pairs.[10]

Figure 2: Results for Eastern/Northern enlargement allowing for heterogeneity of treatment in initial business cycle correlation, structural difference and distance between region pairs

Source: Cambridge Econometrics, own calculations.
Notes: Figure plots coefficients for a regression as in equation (3-1) when stratifying the sample by quartiles of initial correlations (top panel), structural difference (middle panel) and distance (bottom panel) between regions. Full regression outputs are reported in the Annex (see Table A2). The reference groups are region pairs of pre-existing countries for both enlargements. The business cycle correlation measure is based on a seven-year rolling window of Corbae-Ouliaris filtered data (denoted as [rw7|co]).

[10] We also conducted some tests for different effects for individual countries (for Austria and Cyprus and Malta). These suggest that the omission of individual countries usually only has minor effects, focusing only on one country may, however, change results. Explaining these differences across countries could be a topic of future research.

To test these hypotheses (using our baseline measures of business cycle synchronisation and structural difference) we ran a series of further regressions in which region pairs were separated according to (a) the quartiles of business cycle correlations between these regions in the year before EU-accession, (b) the quartiles of structural differences between regions prior to enlargement, and (c) the quartiles of the distance between regions. We applied equation (3-1) to each of these quartiles separately. The results are graphically represented in Figure 2.[11] They suggest that region pairs already affected by enlargement with rather synchronised business cycles before accession (i.e. belonging to a higher quartile) also experienced the largest reduction or the smallest increase of cyclical synchronisation relative to unaffected region pairs after both integration steps. This holds for both types of affected region pairs. Further, structural differences for mixed and acceding region pairs diverged more (for Eastern enlargement) or converged less (for Northern enlargement) relative to unaffected region pairs than between regions whose business cycle was less synchronous before EU-accession.

Also more similar regions in terms of sector structure (i.e. belonging to the first quartile) before enlargement experienced higher decreases or lower increases in business cycle synchronisation in both EU-enlargements (middle panel of Figure 2). The only exceptions are acceding region pairs in the case of Northern enlargement. In addition, affected region pairs that already differed substantially in sector structure prior to Eastern enlargement exhibited the strongest increase in structural differences relative to unaffected region pairs. For Northern enlargement the same applies to acceding region pairs.

Patterns with respect to distance (bottom panel of Figure 2) are less clear cut. Here mixed (acceding) region pairs that are more distant from each other experienced the lowest (highest) increases in structural difference relative to unaffected region pairs, but the largest increases

[11] Detailed regression outputs and results showing that using internal (i.e. within-country) region pairs as a reference group does not alter findings. Table A3 and Table A4 in the Appendix provide the respective results.

in business cycle synchronisation for Eastern enlargement. For Northern enlargement a markedly different behavior in mixed and acceding region pairs is found. In the former, both business cycle synchronisation and structural differences increased most in the region pairs closest to each other. In the later the effects of enlargement oscillate substantially between different quartiles.

8. Conclusions

EU-accession by the 10 member states that joined the EU in May 2004 and Northern enlargement in 1995 had rather different effects on business cycle synchronisation and structural differences. Business cycles became less synchronous and differences in sector structure increased between NUTS-3 region pairs located in different acceding countries and mixed region pairs relative to region pairs of pre-member countries in the case of Eastern enlargement. For Northern enlargement, by contrast, results are less robust.

These differences suggest that the institutional as well as geographic, economic and structural differences between these two rounds of enlargement may have led to rather different patterns of adjustment. This is corroborated when considering different quartiles of the distribution of initial business cycle correlations and structural differences. In both cases of enlargement, regions with rather synchronised business cycles before accession also experienced the smallest increase (the largest reduction) of business cycle synchronisation after enlargement. Also structural differences between these regions diverged more (converged less) than in region pairs whose business cycles were less synchronous before enlargement. Similarly, region pairs that were more alike in terms of sector structure before enlargement experienced higher decreases (lower increases) in structural differences, which in accordance with Krugman's hypothesis also led to a higher reduction (smaller increases) in business cycle synchronisation.

