UNIVERSITY OF ECONOMICS, PRAGUE
FACULTY OF INFORMATICS AND STATISTICS

ON AUTOMATING AND EXTENDING CONSTRUCTION OF BUSINESS CYCLE COMPOSITE INDICATORS

Doctoral Thesis

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Declaration

I declare that I carried out this doctoral thesis independently and cited all used sources and literature.

Prague, June 9, 2019

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Abstract

Composite indicators are a widespread method for business cycle analysis, especially because they can be easily interpreted although they summarize multidimensional relationships between individual economic time series. The composite indicators can be divided into leading, coincident and lagging ones with regard to the reference time series (usually GDP or industrial production index). The composite leading indicators (CLIs) are the most frequently constructed type of these indicators as they can predict the future states of the economic activity.

The methodology of the composite indicators construction is described in detail by several organizations and it is always based on many subjective expert choices and decisions. This thesis proposes a new algorithmic approach which enables to fully automate the whole computational process. This method allows to create the composite indicators faster than any other available technique and it replaces the subjectivity of choices and increases tractability of the calculations.

This thesis, based on computational statistics, aims to describe the modifications that are needed to fully automate the construction of the composite indicators. It compares the results with the CLIs which are regularly published by the Organization for Economic Co-operation and Development (OECD) and shows, that the process can be automated. A simple set of rules is designed to enable objective comparison between two composite indicators. This thesis also suggests how to extend the OECD methodology to improve the CLIs performance and to analyse the relationships between the business cycles of multiple countries.

Key words: business cycle analysis, composite indicators, algorithmic approach, automation of computational process in Python

Abstrakt

Kompozitní ukazatele jsou velmi rozšířenou metodou pro analýzu hospodářského cyklu, protože je lze velmi snadno interpretovat i přesto, že se skládají z mnoha ekonomických indikátorů. Tyto ukazatele lze rozdělit na předstihové, souběžné a zpožďující se podle jejich vztahu k referenční časové řadě (většinou HDP nebo index průmyslové produkce). Nejčastěji se sestavují předstihové kompozitní ukazatele, protože dokáží predikovat budoucí stavy ekonomické aktivity.

Metodika konstrukce kompozitních ukazatelů byla v minulosti detailně popsána několika organizacemi a vždy závisela na mnoha subjektivních rozhodnutích a expertních znalostech jejích tvůrců. Tato práce navrhuje novou algoritmickou metodu, která umožní plně automatizovat celý proces výpočtu. Díky tomuto přístupu mohou být kompozitní ukazatele vytvořeny rychleji, než kteroukoliv jinou dostupnou metodou, je snížen vliv subjektivních rozhodnutí a zároveň usnadněna kontrola celého výpočetního procesu.

Tato disertační práce založená na metodách výpočetní statistiky popisuje úpravy metodiky, které je nutné provést, aby bylo možné výpočty kompozitních ukazatelů automatizovat. Srovnává výsledky s předstihovými ukazateli, které pravidelně publikuje Organizace pro hospodářskou spolupráci a rozvoj (OECD), a ukazuje, že celý proces výpočtu skutečně může být automatizován. Porovnání kompozitních ukazatelů probíhá pomocí nově navržených pravidel, které zajišťují objektivitu výsledků. Tato práce také popisuje, jak rozšířit metodiku OECD, aby se zvýšila kvalita vytvořených kompozitních ukazatelů a aby bylo možné analyzovat vztahy mezi hospodářskými cykly více zemí.

Abstrakt

Klíčová slova: analýza hospodářského cyklu, kompozitní ukazatele, algoritmizace, automatizace výpočtů v Pythonu

Contents

Abbreviations

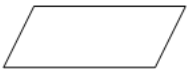
API	Application programming interface
AUS	Australia
AUT	Austria
CACIS	Cyclical Analysis and Composite Indicators System
CIF	Composite Indicators Framework
CLI	Composite leading indicator
CZE	Czech Republic
DEU	Germany
EI	Economic indicator
FIN	Finland
GDP	Gross domestic product
HP filter	Hodrick-Prescott filter
IDE	Integrated development environment
IIP	Index of industrial production
JPN	Japan
KOR	Republic of Korea
MEI	Main economic indicators (name of OECD database)

MEI_ARCHIVE	Archive of past data editions of main economic indicators (name of OECD database)
MEX	Mexico
NZL	New Zealand
OECD	Organization for Economic Co-operation and Development
POL	Poland
PyPI	Python Package Index
QNA	Quarterly national accounts (name of OECD database)
RS	Reference series
SVK	Slovakia
USA	United States of America
ZAF	Republic of South Africa

Symbols used in flowcharts

Flowchart nodes

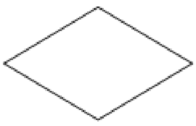
Start or end of the flowchart



Input data

Process

Subprocess



Decision

Document

Off-page reference

Slice notation

l[i]	i^{th} element of the list *l* (returns number or string)
l[-i]	i^{th} element from the end of the list *l* (returns number or string)
l[i : j]	Elements from i^{th} to j^{th} position of the list *l* (returns list)

l[i :]	Elements from i^{th} position to the end of the list *l* (returns list)
l[: j]	Elements from the beginning to the j^{th} position of the list *l* (returns list)
df[i , :]	i^{th} row of the data frame *df* (returns data frame)
df[-i , :]	i^{th} row from the end of the data frame *df* (returns data frame)
df[i : j, :]	Rows from i^{th} to j^{th} position of the data frame *df* (returns data frame)
df[: , k]	k^{th} column of the data frame *df* (returns data frame)
df[: , 'string']	Column denoted by label *'string'* in the data frame *df* (returns data frame)
df[i, k]	i^{th} row of k^{th} column of the data frame *df* (returns data frame)
df[i, 'string']	i^{th} row of the column denoted by label *'string'* in the data frame *df* (returns data frame)
df[i : j, k]	Rows from i^{th} to j^{th} position of the k^{th} column of the data frame *df* (returns data frame)
df[i : j, 'string']	Rows from i^{th} to j^{th} position of the column denoted by label *'string'* in the data frame *df* (returns data frame)

Functions

a1 / a2	Element-wise division of arrays *a1* and *a2* (both *a1* and *a2* can be lists or data frame columns with the same size, returns list or data frame column with the same index and row labels as array *a1*)
abs(x)	Absolute value of *x* (returns number)
append(a1, a2)	Append arrays *a1* and *a2* (both *a1* and *a2* can be lists or data frame columns, returns list or data frame column)
avg(a)	Average value of elements of array *a* (*a* can be list or data frame column with numeric values, returns number)
column(df)	List of column labels of data frame *df* (returns list)
count(a)	Count of not null elements of array *a* (*a* can be list or data frame column, returns number)

cumsum(a)	Cumulative sum of array *a* (*a* can be list or data frame column with numeric values, returns list or data frame column)
dropnull(a)	Array *a* without null or NA elements (*a* can be list or data frame column, returns list or data frame column)
index(df)	List of row labels of data frame *df* (returns list)
len(l)	Length of the list *l* (returns number)
max(a)	Maximum of the elements of array *a* (*a* can be list or data frame column with numeric values, returns number)
median(a)	Median of the elements of array *a* (*a* can be list or data frame column with numeric values, returns number)
min(a)	Minimum of the elements of array *a* (*a* can be list or data frame column with numeric values, returns number)
min(a, key = abs)	Minimum of the elements of array *a*, when elements are sorted according to their absolute values (*a* can be list or data frame column with numeric values, returns number)
ncol(df)	Number of columns of data frame *df* (returns number)
nrow(df)	Number of rows of data frame *df* (returns number)
rank(a, asc = True)	Rank values of array *a* in ascending order (*a* can be list or data frame column with numeric values, returns list or data frame column)
rank(a, asc = False)	Rank values of array *a* in descending order (*a* can be list or data frame column with numeric values, returns list or data frame column)
std(a)	Standard deviation of the elements of array *a* (*a* can be list or data frame column with numeric values, returns number)

Introduction

Although we are now in the phase of economic expansion, the public attention has been focused on the possibilities of forecasting the business cycle movements since the recent Great Recession in 2007. One of the methods used for the business cycle analysis is based on the study of composite indicators, which combine several individual economic time series with a strong relationship with the cycle behaviour. The composite indicators can capture the cyclical movements of the economy better than any of these individual series on their own.

The original purpose of the composite indicators is to analyse the dating of the business cycle turning points. This thesis describes the composite leading indicators (CLIs) and their predictive properties. CLIs should be able to forecast the switches between the expansion and recession phases of the economy up to several months in advance. Although some authors claim that the predictive power of CLIs is rather limited, this thesis shows that the CLIs are at least able to indicate the turning points of the business cycle before they are apparent in other indicators (e.g., gross domestic product). Therefore, the CLIs are considered to be a useful tool for the business cycle analysis.

However, this thesis aims to go further and show, that if their construction is properly automated, the CLIs can serve to different purposes than just predicting the business cycle turning points. It shows, how to include the international data in the construction and then use the results to analyse the leading influences between the business cycles of multiple countries.

Nowadays, there are several organisations, that define their own methodologies and publish their business cycle composite indicators on regular basis, e.g., the Organization for Economic Co-operation and Development (OECD) or Conference board. Even the European Commission launched their own Competence Centre on Composite Indicators and Scoreboards (COIN) in 2016. Moreover, there are many authors from academia and national statistical offices, who also contribute to this topic. It therefore comes as a surprise, that there are no publicly available software programs, R packages or Python libraries, that would support the whole computational process and its automation.

The current state of the art is based on many subjective expert choices and decisions as the construction of the composite indicators depends on many hyperparameters and requires substantial manual interventions. This thesis introduces a new algorithmic procedure which enables to fully automate the whole construction of the composite indicators. To the best of my knowledge, this is the first attempt to create such algorithmic approach. This new method allows to create the composite indicators faster than any other available technique and it, therefore, enables the researchers to try more scenarios with different settings (e.g., to experiment with various input data sets, adjusting hyperparameters or testing several detrending methods). Some calculations presented in this thesis, especially the international influence analysis, wouldn't be possible without this automated approach. The new method also replaces the subjectivity of choices and increases tractability of the calculations. On the other hand, it reduces the role of the experts in modelling which may lead to mechanic selections that are not optimal.

The constructed composite indicators are compared with the reference series (time series which corresponds with the movements of the business cycle well, usually GDP) and multiple criteria are used to describe their performance, e.g., the number of missing turning points, the mean lead time of the turning points, the maximum value of cross correlation coefficient. The performance of the constructed composite indicator is therefore described by several metrics and deciding, whether it is a good or a poor indicator, is nowadays a subjective choice of its creator.

This thesis has three objectives:

- to identify the crucial steps of the modelling which can be automated and to introduce the new algorithmic approach to the construction of leading composite indicator,
- to propose a simple set of clear rules to objectivise comparison between the performance of the newly created composite indicators with the state-of-art composite indicators,
- to suggest how to extend the leading composite indicators construction with international data (this thesis shows, that the composite indicators can thus be used to analyse the relationships between business cycles of several countries rather than just to predict their turning points).

This thesis combines several fields to create an innovative application of the current state of the art: *economics* (business cycle analysis), *computational statistics* (analysing large data sets of time series) and *programming* (automation of the whole process). These areas belong under the broader and nowadays truly hyped term *data science*.

Chapter 1 will introduce the basic concepts of the business cycle analysis and it will briefly summarize the history of the composite indicators in the Czech Republic and the whole world and it will present alternative approaches to the composite indicators construction.

The OECD methodology will be thoroughly described in chapter 2. This methodology will be invoked through the whole thesis and it will serve as the foundation for the automation and all the proposed alterations of the construction process.

Chapters 3 - 5 will define the main ideas of this thesis: automation, tractability and objectivity of the computation. Chapter 3 will present the newly created Python library for automated construction of the business cycle composite indicators and it will compare this library with other available software solutions. Chapter 4 will discuss the assumptions and adjustments to the methodology that are needed to create the fully algorithmic approach presented in this thesis and incorporated into the newly developed software solution introduced in the previous chapter. This chapter will also point out what parts of the methodology are the most troublesome to automate and it will give some examples to better describe the algorithmic method. Chapter 5 will summarize the metrics, which are nowadays used to compare the performance of two composite indicators and it will propose a set of clear rules to bring some objectivity into the decision process.

Chapter 6 will utilize the theoretical bases introduced in the previous chapters and it will compare the results of the automated calculation with the CLIs created and published by the OECD experts. It will demonstrate, that it really is possible to fully automate the construction of the composite indicators.

Chapter 7 will propose a new way how to utilize the new algorithmic approach to extend the composite indicators construction with international economic series. It will show how to use the composite indicators to assess the relationships between the business cycles of several countries. It will propose a new metric (and visualisation) of leading influences based on the composition of the CLIs.

Chapter 8 will discuss how to test the performance of the composite indicators in the *real-time* mode and whether the CLIs will really be able to predict the movements of the economy.

1 Business cycles and composite indicators

1.1 Classical and deviation business cycles

The business crisis phenomenon was first described by Italian Swiss economist Jean Charles Léonard de Sismondi in 1819, who was deeply affected by the recent European recession. In 1833 John Wade, the English journalist, was the first one to mention alterations between periods of prosperity and depressions, unlike the earlier economists, who focused only on causes of crises. Wade also noticed, that the business cycles were completed in five or seven years-long intervals (Mitchell, 1927).

In 1930's two American economists, Arthur Frank Burns and Wesley Clair Mitchell, worked on new methods how to measure business cycles and determine recessions. According to Burns and Mitchell (1946, p. 3), the business cycles are "a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle".

Burns (1951, p. 3) later emphasized again the importance of the co-movement among economic series, because "the critical feature that distinguishes (business cycles) from the commercial convulsions of earlier centuries or from the seasonal and other short-term variations of our own age is that the fluctuations are widely diffused over the economy – its industry, its commercial dealings, and its tangles of finance. The economy of the western world is a system of closely interrelated parts."

Burns and Mitchell definition has been used by National Bureau of Economic Research (NBER), Conference Board or by other institutions till this day. Nevertheless, Del Negro (2001, p. 2) offers a useful approximation of the business cycle phases: "the beginning of a recession (the end of an expansion) is defined as the first of two consecutive quarters of decline in real GDP. By analogy, the end of a recession (or the beginning of an expansion) is marked by the first of two consecutive quarters of real GDP growth (...). The beginning and end of a recession are turning points in real GDP: the beginning represents a peak in real GDP while the end represents a trough."

This type of business cycle became later known as the *classical business cycle*. The recessions meant the decline in the absolute level of economic output.

However, most European economies experienced rather declines in growth rates of output than the real declines in its level. Mintz (1969) therefore proposed the new definition of business cycles, which became later known as *growth* or *deviation cycles*. The deviation cycle was obtained by removing trend from the reference time series (usually GDP) and could be interpreted as the output gap (the difference between the actual and potential economy output). Mintz also brought up new terms: speedups and slowdowns of the economy instead of expansions and recessions known from Burns and Mitchell's classical cycles.

Nowadays economists and various organisations still work with both classical and deviation cycles. OECD usually analyses the deviation cycles and treats the slowdowns like recessions. On the other hand, authors from the Conference Board (Zarnowitz and Ozyildirim, 2006) point out, that all the recessions involve slowdowns but not all slowdowns involve recessions and therefore the deviation cycles are more numerous than the classical business cycles and they can cause the shifts in the turning points dates.

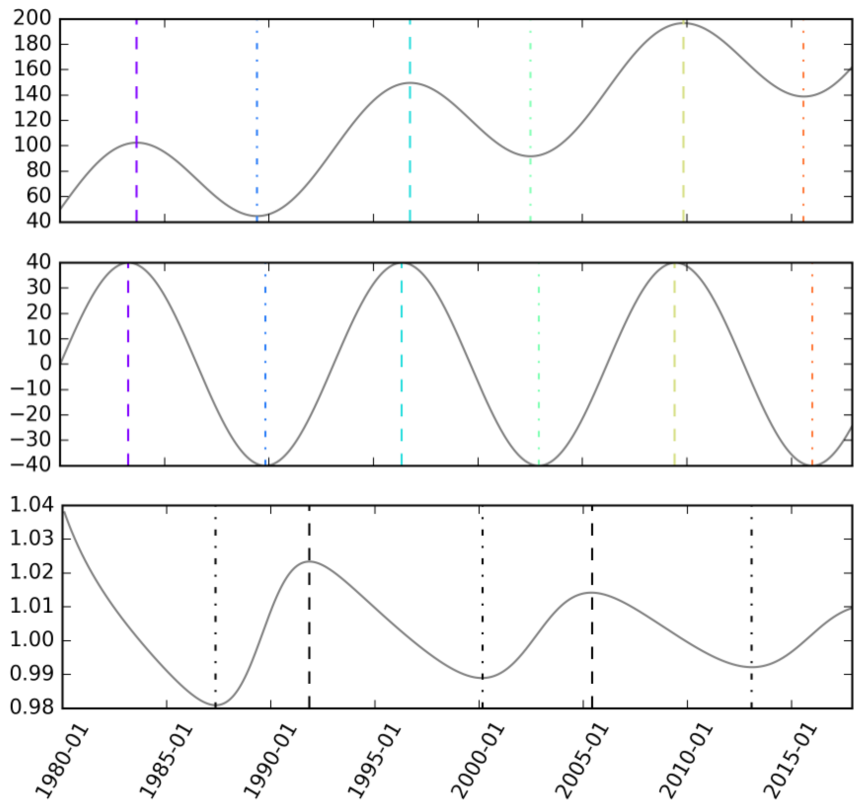


Figure 1.1 – Schema of turning points dates of the artificial classical business cycle (upper chart), deviation cycle (middle chart) and month-to-month growth rates (lower chart).
Source: Own construction

Figure 1.1 illustrates these shifts of the turning points of the classical business cycle, the deviation cycle and month-to-month growth rates, which are also sometimes used to detrend the economic series and to analyse the cycle. All the data in these charts are artificial and the upper chart could represent for example the real GDP in a currency unit. The vertical lines highlight the dates of the turning points: the matched turning points are marked in the same colour. The peaks and troughs of the growth rates are too far to be matched with any of the classical cycle turning points, so they are marked in black.

As the deviation cycle is created by removing the trend from the classical business cycle (for more information, see chapter 2 and 4), it leads the business cycle in peaks and lags in troughs. The month-to-month growth rates start to decrease when the classical business cycle is still rising, but its growth tends to slow down. When the growth rates fall below one, the business cycle is at its maximum and starts to decline and vice versa. In other words, the dates of the peaks and troughs of the growth rates correspond to the inflection points of the classical business cycle.

This thesis focuses on the deviation business cycle as it is more common among European countries.

1.2 Business cycle analysis

The public attention is usually drawn to the possibilities of business cycle analysis (and forecasting the future moves of the economy) during the time of crises like the recent Great Recession in 2007. The general question is whether such crisis could have been predicted by economists.

There are many methods on business cycle analysis. Eurostat (2017) overviews some of these approaches:

- autoregressive integrated moving average (ARIMA) and vector autoregression (VAR) models which are based on time series analysis and doesn't invoke any economic theory,
- Markov switching model that can deal with occasional discrete shifts in time series unlike ARIMA and VAR models,
- unobserved components models that decompose the analysed indicators into unobserved components with direct economic interpretations,
- dynamic factor models which assume that few latent factors drive a large number of the economic variables,
- dynamic stochastic general equilibrium (DSGE) which requires strong economic assumptions,

- composite indicators which aggregate multiple selected economic series and which are used to analyse the switches between the states of the economic activity. This approach will be thoroughly described in this thesis

Analysis of the business cycle utilizes historical data and the methods mentioned above look for the univariate or multivariate hidden patterns in these data. Some of these methods can be used also to predict the level or the turning points of the economy.

1.3 Business cycle composite indicators

The composite indicators approach browses through many economic series and selects those, which show the strongest relationship with the business cycle movements. It combines them into single composite indicator which should be able to describe the business cycle movements better than any of these individual series by itself.

The composite indicators can be divided into three groups according to their relationships with the state of the economy (Zarnowitz, 1992):

- Composite leading indicators (CLIs), which should be able to predict when will the economy switch from the expansion into the recession (or from the speedup into the slowdown) or vice versa.
- Composite coincident indicators, which serve mainly to confirm the hypothesis about the state the economy is currently in.
- Composite lagging indicators, which should certify the cycle behaviour and the correct dating of the turning points.

This thesis focuses on the leading indicators, which are the most frequently constructed type of composite indicators.

The business cycle composite indicators, among other merits, can be easily interpreted despite the fact that they summarize multidimensional relationships between the economic indicators. Their construction is based mostly on the analysis of the peaks and troughs of the economic time series (for more details, see chapter 2). CLIs therefore aim to predict when the economy will switch from one state into another, but they cannot forecast the level of economy.

Czesaný and Jeřábková (2009b) summarize pros and cons of the composite indicators:

- Pros:
  - they provide up-to-date information on the past, present and future of the economic activity,
  - they provide early warning signals of the switches of the economy,
  - they combine several individual economic series and therefore minimize the risk of false signals,
  - their lead time is more consistent than the lead time of the individual economic series, therefore they show better predictive properties,
  - it is easier to interpret one composite indicator than a bunch of individual economic time series,
  - they can summarize complex economic events.
- Cons:
  - the computation requires many arbitrary steps, e.g., setting the weights of the selected individual economic series during the *aggregation* phase of the construction (for more information, see section 2.4),
  - they can be used only for short-term predictions (for more information, see chapter 8).

