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

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Abstract

This paper describes the methodologies used for constructing a composite leading indicator for the Austrian economy (CLI_{AT}). First, a selection of those monthly indicators which overall fare best in showing a 'steady' leading behaviour with respect to the Austrian business cycle was performed. The analysis was carried out by means of statistical methods out of the time-series domain as well as from the frequency domain. Thirteen series have been 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 and the weights have been obtained by means of principal components analysis. Further, idiosyncratic elements in the CLI_{AT} have been 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 it is shown that the CLI_{AT} carries important business cycle information, that its inclusion in a forecasting model can increase the projection quality of the underlying reference series.

JEL classification: C32, C53, E32, E37.

Keywords: Business cycles, turning points, cyclical analysis, leading indicators, composite indicators, HP filter, principal components, out-of-sample forecasting.

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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, so-called 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 70-80s 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 & 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 & 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 are widely used by the OECD to predict growth cycles in the economies of their member countries.

[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.

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, analyses pre-selected leading, coincident and lagging economic indicators according their turning 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 & 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 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 includes series on industrial production, trade, prices and wages, the labour market, international trade, financials and commodity market, and, among qualitative data, business and consumer surveys.
In the dataset on hand, most time series start in the early to mid 80s. 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 decided to restrict the sample period to range between January 1988 and December 2008, in

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

total 252 monthly observations. With this data range, the initial dataset of more than 150 time series was 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.

Table 1: Key Areas

	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 have been transformed seasonally adjusted with Tramo-Seats[3]. Unit root tests showed 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 Appendix A.

2.1 Selecting the reference series

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

Following Scheiblecker (2007) it was decided to 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.

[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.

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 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 will eliminate 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 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 decided to 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 $[\pi/16, \pi/3]$. 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

$$\nu_k = \frac{\sin kb - \sin ka}{k\pi} - \frac{1}{2K+1}\sum_{k=-K}^{K}\frac{\sin kb - \sin ka}{k\pi} \qquad \textbf{(2-1)}$$

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

[6] It is to note that in more recent papers concerning cyclical analysis it is argued that modern business cycles may last longer and have shorter cyclical fluctuations. For example, Agresti and Mojon (2001) propose 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.

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]

Figure 1 shows the business cycle chronology of the reference series Y_{exFA}^{GVA} with its turning points over the sample period 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 third quarter of 2000, respectively. In both cases the bottom in the cycle is reached around 5 to 7 quarters after the cyclical peak.

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 current 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.

In overall, the turning point chronology derived in this work is similar to those found in other studies identifying turning points for Austrian (see e.g. Scheiblecker, 2007; Artis et al., 2004).

[8] Note that most approaches are concerned obtaining filtered values for the *K* end-of-sample periods. The method I choose and implemented in BUSY consists 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: Business Cycle Chronology of the Reference Series Y_{exFA}^{GVA}