Given the rather different results for different enlargement episodes but the rather similar distributional results, future research should thus focus on developing more differentiated hypotheses on the effects of EU-enlargement and the formation of EMU on business cycle synchronisation and sector specialisation, which take explicit consideration of starting conditions. This may be of high policy relevance given that the European Commission was negotiating on membership with six countries in 2014, which all differ widely in economic development and level of integration with the EU, whereas seven countries with equally disparate starting conditions from the Eastern enlargement rounds in 2004 and 2007 were still waiting to join EMU at that time.

References

Angrist, J.D. and Pischke, J. (2009): Mostly Harmless Econometrics: An Empiricist's Companion, Princeton, Princeton University Press.

Artis, M.J. and Okubo, T. (2011): 'Does International Trade Really Lead To Business Cycle Synchronization? – A Panel Data Approach', *The Manchester School*, Vol. 79(2), pp. 318-332.

Artis, M.J., Marcellino, M.G. and Proietti, T. (2004): Characterizing the Business Cycle for Accession Countries, *Centre for Economic Policy Research Discussion Paper*, No. 4457.

Barrios, S. and de Lucio, J.J. (2003): 'Economic Integration and Regional Business Cycles: Evidence from the Iberian Regions', *Oxford Bulletin of Economics and Statistics*, Vol. 65(4), pp. 497-515.

Barrios, S., Brülhart, M., Elliot, R.J.R. and Sensier, M. (2003): 'A Tale of Two Cycles: Co-fluctuations between UK Regions and the Euro Zone', *The Manchester School*, Vol. 71(3), pp. 265-292.

Bayoumi, T. and Eichengreen, B. (1993): 'Shocking Aspects of European Monetary Unification', in: Torres F. and Giavazzi F. (Eds.): Growth and Adjustment in the European Monetary Union, Cambridge University Press, pp. 193-230.

Belke, A. and Heine, J.M. (2006): 'Specialisation patterns and the synchronicity of regional employment cycles in Europe', *International Economics and Economic Policy*, Vol. 3(2), pp. 91-104.

Bertrand, M., Duflo, E. and Mullainathan, S. (2004): 'How Much Should We Trust Differences-in-Differences Estimates?', *The Quarterly Journal of Economics*, Vol. 119(1), pp. 249-275.

Cerqueira, P.A. and Martins, R. (2009): 'Measuring the determinants of business cycle synchronization using a panel approach', *Economics Letters*, Vol. 102(2), pp. 106-108.

Cerqueira, P.A. (2013): 'A closer look at the world business cycle synchronization', *International Economics and Economic Policy*, Vol. 10(3), pp. 349-363.

Christodoulopoulou, S. (2014): 'The effect of currency unions on business cycle correlations: the EMU case', *Empirica*, Vol. 41, pp. 177-222.

Chung, S. and Hewings G.J.D. (2015): 'Competitive and Complementary Relationship between Regional Economics: A Study of the Great Lake States', *Spatial Economic Analysis*, Vol. 10(2), pp. 205-229.

Clark, T.E. and van Wincoop, E. (2001): 'Borders and Business Cycles', *Journal of International Economics*, Vol. 55(1), pp. 59-85.

Corbae, D. and Ouliaris, S. (2006): 'Extracting Cycles From Non Stationary Data', *Econometric Theory and Practice*, Cambridge, Cambridge University Press, pp. 167-177.

Corbae, D., Ouliaris, S. and Phillips, P.C.B. (2002): 'Band Spectral Regression with Trending Data', *Econometrica*, Vol. 70(3), pp. 1067-1109.

EC (1990): One Market, One Money. An Evaluation of the Potential Benefits and Costs of Forming an Economic and Monetary Union, *European Economy*, No. 44.

Fatás, A. (1997): 'EMU: Countries or regions? Lessons from the EMS experience', *European Economic Review*, Vol. 41, pp. 743-751.

Frankel, J.A. and Rose, A.K. (1997): 'Is EMU more justifiable ex post than ex ante', *European Economic Review*, Vol. 41, pp. 753-760.