Hindls and Hronová (2012, p. 792) add another advantage of the methods based on the turning points analysis: "Neither adaptive nor stochastic models are needed to

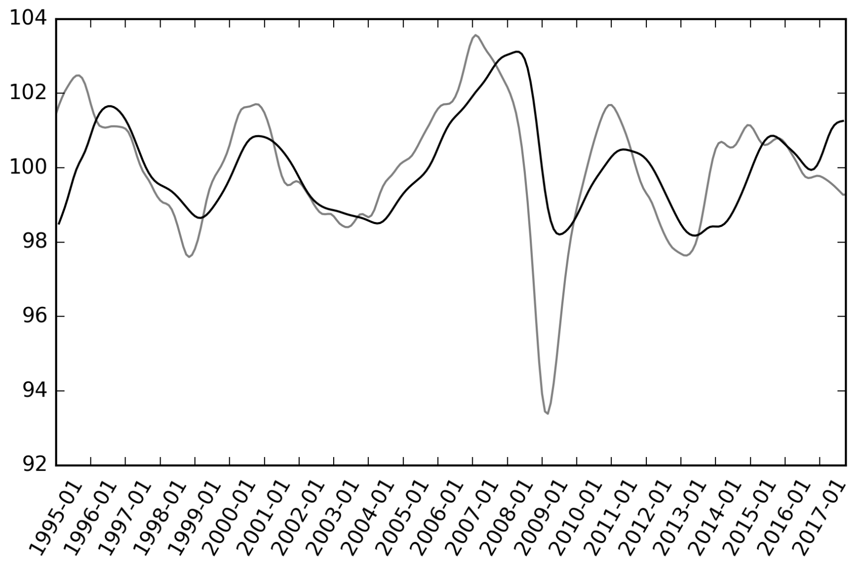


Figure 1.2 – Comparison of the normalised cyclical component of Czech GDP (black line) and amplitude adjusted CLI published by OECD (gray line).
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

describe the turning points of the specified indicator, thus we don't have to test and meet any statistical assumptions (which is often complicated)."

One of the disadvantages mentioned by Czesaný and Jeřábková (2009b) – the series of arbitrary steps of the computation – sometimes invokes experts' distrust of composite indicators. Chapters 2 and 4 overview the parts of the construction most dependent on individual decisions and expert knowledge of the data analyst. The algorithmic approach presented in this thesis can reduce the number of individual interventions and easily keep track of any hyperparameters used during the computation. Therefore, it can be a way to eliminate one of CLIs disadvantages.

Figure 1.2 depicts normalised cyclical component of Czech GDP[1] (reference series) and the CLI constructed by OECD. The turning points of the CLI clearly show the leading behaviour. The amplitude of the CLI however cannot be compared with the amplitude of the GDP cycle: Eurostat (2017) states that "the appropriate interpretation

[1]Downloaded from OECD QNA database. Code: B1_GE, full name: Gross domestic product - expenditure approach, measure code: LNBQRSA, measure full name: National currency, chained volume estimates, national reference year, quarterly levels, seasonally adjusted.

of the numeric values of the CLI relates to the degree of confidence one can attach to the CLI outlook – the further a peak or trough is from the long-term trend conventionally set to 100, the greater the confidence that can be attached to the CLI outlook".

1.4 Brief history of composite indicators

Burns and Mitchell (1946) published work on business cycle indicators which contained one of the first lists of leading, coincident and lagging indicators as well as a set of instructions how to track the cycle. Burns and Mitchell's methodology spread worldwide in the following years. It was executed manually and it required lots of personal judgment and therefore it wasn't quite objective. Their book was also criticized by Koopmans (1947), as unbendingly empiricist and as the measurement without the theory.

In 1969 Ilse Mintz proposed deviation cycles based on speedups and slowdowns of the economy. It was possible then because the rapid development of information technology enabled to automatically process and detrend the time series.

In 1971 Gerhard Bry and Charlotte Boschan introduced their algorithm to automate the turning points detection. It was one of the first programmed approaches that were published and it was widely implemented during the next years. OECD, Conference Board and other organizations still use the Bry-Boschan algorithm with only slight changes.

OECD methodology described by Nardo et al. (2005) or Gyomai and Guidetti (2012) consists of five steps: 1. *pre-selection phase*, which is passed only by long time series of indicators which have justified economic relationship with the reference series, broad coverage of economic activity and high frequency of observations, 2. *filtering phase*, when the time series are seasonally adjusted and de-trended, 3. *evaluation phase*, when only the best individual indicators with the strongest relationship with the reference series are selected to be included in the composite indicator, 4. *aggre-*

gation phase, when the composite indicators are created and 5. *presentation of the results*. For more information on the Conference Board methodology, see its Business Cycle Indicators Handbook (The Conference Board, 2001) or Ozyildirim et al. (2010). General findings on composite indicators as well as detailed remarks on OECD, Conference Board and other methodologies were elaborately summarized in Eurostat (2017).

Authors all around the world have invoked OECD, Conference Board or other composite indicators methodologies and have proposed their own improvements to specific parts of these processes:

Svatoň (2011) proposed the Granger causality test to limit the number of candidate series during the *pre-selection* phase.

Zarnowitz and Ozyildirim (2006, p. 159) compared application of phase-average trend (PAT) with Hodrick-Prescott and Baxter-King band pass filters during the *filtering* phase of composite indicators construction. They stated that "the results of PAT show great similarity to the results obtained with the Hodrick-Prescott and band-pass filtering methods, but in matters of detail PAT is often superior." On the other hand, Nilsson and Gyomai (2011, p. 1) later performed the similar comparison of PAT, Hodrick-Prescott and Christiano-Fitzgerald filter and found out that "PAT detrending method is outperformed by both the Hodrick-Prescott or Christiano-Fitzgerald filter. In addition, the results indicate that the Hodrick-Prescott filter outperforms the Christiano-Fitzgerald filter in turning point signal stability but has a weaker performance in absolute numerical precision." Vraná (2013a,b) discussed detrending the time series with Hodrick-Prescott filter, month-to-month and year-to-year growth rates. Harding and Pagan (2002) argued, that there was in fact no need to perform detrending operations before analysing the business cycle.

The evaluation phase (and especially turning points detection) also drew a great number of suggestions: Hamilton (1989) introduced Markov switching approach later modified by Levanon (2010) to evaluate the recession signal across many indicators.

Del Negro (2001) compared Bayesian vector autoregression model with a probit model and found that the later one is more precise in indicating the exact timing of a recession. Bruno et al. (2004) studied combinations of parametric and non-parametric methods and their impact on the business cycle dating. Gallegati (2014) proposed wavelet-based composite indicator, which provided early warning signals of turning points. Hindls and Hronová (2012) and Marek et al. (2017) showed how to use probit analysis to estimate the probability of occurrence of the turning points.

Zhou and Ang (2009) introduced a mathematical programming approach to optimize the weights of individual indicators for human development index. Hudrlíková and Fischer (2011) compared equal weights with weights gained by principal component analysis and benefit of doubt approach (method based on data envelope analysis) on the example of Europe 2020 indicators. Similar techniques could be used during the *aggregation* phase of the business cycle composite indicators construction as well.

Authors often assess the quality of the constructed composite indicator by *ex-post* analysis only (evaluation on the actual data set). This is equivalent to testing the predictive model performance on the training data, which can easily lead to overestimation of the model quality. Moreover, there is a lag before publishing the economic series and these series are often subjects of revisions, which can also worsen the out-of-sample model performance. The *real-time* analysis considers these drawbacks and provides more reliable results. Diebold and Rudebusch (1991) tried to predict values of industrial production index with CLI and found, that it performed admirably during the *ex-post* evaluation, but failed during the *real-time* analysis. On the other hand, McGuckin and Ozyildirim (2004) stated, that leading indicators provided useful forecasting information in both *ex-post* and *real-time* analyses. They also speculated that the "poor real time performance found by some researchers might have been because the leading index was not as up-to-date as some financial indicators". Pain et al. (2014) described the changes in forecasting techniques after the Great Recession in 2007 and showed, how the *real-time* analysis could have helped to predict the following expansion in 2009. Astolfi et al. (2016) compared the *ex-post* and *real-time* performance of several OECD CLIs and showed, that they "were able to anticipate the Great Recession in G7 countries at an early stage, although, by their very nature, they could not give an indication on the depth of the coming crisis".

Useful hints can be found also in papers focused on other types of composite indicators as the process of their construction is often similar. For example, Hudrlíková (2013) compared different methods of normalization, weighting and aggregation, which could all be applicable also on the business cycle composite indicators.

1.5 Composite indicators of Czech business cycle

OECD has published CLI for the Czech Republic since 2006 (OECD, 2006) with one major revision in 2012 (OECD, 2012). However, there are several other authors besides OECD who studied business cycles of the Czech economy:

Poměnková (2010) focused on the cyclical behaviour of Czech industrial production and compared several detrending and dating methods (including Bry-Boschan algorithm).

Czesaný and Jeřábková (2009b) summarized OECD, Eurostat and the Conference board methodologies of composite indicators construction, and they also covered the proper turning points analysis, but the *evaluation* phase in their later work (Czesaný and Jeřábková, 2009a) was based solely on the analysis of cross-correlations between the economic indicators.

Other Czech (and Slovak) authors also simplified the *evaluation* phase of the computational algorithm, see Pošta and Valenta (2011), Svatoň (2011) or Tkáčová (2012, 2014). Vraná (2014a,b) later demonstrated, that such adjustments could decrease the performance of the Czech composite indicators.

These authors had also different approaches to the *aggregation* phase: Czesaný and Jeřábková (2009a) and Vraná (2014a,b) used normalised series and combined them into the composite indicators without any weighting scheme. Pošta and Valenta (2011) claimed to use uneven weights, but these were defined as inverse standard deviations of the respective economic series and their approach was therefore analogous to standardizing the series and using equal weights. Svatoň (2011) compared two weighting schemes: equal weights and weights derived from principal component analysis, but he claimed that these two methods of *aggregation* produced almost identical results. Tkáčová (2012) also compared two weighting schemes: equal weights and weights according to the cross-correlation coefficients, but neither she concluded that the uneven weights would have significantly improved the performance of the CLI.

2 OECD methodology of composite indicators construction

This chapter presents the OECD methodology of composite indicators construction. Alternative approaches and possible modifications of this process were discussed in sections 1.4 and 1.5. Most of the Czech authors refer to the OECD methodology when building their composite indicators and thus this approach has been also selected as the core method for this thesis.

However popular, the OECD technique described in this chapter is today based on many subjective expert choices and requires substantial manual interventions. The methodology is therefore further discussed in chapter 4 which proposes a new algorithmic procedure to fully automate and objectivise the whole process of the CLI construction.

2.1 Pre-selection

2.1.1 Reference series

The construction of the composite indicators is highly dependent on the selection of a reference time series which should approximate the moves of the whole economy well. It has the key role also during the quality evaluation because the performance of the composite indicators is assessed with respect to this series. E.g., if the turning points of the constructed CLI show a constant lead before the turning points of the reference series, we suppose the CLI would show the same constant lead before the turning points of the business cycle.

GDP or index of industrial production (IIP) are usually used as the reference series. GDP should respond to the cyclical movements better but it is quarterly statistics and it needs to be converted to the monthly estimates (otherwise the analysis results would also be available only quarterly, which is undesirable especially for predictions). IIP is the monthly indicator but it describes only one part of the economy.

OECD had used the industrial production index until March 2012, but Fulop and Gyomai (2012, p. 7) demonstrated that "although the IIP works well as a GDP proxy for some countries, for the majority of the OECD economies and major non-member economies the cyclical components of the IIP and GDP are not sufficiently synchronized". Therefore OECD switched to the adjusted monthly GDP which is also used as the reference series in this thesis.

2.1.2 Individual economic indicators

The composite indicators consist of so-called *component* time series (or *component* indicators) which are selected from individual economic indicators. Therefore the initial selection of these individual economic indicators may influence the quality of the final composite indicator. Gyomai and Guidetti (2012) describe the eligible economic indicators that should pass the *pre-selection* phase as

- the long time series,
- with the justified economic relationship with the reference series,
- with the broad coverage of economic activity,
- with the high frequency of observations (preferably monthly),
- which are not a subject to any significant revisions,

- which are published soon.

2.2 Filtering

The second phase of the composite indicator construction is called the *filtering*. The main task of this stage is to decompose the reference series and the individual economic indicators and find their cyclical components. This means that the trend and the seasonal components must be removed from all the analysed time series.

OECD uses TRAMO module from TRAMO/SEATS algorithm provided by Bank of Spain (Maravall, 1996) to automatically identify outliers and seasonally adjust the time series (OECD, 2010b). For more information, see section 4.4.1.

OECD had used the phase-average trend method to detect (and remove) the trend component of the time series till December 2008. For more information on phase-average trend, see Zarnowitz and Ozyildirim (2006). However, Nilsson and Gyomai (2011) proclaimed, that Christiano-Fitzgerald and Hodrick-Prescott filters tended to perform better. OECD then switched to the Hodrick-Prescott filter as it provided detrended time series, which gave early, clear and steady turning point signals.

Nilsson and Gyomai (2011) also recommended to create short horizon (e.g., 2 months) forecasts of the time series before applying the Hodrick-Prescott filter to increase the stability of its results. The Hodrick-Prescott filter decomposes the whole time series at once and therefore even the estimated values at the beginning of the trend and cyclical component may change when new observations are added to the end of the analysed series. The *stabilizing forecasts* help to reduce this undesirable effect of data revisions and data updates. Again, OECD utilizes the TRAMO/SEATS algorithm to automatically create these short-term forecasts.

The original Hodrick-Prescott filter divides the time series y_t[1] into two parts (Nilsson and Gyomai, 2011)

$$y_t = \tau_t + c_t, t = 1,2,...,T, \tag{2.1}$$

where t is time, T is number of observations, τ_t is the trend component and c_t is the cyclical component of the series y_t. The original version of Hodrick-Prescott filter doesn't consider the noise component of the time series y_t.

Hodrick-Prescott filter further optimizes expression

$$\min_{\tau_t} \left[\sum_t \left(y_t - \tau_t\right)^2 + \lambda \sum_t (\tau_{t+1} - 2\tau_t + \tau_{t-1})^2 \right], t = 1,2,...,T, \lambda > 0. \tag{2.2}$$

The first part of the formula minimizes the difference between the trend and the original series while the other smooths the trend as much as possible at the same time. The λ parameter prioritize the latter from these two contradictory goals – the higher the λ, the smoother the trend.

Hodrick-Prescott filter deals with the series as with the system of sinusoids and it keeps in the trend component only those with low frequency (high wavelength). According to OECD the business cycles last 10 years (120 months) at maximum therefore the fluctuations with lower wavelength should be kept in the cyclical component. Nilsson and Gyomai (2011) also experimented with the maximum cycle length of 8 years (96 months).

Ravn and Uhlig (2002) thoroughly discuss how to set the value of the λ parameter according to the frequency of observations of the analysed time series. They recommend setting the λ parameter equal to 129 600 to get the best smoothing results for monthly series.

[1] OECD methodology assumes, that the time series y_t is now seasonally adjusted (if the original time series contained seasonal component) and includes short horizon stabilizing forecasts.

Nilsson and Gyomai (2011) advise to apply the Hodrick-Prescott filter twice: first with high λ to find the trend component and then with low λ to smooth the cyclical component. They do not mention the specific values of λ, but the OECD's website on composite indicators (OECD, 2017a) states, that "the default settings are (...) $\lambda = 133\,107.94$ and $\lambda = 13.93$ respectively". When the Hodrick-Prescott filter is applied twice, the decomposition of the (seasonally adjusted) time series y_t from equation (2.1) has to be divided into two formulas

$$y_t = \tau_t + c'_t, t = 1, 2, ..., T, \tag{2.3}$$

and

$$c'_t = c_t + a_t, t = 1, 2, ..., T, \tag{2.4}$$

where t is time, T is number of observations, τ_t is the trend component, c'_t is the combination of the cyclical and the noise component, c_t is the cyclical component and a_t is the noise component of the series y_t.

Figures 2.1 and 2.2 illustrate the effects of the filter on Czech GDP. It may seem that the trend component from the first figure still shows some cyclical behaviour, but as the Zarnowitz and Ozyildirim (2006, p. 171) declare: "smoothness in trends is desirable, linearity over short periods may be, linearity over long periods is not".

Gyomai and Guidetti (2012) state that OECD normalises the cyclical component of the time series using the formula

$$z_t = \frac{\widehat{c}_t - \overline{x}_c}{MAD_c} + 100, t = 1, 2, ..., T, \tag{2.5}$$

where t is time, T is number of observations, $\widehat{c}_t$ is the cyclical component estimated by Hodrick-Prescott filter, $\overline{x}_c$ is the arithmetic mean of the cyclical component calcu-

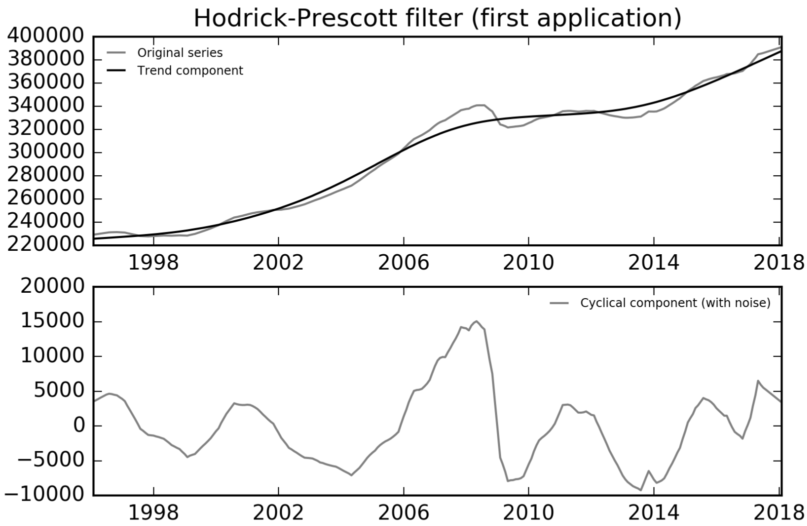


Figure 2.1 – The first application of Hodrick-Prescott filter on Czech GDP (national currency, monthly estimates, seasonally adjusted, with stabilizing forecasts) with high λ parameter to detect the trend component (λ = 133 107.94).
Source: Own construction based on OECD QNA Database (December 2017)

lated as

$$\overline{x}_c = \frac{1}{T}\sum_t \widehat{c}_t, \tag{2.6}$$

and MAD_c is the mean absolute deviation of the cyclical component calculated as

$$MAD_c = \frac{1}{T}\sum_t |\widehat{c}_t - \overline{x}_c|. \tag{2.7}$$

The normalised version of Czech GDP cycle is depicted on figure 2.3.

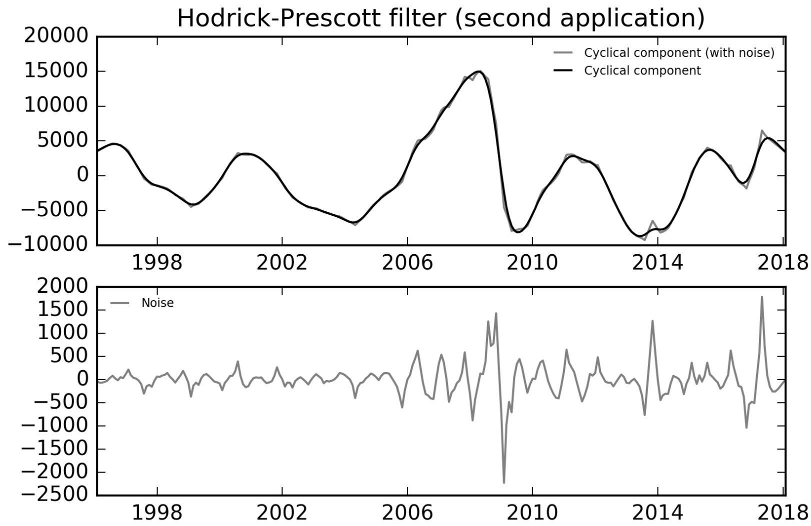


Figure 2.2 – The second application of Hodrick-Prescott filter on detrended Czech GDP with low λ parameter to smooth the cyclical component ($\lambda = 13.93$).
Source: Own construction based on OECD QNA Database (December 2017)

2.3 Evaluation

2.3.1 Turning points detection

Turning points of the business cycle are the peaks and troughs when the economy switches from expansion (resp., speedup) phase into recession (resp., slowdown) phase and vice versa. Turning points of the business cycle are estimated as the turning points of the normalised cyclical component of the reference series. Not every local peak or trough of the cycle is considered a turning point. OECD uses the Bry-Boschan algorithm (Bry and Boschan, 1971) to determine the turning points.

The algorithm starts with identification of the local minima and maxima (i.e., local peaks and troughs) and then eliminates those, which don't meet criteria defined by Bry and Boschan (e.g., cycles[2] shorter then 15 months[3], cycle phases[4] shorter then 5 months[5] or extremes near the end of the time series). The algorithm also suggests

[2]From peak to next peak or from trough to next trough.
[3]OECD (2010b) alternatively sets the default minimum cycle length to 24 months.
[4]From peak to next trough or from trough to next peak.
[5]OECD (2010b) alternatively sets the default minimum phase length to 9 months.

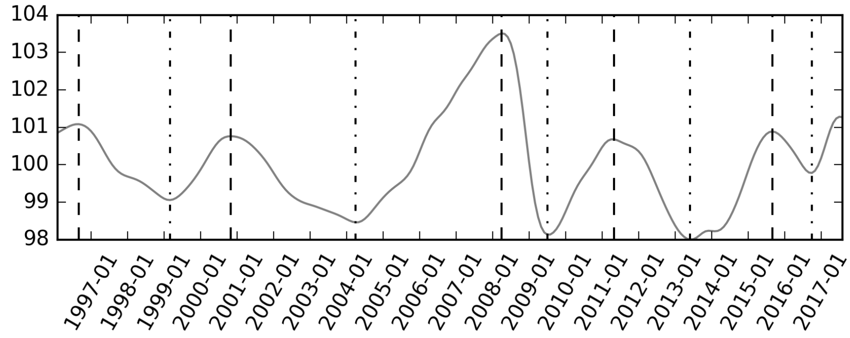


Figure 2.3 – Turning points detected by the Bry-Boschan algorithm in the normalised cyclical component of the Czech GDP.
Source: Own construction based on OECD QNA Database (December 2017)

the best practices for dealing with anomalous situations (e.g. double turns). Chapter 4 discusses this process in more detail and provides step by step examples.

When Gerhard Bry and Charlotte Boschan introduced their algorithm for turning points detection in 1971, it was one of the first programmed approaches that were published and with the fast development of information technologies was then widely implemented. The Bry-Boschan algorithm gave similar results as the manual analysis of the cycle and enabled to process large data sets very quickly.

In their first proposal, Bry and Boschan applied 12-month moving average, Spencer curve and then again a short-term moving average of 3 to 6 month – all these methods served to smooth the time series and to enable detection of the turning points. Nowadays the Bry-Boschan algorithm can be simplified as these smoothing techniques are no longer necessary because some other methods (e.g., Hodrick-Prescott filter) are used to smooth the time series without shifting the turning points.