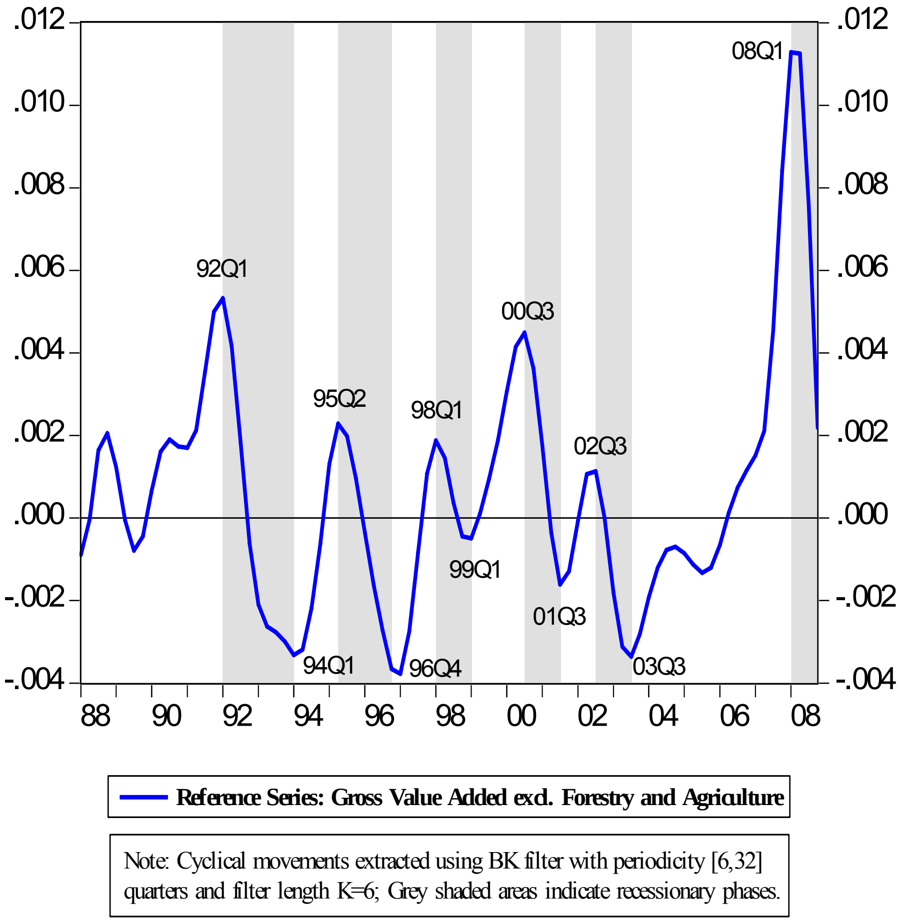

Table 2: Turning Points of the Reference Series Y_{exFA}^{GVA}

Peak (P)	Trough (T)	Cycles: P to P	Cycles: T to T	Phases: P to T	Phases: 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

The next step after the selection of 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 out of the time-series domain as well as from the frequency domain[9]. Since the analysis is focused on the cyclical component, the business cycle information has been 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.[10] 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 starts with summarising the findings from this analysis in presenting the set of those 14 indicators that overall fared 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 and Section 3.2 will discuss the findings for $\chi_t^{(14)}$ in more detail; while the detailed results for all 91 indicators are shown in Appendix B.

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[11], 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,

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

[10] 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.

[11] 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: $BCC = \left[\left(industry_{CC} + 200\right) \times \left(construction_{CC} + 200\right) \times \left(retail_{CC} + 200\right)\right]^{1/3} - 200$

insofar as business and consumer confidence surveys exhibit in general a strong positive leading correlation with the overall state of economic activity.

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

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 have been selected.

In 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 out of 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 was used to determine whether the indicator series has explanatory power for future values in the reference series or vice versa. Series have been, depending on their order of integration, transformed into first- or second-difference stationary series. The order of integration has been determined by the Augmented Dickey-Fuller (ADF) test[12].

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 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[13] 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, Forni & Reichlin, 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.

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[12] 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.

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

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[14], the original Bry & Boschan (1971) routine. The turning points of each individual series are compared to the ones found in the reference series and 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, as measured by the lag at which the closest cross-correlation occurs (see Section 3.1.1), if the individual indicator series $x_{i,t}$ is to give reliable 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[15]. 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 due to 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 an identification and selection criteria, the following commonly used measures are applied: (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

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

[15] 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.

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. The 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, has been accomplished. The classification is based on the following rules: if mean delay is greater than 1 (-1), then the indicator is leading (lagging) by more than one period and if mean delay is between this threshold, then the indicator is classified as coincident.

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

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 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 up to a full year, with the lead time at cyclical troughs being more pronounced. The average durations of cycles, i.e. 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}.

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.

Table 4: Selected 'Leading' 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		(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	Businss 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.

3.3 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 to 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 decided to eliminate this indicator series from $\chi_t^{(14)}$.