Frankel, J.A. and Rose, A.K. (1998): 'The Endogeneity of the Optimum Currency Area Criteria', *The Economic Journal*, Vol. 108, pp.1009-1025.

Gächter, M. and Riedl, A. (2013): One Money, One Cycle? The EMU Experience, *Oesterreichische Nationalbank*, Working Papers, No. 186.

Goncales, C.E.S., Rodrigues, M. and Soares, T. (2009): 'Correlation of Business Cycles in the Euro Zone', *Economics Letters*, Vol. 102(1), pp. 56-58.

Kalemli-Ozcan, S., Sørensen, B.E. and Oved, Y. (2001): 'Economic Integration Industrial Specialization, and the Asymmetry of Macroeconomic Fluctuations', *Journal of International Economics*, Vol. 55 (1), pp. 107-137.

Krugman, P. (1991): Geography and trade, Cambridge, MIT Press.

Krugman, P. (1993): 'Lessons of Massachusetts for EMU', in: Torres F. and Giavazzi F. (eds.), Adjustment and Growth in the European Monetary Union, Cambridge, Cambridge University Press, pp. 241-261.

Montoya, L.A. and de Haan, J. (2008): 'Regional business cycle synchronization in Europe?', *International Economics and Economic Policy*, Vol. 5(1-2), pp. 123-137.

Mundell, R. (1961): 'A Theory of Optimum Currency Areas', *American Economic Review*, Vol. 51, pp. 657-665.

Park, Y. and Hewings, G.J.D. (2012): 'Does Industry Mix Matter in Regional Business Cycles?', *Studies in Regional Science*, Vol. 42(1), pp. 39-60.

Ravn, M.O. and Uhlig, H. (2002): 'On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations', *The Review of Economics and Statistics*, Vol. 84(2), pp. 371-376.

Siedschlag, I. and Tondl, G. (2011): 'Regional Output Growth Synchronization with the Euro Area', *Empirica*, Vol. 38, pp. 203-221.

Chapter III

Appendix

Table A1: Robustness tests for Eastern and Northern enlargement with respect to business cycle synchronisation