Figure 2.3 presents turning points of the normalised cyclical component of Czech GDP (reference series) found by the Bry-Boschan algorithm. Turning points are detected also in all the analysed individual economic indicators. The normalised cyclical components of these individual economic indicators (and their turning points) are then compared with the cyclical component of the reference series. Some of the economic indicators can show counter-cyclical behaviour – they tend to rise when the economy is slowing down and vice versa, e.g., consumer price indices. Such time series need to be inverted before next steps.

2.3.2 Evaluation and selection of component series

OECD uses several metrics to evaluate the relationship between the individual economic indicator and the reference series (for more information, see chapter 4):

- the average lead (lag) times between their turning points,
- number of extra and missing turning points,
- value and lead (lag) of maximal cross correlation between their cyclical components.

After each indicator is compared with the reference series, only the best-performing ones are selected to be included in the composite indicator. The selected individual economic indicators are called *component indicators* or *component time series*.

The number of selected series may differ across the countries and depends on the expert judgement of the data analyst. OECD (2010b) and other authors define the selection criteria very vaguely, see chapter 4 for more information. None of the available sources, to my best knowledge, provides the clear set of instructions on prioritizing between often contradictory goals: e.g., minimizing the number of missed and extra turning points while maximizing the leading time and cross correlation coefficient of the newly constructed CLI. This part of the construction therefore requires substantial individual choices and expert knowledge from the researchers.

However, the performance of the composite indicators may easily decrease when additional economic series are added among their components. E.g. when one would use a non-inverted counter-cyclical indicator as part of the CLI, it would mitigate the turning points signals given by the other component series and this would decrease the quality of the CLI.

Turning points detection and evaluation are the parts of the composite indicators construction, which are covered poorly by current software programs. Some researchers thus try to avoid it by using only cross correlations analysis during the *evaluation* phase. However, Eurostat (2017, p. 286) states, that "whereas the correlation value at the peak provides a measure of how well the cyclical profiles of the indicators match, the size of correlations cannot be the only indicators used for component selection".

2.4 Aggregation

During this phase, the component series (i.e., the selected individual economic series) are aggregated into leading, coincident or lagging composite indicators. This thesis focuses on the leading composite indicator which is able to predict the next peak or trough of the business cycle and which is therefore the most frequently constructed type of composite indicators.

Different weighting schemes can be utilized during the *aggregation*, but OECD uses equal weights so all the input series have the same impact on the constructed CLI. However, OECD normalises the individual economic indicators before the *aggregation* (formula 2.5) which is analogous to using inverse standard deviations as weights of the times series, which were normalised only by subtracting the mean value. Svatoň (2011) and Tkáčová (2012) compared equal weights with different weighting schemes, but they both claimed that the uneven weights had no significant impact on the quality of their results.

Another possibility during this phase is to lag-shift the input series with a longer lead, so their signals don't get neutralized by series with a shorter lead. This can cause the signals with shorter lead, but enhanced quality.

OECD uses the *chain linking* method of aggregation to prevent jumps and discontinuities caused by unavailability of some of the selected economic time series during the analysed time period (e.g., missing observations or different beginning dates).

The *chain linking* defines the CLI in time t as

$$CLI_1 = 100, \tag{2.8}$$

$$CLI_t = \frac{\sum_i w_i \delta_{i,t,t-1} z_{i,t}}{\sum_i w_i \delta_{i,t,t-1} z_{i,t-1}} CLI_{t-1},\ t = 2, 3, ..., T, \tag{2.9}$$

where $z_{i,t}$ is the value of normalized cyclical component of i^{th} economic time series at time t, $\delta_{i,t,t-1}$ is the indicator whether the i^{th} economic time series is available in both time periods t and $t-1$ ($\delta_{i,t,t-1} = 1$ if true and $\delta_{i,t,t-1} = 0$ otherwise) and w_i is the weight of i^{th} economic time series, $w_i \in < 0, 1 >$, $\sum_i w_i = 1$.

If no weighting scheme is applied then

$$w_i = \frac{1}{n},\ i = 1, 2, ..., n, \tag{2.10}$$

where n is number of economic time series selected to be aggregated into composite indicator. The CLI is published when

$$\sum_i w_i \delta_{i,t,t-1} >= 0.6. \tag{2.11}$$

This means that at least 60 % of selected economic time series must be available in time t to publish the CLI when no weighting scheme is applied. For more details on chain linking, see Eurostat (2017).

2.5 Presentation of the results

OECD publishes the final CLI in three forms:

- the original values of CLI which can be compared with normalized values of the cyclical component of the reference series (see figure 1.2),
- the trend restored CLI which can be compared with the (seasonally adjusted) values of the reference series,

- the 12-month growth rate of CLI which can be compared with the 12-month growth rate of the reference series.

2.6 Regular composite indicators updates

When the structure of the composite indicator is determined, the actual values of the indicator are published regularly, usually monthly. The computation process of these monthly updates is similar to the one described above, but the *pre-selection* and *evaluation* phases are omitted, as these steps are necessary only to find the eligible component series.

3 Composite Indicators Framework (CIF)

The methodology of CLI construction is described in detail by several organizations. It therefore comes as a surprise, that no publicly available software program supports the whole computational process or its automation. This is probably caused by the lack of an algorithmic approach to the whole calculation. Some parts are well described (e.g., the aggregation of the selected component time series), but other parts are usually based on many expert decisions and require substantial manual interventions (e.g., selection of the component series which should be part of created composite indicator).

A new solution is proposed to fill this gap. The new software program runs the analysis in the fully automated fashion, therefore the algorithmic approach had to be developed (for more details, see chapter 4). The solution enables the users to easily analyse and visualize larger volumes of data than any other available program with a greater tractability of the calculations. Researchers from now on will not have to spend their time deploying the basic tasks, e.g., how to detect turning points or evaluate and aggregate the series. They will be allowed (and encouraged) to download the new library and start collaborating on its future development

In this chapter, existing software programs suitable for constructing composite indicators and the newly proposed Composite Indicators Framework (CIF) are described and compared.

3.1 Available software programs

This thesis overviews some of the existing software solutions suitable for business cycle analysis: CACIS (OECD, 2010b), EViews (IHS Global Inc., 2014a,b), Python (Python Software Foundation, 2015) and R (R Development Core Team, 2008) in alphabetical order. These are selected as they cover most of the tasks required to construct the composite indicators.

Python and R are free and general software environments very popular in data science. They provide a great selection of packages with many functions and methods, so their users don't need to write them from scratch. Moreover, it is also possible (although sometimes time-consuming) to program the missing pieces.

EViews is oriented mainly on the time series analyses and forecasting. It provides the basic graphical user interface, but also requires the knowledge of its own programming language. It is the only commercial software discussed in this chapter.

OECD offers its own Cyclical Analysis and Composite Indicators System (CACIS). It is designed directly to compute the composite indicators and therefore it provides the most exhaustive pallet of functions in this area. However, the publicly available version hasn't changed much since 2010, its user interface and generated visualizations are obsolete and the functions are provided without any options to customize them.

CACIS and EViews require the Windows operating system to run.

3.2 Newly proposed solution

None of the existing solutions provides all the functions required to create composite indicators without any manual interventions and subjective decisions. The switching between several software programs would be uncomfortable, slow and it would make the automation of the process impossible. Therefore the new solution is proposed: this thesis introduces a new Python library called CIF, which attempts to fill the gap in the currently available software repertoire.

CACIS was developed directly to analyse the business cycle, but it doesn't enable some basic requirements like loading the data directly from OECD application programming interface (API) or making adjustments to the graphs. It also doesn't provide any guidance on selection of the component series (which is the most crucial part of the composite indicators construction). EViews provides even less of the specified tasks, and its results are only slightly more controllable by the user. Therefore, the new solution could have been based either on Python or R. After some experiments, Python was selected as it provides elegant syntax, better performance and its existing libraries show higher compatibility with each other.

If users miss some functions, the Python-based interface of CIF guarantees that they can write them by themselves and easily integrate them into the computing process.

CIF is publicly available as an open-source project on GitHub[1], which is the internet platform for sharing, collaboratively developing and documenting code. CIF nowadays offers thousands of lines of code in 34 functions designed specifically to construct the composite indicators.

3.3 Comparing functions

Table 3.1 overviews the selected software solutions and evaluates them in the fields most essential for constructing composite indicators.

[1] Available at https://github.com/LenkaV/CIF.

EViews, Python and R allow loading data from versatile data sources (databases as well as data files). Python and R can also communicate with other applications via application programming interface (API), which enables them to download data directly from organizations like OECD when connected to the internet. However, Python does not process such data automatically so additional steps are needed to transform it into a general data table format. R has offered package *OECD* since 2015, which can connect directly to the OECD API. This package is relatively new and unfortunately was not available, when I started working on the algorithmic approach to the composite indicators construction. It is nowadays still in a beta version which is released for community testing and which may be unstable. CACIS can load data from excel and csv files only, so it requires lots of manual work while downloading and preparing input data.

CIF focuses mainly on the automation of the composite indicators construction, therefore lots of effort had to be made to algorithmize the whole process, which is usually based on many subjective expert choices. The notes on the algorithmization are summarized in chapter 4. CIF is designed to save the time of the users, so they can just load the input data and the result is delivered with their minimal effort and without manual intervention. Alternatively, the user can specify only the country of the interest and the available data are downloaded directly from OECD API (other APIs will be added in the future, e.g., Eurostat). These functions allow the users to quickly compare results across many countries and eliminate the time needed for the bothersome data transformations. The automation enables to process large amounts of data quickly: around 10 minutes to download and process data, calculate the CLI and evaluate and visualize the results from the complete Czech data available in the OECD database.

All the presented software solutions can perform the basic time series transformations: seasonal adjustments, detrending, smoothing and normalization. The other tasks which are necessary to construct composite indicators (turning points detection, turning points matching and aggregation of the series) are offered only by CIF and

Table 3.1 – Overview of software tasks necessary for composite indicators construction (*available* = fully supported, *generic* = supported, but some manual adjustments needed, *x* = not supported).

Actions	CACIS	EViews	Python	R	CIF
Loading data from files	excel or csv only	available	available	available	available
Loading data from databases	x	available	available	available	available
Loading data from generic API	x	x	available	available	available
Loading data from OECD API	x	x	x	available	available
Conversion of quarterly to monthly time series	available	available	x	available	available
Seasonal adjustment and outlier detection (TRAMO/SEATS)	available	available	available	available	available
Detrending and smoothing (Hodrick-Prescott filter)	available	available	available	available	available
Normalization	available	generic	generic	generic	available
Turning points detection (Bry-Boschan alg.)	available	x	x	quarterly data only	available
Turning points matching	available	x	x	x	available
Cross correlations analysis	available	generic	generic	generic	available
Selection of the component series	x	x	x	x	available
Aggregation	available	x	x	x	available
Evaluation (ex-post)	available	x	x	x	available
Evaluation (real time)	x	x	x	x	available
Comparison of performance of two indicators	x	x	x	x	available
Scoring the new data set	x	x	x	x	available
Visualization	available	generic	generic	generic	available
Custom development	x	x	available	available	available
Automation	x	x	generic	generic	available
Logs	x	x	generic	generic	available

Source: Own construction

CACIS, but CACIS requires substantial manual interventions. R also contains package *BCDating* for turning points detection, but it works only with quarterly time series.

The selection of the component series is one of the most important parts of the calculation because the composition directly influences the performance of the composite indicators (e.g., the lead of the indicator or number of missed or false signals). However, it is also one of the least described parts. The OECD (as well as other authors) gives only some general advice on the subject, but the final act of selection is supposed to be subjective and based on the *intuition* and expert knowledge of the researcher (OECD, 2010b). CIF is the only one of the existing solutions, that offers the automated selection of the component series.

When the indicators are constructed, their performance should be evaluated. There are several criteria used to asses the quality of the composite indicators (e.g. length of the mean lead/lag of the turning points or number of false signals). For more information on the criteria, see chapter 5. CACIS offers only the *ex-post* analysis of composite indicators performance. The differences between the *ex-post* and *real-time* analysis are thoroughly described in chapter 8. The *ex-post* analysis usually overestimates the quality of constructed indicator and therefore should be accompanied by the *real-time* analysis, which considers also the historical revisions of economic series. CIF offers both of these types of quality assessment.

Comparing two versions of a composite indicator is quite difficult, because of the multiple criteria, that are used to evaluate their performance. The performance is often superior when measured by one of the quality criteria, but inferior when measured by other (e.g., the newly created CLI shows longer mean lead than the original one, but it also generates a higher number of false signals). Existing software programs don't deal with this problem and researchers often judge the changes in performance with a great amount of subjectivity. CIF is the only solution which proposes methodology how to objectively compare two indicators.

Python and R offer a vast number of visualization libraries and packages and therefore enable almost any type of diagrams. EViews also provides some visualization capabilities but (compared to the previously mentioned solutions) they are limited. None of these programs contains the exact charts needed to illustrate the cycle analyses and CLI construction (e.g., comparison of turning points). As CACIS is the only existing program developed directly to analyse the business cycle, it contains the necessary visualizations, but it doesn't enable the users to alter them in any way. In contrast, newly proposed CIF provides a great variety of fully adjustable charts and other diagrams that can accompany the cycle analysis.

CIF also records the whole computational process and saves the logs for later examination.

3.4 Used technologies

CIF is built upon several software solutions, which are introduced in this section.

CIF is written in Python 3.5, high-level general-purpose programming language, for more information see Python Software Foundation (2015). The first version of Python was introduced in 1989 and its libraries nowadays cover many different types of problems. It is now one of the most popular tools for data science: figures 3.1 and 3.2 show the comparison of worldwide *popularity* of Python and R. The popularity here is measured by number of searches of specified query in Google. There is a clear trend: R exceeds Python for searches connected with statistics, while Python has become substantially stronger in the area of data science during the last two years. This is logical, because the data science connects statistics with programming and Python, which is a much more general language than R, is thus more suitable. The second graph also depicts the increase of popularity of the term data science itself. The data for these charts were gained from Google Trends[2]. Google News Lab (2016) explains, that the provided data sets are unbiased samples from Google search data, normalized

[2]Available at https://trends.google.com.

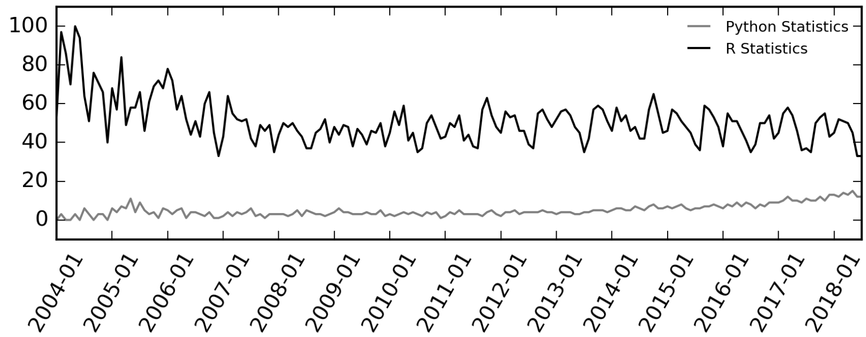


Figure 3.1 – Comparison of Google searches of term 'statistics' in connection with Python (gray line) and R (black line). Maximal number of searches is artificially set to 100.
Source: Google Trends (July 2018)

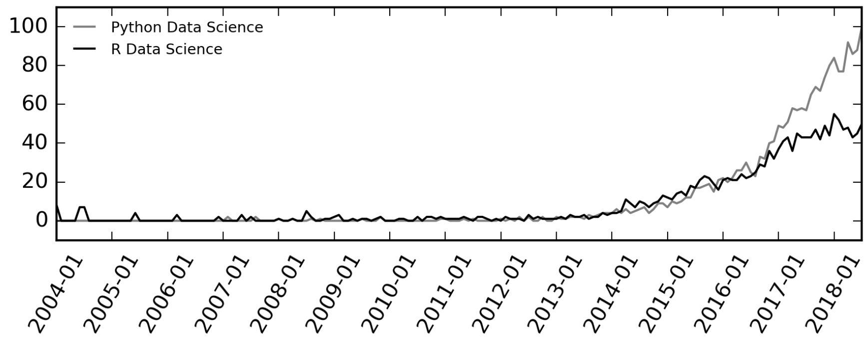


Figure 3.2 – Comparison of Google searches of term 'data science' in connection with Python (gray line) and R (black line). Maximal number of searches is artificially set to 100.
Source: Google Trends (July 2018)

according to the number of overall searches (this removes the influence of the increasing number of Google users and queries) and 100 is artificially set as the maximum for any selected query and time period.

CIF utilizes many Python libraries. Especially *request* to download data from the internet, *pandas*, *numpy* and *re* to work with data sets, time series models from *statsmodels* or *matplotlib* for visualisations.

The Python scripts can be run directly from the command prompt (Windows) or terminal (Mac OS) or in one of the integrated development environments (IDEs). During the initial phase of the programming, I usually use Spyder which is very similar to the well-known R Studio IDE for R. It provides a console, autocompletion, variable browser and integrated help and it is distributed together with Python. I prefer Jupyter Lab for the later phase: sharing and publishing the examples of code. Jupyter Lab is the interactive environment which combines the code, visualisations and other results, with markdowns, that can be used to explain specific parts of code[3].

The development of any solution would be very difficult without a version control system. I use public git repository on GitHub and private git repository on Bitbucket to track the changes in all my codes and all the texts of my publications. The git system also enables to create project Wiki pages and to manage reported issues.

3.5 Installing CIF

CIF is Python library listed in the Python Package Index (PyPI)[4] installable by the standard Python *pip* command. The first beta version was released on 15$^{\text{th}}$ April 2018. The beta version of the library is still under construction – new functions are added and existing functions are extended frequently. Appendix A provides the minimal example of the code to calculate the CLI and appendix B offers the complete list of available functions with short descriptions.

[3]Example of CIF minimal pipeline in Jupyter format is available at https://github.com/LenkaV/CIF/blob/master/examples/CI_minimalPipeline.ipynb.

[4]Available at https://pypi.org/project/cif/.

4 Algorithmic approach to the composite indicators construction

The current state of the art is based on many subjective expert decisions which make the automation of the composite indicators construction so difficult, that there is currently no solution that would offer the fully algorithmic approach, with the exception of the newly proposed CIF.

This is, to the best of my knowledge, the first attempt to create such a comprehensive approach to the composite indicators computation. This method allows to create the composite indicators faster than any other available technique and it, therefore, enables the researchers to try more scenarios with different settings (e.g., to experiment with various input data sets, adjusting hyperparameters or testing several detrending methods). The new method also minimize the subjectivity of expert choices and increases tractability of the calculations.

This chapter summarizes the assumptions and adjustments of the OECD methodology, that are necessary to enable the fully algorithmic approach. The whole process is visualized with flowcharts, which describe the workflow of the algorithm.

4.1 Flowcharts

This chapter utilizes flowcharts to illustrate the algorithmic approach of the CIF package. The flowcharts are diagrams used to represent algorithms or other workflows. Each step of the algorithm is shown as a separate box, e.g., input data specification, processes, subprocesses or decision nodes (for the meaning of each box type, see list of Symbols used in flowcharts in the beginning of the thesis). The boxes are connected with arrows to indicate the sequence of processes. The subprocesses refer to other flowcharts or equations.

All the flowcharts presented in this thesis were designed in Microsoft Visio.

The logic of composite indicators construction is simplified as much as possible to be captured in the flowcharts. For the full algorithm, please see the complete code available on GitHub.

4.2 Automating the process

Figure 4.1 offers the high-level overview of the whole construction process. The most of the subprocesses corresponds to the OECD construction phases introduced in chapter 2: *pre-selection* and data preparation (composed here of two subprocesses), *filtering*, *evaluation* of the individual economic series and selection of the component series (composed here of four subprocesses), *aggregation* and *presentation of the results*. The flowchart adds another subprocess between *aggregation* and *presentation* phases: *evaluation* of the created composite indicator. There are several possible approaches to this evaluation: *ex-post analysis*, *real-time analysis* or *comparison with state-of-art composite indicator*. It is not usual to perform all of these methods together, therefore they are placed next to each other in the flowchart.

The boxes in the flowchart are coloured according to a completeness of their description available in current literature. The algorithms of the green subprocesses are very well described. The orange subprocesses contain algorithms, which are not described

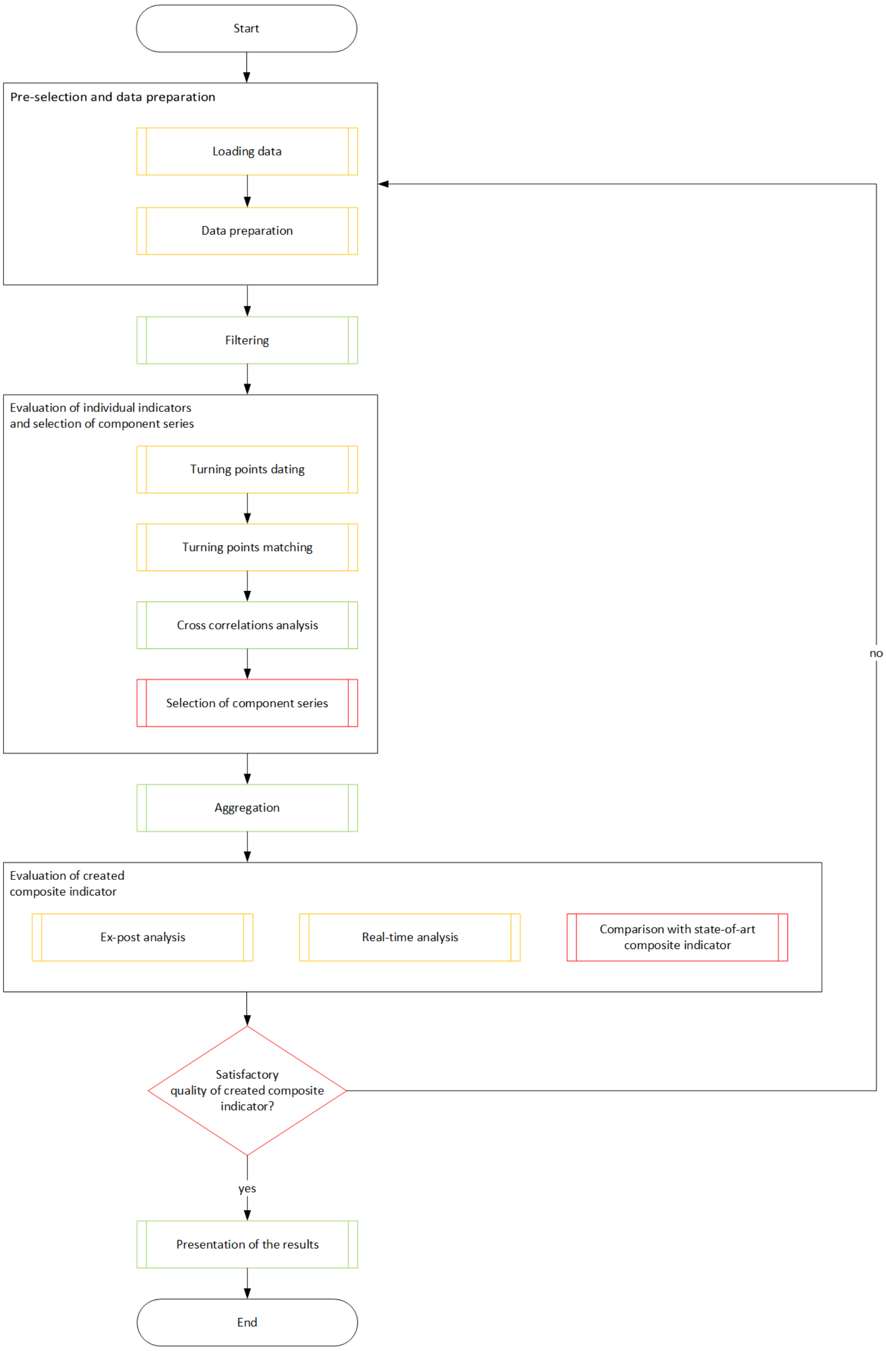


Figure 4.1 – Flowchart of the composite indicators construction (*green* = algorithm is fully described in existing literature, *orange* = algorithm is only partially described or many adjustments are needed to enable automation, *red* = based solely on subjective decisions according to current literature).
Source: Own construction

in sufficient detail or which demand some alterations due to the automation of the process. The subprocesses in the red boxes are explained only briefly and the researchers are left with the trial and error method. As one of the key parts of the computation – the *selection of the component series* – is also one of the least described, the composite indicators results are nowadays based mainly on a subjective judgement and a level of experience of a researcher.