Table 5: Data Timeliness and Revision

		Timeliness [1]	**Revision**	**Element of CLI_{AT}** [6]
x_i		(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.

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 which will be used for construction of the CLI_{AT} is highlighted in Table 5 column (3). I will refer to it in subsequent sections as $\chi_t^{(13)}$.

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 been used to forecast growth of economic activity in Austria.

I choose the OECD Composite Leading Indicator[16], the OeNB Economic Indicator (OEI)[17] and the Bank Austria Business Indicator[18] 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, have not been classified as 'leading' with respect to the reference series Y_{exFA}^{GVA} chosen in this study.

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.

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

[17] 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).

[18] 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.

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:[19]

- 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

[19] 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., 2008).

- third, short-term irregularities in the constructed CLI_{AT} are eliminated using once again the HP filter (see Section 4.3).

I will construct three different composite leading indices, $\Omega = \left\{\Psi_{full}^{pca}, \Psi_{full}^{ew}, \Psi_{flash}^{pca}\right\}$, 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 decided to 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, those are the seven business and consumer survey indicators and the two stock market indices.

4.1 De-trending

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[20] relating to spurious cyclical behaviour using the HP method for de-trending (see e.g. Canova 1998; Harvey & Jaeger 1993), the HP filter is still, due to its simple estimation, widely used amongst business cycle researchers and practitioners.

I will 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

[20] 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

and both OECD CLI series. These indicators are therefore considered in their de-trended form in the construction steps which follow.

4.1.1 Hodrick-Prescott Filter - Methodology

Technically, the HP filter is a two-sided symmetric linear high-pass filter that generates the smoothed series by minimising the variance of the underlying series around the trend component, depending on a penalty factor that constrains the second difference of the trend.
The HP-filter solves the minimisation problem:

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

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.[21] 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:

$$\lambda_s = s^m \times \lambda_q \qquad \textbf{(4-2)}$$

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[22]; and λ_q is set to 1600 the value for quarterly data. 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 converts in the frequency domain perspective to a cut-off point of the high-pass filter to roughly below 120 month[23], i.e. all frequencies are wiped out above this threshold.

---

[21] 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.
[22] Using m=2 reveals the original Hodrick-Prescott values for λ.
[23] 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.

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.

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

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[24].

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 at the OECD for their 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.

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

The factor loadings a_{ij} (with i=1…n, j=1…k), are chosen such that the following conditions are satisfied[25]: (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

[24] 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).

[25] 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.

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. From rule of thumb-criteria the number of principal components is usually chosen from the following criteria: (1) the number of eigenvalues larger than one; the number of components that (2) contribute individually to the explanation of overall variance by more than 10%; and (3) have a cumulative explanation power of the overall variance by more than 60%.

The weights v_i of series $x_{i,t}^{z}$ in the CLI_{AT} is 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:[26]

$$v_i = a_{ik}^2 \times \varphi_k \tag{4-5}$$

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

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 $i \leq j \leq m$); 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.

4.2.2 Principal component analysis (PCA) - Results

Table 7 displays the results derived from PCA regarding CLI_{AT} Ψ_{full}^{pca}. Applying the rules of thumb for determining the number of factors gives two principal components, which account for about 79% of 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

[26] The approach used to obtain individual series weights follows the technique described in Nicoletti et al (1999); 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.

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%.

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 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 7: PCA Results - Individual Series Weights

CLI_{AT} Ψ^{pca}_{full}	**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.