Integration Step	Eastern Enlargement												Northern Enlargement											
Time Dimension	Full-Panel						2-Years-Panel						Full-Panel						2-Years-Panel					
Reference Group	EU-15		Within-country		EU-15 but non EMU		EU-15		Within-country		EU-15 but non EMU		EU-12		Within-country		EU-12 but only EMU		EU-12		Within-country		EU-12 but only EMU	
Model Spec.	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Measure	Augmented Cerqueira-Martins based on Corbae-Ouliaris filter [cm*|co]																							
Mixed (i,j)	-0.087***	-0.087***	-0.14***	-0.14***	-0.20***	-0.20***	-0.10***	-0.11***	0.013**	-0.0067	0.50***	0.47***	0.022***	0.023***	0.11***	0.11***	0.057***	0.056***	0.074***	0.072***	-0.12***	-0.11***	0.25***	0.24***
	(0.0022)	(0.0022)	(0.0029)	(0.0029)	(0.0120)	(0.0120)	(0.0047)	(0.0048)	(0.0061)	(0.0062)	(0.0250)	(0.0250)	(0.0027)	(0.0027)	(0.0036)	(0.0036)	(0.0034)	(0.0034)	(0.0068)	(0.0068)	(0.0085)	(0.0086)	(0.0088)	(0.0088)
Acceding (i,j)	-0.31***	-0.31***	-0.37***	-0.36***	-0.22***	-0.21***	-0.37***	-0.37***	-0.26***	-0.27***	0.20***	0.21***	0.082***	0.080***	0.17***	0.17***	0.31***	0.31***	0.075**	0.066*	-0.12***	-0.12***	0.45***	0.46***
	(0.0086)	(0.0086)	(0.0088)	(0.0089)	(0.0140)	(0.0140)	(0.0190)	(0.0190)	(0.0190)	(0.0190)	(0.0300)	(0.0300)	(0.0150)	(0.0150)	(0.0150)	(0.0150)	(0.0230)	(0.0230)	(0.0370)	(0.0370)	(0.0370)	(0.0370)	(0.0640)	(0.0640)
ln(Struct. Diff.)		-0.036***		-0.037***		-0.044***		-0.0085		0.14***		0.21***		-0.054***		-0.061***		-0.057***		-0.13***		-0.21***		-0.26***
		(0.0027)		(0.0040)		(0.0110)		(0.0059)		(0.0089)		(0.0250)		(0.0024)		(0.0042)		(0.0033)		(0.0078)		(0.0120)		(0.0100)
ln(GVA p.c. Diff.)		-0.20***		-0.19***		-0.73***		-0.45***		-0.44***		-1.40***		-0.036***		-0.20***		0.057***		0.20***		-0.17**		-0.019
		(0.0150)		(0.0240)		(0.0650)		(0.0280)		(0.0450)		(0.1200)		(0.0130)		(0.0280)		(0.0160)		(0.0420)		(0.0760)		(0.0500)
N	6,325,770	6,325,770	2,832,310	2,832,310	359,520	359,520	1,265,154	1,265,154	566,462	566,462	71,904	71,904	6,009,240	6,009,240	2,228,962	2,228,962	3,927,300	3,927,300	801,232	801,232	297,196	297,196	523,640	523,640
R-sq	0.011	0.011	0.018	0.018	0.047	0.048	0.004	0.005	0.001	0.002	0.016	0.033	0.005	0.005	0.011	0.011	0.006	0.006	0.006	0.007	0.001	0.004	0.014	0.016
Measure	7-years rolling window based on Hodrick-Prescott filter [rw7|hp]																							
Mixed (i,j)	0.0011	0.0075***	-0.048***	-0.044***	-0.086***	-0.081***	0.046***	0.063***	-0.060***	-0.050***	-0.17***	-0.16***	-0.012***	-0.0088***	0.17***	0.17***	-0.030***	-0.025***	0.0074***	0.0094***	0.16***	0.16***	0.10***	0.10***
	(0.0011)	(0.0011)	(0.0014)	(0.0014)	(0.0054)	(0.0054)	(0.0015)	(0.0015)	(0.0019)	(0.0019)	(0.0071)	(0.0071)	(0.0016)	(0.0016)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0025)	(0.0025)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Acceding (i,j)	-0.025***	-0.022***	-0.074***	-0.072***	-0.062***	-0.064***	0.12***	0.14***	0.018***	0.026***	-0.011	-0.011	-0.0046	0.0011	0.18***	0.18***	0.040***	0.048***	0.050***	0.052***	0.20***	0.20***	0.40***	0.41***