The OECD (2010b, p. 31) describes the ambiguity of the construction in the following way: ”As in any multi-criteria problem, there is no ideal solution optimizing all the conditions at the same time and therefore compromises have to be found. However, despite the fact that there is no unique way to build a composite indicator and several criteria can be applied, most of the building procedures usually include a preliminary study of the available series. Then, users select the first list of possible components. After aggregating these components, the resulting composite indicator is evaluated with respect to the reference series. The next step generally involves removing some components or adding other series in order to improve the composite indicator. This process ends when the user is satisfied with the cyclical features of one particular aggregate.” Other authors, for example Gyomai and Guidetti (2012) or Eurostat (2017), also describe the composite indicators methodology in the way, that requires lot of manual interventions.

However, the following chapters show, that the automation of the whole process is possible when several assumptions about hyperparameters are made. On the other hand, the CIF aspires to be more than a black box, so each parameter can be further customized by the users and its default value serves as a recommendation rather than a rule. The default values enable users to create their first CLI in CIF quickly and with a reasonable performance, as is shown in chapter 6. Appendix A provides the minimal example of code needed to calculate the CLI in CIF.

4.3 Pre-selection

4.3.1 Loading data

The *pre-selection* phase of OECD methodology serves to select individual economic indicators eligible to enter the composite indicators (the length, the economic relationship with the reference series or the frequency of observations should be considered). The basics of the data loading process are captured in the figure 4.2.

The *pre-selection* cannot be fully automated: the initial selection of the economic indicators is the responsibility of the CIF user. If the series are selected in the wrong way (e.g., only economic indicators, which have no connection to the reference series), the resulting leading indicator will be of poor quality.

However, even this part can be automated for some countries as OECD created the main economic indicators (MEI) database[1]. This database contains the series, that comply with the *pre-selection* criteria as defined in chapter 2. It offers economic series from several areas, e.g., business tendency and consumer opinion surveys, international trade or labour market statistics. OECD (2010b) also recommends using the series from the MEI database in its CACIS software user manual.

The reference series (GDP) can be automatically downloaded from another OECD database: quarterly national accounts (QNA).

Users can browse the database manually and download the selected subset of series as excel, csv or xml file. OECD also provides an application programming interface (API)[2] which enables automated access to its databases. CIF library provides the function *createDataFrameFromOECD()*, which creates the query to download OECD data directly from the Python environment. The user needs to define the name of the database and optionally several additional parameters, e.g., location (country of interest), subjects (codes of selected economic time series), frequency or start and end date. If the ad-

[1] Available at http://www.oecd.org/std/oecdmaineconomicindicatorsmei.htm.
[2] Available at https://data.oecd.org/api/.

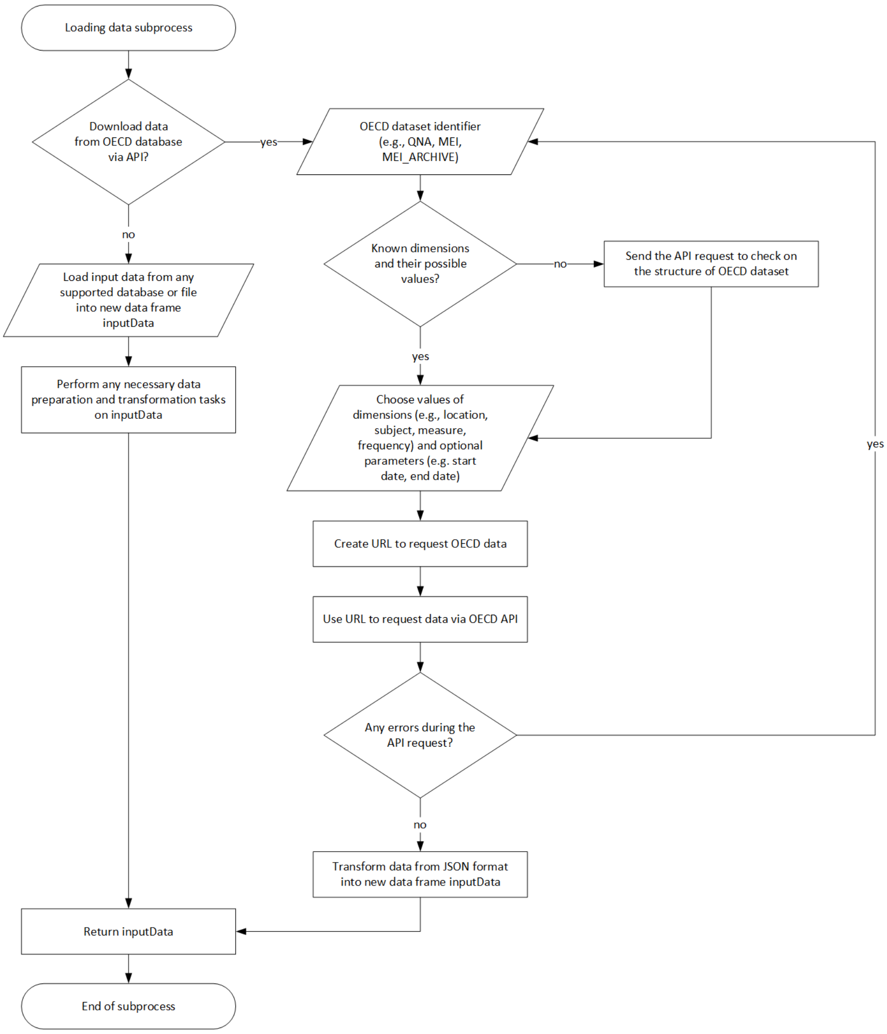


Figure 4.2 – Flowchart of loading data subprocess.
Source: Own construction

{"header":{"id":"61013fb9-2e8d-41a3-86c6-40c50ff3a9b6","test":false,"prepared":"2017-12-09T08:54:15.3337898Z","sender":{"i
d":"OECD","name":"Organisation for Economic Co-operation and
Development"},"links":[{"href":"https://stats.oecd.org:443/SDMX-JSON/data/QNA/CZE.B1_GE..Q/all?dimensionAtObservation=AllD
imensions","rel":"request"}]},"dataSets":[{"action":"Information","observations":{"0:0:0:0:0":[1511480.0,0,null,0,0,null],
"0:0:0:0:1":[1558212.0,0,null,0,0,null],"0:0:0:0:2":[1618900.0,0,null,0,0,null],"0:0:0:0:3":[1651780.0,0,null,0,0,null],"0
:0:0:0:4":[1766796.0,0,null,0,0,null],"0:0:0:0:5":[1796280.0,0,null,0,0,null],"0:0:0:0:6":[1830164.0,0,null,0,0,null],"0:0
:0:0:7":[1873544.0,0,null,0,0,null],"0:0:0:0:8":[1909120.0,0,null,0,0,null],"0:0:0:0:9":[1924184.0,0,null,0,0,null],"0:0:0
:0:10":[1963604.0,0,null,0,0,null],"0:0:0:0:11":[2029120.0,0,null,0,0,null],"0:0:0:0:12":[2089480.0,0,null,0,0,null],"0:0:
0:0:13":[2150904.0,0,null,0,0,null],"0:0:0:0:14":[2175672.0,0,null,0,0,null],"0:0:0:0:15":[2160376.0,0,null,0,0,null],"0:0
:0:0:16":[2175316.0,0,null,0,0,null],"0:0:0:0:17":[2221936.0,0,null,0,0,null],"0:0:0:0:18":[2251220.0,0,null,0,0,null],"0:
0:0:0:19":[2299052.0,0,null,0,0,null],"0:0:0:0:20":[2306424.0,0,null,0,0,null],"0:0:0:0:21":[2365964.0,0,null,0,0,null],"0
:0:0:0:22":[2412316.0,0,null,0,0,null],"0:0:0:0:23":[2438432.0,0,null,0,0,null],"0:0:0:0:24":[2492376.0,0,null,0,0,null],"
0:0:0:0:25":[2542496.0,0,null,0,0,null],"0:0:0:0:26":[2600416.0,0,null,0,0,null],"0:0:0:0:27":[2642648.0,0,null,0,0,null],

Figure 4.3 – Example of data retrieved from OECD API in JSON format.
Source: OECD MEI Database (December 2017)

Index	('CZE', 'B1_GE', 'HCPCARSA')	('CZE', 'B1_GE', 'HVPVOBARSA')	('CZE', 'B1_GE', 'LNBQR')	('CZE', 'B1_GE', 'LNBQRSA')	('CZE', 'B1_GE', 'VIXOBSA')
1995-Q3	13954.51403	19139.68671	nan	nan	nan
1995-Q4	13905.16467	18995.87289	nan	nan	nan
1996-Q1	14385.9651	19509.15457	647959	687413	69.392479
1996-Q2	14529.21678	19607.31929	693526	690671	69.721365
1996-Q3	14632.32424	19686.29692	708851	693453	70.002201
1996-Q4	14709.43687	19702.47424	717132	693821	70.039349
1997-Q1	14765.56802	19685.19018	649485	692809	69.937191
1997-Q2	14708.11472	19571.697	694065	688681	69.52048
1997-Q3	14658.08445	19438.49666	701741	683994	69.04734

id	name
HCPCARSA	Per Head, US $, current prices, current PPPs, seasonally adjusted
HVPVOBARSA	Per Head, US $, constant prices, fixed PPPs, OECD reference year, seasonally adjusted
LNBQR	National currency, chained volume estimates, national reference year, quarterly levels
LNBQRSA	National currency, chained volume estimates, national reference year, quarterly levels, seasonally adjusted
VIXOBSA	Volume index, OECD reference year, seasonally adjusted

Figure 4.4 – Example of data retrieved from OECD API in data frame format. Upper table contains several measures of one economic indicator (Czech GDP, quarterly data) and lower table lists full names of corresponding measures.
Source: Own construction based on OECD QNA Database (December 2017)

ditional parameters are not provided, CIF tries to download the whole database. However, OECD limits the queries to return 1 000 000 observations at maximum.

OECD returns the data in JSON format, CIF transforms it automatically into a more convenient *data frame* format. Data frame is a fundamental data structure in Python, R and other software environments for data analysis: the variables are stored in columns, observations in rows and values in cells. Figures 4.3 and 4.4 represent the data in a raw JSON format and after transformation into a data frame, respectively. CIF also processes and saves the full names of series and measures, which are otherwise coded in the data frame.

Another function, *getOECDJSONStructure()*, is designed to return names and codes of the economic indicators stored in specified OECD database together with names and codes of their measures (e.g., the currency of the observations). This is convenient when users start working with a new database and they are not sure, what codes would be accepted in the query to download the data.

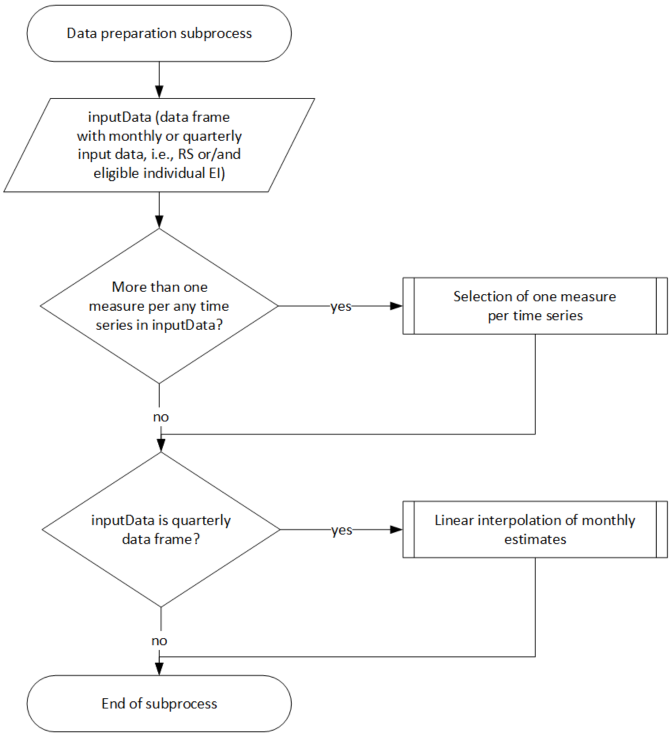


Figure 4.5 – Flowchart of data preparation subprocess (RS = reference series, EI = economic indicator).
Source: Own construction

4.3.2 Data preparation

Figure 4.5 overviews the next steps of *pre-selection* phase after the eligible economic indicators are loaded. First, the data frame is checked for duplicated columns (time series, which measure the same economic event, recorded several times, each time using different units). Next, the quarterly series are interpolated into monthly estimates. Both of these subprocesses are described in the following sections.

Selecting only one measure per economic indicator

OECD provides the majority of their economic indicators measured using several units (i.e., measures): in national currency/US dollars, in current prices/constant prices, seasonally adjusted or not, growth rates, etc. For example, the data frame captured

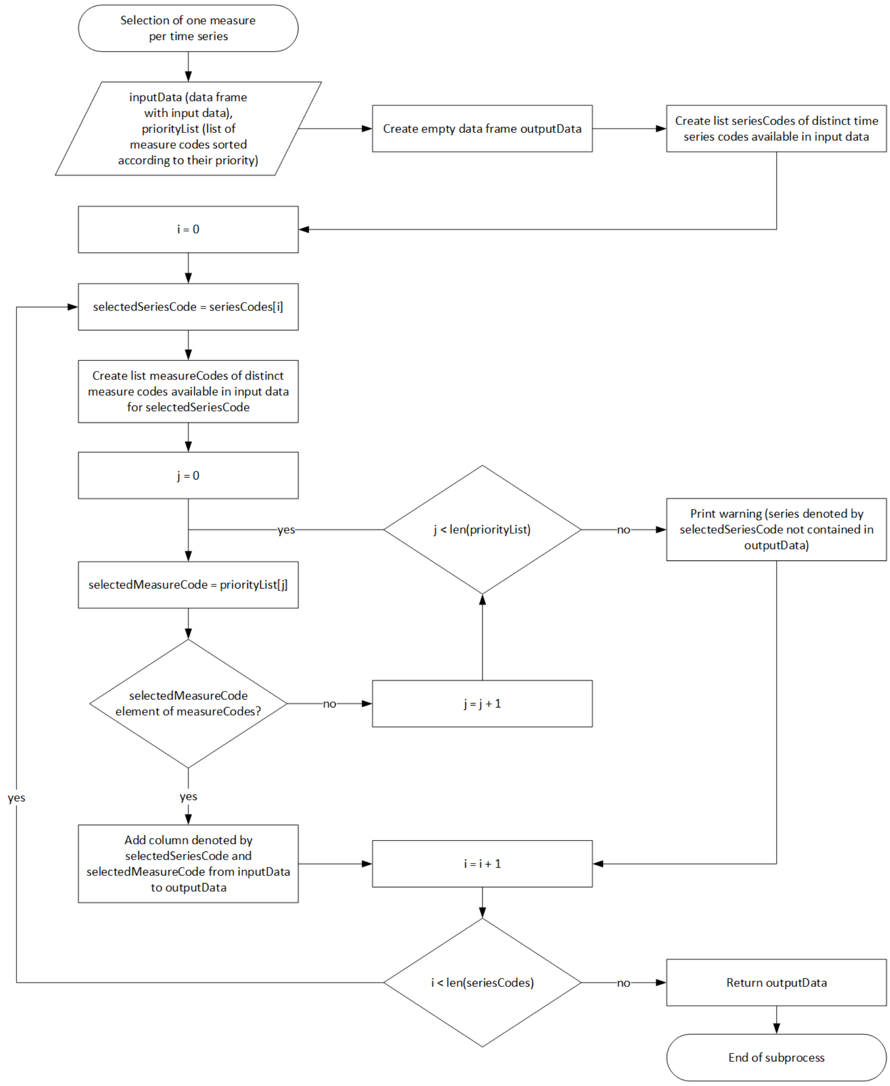


Figure 4.6 – Flowchart of one measure selection.
Source: Own construction

in figure 4.4 shows several versions of Czech GDP. However, not all the measures are available for each indicator.

Researchers usually need to receive only one measure per economic indicator, the data would be duplicated during the further analyses otherwise. Nowadays, they can select the measure randomly or they need to manually specify the exact measure for each indicator.

CIF offers the function *getOnlyBestMeasure()* to select only one measure per one economic indicator according to the priorities set by the user. The CIF user sort possible measures according to his or her preferences and CIF returns the top available measure for each economic indicator as is shown in figure 4.6.

Interpolation of quarterly data

Another CIF function (*createMonthlySeries()*) is important for quarterly indicators (e.g., GDP, which is typically used as the reference series), because they need to be transformed into monthly estimates before the next phase.

Although there are many sophisticated methods, how to convert the quarterly data to monthly estimates, CIF uses the simple linear interpolation. The Eurostat (2017, p. 282) explains, that ”the linear interpolation technique may appear simplistic, but in the context of the CLI, the methodology chosen for interpolation has little impact on the final business cycle estimate. This is mainly because the smoothing filters in a later stage in the filter sequence dampen sub-annual variations in the time series, bringing the resolution of monthly and quarterly series closer together.”

CIF utilizes linear interpolation provided by *pandas* data frame in Python[3].

Figure 4.7 shows example of the monthly estimates of Czech GDP using linear interpolation.

[3] For more details, see https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.interpolate.html.

Index	CZE_B1_GE_LNBQRSA
1996-02-01 00:00:00	229137.6667
1996-03-01 00:00:00	229499.6667
1996-04-01 00:00:00	229861.6667
1996-05-01 00:00:00	230223.6667
1996-06-01 00:00:00	230532.7778
1996-07-01 00:00:00	230841.8889
1996-08-01 00:00:00	231151
1996-09-01 00:00:00	231191.8889
1996-10-01 00:00:00	231232.7778
1996-11-01 00:00:00	231273.6667
1996-12-01 00:00:00	231161.2222

Figure 4.7 – Example of data processed by CIF: only one measure of Czech GDP selected according to the user's preferences, index and column renamed, monthly estimates. Source: Own construction based on OECD QNA Database (December 2017)

4.4 Filtering

Figure 4.8 overviews the *filtering* phase of the composite indicators construction. The algorithm loops through all the economic indicators (reference series or the eligible individual economic indicators), detects (and adjusts for) their seasonality and estimates their cyclical components.

Some of the individual economic indicators can move in counter-cyclical manner to a reference series. Therefore the algorithm optionally creates inverted time series to consider such behaviour.

The flowchart contains three subprocesses (removal of the seasonal component, detection of cyclical component and normalisation), which are described in following sections.