Table 8: Individual Series Weights - Summary

x_i		CLI$_{AT}$		
		Ψ^{pca}_{full}	Ψ^{ew}_{full}	Ψ^{pca}_{flash}
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:

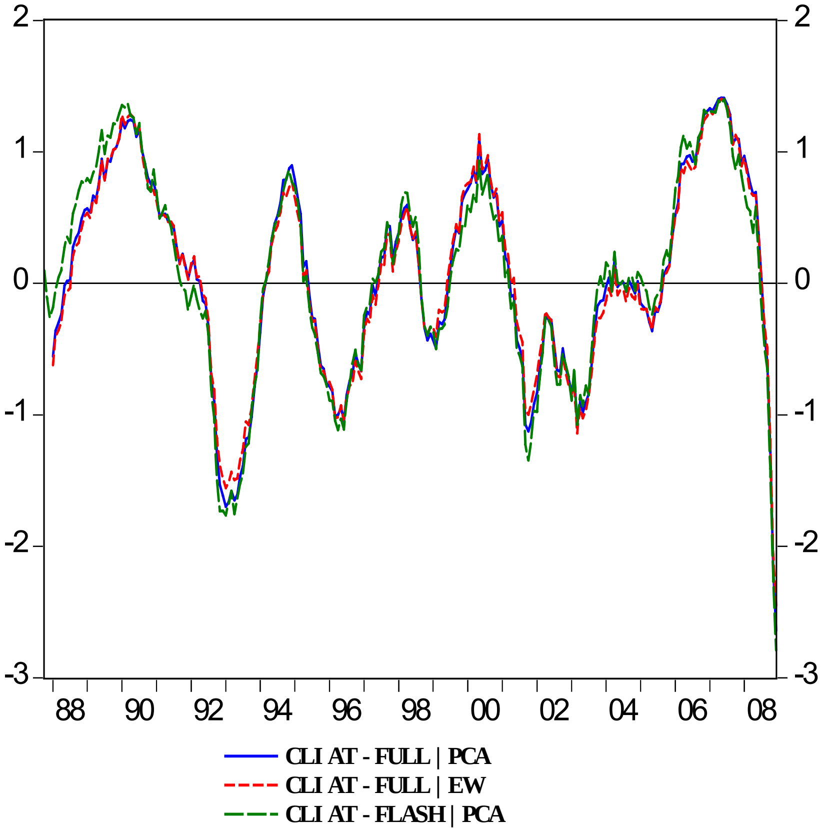
$$\psi_t = \sum_{i=1}^{k} v_i x_{i,t}^z \text{ and } \Psi\left\{\vdots\right\}\Big|_1^T = \left\{\psi_1, \ldots, \psi_T\right\} \quad \textbf{(4-7)}$$

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 $\Psi\left\{\vdots\right\}\Big|_1^T$ 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, it was decided to apply the HP filter again on $\Psi\left\{\vdots\right\}\Big|_1^T$ in order to smooth the series, i.e. eliminating those irregular movements and preserving the business-cycle frequencies.[27]

[27] 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 their 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 previously discussed, the selection of the smoothing parameter λ is the crucial determination in 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 such that the gain for $\omega > \omega_c$ is smaller than 0.5 is found as