	(0.0044)	(0.0044)	(0.0045)	(0.0045)	(0.0065)	(0.0066)	(0.0055)	(0.0055)	(0.0056)	(0.0057)	(0.0084)	(0.0084)	(0.0091)	(0.0091)	(0.0092)	(0.0092)	(0.0130)	(0.0130)	(0.0150)	(0.0150)	(0.0150)	(0.0150)	(0.0240)	(0.0240)
ln(Struct. Diff.)		-0.0041***		-0.020***		-0.0016		-0.065***		-0.072***		-0.072***		0.013***		0.020***		0.020***		-0.029***		0.0087**		-0.078***
		(0.0012)		(0.0018)		(0.0048)		(0.0019)		(0.0028)		(0.0075)		(0.0014)		(0.0023)		(0.0019)		(0.0029)		(0.0042)		(0.0036)
ln(GVA p.c. Diff.)		0.31***		0.25***		0.52***		0.32***		0.25***		0.32***		-0.25***		-0.21***		-0.32***		-0.31***		-0.32***		-0.35***
		(0.0080)		(0.0130)		(0.0370)		(0.0091)		(0.0150)		(0.0380)		(0.0083)		(0.0170)		(0.0097)		(0.0160)		(0.0280)		(0.0190)
N	6,325,770	6,325,770	2,832,310	2,832,310	359,520	359,520	1,265,154	1,265,154	566,462	566,462	71,904	71,904	6,009,240	6,009,240	2,228,950	2,228,950	3,927,300	3,927,300	801,232	801,232	297,194	297,194	523,640	523,640
R-sq	0.340	0.341	0.377	0.378	0.327	0.329	0.445	0.447	0.515	0.516	0.484	0.487	0.056	0.057	0.123	0.123	0.095	0.095	0.089	0.09	0.176	0.177	0.15	0.15
Measure	8-years rolling window based on Corbae-Ouliaris filter [rw8|co]																							
Mixed (i,j)	0.012***	0.020***	-0.0047***	0.0014	-0.12***	-0.11***	0.028***	0.046***	-0.053***	-0.042***	-0.16***	-0.15***	-0.0035**	-0.0015	0.095***	0.094***	-0.016***	-0.012***	-0.012***	-0.010***	0.11***	0.11***	0.065***	0.067***
	(0.0010)	(0.0010)	(0.0013)	(0.0013)	(0.0047)	(0.0047)	(0.0013)	(0.0014)	(0.0017)	(0.0017)	(0.0059)	(0.0059)	(0.0016)	(0.0016)	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Acceding (i,j)	-0.12***	-0.11***	-0.13***	-0.13***	-0.14***	-0.14***	-0.031***	-0.020***	-0.11***	-0.10***	-0.083***	-0.084***	-0.018*	-0.012	0.081***	0.082***	0.014	0.021	0.017	0.02	0.14***	0.14***	0.33***	0.33***
	(0.0041)	(0.0041)	(0.0041)	(0.0042)	(0.0059)	(0.0059)	(0.0049)	(0.0049)	(0.0050)	(0.0050)	(0.0071)	(0.0071)	(0.0093)	(0.0093)	(0.0093)	(0.0093)	(0.0140)	(0.0140)	(0.0120)	(0.0120)	(0.0130)	(0.0130)	(0.0180)	(0.0180)
ln(Struct. Diff.)		-0.011***		-0.053***		-0.0085**		-0.052***		-0.081***		-0.054***		0.034***		0.028***		0.021***		-0.0022		0.028***		-0.024***
		(0.0011)		(0.0016)		(0.0041)		(0.0017)		(0.0024)		(0.0065)		(0.0014)		(0.0021)		(0.0019)		(0.0024)		(0.0035)		(0.0029)
ln(GVA p.c. Diff.)		0.37***		0.24***		0.51***		0.44***		0.28***		0.30***		-0.18***		-0.064***		-0.24***		-0.31***		-0.38***		-0.40***
		(0.0075)		(0.0120)		(0.0320)		(0.0082)		(0.0130)		(0.0330)		(0.0079)		(0.0150)		(0.0093)		(0.0140)		(0.0230)		(0.0160)
N	6,325,770	6,325,770	2,832,310	2,832,310	359,520	359,520	1,265,154	1,265,154	566,462	566,462	71,904	71,904	6,009,240	6,009,240	2,228,970	2,228,962	3,927,300	3,927,300	801,232	801,232	297,196	297,196	523,640	523,640
R-sq	0.308	0.309	0.348	0.349	0.283	0.285	0.370	0.374	0.438	0.441	0.306	0.309	0.038	0.039	0.063	0.063	0.063	0.064	0.059	0.061	0.145	0.147	0.099	0.102