4.4.1 Removal of seasonal component and stabilizing forecasts

OECD uses TRAMO module from TRAMO/SEATS algorithm provided by Bank of Spain (Maravall, 1996) to identify outliers, seasonally adjust the time series and provide short horizon stabilizing forecasts before detrending the series (OECD, 2010b). CIF utilizes

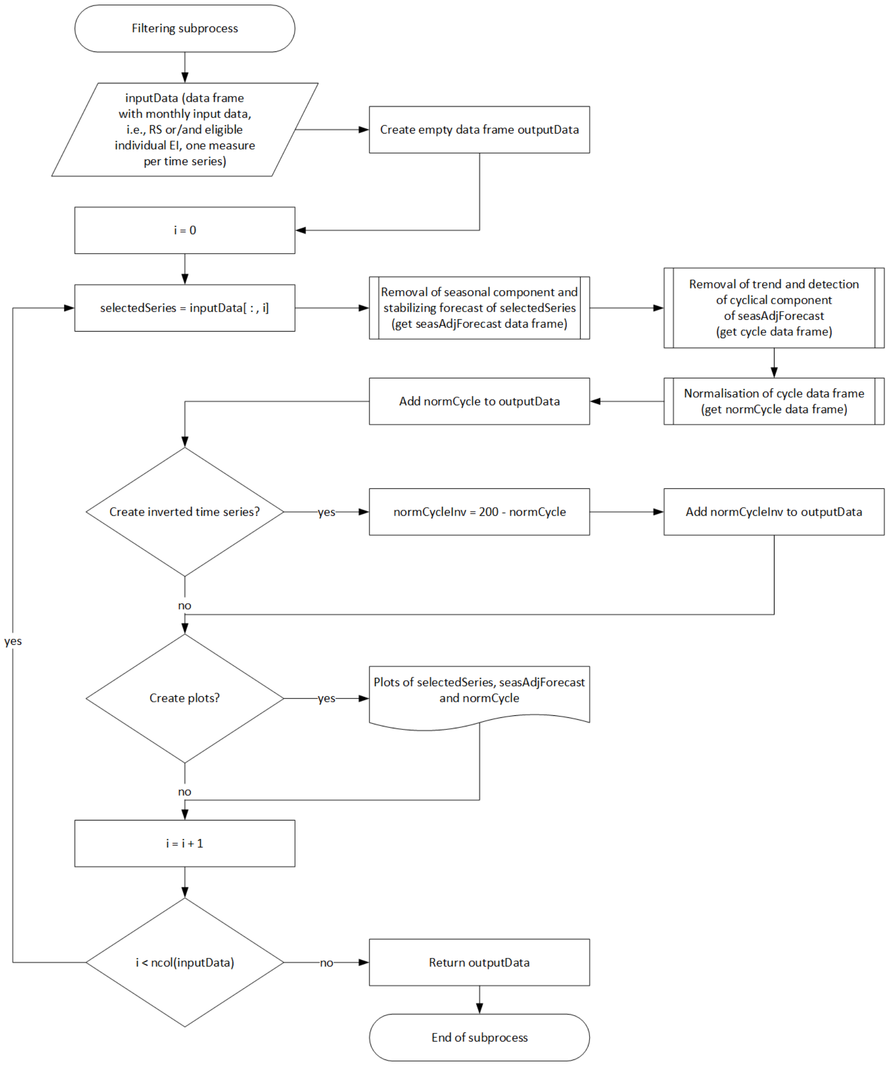


Figure 4.8 – Flowchart of filtering subprocess (RS = reference series, EI = economic indicator). Source: Own construction

the X-13ARIMA-SEATS Seasonal Adjustment Program developed by United States Census Bureau (U.S. Census Bureau, 2017) because it is already integrated into Python via the Statsmodels library. Both of these programs offer similar functionality: they automatically fit several (seasonal) ARIMA models and then select the best one.

Figure 4.9 reveals, that X-13ARIMA-SEATS program is called three times during the process: 1) to receive the best ARIMA model specification, 2) to get the seasonally adjusted series (if seasonality is detected in the time series), and 3) to create short horizon stabilizing forecasts.

The necessity of stabilizing forecasts relates to the application of Hodrick-Prescott filter in the following stage of the computation. When new observations are added to the time series, even the past states of its trend and cyclical component found by Hodrick-Prescott filter can change as Hodrick-Prescott filter deals with the whole series at once (unlike some other methods, e.g., moving averages). This can cause undesirable dynamic changes in the whole cyclical component. Nilsson and Gyomai (2011) state that "by forecasting at each iteration (they) would compensate for the highly asymmetric nature of (their) band pass filters at the end of the time series and have beneficial effects on the stability of the cyclical estimate". Therefore these short horizon stabilizing forecasts were implemented in the CIF package. The default length of the forecasts in CIF is set to 6 months, but users can easily override the value of this parameter.

The X-13ARIMA-SEATS program is the only program, with the exception of Python, which is required to run the analyses in CIF. It can be freely downloaded from the U.S. Census Bureau website. However, if the user selects only seasonally adjusted series during the initial data transformations, this step can be skipped. The seasonal ajustment is also usually the longest part of the whole CLI calculation because the external program is called and several models are fitted per each time series.

The steps described in figure 4.9 are covered by a CIF function called *getSAForecasts()*.

4.4.2 Removal of trend component and detection of cyclical component

After the seasonal adjustment, the time series (reference series as well as individual economic indicators) are ready for the cyclical component detection using Hodrick-Prescott filter (equation 2.2). Figure 4.10 shows how the Hodrick-Prescott filter is applied twice during this phase. First Hodrick-Prescott filter features a high λ parameter to estimate the trend. After the trend is removed, the remainder is the cyclical component combined with noise (figure 2.1). Then, the Hodrick-Prescott filter with

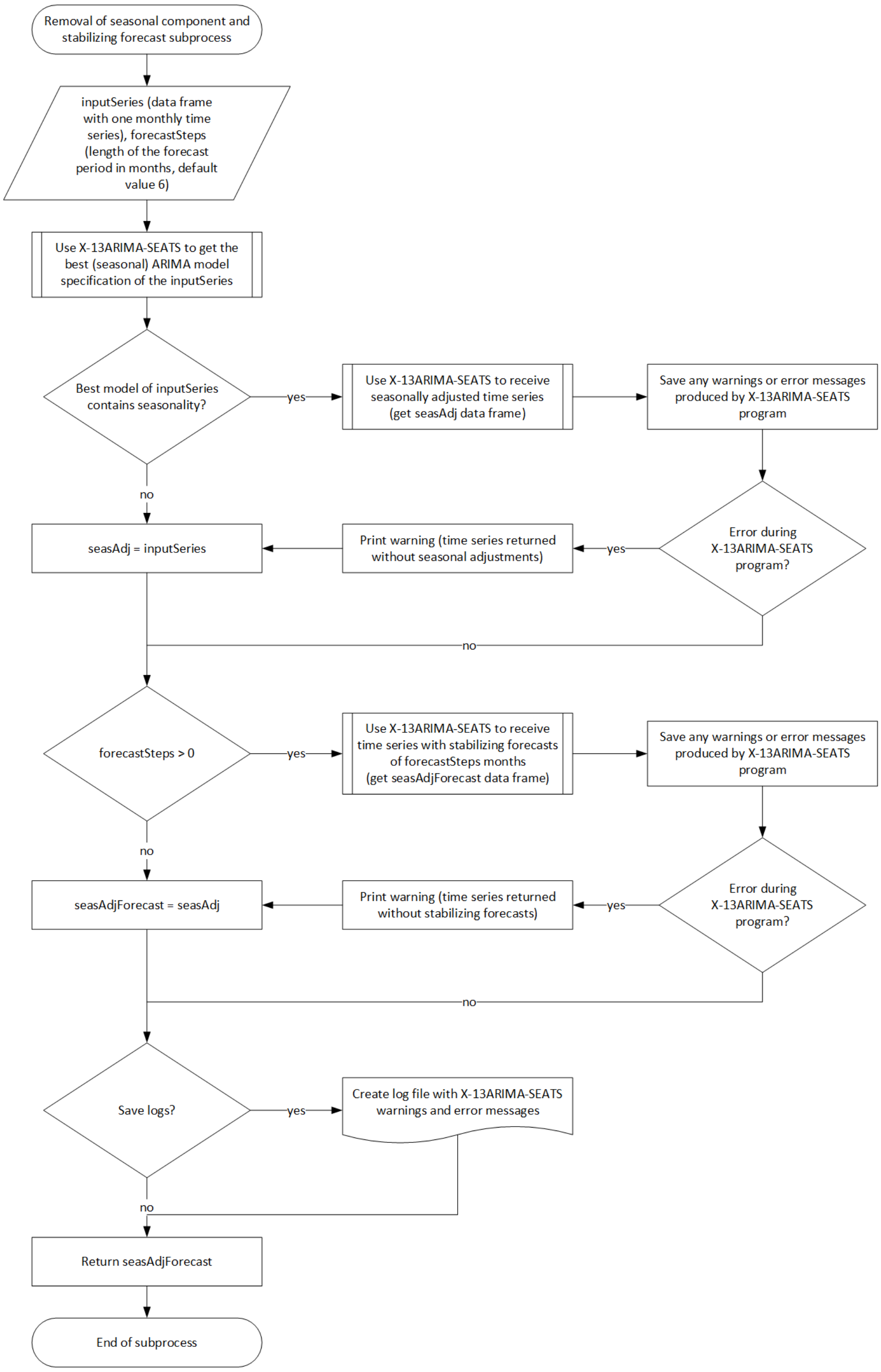


Figure 4.9 – Flowchart of seasonal component removal and stabilizing forecasts.
Source: Own construction

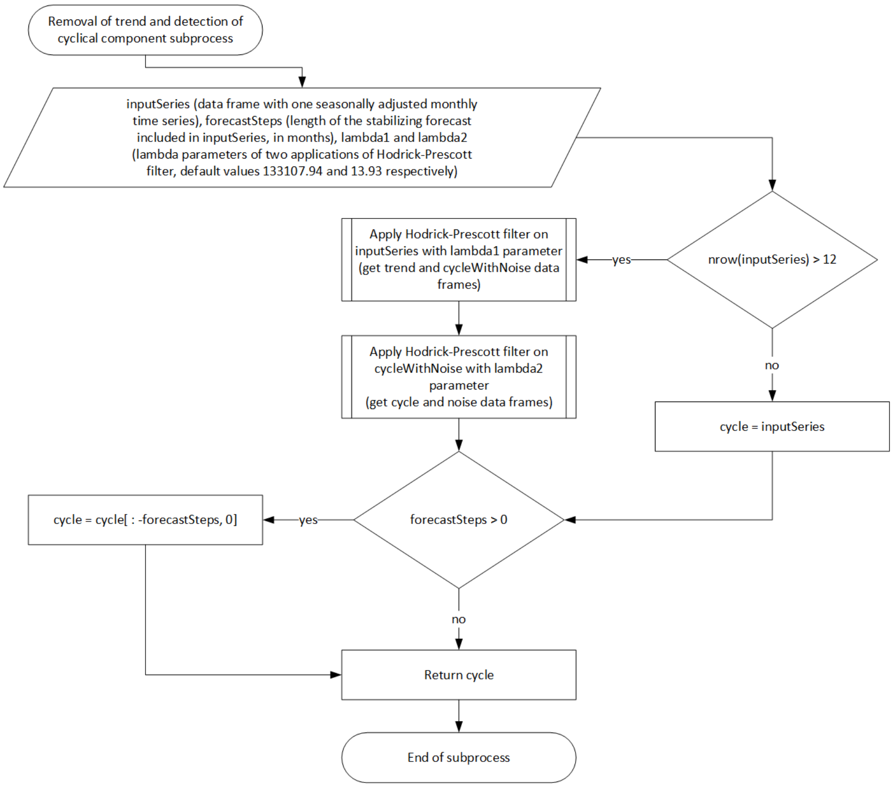


Figure 4.10 – Flowchart of trend component removal and cyclical component detection. Source: Own construction

a low λ parameter is applied again on the remainder time series, which is decomposed into cycle estimate and noise time series (figure 2.2).

OECD (2017a) recommends to set the first λ parameter to 133 107.94 and the second λ parameter to 13.93. These are the default values used in the function *applyHPTwice()* in the CIF package, but users are allowed to choose different values (e.g., 129 600 as recommended by Ravn and Uhlig (2002), who apply the Hodrick-Prescott filter only once).

4.4.3 Normalisation of the cyclical component

The cyclical components of the reference series and the individual economic indicators are then normalised using equation 2.5. This step is covered by CIF function *normaliseSeries()*.

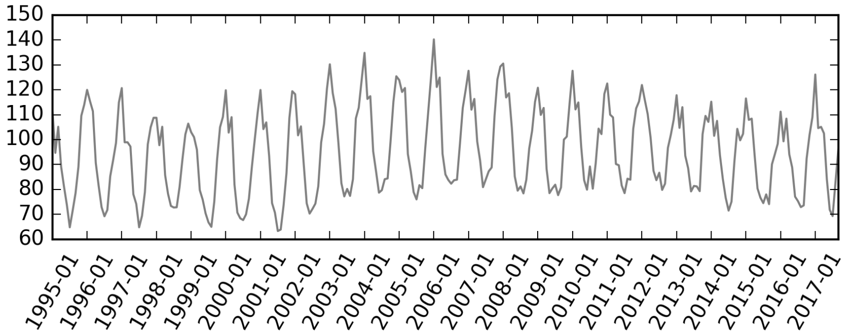


Figure 4.11 – Czech energy production index – original time series.
Source: OECD MEI Database (December 2017)

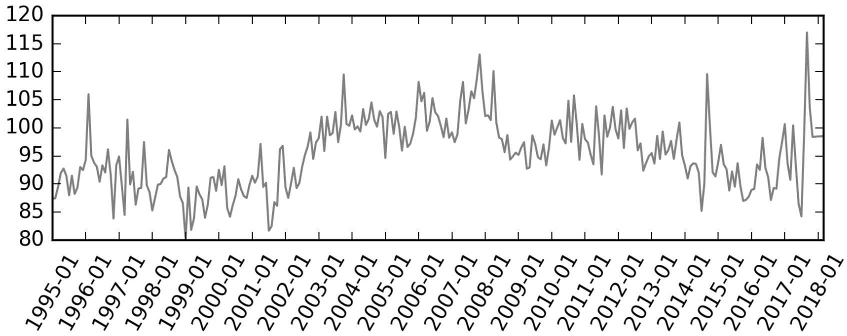


Figure 4.12 – Czech energy production index – seasonally adjusted and with stabilizing forecasts.
Source: Own construction based on OECD MEI Database (December 2017)

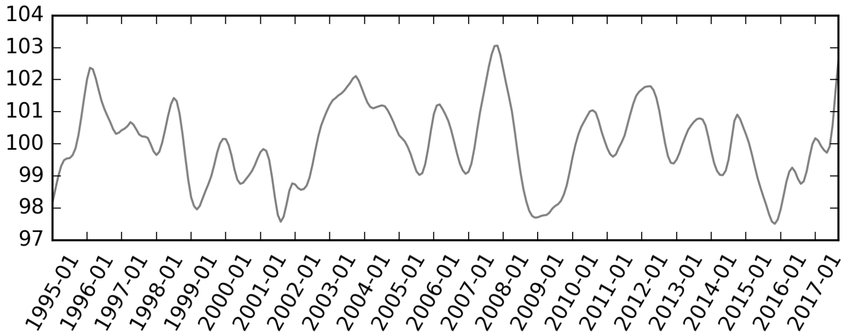


Figure 4.13 – Czech energy production index – normalised cyclical component.
Source: Own construction based on OECD MEI Database (December 2017)

Figures 4.11, 4.12 and 4.13 illustrate the transformations of Czech energy production index[4], which were described in sections 4.4.1, 4.4.2 and 4.4.3. They depict the original time series first, then the seasonally adjusted version with stabilizing forecasts of 6 months and then the normalised cyclical component of this time series.

CIF offers function *pipelineTransformations()* to pass the whole *filtering* phase of composite indicators construction at once. This command wraps other CIF functions introduced in this section.

4.5 Evaluation of individual indicators and selection of the component series

The goal of this phase is to compare each individual economic indicator with the reference series and to assess whether it should be included in the composite indicator. The main criteria are based on the turning points analysis (average lead and lag times between the turning points and number of extra and missing turning points) or the overall conformity between the cycles (value and lead/lag of maximal cross correlation).

4.5.1 Turning points dating

The original nonparametric Bry-Boschan algorithm (Bry and Boschan, 1971) was introduced before the Hodrick-Prescott filter became widespread. Therefore, its authors had to use different smoothing methods, which tended to shift the turning points. The algorithm described by figure 4.14 assumes the usage of Hodrick-Prescott filter during the previous phases and thus uses simplified version of Bry-Boschan method, which was designed for this thesis. The simplified algorithm coincide with the rules about minimal lengths of cycles, phases, etc., which were originally introduced by Bry and Boschan.

[4]Code: PREND401, full name: Production > Energy > Production and distribution of electricity, gas, steam and air conditioning > Total, measure code: IXOB, measure full name: Index 2010=100.

Figure 4.14 loops through the time series contained in the analysed data frame (reference series or individual economic indicators), finds their local extremes and then eliminates those, which doesn't comply with Bry-Boschan criteria. The flowchart refers to five subprocesses (some of them are repeated more than once) – their flowcharts are located in appendix C.

The turning points dating algorithm is illustrated with the normalised cyclical component of the Czech energy production index, which was introduced in the previous section. The standard procedure goes as follows:

- **Looking for local extremes:** The algorithm (described in figure C.1, CIF function *getLocalExtremes()*) marks all suspicious local maxima (resp., minima), which are higher (resp., lower) than the 5 neighbouring observations on each side. See figure 4.15 for the local extremes found in the normalised cyclical component of the Czech energy production index.
- **Checking the turning points alterations:** Two algorithms are combined in this step. First one to check the neighbourhood of each local maximum (resp., minimum) for higher (resp., lower) points (described in figure C.2, CIF function *checkNeighbourhood()*). Second one to prevent sequences of multiple peaks or troughs (described in figure C.3, CIF function *checkAlterations()*). The analysed economic time series contains three consecutive peaks in December 2001, October 2003 and July 2004. Only the highest one of those peaks (October 2003) is kept and the other two are deleted, see figure 4.16.
- **Checking minimal length of the cycle (default length 15 months):** Algorithm (described in figure C.4, CIF function *checkCycleLength()*) computes the length of the periods between each cycle (from peak to peak and from trough to trough). If the cycle is shorter than the minimum value set by the user, the lower (resp., higher) of those two peaks (resp., troughs) is deleted. Figure 4.17 shows the analysed economic time series after four peaks (April 1997, February 2001, Septem-

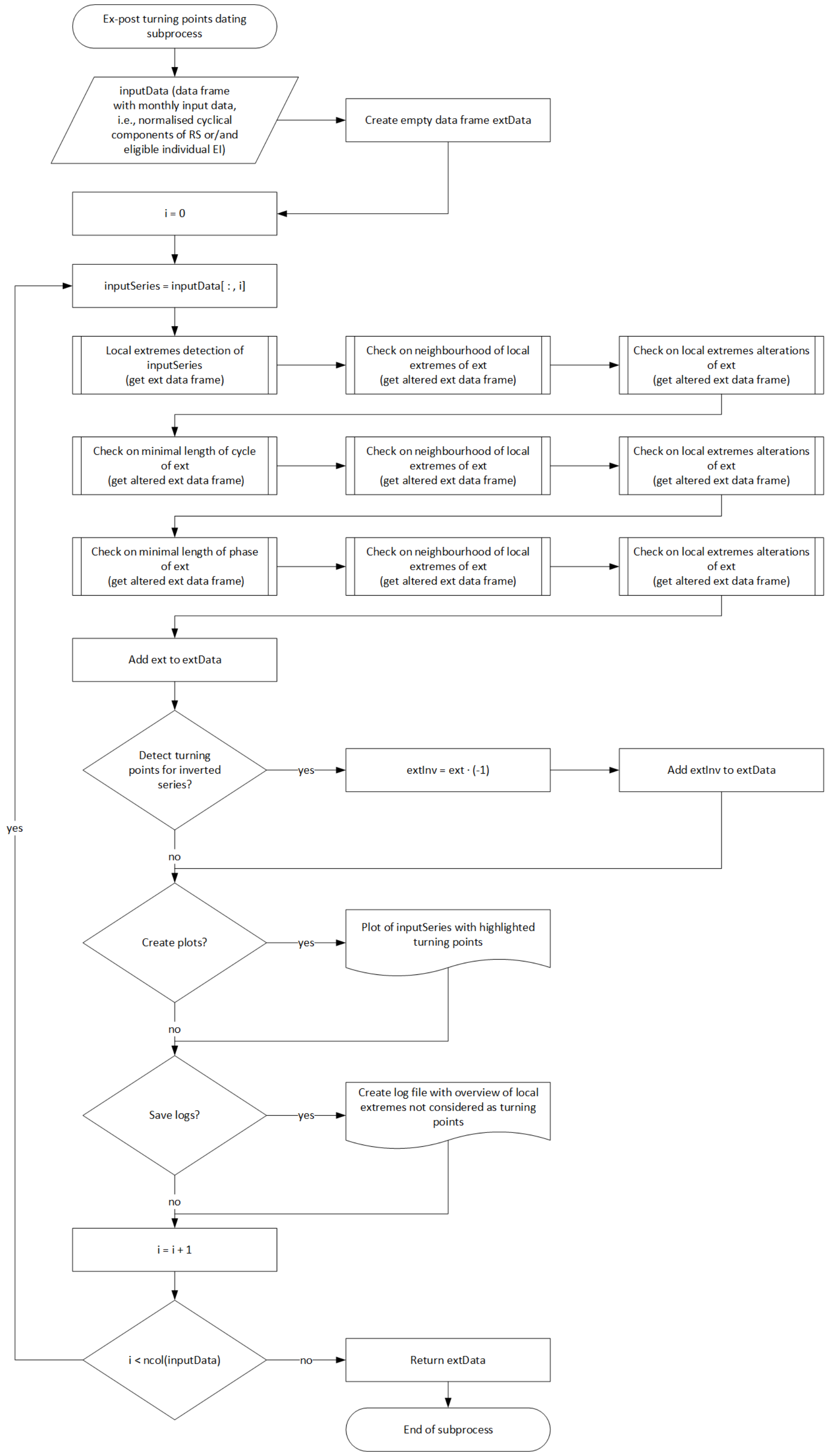


Figure 4.14 – Flowchart of *ex-post* turning points detection (RS = reference series, EI = economic indicator).
Source: Own construction

ber 2013 and May 2016) and four troughs (November 1996, January 1998, June 2000 and August 2016) were deleted.

- **Checking the turning points alterations again:** After the short cycles have been deleted, the series can contain sequences of multiple peaks or troughs again. Therefore the alterations of the turning points are checked for the second time. The peak in July 1998 and the trough in December 2012 had to be discarded from the normalised cyclical component of the Czech energy production index, see figure 4.18.
- **Checking minimal length of the phase (default length 5 months):** The lengths of phases between each pair of peak and trough should be longer than 5 months, otherwise these phases are deleted by CIF function *checkPhaseLength()* (described in figure C.5). Two peaks (October 2014 and January 2017) were removed from the analysed economic time series, see figure 4.19.
- **Checking the turning points alterations for the last time:** Finally, the alterations of turning points are checked again and extra troughs (May 2014 and May 2017) are discarded, see figure 4.20. This figure shows the final dating of the turning points of the Czech energy production index.

Moreover, CIF offers function *pipelineTPDetection()* where all the mentioned functions are nested. That means, that CIF users can get the turning points of the time series easily with one command.

4.5.2 Turning points matching

This section presents, how the turning points of each individual economic indicator are compared with the turning points of the reference series. While the theory behind this part of the composite indicators construction is described well in current literature, the algorithm is offered only by the CACIS software program (OECD, 2010b) and its details are not publicly available. The algorithm therefore needed to be *reinvented* to enable the fully automated process in CIF.