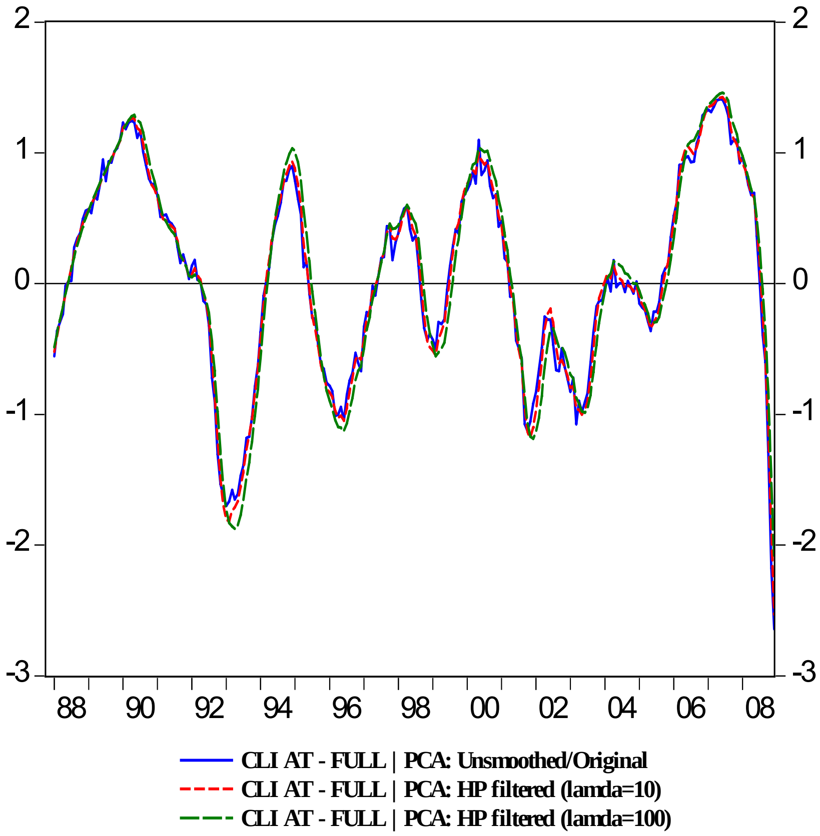
$$\lambda = \left[4 \times (1 - \cos(\omega_c))^2\right]^{-1} \quad \textbf{(4-8)}$$

where $w_c = 2\pi/p$, and p denotes the number of periods it takes to complete a full cycle.

Some sensitivity analysis has been 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} $\Psi^{pca}_{full}|_1^T$. It can be seen that a good part of the noise has been removed in both smoothed series.[28]

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

Figure 4#2: Unsmoothed vs. HP filtered CLI_{AT}



From further visual inspection within the set of λ [10, 100] considered the value of λ=20 appeared sufficient to remove the noise in the unsmoothed CLI_{AT}; this value corresponds to p=13.2 months, thus, removing 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.[29] For a thorough discussion of the endpoint problem in the HP filter see, for example, King & Rebelo (1993) or Kaiser & Maravall (1999/2001). Besides, the one-sided HP filter gives rise to a phase shift in the filtered series thereby possibly delaying the detection of turning points.

[29] 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-King (1999) and Christiano-Fitzgerald (2003).

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 will 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 has been 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[30]. 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

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

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

The quasi 'real-time' smoothed CLI_{AT} output series $\tilde{\Psi}\{\cdot\}|_1^t$ 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 $\tilde{\Psi}\{\cdot\}|_1^T$. With both sets of smoothed CLIs on hand it is now possible to check for the existence of phase-shifts between these series.

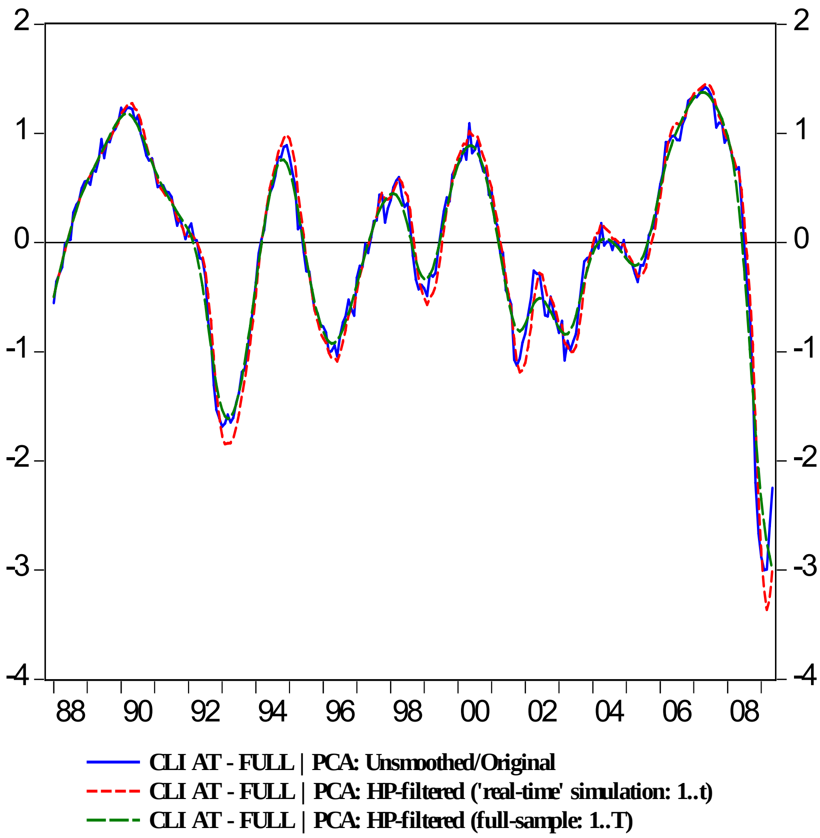
Figure 4 displays the 'real-time' and full-sample HP filtered CLI_{AT} as well as the unsmoothed version. It can be seen that most of the idiosyncratic noise contained in $\Psi_{full}^{pca}|_1^T$ has been