Source: Cambridge Econometrics, own calculations. Note: See notes to Tables 2 and 3.

Table A2: Results allowing for heterogeneity of treatment

Dep. Variable	Business Cycle Correlation [rw7|co]				Structural Difference			
Quartile	1st	2nd	3rd	4th	1st	2nd	3rd	4th
	Eastern Enlargement							
Reference Group	EU-15							
Q-Indicator	Business Cycle Correlation [rw7|co]							
Mixed (i,j)	-0.0041**	-0.028***	-0.053***	-0.070***	0.027***	0.026***	0.024***	0.023***
	(0.0017)	(0.0018)	(0.0017)	(0.0016)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Acceding (i,j)	-0.057***	-0.093***	-0.13***	-0.14***	0.036***	0.030***	0.028***	0.029***
	(0.0089)	(0.0075)	(0.0067)	(0.0055)	(0.0012)	(0.0010)	(0.0010)	(0.0010)
N	1,581,450	1,581,440	1,581,440	1,581,440	1,581,450	1,581,440	1,581,440	1,581,440
R-sq	0.663	0.442	0.200	0.034	0.037	0.034	0.031	0.028
Q-Indicator	Structural Difference							
Mixed (i,j)	-0.020***	-0.018***	-0.0088***	0.0075***	0.016***	0.021***	0.027***	0.038***
	(0.0024)	(0.0021)	(0.0021)	(0.0023)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Acceding (i,j)	-0.20***	-0.18***	-0.14***	-0.064***	0.016***	0.023***	0.036***	0.050***
	(0.0070)	(0.0085)	(0.0100)	(0.0140)	(0.0007)	(0.0010)	(0.0014)	(0.0020)
N	1,581,450	1,581,440	1,581,440	1,581,440	1,581,450	1,581,440	1,581,440	1,581,440
R-sq	0.325	0.301	0.287	0.242	0.131	0.038	0.044	0.101
Q-Indicator	Distance (in km)							
Mixed (i,j)	-0.0016	-0.012***	-0.041***	0.0088***	0.025***	0.024***	0.028***	0.023***
	(0.0024)	(0.0021)	(0.0022)	(0.0023)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Acceding (i,j)	-0.20***	-0.22***	-0.19***	0.26***	0.028***	0.029***	0.035***	0.048***
	(0.0057)	(0.0090)	(0.0140)	(0.0180)	(0.0007)	(0.0011)	(0.0017)	(0.0023)
N	1,581,450	1,581,440	1,581,440	1,581,440	1,581,450	1,581,440	1,581,440	1,581,440
R-sq	0.321	0.348	0.297	0.198	0.034	0.033	0.039	0.031
	Northern Enlargement							
Reference Group	EU-12							
Q-Indicator	Business Cycle Correlation [rw7|co]							
Mixed (i,j)	0.037***	0.020***	0.019***	0.0021	0.0092***	0.0012**	-0.0014***	-0.0014***
	(0.0032)	(0.0033)	(0.0030)	(0.0025)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
Acceding (i,j)	0.01	-0.037*	-0.045**	-0.059***	0.00072	-0.0079***	-0.0097***	-0.011***
	(0.0150)	(0.0190)	(0.0180)	(0.0160)	(0.0019)	(0.0020)	(0.0018)	(0.0015)
N	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310
R-sq	0.174	0.039	0.074	0.241	0.045	0.029	0.022	0.019
Q-Indicator	Structural Difference							
Mixed (i,j)	-0.004	-0.0028	-0.0068**	-0.033***	-0.0013***	-0.0059***	-0.0071***	-0.0028***
	(0.0029)	(0.0032)	(0.0034)	(0.0041)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Acceding (i,j)	-0.043***	-0.016	-0.0059	0.018	-0.016***	-0.026***	-0.020***	-0.0045*
	(0.0140)	(0.0180)	(0.0240)	(0.0390)	(0.0013)	(0.0015)	(0.0019)	(0.0025)
N	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310
R-sq	0.042	0.038	0.032	0.021	0.133	0.026	0.051	0.218
Q-Indicator	Distance (in km)							
Mixed (i,j)	0.043***	-0.048***	-0.014***	-0.015***	0.013***	0.0016***	-0.014***	0.0079***
	(0.0039)	(0.0039)	(0.0033)	(0.0028)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
Acceding (i,j)	-0.11***	-0.053**	-0.0096	-0.0055	-0.011***	-0.0024	-0.014***	-0.0021
	(0.0250)	(0.0240)	(0.0180)	(0.0150)	(0.0021)	(0.0019)	(0.0016)	(0.0016)
N	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310	1,502,310
R-sq	0.036	0.028	0.035	0.036	0.029	0.039	0.03	0.03

Source: Cambridge Econometrics, own calculations.