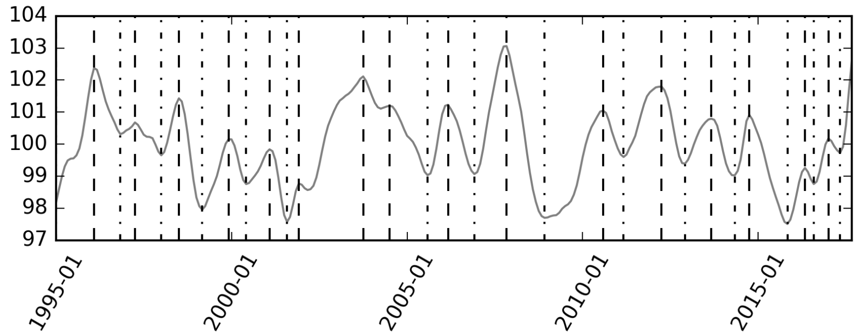


Figure 4.15 – Normalised cyclical component of the Czech energy production index – local extremes.
Source: Own construction based on OECD MEI Database (December 2017)

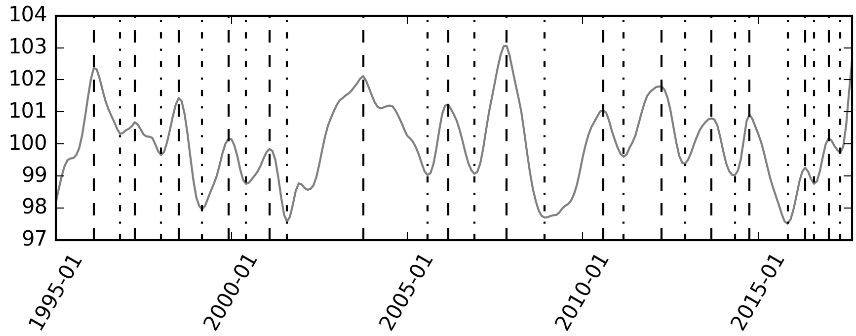


Figure 4.16 – Normalised cyclical component of the Czech energy production index – after first alteration check.
Source: Own construction based on OECD MEI Database (December 2017)

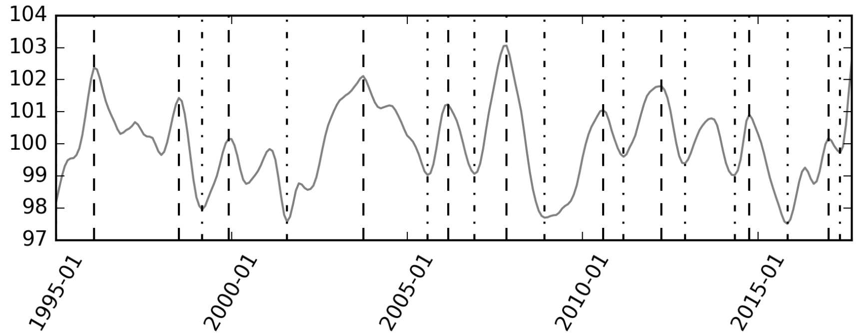


Figure 4.17 – Normalised cyclical component of the Czech energy production index – after cycle length check.
Source: Own construction based on OECD MEI Database (December 2017)

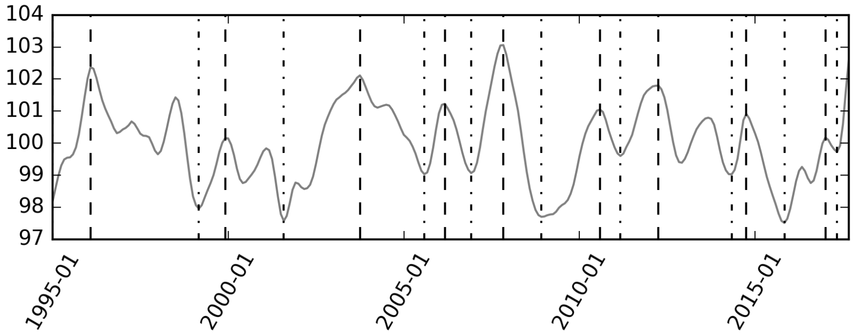


Figure 4.18 – Normalised cyclical component of the Czech energy production index – after second alteration check.
Source: Own construction based on OECD MEI Database (December 2017)

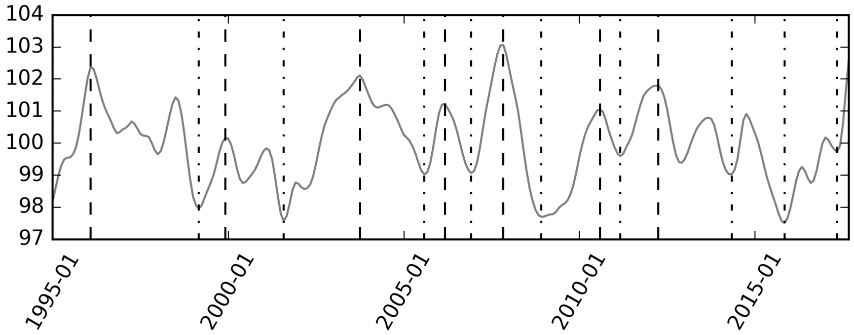


Figure 4.19 – Normalised cyclical component of the Czech energy production index – after phase length check.
Source: Own construction based on OECD MEI Database (December 2017)

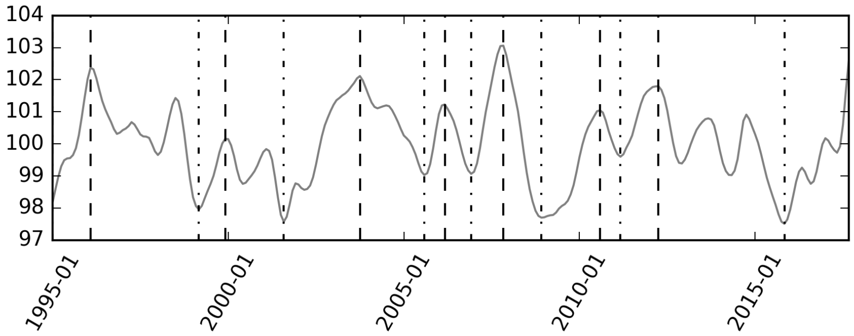


Figure 4.20 – Normalised cyclical component of the Czech energy production index – after third alteration check. These are the turning points detected by Bry-Boschan algorithm.
Source: Own construction based on OECD MEI Database (December 2017)

Eurostat (2017, p. 285) specifies, that the matching algorithm "searches in a neighbourhood of 24 months lead and 9 months lag for a corresponding turning-point (peak for a peak, trough to a trough) in the (potential) component series to be matched". E.g., if the peak in the reference series occurs in January 2016, the algorithm looks for the peak in the individual economic indicator from January 2014 (24 months before) to October 2016 (9 months after). If there are no such peaks, the economic indicator missed this turning point of the reference series. If there is more than one peak in the economic indicator during the observed period, the turning point of the reference series is matched with the closest one. The economic indicators extremes, that were not matched with any turning points in the reference series, are called extra turning points or false signals.

Figure 4.21 explains the details of the automated matching algorithm used in CIF. While none of the previous flowcharts distinguished between the individual economic indicators and the reference series, this is the first one, where the reference series has to be provided separately in its own data frame.

The algorithm loops through all the available economic indicators. If the reference series contains any turning points, two subprocesses are run: first one locates matched and missing turning points (described in figure C.6) and second one checks that there are no chronological discrepancies in the order of the matched turning points (for more information, see figure C.7). If the analysed individual economic indicator contains any turning points, subprocess which locates the extra turning points is run (see figure C.8).

These steps are covered by the CIF function *pipelineTPMatching()*. When this function looks for the matched turning points, it uses 24 months lead and 9 months lag defined by Eurostat (2017) as the default values, but it allows users to alter them via its parameters. The function can therefore look in the broader or narrower neighbourhood around the reference series turning points. Figure 4.22 presents a visualisation created by CIF with the default values. It shows the normalised cyclical component of the reference series (GDP) and its turning points in the upper chart. The lower

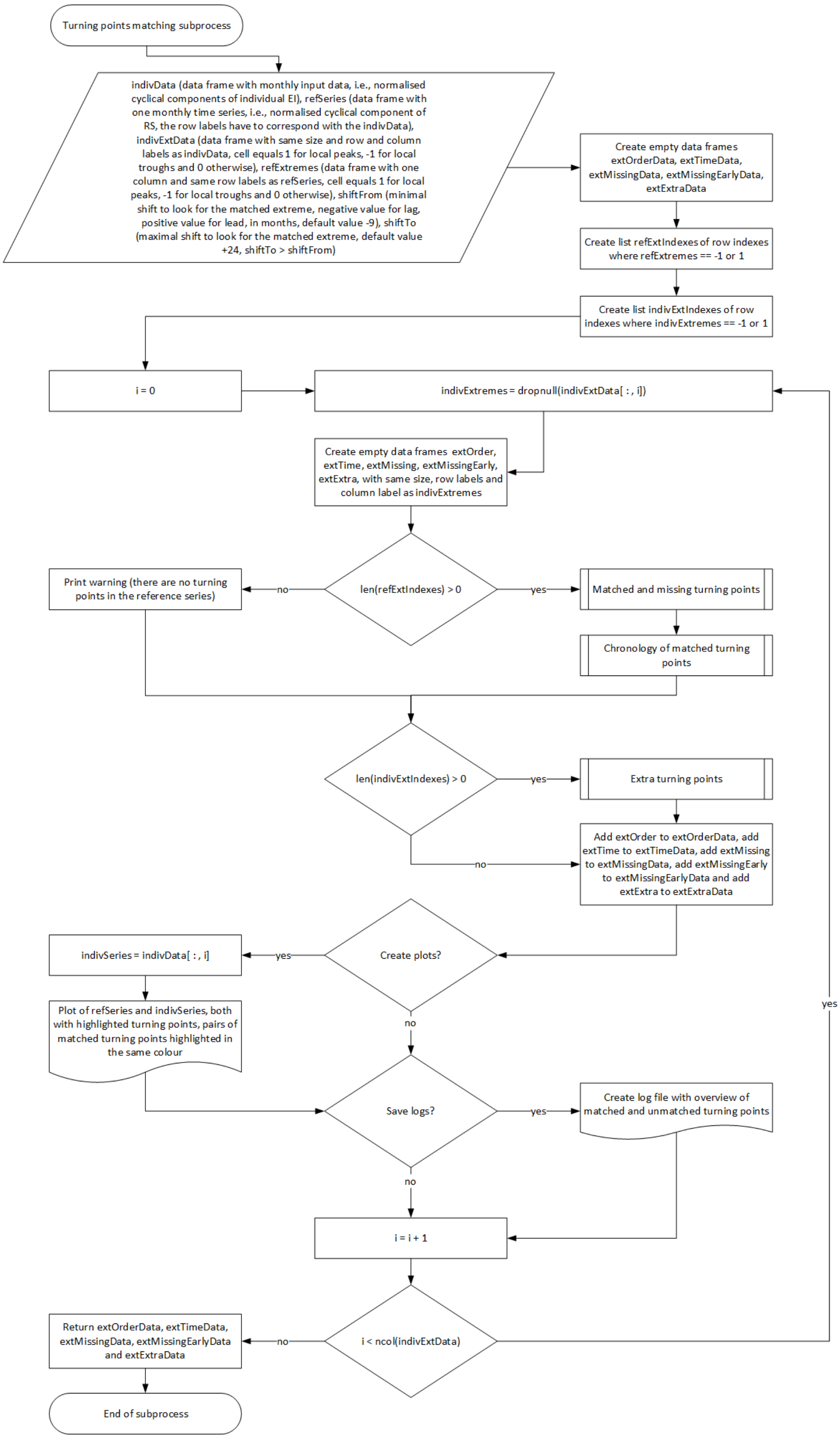


Figure 4.21 – Flowchart of turning points matching (RS = reference series, EI = economic indicator).
Source: Own construction

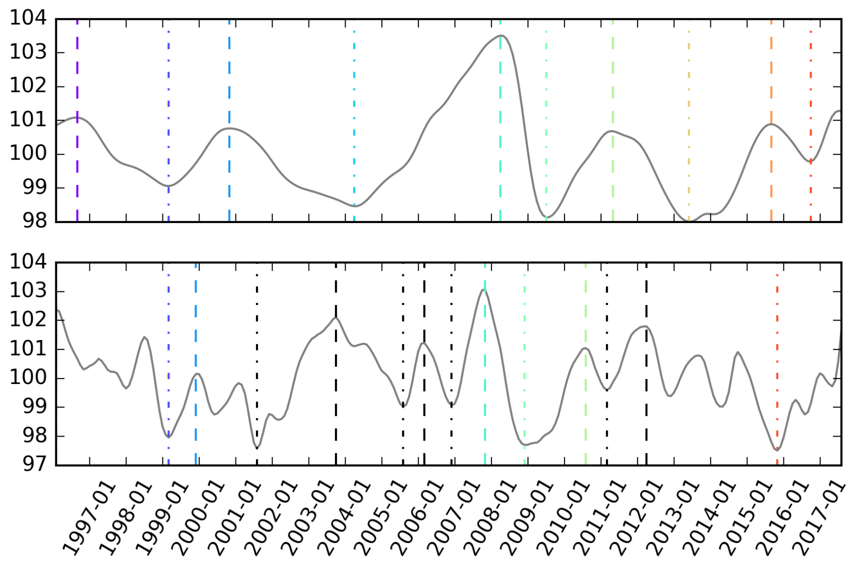


Figure 4.22 – Comparison of turning points of Czech GDP (upper chart) and Czech energy production index (lower chart) detected by the Bry-Boschan algorithm in the normalised cyclical components of the series. Extra turning points are marked in black.
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

chart contains the normalised cyclical component of the Czech energy production index. Its extremes are coloured according to the relevant turning points in GDP and the extra turning points are marked in black. The extreme that responds to the first peak in GDP occurred in February 1996 and cannot be seen on the chart as the chart x-axis is set according to the reference series.

There is a discrepancy between the scales of y-axes, which is intentionally kept in this chart type. This plot should serve mainly to compare the turning points and not the level of the series, because the amplitude of the composite indicator can be interpreted only as the confidence of the CLI outlook and never to analyse the level of the economy (see section 1.3 for more information on this topic).

4.5.3 Cross correlations analysis

Cross correlations analysis is another method that is used by OECD to determine the relationship between the reference series and the individual economic indicators. Cross correlations measure linear dependency between the normalised cyclical components of the reference series and selected individual economic indicator with applied time-lag. For each analysed economic indicator, the maximal value of cross correlations is found as well as the time-lag where the maximum occurs.

OECD doesn't consider the risk of *spurious correlation* described by Granger and Newbold (1974). Due to spurious correlation, two economic indicators may be correlated even though neither has a causal effect on the other. However, OECD uses cross correlations to compare the time series whose trend and seasonal components were removed, therefore the risk of spurious correlation is mitigated. This thesis follows the OECD methodology and the research of spurious relationships in context of composite indicators remains as a future work.

The process of cross correlations analysis is summarized in figure 4.23. The flowchart consists mostly of data preparation processes, which guarantee that the compared time series are of the same length. Then the sample Pearson correlation coefficient is calculated as

$$r_{xy} = \frac{\sum_t \left(z_{ref,t} - \overline{z}_{ref}\right)\left(z_{ei,t} - \overline{z}_{ei}\right)}{\sqrt{\sum_t \left(z_{ref,t} - \overline{z}_{ref}\right)^2}\sqrt{\sum_t \left(z_{ei,t} - \overline{z}_{ei}\right)^2}}, \tag{4.1}$$

where $z_{ref,t}$ and $z_{ei,t}$ are the values of normalised cyclical components of the reference series and individual economic indicator (with applied time-lag according to the flowchart) in time t, respectively. $\overline{z}_{ref}$ and $\overline{z}_{ei}$ stand for the arithmetic mean of the normalised cyclical components of the reference series and individual economic indicator, respectively. Both $\overline{z}_{ref}$ and $\overline{z}_{ei}$ are equal to 100, if the time series were normalised according to equation (2.5). The correlation coefficient lies between -1 and 1. A value of 1 (resp., -1) stands for total positive (resp., negative) linear dependency between the two time series. A value of 0 means that there is no linear dependency.

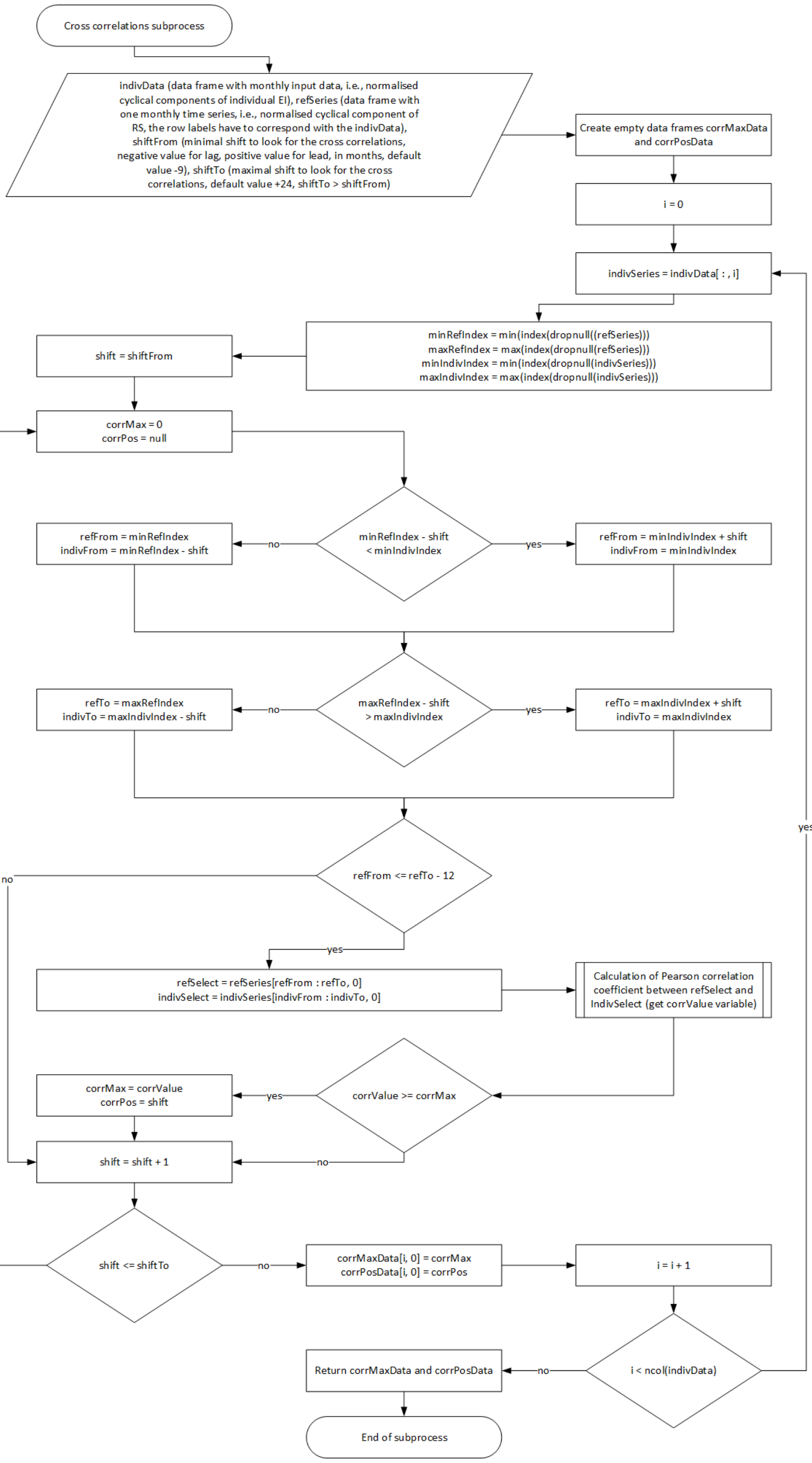


Figure 4.23 – Flowchart of cross correlation analysis (RS = reference series, EI = economic indicator).
Source: Own construction

The advantage of cross correlations is that they are easy to compute and that their results can be quickly evaluated. However, cross correlations measure only general fit between the cyclical components of the individual indicators and the reference time series. The goal of the composite leading indicators is nevertheless to predict the turning points of the reference time series not to forecast the level of the economy. This can cause problems because some of the indicators can show strong linear dependency on the reference time series and still miss some of the cycles, contain extra cycles or the lead (lag) times of their turning points can significantly fluctuate.

In the Czech Republic it has become common practice to use only cross correlations to test the relationships between the cyclical components of the individual indicators and the reference series; see Czesaný and Jeřábková (2009a) or Tkáčová (2012, 2014). However, it is recommended to use the cross correlations combined with other criteria (Gyomai and Guidetti, 2012). Vraná (2014b) compares results of the cross correlation analysis with the Bry-Boschan algorithm. The research has revealed that construction based solely on cross correlation analysis resulted in selection of different component series and caused a decreased performance of the created composite indicator.

As CIF contains the proper turning points detection, it can help researchers to avoid similar quality endangering shortcuts. However, CIF also supports cross correlation analysis as important part of evaluation process (function *crossCorrelation()*).

4.5.4 Selecting component indicators

Selection of component series, which will constitute the composite indicator, is one of the main tasks of CLI construction with a direct influence on its performance. However, this is also the part, which is least described in current literature and the selection process is, therefore, left to intuition and expert knowledge of the analyst performing the computation. I personally consider the formalization and automation of this phase as a key contribution of the algorithmic approach introduced in this thesis.

OECD (2010b, p. 31) defines the selection criteria quite vaguely: ”Ideally, potential component series should have a mean lead greater than 2 and a correlation at peak greater than 0.5 (with a peak lead equal or greater than 2). (...) Furthermore, users should bear in mind that a series provides valuable information if it does not flag too many extra cycles and does not miss too many turning points. In choosing between a series having less false signals and one with less missed turning points, users should prefer the latter”. Other OECD authors (Fulop and Gyomai, 2012, p. 4) suggest another setting for coincident indicators: ”For missed and extra turning points more than 2 were considered as a bad match. For mean, median and peak phase-shift a range +/- 2 months was tolerated. (...) For the standard deviation a 6 months threshold was set. (...) For correlation 0.7 was the threshold.” Eurostat (2017, p. 286) states that ”the lead at which the highest correlation occurs should not be too different from the median lead if the composite leading indicator is to provide reliable information about approaching turning points and the evolution of the reference series”.