[30] 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.

removed in the HP filtered output series. Contrasting the CLI$_{AT}$ $\widetilde{\Psi}^{pca}_{full}|^{t}_{1}$ with $\widetilde{\Psi}^{pca}_{full}|^{T}_{1}$ 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' those signals may be exaggerated.

In overall, given that the 'real-time' HP filtered CLI$_{AT}$ $\widetilde{\Psi}^{pca}_{full}|^{t}_{1}$ performs quite well and the simulation setting represents the more pragmatic use-case I use $\widetilde{\Psi}\left\{\cdot\atop\cdot\right\}|^{t}_{1}$ 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.

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



5 Performance of the CLI for the Austrian economy

The performance of the CLI_{AT} over time is a crucial determinant of the indicators 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, and discussed in the subsequent section, is the indicator's ability to reduce forecast errors of the underlying reference series, hence, 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 same statistical methods as outlined in Section 3. I decided to include the OECD CLI for Austria as well in the analysis to compare the CLI_{AT} performance against this already existing composite leading indicator[31]. First and foremost, the CLI_{AT} should exhibit a steady leading behaviour with respect to the reference cycle in Y_{exFA}^{GVA}.

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.

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[32] displayed shows on average higher cyclical amplitudes but with regards to turning points the series is almost similar to the constructed CLIs.

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.

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[31] 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.