Note: Table reports coefficients for a regression as in equation (1) when stratifying the sample by quartiles of initial correlations (top panel), structural difference (medium panel) and distance (bottom panel) between regions. Values in brackets are clustering corrected (by region pair) standard error of the estimate. ***, (**), (*) signify significance at the 1% (5%) (10%) significance level, respectively. Region pair and time fixed effects are not reported. R-sq is the within R^2 value of the regression, N is the number of observations. The reference groups are region pairs of pre-existing countries for both enlargements. The business cycle correlation measure is based on a seven-year rolling window of Corbae-Ouliaris filtered data (denoted as [rw7|co]).

Table A3: Results for Eastern enlargement allowing for heterogeneity of treatment

Reference Group	Within-Country							
Dep. Variable	Business Cycle Correlation [rw7|co]				Structural Difference			
Quartile	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Q-Indicator	Business Cycle Correlation [rw7|co]							
Mixed (i,j)	0.0040*	-0.047***	-0.098***	-0.12***	0.024***	0.020***	0.018***	0.017***
	(0.0023)	(0.0023)	(0.0022)	(0.0019)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Acceding (i,j)	-0.049***	-0.12***	-0.17***	-0.20***	0.033***	0.025***	0.022***	0.023***
	(0.0092)	(0.0076)	(0.0067)	(0.0056)	(0.0012)	(0.0010)	(0.0010)	(0.0010)
N	708,080	708,080	708,080	708,070	708,080	708,080	708,080	708,070
R-sq	0.692	0.469	0.235	0.066	0.067	0.073	0.067	0.060
Q-Indicator	Structural Difference							
Mixed (i,j)	-0.0070**	-0.025***	-0.030***	-0.040***	0.018***	0.020***	0.023***	0.032***
	(0.0030)	(0.0028)	(0.0029)	(0.0031)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Acceding (i,j)	-0.18***	-0.19***	-0.17***	-0.13***	0.018***	0.022***	0.030***	0.043***
	(0.0078)	(0.0087)	(0.0095)	(0.0120)	(0.0007)	(0.0010)	(0.0012)	(0.0017)
N	708,080	708,080	708,080	708,070	708,080	708,080	708,080	708,070
R-sq	0.338	0.330	0.325	0.311	0.166	0.088	0.055	0.052
Q-Indicator	Distance (in km)							
Mixed (i,j)	0.012*	0.0024	0.015***	-0.021	0.023***	0.022***	0.020***	0.049***
	(0.0064)	(0.0031)	(0.0047)	(0.0170)	(0.0007)	(0.0004)	(0.0005)	(0.0012)
Acceding (i,j)	-0.22***	-0.18***	-0.19***	0.012	0.025***	0.025***	0.025***	0.064***
	(0.0120)	(0.0072)	(0.0085)	(0.0220)	(0.0012)	(0.0008)	(0.0010)	(0.0020)
N	708,080	708,080	708,080	708,070	708,080	708,080	708,080	708,070
R-sq	0.347	0.370	0.335	0.262	0.018	0.046	0.090	0.111

Source: Cambridge Econometrics, own calculations.

Note: Table reports coefficients for a regression as in equation (1) when stratifying the sample by quartiles of initial correlations (top panel), structural difference (medium panel) and distance (bottom panel) between regions. Values in brackets are clustering corrected (by region pair) standard error of the estimate. ***, (**), (*) signify significance at the 1% (5%) (10%) significance level, respectively. Region pair and time fixed effects are not reported. R-sq is the within R^2 value of the regression, N is the number of observations. The reference groups are internal (i.e. within-country) region pairs. The business cycle correlation measure is based on a seven-year rolling window of Corbae-Ouliaris filtered data (denoted as [rw7|co]).