Selection criteria

Figures 4.24 and 4.25 depict the workflow of automated selection process, which incorporates all of the criteria mentioned above. Each individual economic series is described by ten characteristics, which aggregate the information gained during turning points detection, turning points matching and cross correlation analysis:

- *number of missing turning points* – number of reference series turning points, which overlap with the time period of the evaluated economic indicator but which are not matched with any of its turning points,
- *number of early missing turning points* – number of turning points, which occur in the reference series before the economic indicator is available (i.e., the economic indicator is shorter than the reference series),

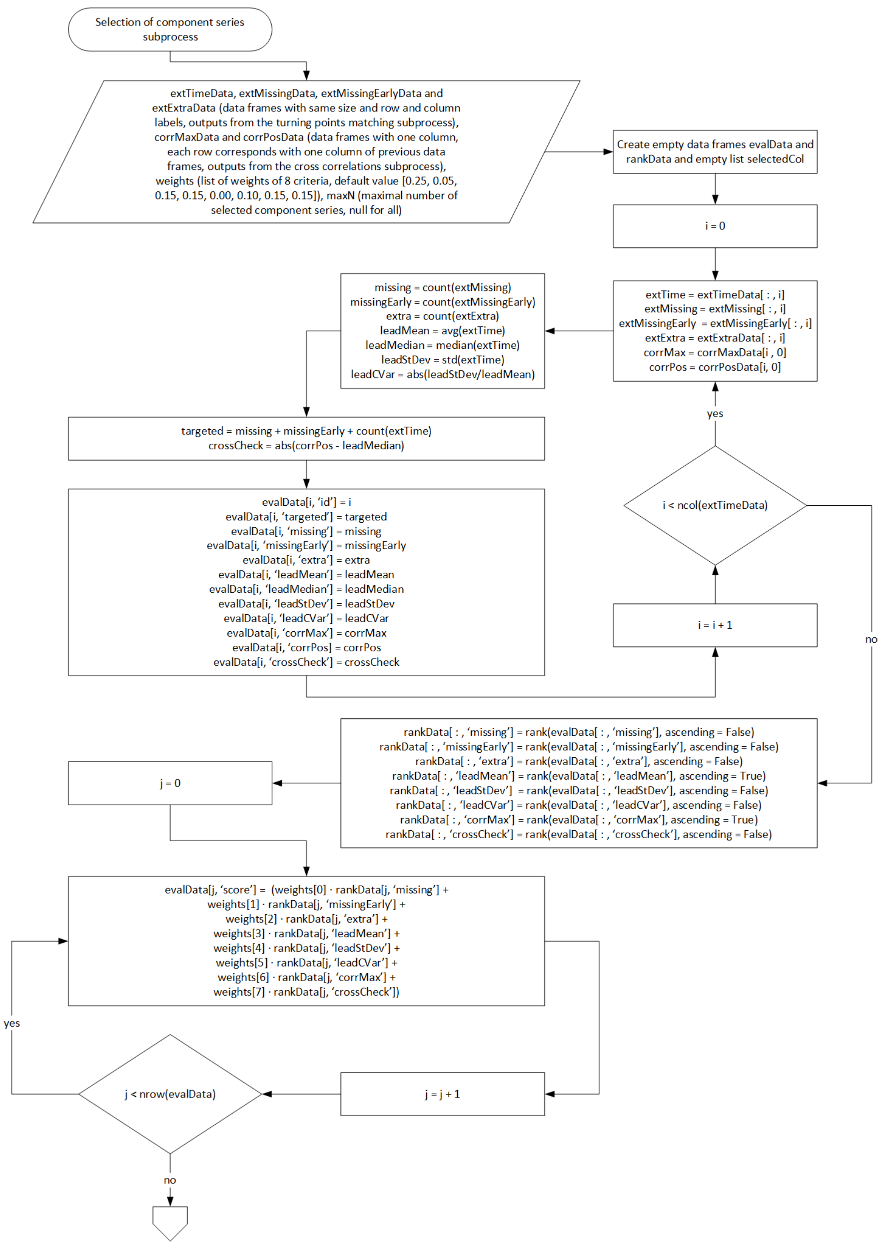


Figure 4.24 – Flowchart of first part of component indicators selection.
Source: Own construction

- *number of extra turning points* (or *number of false signals*) – number of turning points of the economic indicator, which aren't matched with any of the turning points of the reference series,
- *mean lead time* of economic indicator turning points, which are matched with reference series turning points,

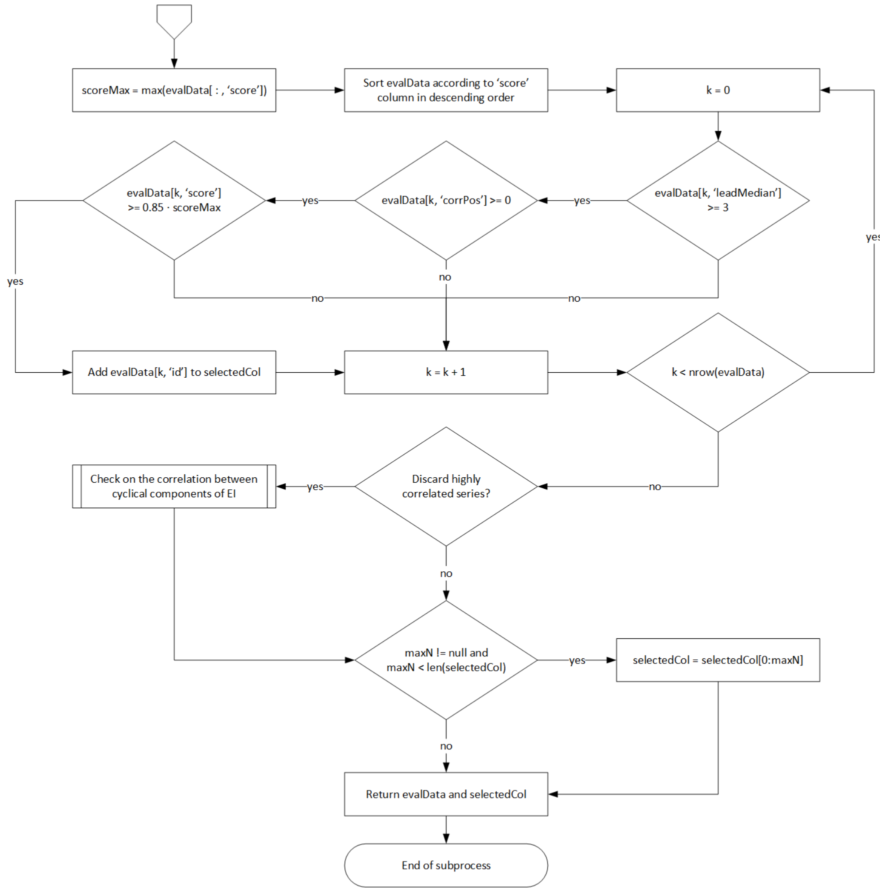


Figure 4.25 – Flowchart of second part of component indicators selection.
Source: Own construction

- *median lead time* of economic indicator turning points, which are matched with reference series turning points,
- *standard deviation of the lead time* of economic indicator turning points, which are matched with reference series turning points,
- *coefficient of variation of the lead time* of economic indicator turning points, which are matched with reference series turning points,
- *maximum of cross correlation coefficient* between normalised cyclical components of the reference series and economic indicator with applied time-lag,
- *position of cross correlation peak* – time-lag (negative values for lag, positive values for lead), which initiates the maximal value of cross correlation coefficient,

Table 4.1 – Basic characteristics of Czech energy production compared to Czech GDP.

Indicator	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check
CZE_PREND401_IXOB	10	3	7	7.14	7.0	0.22	5.0	2.0

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

- *cross-check* – the absolute difference between the position of maximal cross correlation and the median lead time.

If the recommended default values were used during the previous steps of the computation, the values of mean lead time, median lead time and cross correlation peak position range from 24 months lead to 9 months lag. Example of some of these statistics for the Czech energy production index, introduced in the previous sections, is shown in the table 4.1.

When constructing any type of composite indicators (leading, coincident or lagging), analyst should prefer economic indicators with low number of missing, early missing and extra turning points, low standard deviation and coefficient of variation of lead time, high value of cross correlation coefficient and minimal cross-check value. For leading composite indicators, mean lead time, median lead time and position of cross correlation peak should be maximized. These criteria are often contradictory, e.g., economic indicators without any missing turning points often contains many false signals and vice versa.

Criteria prioritization

CIF could have used the *brute computational force* and loop through all the combinations of relevant sets of individual economic indicators, aggregate them into many composite indicators, compare them with the reference series and select the best performing one. However, subtler way was proposed to accelerate the construction. As the instructions published in OECD papers are not clear or unambiguous, the algorithm lets users set weights in order to prioritize between contradictory goals: e.g., to prefer series with minimum missing turning points and maximal mean lead, while paying less attention to the number of extra signals. The default values of these weights are chosen (for more information, see figure 4.24 or CIF function *pipelineEvaluation()*), so the users can get initial results without any unnecessary interventions. However, the system is fully parametrized and the weights can be easily changed if the obtained results are of insufficient quality.

The default weights were gained by trial and error method and they are nowadays set in the way, that returns the results similar to the OECD CLIs (see chapter 6). To get more precise values of the weights, this could be formulated as an optimization problem, where we would minimize the differences between our and OECD CLIs. However, the optimization remains for future research as the results are already satisfactory.

The default weight of the standard deviation is set to 0 as the OECD CLIs seem not to take it into account. Although Fulop and Gyomai (2012) mention the standard deviation among their constraints, they set it at a relatively high level of 6 months. Other authors doesn't mention the expected value of standard deviation at all (e.g., OECD (2010b), Gyomai and Guidetti (2012) or Eurostat (2017)). The standard deviation is of course partially represented in the coefficient of variation.

Scoring the economic indicators

All the available individual economic indicators are ranked according to the computed characteristics: the higher the rank of the indicator, the better it is when compared to the others in the specific area. E.g., the series with the lowest number of the missing turning points get the highest missing turning points rank or the series with the highest value of cross correlation coefficient get the highest cross correlation rank. The series with the same values are assigned the same rank, which responds to the highest rank in this group. Figure 4.24 explains the details of how to compute the score of each economic indicator.

Table 4.2 – Characteristics and ranks (in parenthesis) of randomly selected Czech economic indicators compared to Czech GDP.

Indicator	Missing	Missing early	Extra	Mean lead time	Standard deviation of lead time	Coefficient of variation of lead time	Cross correlation maximum	Cross-check	Score
CZE_BVCICP02_STSA[5]	0 (6)	3 (1)	2 (6)	3.38 (3)	7.76 (3)	2.30 (3)	0.73 (6)	0.5 (6)	5.00
CZE_CP050000_IXOB[6]	5 (1)	0 (6)	7 (1)	-1.50 (1)	5.89 (5)	3.93 (1)	0.12 (1)	5.5 (4)	1.70
CZE_CP050000_IXOB_INV[7]	1 (5)	0 (6)	3 (4)	9.40 (5)	9.03 (1)	0.96 (5)	0.39 (4)	3.0 (5)	4.75
CZE_LRHUADMA_ST[8]	3 (3)	0 (6)	4 (3)	13.63 (6)	5.07 (6)	0.37 (6)	0.39 (3)	7.5 (2)	3.75
CZE_PITGCD02_IXOB[9]	3 (3)	0 (6)	5 (2)	3.63 (4)	7.35 (4)	2.03 (4)	0.23 (2)	13.0 (1)	2.80
CZE_PRCNTO01_IXOB[10]	1 (5)	0 (6)	2 (6)	3.10 (2)	8.76 (2)	2.83 (2)	0.56 (5)	5.5 (4)	4.30

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Table 4.2 illustrates this process. It shows six randomly selected Czech economic indicators, their basic characteristics and the ranks of each series, when compared with the others in the specific area. E.g., the first series (national business tendency confidence indicator) shows no regular missing turning points and therefore it is the best among the selected indicators (its rank for this criteria equals 6). However, it misses the first three turning points (as it is shorter than the reference series) and therefore it is the worst in this area (with rank equal to 1). The score of this series (using default weights and algorithm presented in figure 4.24) is computed as

$$\begin{aligned} score_{CZE\_BVCICP02\_STSA} &= 0.25 \cdot 6 + 0.05 \cdot 1 + 0.15 \cdot 6 + 0.15 \cdot 3 \\ &\quad + 0.00 \cdot 3 + 0.10 \cdot 3 + 0.15 \cdot 6 + 0.15 \cdot 6 = 5. \end{aligned} \tag{4.2}$$

If there is a series, that is the best in all the observed areas, its score is equal to the number of series (if the sum of weights equals 1). In this case, the best score (6) was not obtained by any of the indicators. The national business tendency confidence indicator (with score 5) is the closest one to this boundary, which means that it is the most suitable one of these six evaluated series to become the part of the composite indicator. That can, of course, mean, that all of the input series are of poor quality and none of them should in fact be included in the CLI. However, the initial selection of the time series is the main responsibility of the researcher, and the algorithm tries to select the best indicators among the input data.

The ranks and scores were computed based on 8 characteristics out of 10. The other two characteristics serves as a hard-coded constraints in the algorithm, as is shown in figure 4.25. The median lead of the economic indicator needs to be greater than or equal to 3 months and position of the cross correlation peak cannot be lagged, otherwise the economic indicator is discarded.

When the non-eligible economic indicators are eliminated and the rest is sorted according to their scores, there is still another important question left: how many indicators should be selected? To my best knowledge, there is not one publication, that would state the preferred number of the component series in the composite indicators. The automated selection algorithm in this thesis utilizes the rule of thumb: only the series with score greater than or equal to $0.85 \cdot scoreMax$ are included in the CLI (for more information, see figure 4.25). Moreover, the analysts can use the *maxN* parameter in CIF to limit the maximal number of selected component series.

4.5.5 Discarding highly correlated indicators

The automated selection algorithm (as well as CIF function *pipelineEvaluation()*) offers to optionally discard highly correlated indicators to prevent duplicities among the component series. The algorithm checks correlations between the normalised cyclical components of each pair of the individual economic series. It uses Pearson correlation coefficient equivalent to equation 4.1. If two indicators are highly correlated (correlation coefficient >= 0.99), only one of them is sent into the composite indicator.

[5] Full name: Business tendency surveys (services) > Confidence Indicators > Composite Indicators > National indicator, measure full name: Level, rate or national currency, s.a.

[6] Full name: Consumer Price Index > Furnishings, household equip. and routine household maintenance (COICOP 05) > Total > Total, measure full name: Index 2010=100.

[7] Full name: Consumer Price Index > Furnishings, household equip. and routine household maintenance (COICOP 05) > Total > Total, measure full name: Index 2010=100, inverted.

[8] Full name: Labour Force Survey - quarterly rates > Harmonised unemployment - monthly rates > Aged 25 and over > Males, measure full name: Level, rate or national currency.

[9] Full name: Producer Prices Index > Type of goods > Durable consumer goods > Domestic, measure full name: Index 2010=100.

[10] Full name: Production > Construction > Total construction > Total, measure full name: Index 2010=100.

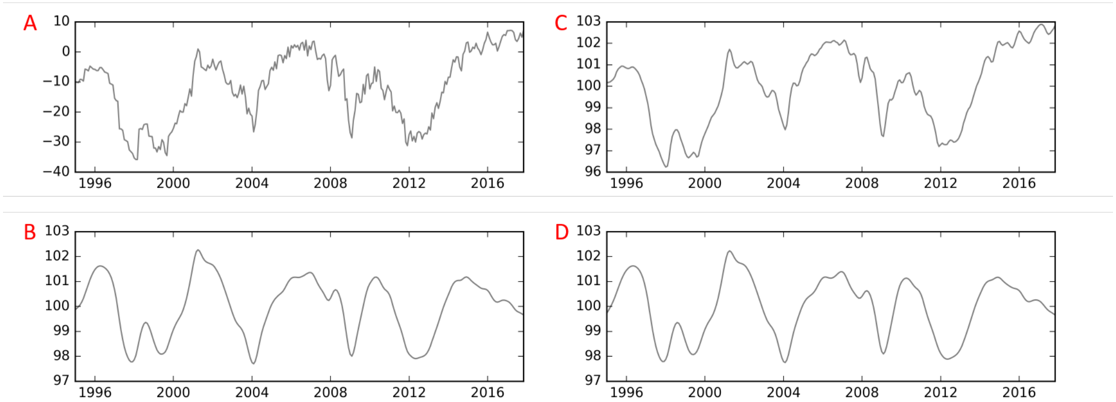


Figure 4.26 – Comparison of the original values (A) and the normalised cyclical component (B) of Czech national consumer confidence indicator and the original values (C) and the normalised cyclical component (D) of OECD consumer confidence indicator for the Czech Republic.
Source: Own construction based on OECD MEI Database (December 2017)

For example, Czech MEI database contains national consumer confidence indicator[11] and OECD consumer confidence indicator[12] (figure 4.26). These two economic indicators are published in different units, so their values look different at a first glance. However, when their cyclical components are compared during the *evaluation* phase, the series are almost identical. Therefore only one of these two series is then included in the Czech composite indicator (see chapter 6).

4.6 Aggregation

Individual economic indicators, selected during previous phases of construction, are aggregated using chain linking method (equations 2.8 and 2.9) and the composite indicator is created. CIF offers function *pipelineCreateCLI()*, which nowadays enables users to create CLI with uniform weights. Possibility to parametrize the weights should be soon added into the library, even though the equal weights usually give similar results as was explained in section 2.4.

[11] Code: CSCICP02, full name: Consumer opinion surveys > Confidence indicators > Composite indicators > National indicator, measure: STSA, measure full name: Level, rate or national currency, s.a.

[12] Code: CSCICP03, full name: Consumer opinion surveys > Confidence indicators > Composite indicators > OECD Indicator, measure: IXNSA, measure full name: Normalised, seasonally adjusted (normal = 100).

According to Gyomai and Guidetti (2012), OECD also incorporates the lag shifting. ”It reflects the lagging of the different selected component series for a given CLI such that, in practice, the lead-times of the component series align with each other, thus maximising the intensity of turning points in the CLI.” This feature also hasn't been added to the CIF yet and remains for the future work.

4.7 Evaluation of created composite indicator

Assessing the performance of the newly created CLI is usually described as *ex-post* analysis, where the actual version of CLI is compared with the actual version of reference series. The *ex-post* analysis is an equivalent process to the comparison of individual economic series and reference series during the *evaluation* phase of CLI construction. Thus the algorithms presented in the previous sections can be reused: detection of turning points (figure 4.14), turning points matching (figure 4.21) and cross correlation analysis (figure 4.23). Only one adjustment is needed: the data frame with a leading composite indicator is used as the input instead of data frame containing individual economic indicators. For more details, see chapter 5.

The *ex-post* analysis can overestimate the quality of constructed composite indicators because it doesn't consider the revisions that are often made to the economic time series. Chapter 8 explains specifics of the *real-time* evaluation and discusses its merits and faults.

4.8 Presentation of the results

CIF offers functions to visualize the computed CLIs as well as functions to visualize the process of the construction:

- function *plotHP()* plots the components of the series during the application of Hodrick-Prescott filter,

- function *compareTwoSeries()* plots two economic time series in one plot (each on its own y-axis), which is convenient for initial comparison of two indicators,
- function *plotIndicator()* shows time series in the same plot as its turning points, which are marked in dashed vertical lines,
- function *compareTwoIndicators()* plots two economic time series with their turning points, the matched and extra turning points are distinguished by different colours,
- function *plotArchive()* illustrates the historical revisions of the time series.

The plots created by these functions are shown in the entire course of this thesis.

4.9 Adjustments to the computational process

CIF runs in the Python environment, which means that users can customize the process or add any functions, that they would find missing.

Even though CIF aims to automatize the composite indicators construction and make the interaction for the users as effortless as possible, it contains several functions instead of one black-box solution. That is fully intentional because it means that users can easily add or skip some steps. Some examples are stated below:

- The function *createDataFrameFromOECD()*, which downloads data from OECD API, can be replaced by any other data source. The new functions can be designed to connect to APIs from other organisations (e.g., Eurostat).
- The Hodrick-Prescott filter in *pipelineTransformations()* function can be substituted by another detrending method (e.g., Christiano-Fitzgerald filter).
- Bry-Boschan dating algorithm can be replaced by other methods (e.g., Markov-switching model) in *pipelineTPDetection()*.

Example of possible adjustment of the computational process is introduced in chapter 7 which enriches the CLIs by international data and proposes how choropleth maps can be used to visualize leading influences among countries.

5 Comparing performance of composite indicators

Section 4.5.4 presented several criteria used to assess the performance of the potential component series when compared with the reference series: minimal number of missing and extra turning points, maximal mean lead, median lead and lead and value of the cross correlation peak. The same criteria are often used to describe the leading properties of the constructed CLI. The performance of the constructed composite indicator is therefore described by several metrics and deciding, whether it is a good or a poor indicator, is a subjective choice of its creator.

Similarly, there are no clearly defined rules on how to compare two indicators. Usually, researchers compare their new indicators with the state-of-art CLIs. These assessments are often subjective and based on visual evaluation or one selected criteria, while the others are ignored.

This chapter provides an overview of methods utilized to compare the performance of the composite indicators nowadays and it discusses the problem of asymmetric measures of relative changes. It proposes simple approach, how to compare performance of two composite indicators, which takes multiple criteria into account.

5.1 Overview of the current comparison methods

The more subjective the construction of composite indicators is, the more focus should be put on the evaluation of the results. Okun (1960, p. 101) states, that ”the possibility of employing a method subjectively does not prevent the objective appraisal of that method. Only if predictive techniques can be evaluated objectively can the accuracy of economic forecasting be viewed as a test of methods rather than of men”. Therefore, when new composite indicators are constructed, researchers often compare them with the state-of-art composite indicators, e.g., OECD or Conference board ones, to point out their strengths or weaknesses.