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

Figure 5: CLI_{AT} vs. Reference Series

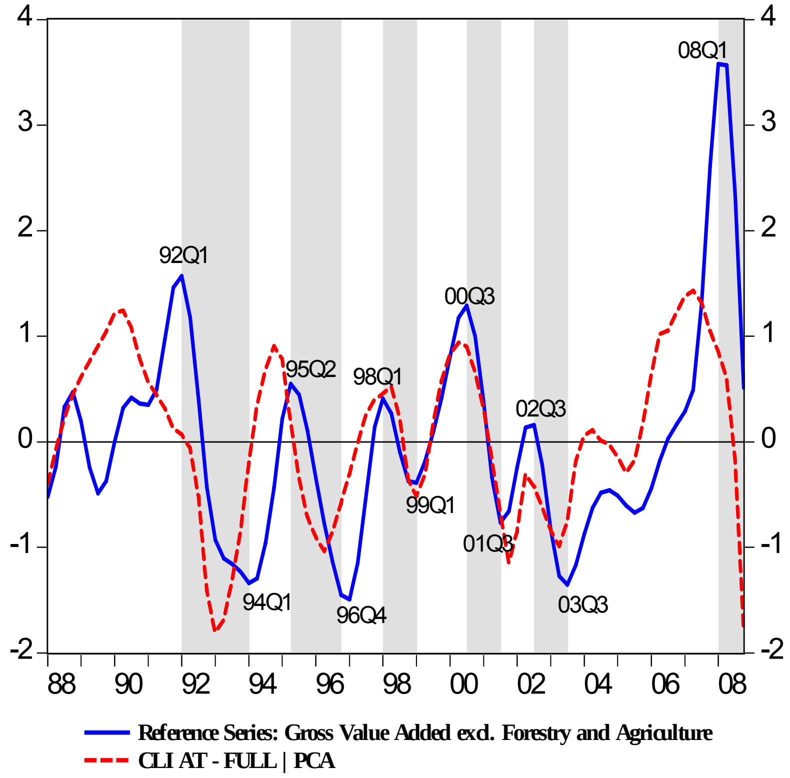
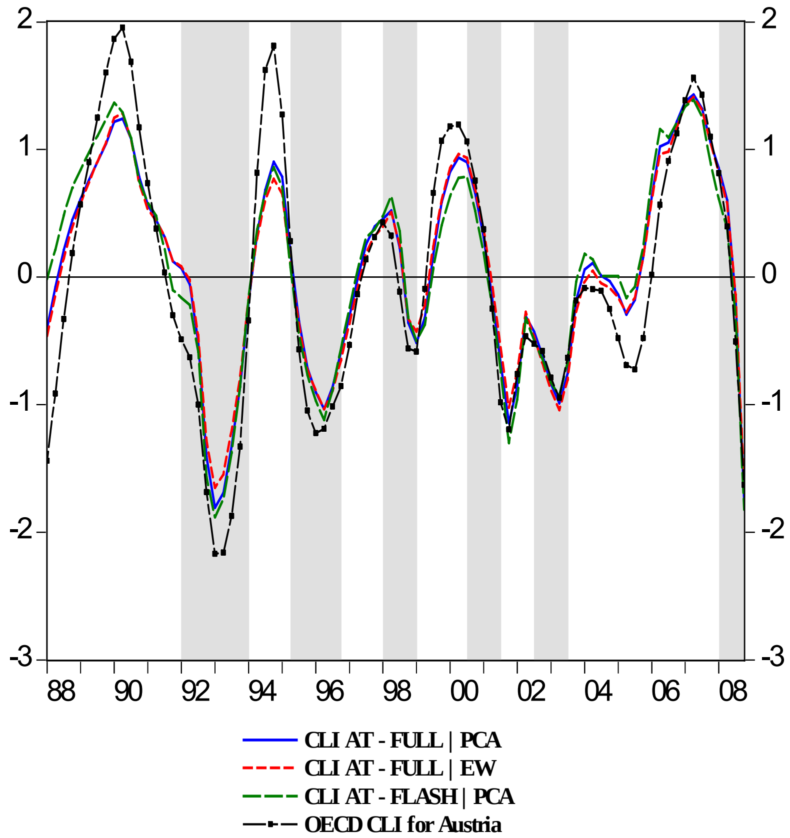


Figure 6: Comparison of different CLIs



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} and 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} $\tilde{\Psi}_{full}^{pca}\vert_1^t$	5.54004 ***	0.90161	0.42	0.59	+2	0.25	+1.05	-2.0	-3.0	-2.0
CLI_{AT} $\tilde{\Psi}_{full}^{ew}\vert_1^t$	4.98645 ***	0.79081	0.43	0.61	+2	0.26	+1.03	-2.0	-3.0	-2.0
CLI_{AT} $\tilde{\Psi}_{flash}^{pca}\vert_1^t$	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 $\tilde{\Psi}_{flash}^{pca}\vert_1^t$ 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.

In 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 to 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 then 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 & 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 decided to 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)[33] 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.

In 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:

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

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

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[33] 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.

information criterion (AIC) at each run. This implies that at each step of the forecast procedure 25 different model estimates were compared and the one with the minimum AIC value was 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.