Table A4: Results for Northern enlargement allowing for heterogeneity of treatment

Reference Group	Within-Country							
Dep. Variable	Business Cycle Correlation [rw7|co]				Structural Difference			
Quartile	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Q-Indicator	Business Cycle Correlation [rw7|co]							
Mixed (i,j)	-0.052***	-0.024***	0.0057*	0.016***	0.0018***	0.0044***	0.0042***	0.0068***
	(0.0040)	(0.0037)	(0.0034)	(0.0037)	(0.0006)	(0.0005)	(0.0005)	(0.0006)
Acceding (i,j)	-0.070***	-0.083***	-0.070***	-0.013	-0.0058***	-0.0056***	-0.0034*	-0.0037
	(0.0140)	(0.0160)	(0.0190)	(0.0240)	(0.0017)	(0.0017)	(0.0018)	(0.0023)
N	557,235	557,235	557,235	557,235	557,235	557,235	557,235	557,235
R-sq	0.162	0.082	0.177	0.4	0.018	0.024	0.026	0.043
Q-Indicator	Structural Difference							
Mixed (i,j)	0.12***	0.12***	0.11***	0.078***	0.016***	0.013***	0.0050***	0.00064
	(0.0041)	(0.0041)	(0.0041)	(0.0042)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Acceding (i,j)	0.069***	0.12***	0.088***	0.11***	0.0021	-0.0052***	-0.014***	-0.0045**
	(0.0180)	(0.0170)	(0.0200)	(0.0260)	(0.0016)	(0.0016)	(0.0016)	(0.0020)
N	557,250	557,235	557,250	557,215	557,250	557,235	557,250	557,227
R-sq	0.086	0.07	0.065	0.055	0.124	0.028	0.046	0.189
Q-Indicator	Distance (in km)							
Mixed (i,j)	0.27***	0.14***	0.028***	-0.14***	0.0097***	0.016***	-0.00041	0.0027
	(0.0082)	(0.0057)	(0.0048)	(0.0190)	(0.0012)	(0.0007)	(0.0006)	(0.0019)
Acceding (i,j)	0.075	-0.068*	-0.026	-0.11***	-0.035***	-0.0062**	-0.0073***	-0.0045**
	(0.0750)	(0.0370)	(0.0170)	(0.0230)	(0.0077)	(0.0028)	(0.0015)	(0.0023)
N	557,230	557,235	557,250	557,235	557,242	557,235	557,250	557,235
R-sq	0.128	0.098	0.039	0.045	0.041	0.044	0.011	0.024

Source: Cambridge Econometrics, own calculations.

Note: Table reports coefficients for a regression as in equation (1) when stratifying the sample by quartiles of initial correlations (top panel), structural difference (medium panel) and distance (bottom panel) between regions. Values in brackets are clustering corrected (by region pair) standard error of the estimate. ***, (**), (*) signify significance at the 1% (5%) (10%) significance level, respectively. Region pair and time fixed effects are not reported. R-sq is the within R^2 value of the regression, N is the number of observations. The reference groups are internal (i.e. within-country) region pairs. The business cycle correlation measure is based on a seven-year rolling window of Corbae-Ouliaris filtered data (denoted as [rw7|co]).

Table B1: Number of NUTS-3 regions

Country	Eastern Enlargement	Northern Enlargement
AT	35	35
BE	44	44
DE	429	326 [1)]
GR	51	51
ES	59	59
FI	20	20
FR	96	96
IE	8	8
IT	107	107
LU	1	1
NL	40	39 [2)]
PT	28	28
SE	21	21
UK	133	133
DK	11	11
EU-15	1,083	979
CZ	14	
SK	8	
SI	12	
CY	1	
MT	2	
LT	10	
LV	6	
EE	5	
PL	66	
HU	20	
EU-10	144	
EU-25	1,227	

Notes:
1) Data on Eastern Germany (NUTS-2 regions DE3, DE4, DE8, DED, DEE and DEG) are omitted.
2) Data on Flevoland (NL230) is missing.

Eidesstattliche Versicherung

Ich versichere hiermit eidesstattlich, dass ich die vorliegende Arbeit selbständig und ohne fremde Hilfe verfasst habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sowie mir gegebenen Anregungen sind als solche kenntlich gemacht. Die Arbeit wurde bisher keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht. Sofern ein Teil der Arbeit aus bereits veröffentlichten Papers besteht, habe ich dies ausdrücklich angegeben.

München, 11. Dezember 2015

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Jürgen Bierbaumer-Polly