Take the forecast for 2000Q3 with *h*=4 as 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:

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

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, dividend 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 $\left\{\tilde{\Psi}^{pca}_{full}\,|_1^t, \tilde{\Psi}^{ew}_{full}\,|_1^t, \tilde{\Psi}^{pca}_{flash}\,|_1^t\right\}$, the unsmoothed CLI_{AT} $\Psi^{pca}_{full}\,|_1^T$ as well as the two-sided HP filtered version $\tilde{\Psi}^{pca}_{full}\,|_1^T$, 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. having 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)]												
$CLI_{AT}\ \tilde{\Psi}^{pca}_{full}\|_1^t$	1.02	0.93	0.83	0.90	1.00	0.93	0.86	0.81	0.77	0.77	0.80	0.82
$CLI_{AT}\ \tilde{\Psi}^{ew}_{full}\|_1^t$	0.98	0.91	0.82	0.87	0.97	0.90	0.82	0.77	0.74	0.77	0.74	0.75
$CLI_{AT}\ \tilde{\Psi}^{pca}_{flash}\|_1^t$	1.02	0.98	0.94	0.98	1.01	1.03	0.96	0.94	0.91	0.89	0.90	0.88
$CLI_{AT}\ \Psi^{pca}_{full}\|_1^T$	0.94	0.92	0.79	0.96	0.98	0.94	0.85	0.85	0.80	0.78	0.80	0.83
$CLI_{AT}\ \tilde{\Psi}^{pca}_{full}\|_1^T$	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 $CLI_{AT}\ \tilde{\Psi}\left\{^{(\cdot)}_{full}\right\}\|_1^t$, performs much better compared to the ‘flash’ version, and, moreover, the equally weighted $CLI_{AT}\ \tilde{\Psi}^{ew}_{full}\|_1^t$ 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 $CLI_{AT}\ \tilde{\Psi}^{pca}_{full}\|_1^T$.

7 Summary and Conclusion

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 is the one provided by the OECD.

I have analysed 91 monthly single indicators, spanning over the period 1988-2008, to select those series which overall fare best in showing a 'steady' leading behaviour with respect to an underlying reference series. As reference series I make use of the time-series real gross value added excluding forestry and agriculture. I follow the growth cycle approach and use 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 have been finally qualified to enter the CLI for the Austrian economy. The analysis was carried out by means of statistical methods out of 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 have supplemented the statistical procedures used.
The study has 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 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 have been corrected for their long-run trend. The de-trending was done 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 have been 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 has been 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 the smoothed CLI_{AT} is exposed to the endpoint problem. In doing so I have simulated a quasi 'real-time' environment; as such the HP filter is repeatedly applied on a sub-sample which is supplemented at each run by one period. It was shown that the 'real-time' smoothed CLI_{AT} does not exhibit severe phase-shifts compared to the full-sample estimate. Consequently, I have 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 one. Further, the performance between different CLIs as well as the OECD CLI has been compared. The difference in the CLIs consists of the weighting method used and number of single indicators combined. The results indicate that overall no significant disparity can be observed.
Finally, I provide 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 is evaluated for forecasting horizons varying from 1 up to 12 quarters. The simulation shows 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 find 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.

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Appendix A: Overview Indicator List - Properties

		Data		
		Seasonal + working day adjustment [1)]	**log Trans-form.**	**Order of Integration**
		(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)

Appendix A: Overview Indicator List - Properties (cont.)

		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	WIFO 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.

Appendix B: Overview Indicator List - Statistical Results

No.	Indicator	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			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

Appendix B: Overview Indicator List - Statistical Results (cont.)

	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

Appendix B: Overview Indicator List - Statistical Results (cont.)

	Surveys	(1)		(2)		(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	<u>Source: Austrian Institute of Economic Research (WIFO)</u>																
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	WIFO 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
	<u>Source: European Commission</u>																
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
	<u>Source: Ifo Institute for Economic Research, Munich</u>																
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.

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