Measuring the performance of CLI (both, newly created CLI or state-of-art CLI) is equivalent process to the comparison of the individual economic series to the reference series, which was described in previous chapter:

- First, the turning points in CLI are found by simplified Bry-Boschan algorithm described in figure 4.14.
- The turning points detected in the CLI are matched with the turning points in the reference series using algorithm depicted in figure 4.21. During this step, the missed and extra signals are discovered.
- The algorithm from figure 4.23 is used to find the maximal cross correlation between the values of the CLI and the normalised cyclical component of the reference series. The time-lag where the maximum occurs is computed as well during this step.
- Finally, the characteristics of the CLI are summarized using the first part of algorithm described in figure 4.24 (the rest of the algorithm – criteria prioritization and selection of the economic indicator – are meaningless for this use case). Therefore, the CLI can be described by several characteristics:

- *number of missing turning points* – number of reference series turning points, which overlap with the time period of the CLI but which are not matched with any of its turning points,
- *number of early missing turning points* – number of turning points, which occur in the reference series before the CLI is available (i.e., the CLI is shorter than reference series),
- *number of extra turning points* (or *number of false signals*) – number of turning points of the CLI, which aren't matched with any of the turning points of the reference series,
- *mean lead time* of CLI turning points, which are matched with reference series turning points,
- *median lead time* of CLI turning points, which are matched with reference series turning points,
- *standard deviation of the lead time* of CLI turning points, which are matched with reference series turning points,
- *coefficient of variation of the lead time* of CLI turning points, which are matched with reference series turning points,
- *maximum of cross correlation coefficient* between normalised cyclical component of the reference series and CLI with applied time-lag,
- *position of cross correlation peak* – time-lag (negative values for lag, positive values for lead), which initiates the maximal value of cross correlation coefficient,
- *cross-check* – the absolute difference between the position of maximal cross correlation and the median lead time.

The characteristics of the newly created CLI are then compared with the characteristics of the state-of-art CLI, e.g., number of missing turning points of the newly created CLI with the number of missing turning points of the state-of-art CLI.

Each of the presented criteria can be used by itself or in combination with some of (or all) the others. However, focusing only on one of these criteria during the evaluation phase can lead to biased conclusions. E.g., appraisal of the newly created CLI based only on the length of the mean lead time and ignoring the other criteria can cause wrong assessment of its performance, because the newly created CLI can show longer lead than the state-of-art CLI but also miss most of the turning points and be totally unhelpful for predicting the future values of the reference series. Therefore, the evaluation of the newly created CLI should take into consideration as many of these criteria as possible.

Zarnowitz and Ozyildirim (2006), Poměnková (2010) and Nilsson and Gyomai (2011) don't compare the resultant composite indicators, but only the cyclical components of the economic series gained by selected detrending methods. Zarnowitz and Ozyildirim (2006) visually assess the differences in charts and discuss only the number of missing and extra cycles. Poměnková (2010) compares the number of missing and extra turning points, cross correlations and the average length of expansion and recession phases. However, she evaluates each of these criteria separately and doesn't define one clear rule, how to assess the overall quality. Nilsson and Gyomai (2011) analyse the revisions of the cyclical components which is applicable to the evaluation of the detrending methods but unfortunately not to our use case.

Bruno et al. (2004) discuss several methods of turning points dating and compare them only according to the number of missing and extra cycles.

Svatoň (2011) evaluates composite indicators visually and emphasizes the missing and extra turning points. He also compares short-term predictions using root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and the Theil inequality coefficient. This is against the basic principles of CLIs which are not supposed to predict the level of the economy and their numeric values serve only as a confidence measure of the turning points occurrence.

Fulop and Gyomai (2012, p. 5) analyse the CLIs performance with IIP and GDP as the reference series. They compare selected criteria with the desired output which is defined as ”number of observed turning points above 7; the proportion of (missed and extra) to ’total targeted turning points’ below 0.5; mean, median and (cross correlation) peak lead above or equal to 2 months; a standard deviation of lead times below 7 months; a correlation above 0.6”. Then they rather subjectively divide the observed countries into three groups: those, where the CLIs showed improved, acceptable and bad performance. They unfortunately don’t formulate any clear rule, how to divide the CLIs into these groups.

Tkáčová (2012, 2014) and Tkáčová and Kišová (2017) use only metrics based on the cross correlation analysis: value and location of the cross correlation peak. Their approach therefore favours the CLIs with a stronger linear relationship with the reference series, but this doesn’t necessarily mean, that their CLIs are going to predict the turning points of the economy well.

5.2 Measuring relative changes

Majority of researchers evaluates the CLIs performance using a few simple criteria. This section describes how to objectivise the comparison of each of these metrics separately. The next section 5.3 proceeds with this topic and shows how to combine these metrics into one measure which could indicate, whether the overall performance of newly created CLI has improved when compared with state-of-art CLI, and remove (or minimize) the subjective motives out of the decision process.

Intuitively, not every change in the value of a metric should be considered as a substantial improvement or deterioration of the CLI performance in the assessed area. For example, the cross correlation peak value of the state-of-art OECD CLI equals 0.79 and the peak value of the newly created CLI equals 0.83. Is this change big enough to draw some conclusion about the behaviour of the new indicator? And what if the new value equals 0.81 or 0.90?

This thesis suggests to evaluate the significance of changes with their relative sizes. Törnqvist et al. (1985) summarized several methods that could be used to measure the relative changes. They define function $H\left(\frac{x_a}{x_b}\right)$ as the indicator of relative difference between two metrics x_a and x_b. The most common way is to calculate the percent change as

$$H_1\left(\frac{x_a}{x_b}\right) = \frac{x_a - x_b}{x_b} \cdot 100 = \left(\frac{x_a}{x_b} - 1\right) \cdot 100 \tag{5.1}$$

or

$$H_1\left(\frac{x_b}{x_a}\right) = \frac{x_b - x_a}{x_a} \cdot 100 = \left(\frac{x_b}{x_a} - 1\right) \cdot 100. \tag{5.2}$$

For example, if the cross correlation peak values of OECD and the newly created CLIs are $x_a = 0.79$ and $x_b = 0.83$, respectively, then the percent change measured by formula (5.1) equals $\left(\frac{0.79}{0.83} - 1\right) \cdot 100 = -4.82\%$ and change measured by formula (5.2) equals $\left(\frac{0.83}{0.79} - 1\right) \cdot 100 = 5.06\%$. Therefore, the difference between the two values can be interpreted as either 4.82% decrease or 5.06% increase. The H_1 metric is clearly not symmetric, because the metrics are symmetric if

$$H\left(\frac{x_a}{x_b}\right) = -H\left(\frac{x_b}{x_a}\right). \tag{5.3}$$

Törnqvist et al. (1985) offer several symmetric equivalents to the H_1 measure, e.g., log percentages or the symmetric percent change. The latter is defined as

$$H_2\left(\frac{x_a}{x_b}\right) = \frac{x_a - x_b}{x_a + x_b} \cdot 200 \tag{5.4}$$

or

$$H_2\left(\frac{x_b}{x_a}\right) = \frac{x_b - x_a}{x_a + x_b} \cdot 200 \tag{5.5}$$

and it will be utilized in this thesis. The symmetrical percentages will be denoted as $\%_s$ to clearly distinguish them from the regular percentages.

In the previously discussed example, the change between the two CLIs equals $\frac{0.79-0.83}{0.79+0.83} \cdot 200 = -4.94\%_s$ or $\frac{0.83-0.79}{0.79+0.83} \cdot 200 = 4.94\%_s$. That means that there is $4.94\%_s$ difference between the OECD cross correlation peak value and the new peak value and the H_2 metric is symmetric according to formula (5.3).

In this thesis, we will consider the change greater than $10\%_s$ as a significant difference between the two values, and any lesser change won't be counted as an improvement or deterioration of the composite indicator performance in the specified area. This value is intentionally rather high: when institutions publish their CLIs, they usually want to be consistent and don't want to make changes to the composition of their CLIs very often. Therefore the new CLI needs to show much better performance than the old one to convince the researchers to publish the updated version. The $10\%_s$ border was set by subjective choice and other authors could prefer other values. However, it is necessary to make such a decision to keep the rest of the calculation as objective as possible.

The change between the cross correlation peak values of the observed CLIs in our example isn't therefore considered as a significant one ($|H_2| < 10\%_s$) and these two CLIs thus show similar cyclical conformity with the reference series.

There is another constraint for the metrics measured in months (mean lead time, median lead time, cross correlation peak location and cross-check): minimal difference of 1 month is required to consider the change a significant one. Shorter changes don't really make any difference for the composite indicators which are published monthly.

For example, we want to compare the OECD and the newly created CLIs according to the value of the median lead ($x_a = 2.5$ months and $x_b = 2$ months, respectively). The symmetrical percentage change is now equal to $\frac{2.0-2.5}{2.0+2.5} \cdot 200 = -22.22\%_s$ (the performance of the new CLI is $22.22\%_s$ lower in this area), but the absolute change is only -0.5 months and the decrease is therefore not considered as substantial enough.

Table 5.1 – Interpretation of the overall performance metric.

Value	Short interpretation	Long interpretation
$N_+ = 0$, $N_- = 0$	Not changed	The performance of the newly created composite indicator is the same as the performance of the state-of-art one. There were no substantial changes in any of the observed metrics.
$N_+! = 0$, $N_-! = 0$, $N_+ = N_-$	Not changed	The performance of the newly created composite indicator is the same as the performance of the state-of-art one. It is substantially superior in some areas but also substantially inferior in others.
$N_+ < N_-$	Deterioration	The performance of the newly created composite indicator is worse than the performance of the state-of-art one. It is substantially inferior in more areas.
$N_+ > N_-$	Improvement	The performance of the newly created composite indicator is better than the performance of the state-of-art one. It is substantially superior in more areas.

Source: Own construction

5.3 Measuring overall performance

The easiest situation occurs when the newly constructed CLI is better (or worse) in all observed areas. This is the only case, that can be assessed truly objectively. However, usually the performance improves while evaluated by some metrics and decreases while measured by the rest of them, e.g. the new CLI shows a lower number of missing turning points but also generates a higher number of false signals.

This thesis proposes an easy solution: counting the number of areas, where the newly created composite indicator is clearly superior (N_+) or inferior (N_-) according to the measure defined in the previous section. If $N_+ > N_-$, the overall performance of the new indicator is considered improved. Table 5.1 overviews possible values of (N_+) and (N_-) and their interpretations.

This approach considers all the metrics equal, but it could easily use some weighting scheme to prioritize between different criteria (e.g., the lower number of missing turning points could be more important than the lower number of extra turning points). However, setting the weights would bring another portion of subjectivity into the calculation and it could unjustly prefer the CIF results, as the CIF uses a similar weighting scheme during the construction of the indicators. Therefore the weights are not used in this thesis.

This approach can also help to discover the strengths and weaknesses of the new methods when several composite indicators are created (e.g., applying the new methodology to data from many countries). It can help to identify the areas, where the performance of the new method is systematically better or worse than the original one.

5.4 Application of proposed performance measures

The proposed evaluation methodology is used in the following chapters of this thesis, i.e., in tables 6.5, 6.6, 7.2, 7.7 and 8.2. All of these tables contain values coloured according to the symmetric percent change metric H_2: *green* cells for characteristics with substantial improvement against the state-of-art composite indicator, *red* cells for characteristics with substantial deterioration against the state-of-art composite indicator and *black* cells for changes, where $|H_2| < 10\%_s$.

These tables also contain a column called *Comparison*, with the total row count of N_+ and N_- metrics – thus the overall performance measure, which is also coloured according to its interpretation.

Moreover, some of these tables (6.5, 7.2 and 8.2) contain the *Comparison* row with the total column count of N_+ and N_-, which identifies the strengths and weaknesses of the newly proposed composite indicator construction methods.

6 Comparison with OECD leading indicators

Previous chapters described the algorithmic approach and how to assess its performance. This chapter discusses the structure of composite indicators published by OECD and those created in CIF. Intuition says, that the performance of these indicators should not differ too much, to show that the automation of the computational process and the new Python library work as expected. However, it can be anticipated, that the results won't be exactly the same, because most of the current OECD indicators were constructed or revised between 2002 and 2012 and they have been released monthly till now with the same structure. For more details on the reviews of published CLIs, see OECD (1997, 2002, 2006, 2010a, 2012, 2017b).

The CLIs constructed in CIF are based on actual data (downloaded from OECD API in December 2017) and therefore reflect the revisions of series and cyclical behaviour during the last years. It would be easier to compare the composite indicators if OECD published the full range of historical data in their archives and CIF could utilize the same historical dataset. Although there really is OECD revision database available, it contains only a limited selection of economic indicators. For more details on OECD archives and its drawbacks, see chapter 8.

The comparison made in this chapter therefore needs to be interpreted very carefully, as it combines the in and out-of-sample performance of OECD CLI and in-sample performance of CIF CLI.

6.1 Data

OECD publishes data for its 35 member countries and some other partner countries (e.g., Indonesia, the People's Republic of China or South Africa). Ten of these countries will be discussed in this chapter:

- Australia (AUS),
- Czech Republic (CZE),
- Germany (DEU),
- Finland (FIN),
- Japan (JPN),
- Republic of Korea (KOR),
- New Zealand (NZL),
- Mexico (MEX),
- United States of America (USA),
- Republic of South Africa (ZAF).

These countries were selected to cover different types of economies all around the world. Three of these countries are from Europe, two from Asia, two from Australia (Oceania), two from America and one from Africa. The selection contains three G7 countries (Germany, Japan and the United States) as well as three developing economies (Korea, Mexico and South Africa). For more information on the country classification, see United Nations (2017).

Table 6.1 overviews basic characteristics of data available in MEI and QNA databases. The ranges of published datasets differ substantially for each country. The longest Australian, German, Finnish, Japanese, Korean, New Zealand and American series are available from January 1955, first South African data from January 1957 and Mexican from January 1963. The shortest series are provided for the Czech Republic which is the youngest from the selected countries (data start at January 1990). Table 6.1 also shows the number of available economic indicators. The second column (called *whole MEI database*) counts all the economic time series returned by querying the OECD MEI database. However, not all of these can be used as the input into composite indicators, because:

- MEI database contains several different measures per each indicator (for more information, see section 4.3.2), so the data are redundant,
- MEI database contains individual economic indicators as well as OECD composite leading indicator and its component series (so the component series are listed twice: once with their original code and once with special 'leading indicator' code).

Therefore the third column (called *number of distinct eligible indicators*) counts only the eligible indicators, which enter the *filtering* phase of the calculation. The New Zealand dataset is the smallest one among the analysed countries. It consists of 18 economic time series. The most economic indicators are available for Korea, the United States and Japan: 266, 261 and 249 respectively.

The GDP downloaded from the QNA database is also provided in several measures (for more information see subsection 4.3.2). The analyses in this thesis prefer seasonally adjusted GDP in national currency[1], because this measure is also available in OECD archives and enables the *real-time* testing of CLIs in chapter 8. The only exceptions are Mexico and South Africa, where the preferred measure is not available

[1] Measure code: LNBQRSA, measure full name: National currency, chained volume estimates, national reference year, quarterly levels, seasonally adjusted.

Table 6.1 – Basic overview of data available in MEI and QNA databases for selected countries.

Country	No. of indicators (whole MEI database)	No. of distinct eligible indicators	MEI data		GDP	
			from	to	from	to
AUS	416	176	1955-01	2017-11	1959-Q3	2017-Q3
CZE	194	98	1990-01	2017-11	1996-Q1	2017-Q3
DEU	216	114	1955-01	2017-12	1991-Q1	2017-Q3
FIN	205	104	1955-01	2017-11	1990-Q1	2017-Q3
JPN	536	249	1955-01	2017-11	1994-Q1	2017-Q3
KOR	527	266	1955-01	2017-11	1960-Q1	2017-Q3
NZL	64	18	1955-01	2017-11	1987-Q2	2017-Q2
MEX	160	69	1963-01	2017-11	1960-Q1	2017-Q3
USA	554	261	1955-01	2017-11	1947-Q1	2017-Q3
ZAF	110	37	1957-01	2017-11	1960-Q1	2017-Q3

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

and the analyses are based on seasonally adjusted GDP in US dollars[2] and seasonally adjusted volume index[3], respectively.

6.2 CLI structure

6.2.1 Czech Republic

After the last revision in 2012 (OECD, 2012), Czech OECD CLI consists of seven economical time series (their codes, measures and full names from the Leading Indicators section of the OECD MEI database are shown in table 6.2):

- three indicators from surveys (demand evolution and production from business tendency surveys and consumer confidence indicator from consumer opinion survey),

[2]Measure code: VPVOBARSA, measure full name: US dollars, volume estimates, fixed PPPs, OECD reference year, annual levels, seasonally adjusted.
[3]Measure code: VIXOBSA, measure full name: Volume index, OECD reference year, seasonally adjusted.

Table 6.2 – Structure of Czech CLI published by OECD.

Country	Subject	Measure	Inverted	Full name
CZE	LOCOBDNO	STSA[4]	False	Leading Indicators OECD > Component series > BTS - Demand or orders inflow > Normalised
CZE	LOCOBPNO	STSA	False	Leading Indicators OECD > Component series > BTS - Production > Normalised
CZE	LOCOCINO	STSA	False	Leading Indicators OECD > Component series > CS - Confidence indicator > Normalised
CZE	LOCOPANO	STSA	False	Leading Indicators OECD > Component series > Balance of payments > Normalised
CZE	LOCOPCNO	STSA	True	Leading Indicators OECD > Component series > Consumer prices > Normalised
CZE	LOCOSPNO	STSA	False	Leading Indicators OECD > Component series > Share prices > Normalised
CZE	LOCOTXNO	STSA	False	Leading Indicators OECD > Component series > Exports > Normalised

Source: OECD MEI Database (December 2017)

- three indicators from the financial sector (capital account from the balance of payments, consumer price index (inverted) and share prices),
- one indicator from the real sector (exports).

Table 6.3 contains the structure of Czech CLI constructed in CIF. Czech CIF CLI consists of nine economical time series:

- seven indicators from surveys (volume of stocks (inverted), production (twice), selling prices and demand evolution (twice) from business tendency surveys and consumer confidence indicator from consumer opinion survey),
- one indicator from the financial sector (share prices),
- one indicator from the real sector (imports).

It is obvious from these tables, that OECD hasn't stuck with one naming convention for their series. They use different codes and names for their leading indicator components than they use for the same time series in the rest of their database (e.g., name "Business tendency surveys (services) > Demand evolution > Future tendency" for the original time series and "BTS - Demand or orders inflow" for the same time

[4] Measure full name: Level, rate or national currency, s.a.
[5] Measure full name: Index 2010=100.
[6] Measure full name: National currency, monthly level.

Table 6.3 – Structure of Czech CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
CZE	BRVSLV02	STSA	True	Business tendency surveys (retail trade) > Volume of stocks > Level > National indicator
CZE	BSPRFT02	STSA	False	Business tendency surveys (manufacturing) > Production > Future Tendency > National indicator
CZE	BSPRTE02	STSA	False	Business tendency surveys (manufacturing) > Production > Tendency > National indicator
CZE	BSSPFT02	STSA	False	Business tendency surveys (manufacturing) > Selling prices > Future tendency > National indicator
CZE	BVDEFT02	STSA	False	Business tendency surveys (services) > Demand evolution > Future tendency > National indicator
CZE	BVDETE02	STSA	False	Business tendency surveys (services) > Demand evolution > Tendency > National indicator
CZE	CSCICP02	STSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > National indicator
CZE	SPASTT01	IXOB[5]	False	Share Prices > All shares/broad > Total > Total
CZE	XTIMVA01	NCML[6]	False	International Trade > Imports > Value (goods) > Total

Source: Own construction based on OECD MEI Database (December 2017)

series published in Leading Indicators section of MEI database). Therefore the comparison of the components of both leading indicators has to be done manually and it is a time-consuming task.

Four of CIF component series match the series in OECD CLI: demand evolution, production and consumer confidence from surveys and share price from the financial sector. CIF CLI contains more survey indicators; production and demand evolution are listed actually twice (both as tendency and future tendency). CIF compares the correlations between the candidate series, so the identical (or very similar) series are included only once in the aggregated composite indicator (see subsection 4.5.5 for more details). However, both of these series passed this exam.

CIF CLI misses some of the indicators from OECD CLI: capital account from balance of payments, which is no longer published in OECD MEI database[7], inverted consumer price index and exports.

CIF CLI contains imports time series instead of exports one, which is included in OECD CLI. Figures 6.1 and 6.2 show the movements of the normalised cyclical components of the imports and exports series and compare their turning points with the turning points of normalised cyclical component of Czech GDP. OECD (2012) states that

[7]It used to be published in previous versions of MEI database under code BPCATD01, full name: Balance of payments (archive) > Capital Account > Total Debit > Total.

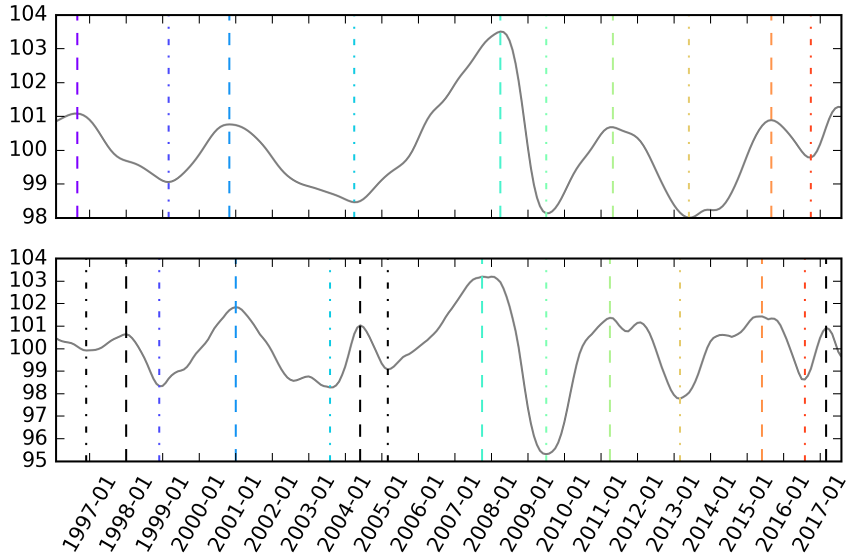


Figure 6.1 – Comparison of turning points of Czech GDP (upper chart) and Czech imports (lower chart) detected by the Bry-Boschan algorithm in the normalised cyclical components of the series. Extra turning points detected in imports are marked in black (4 regular extras and one at the end of the series, which could still be matched in the future).
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

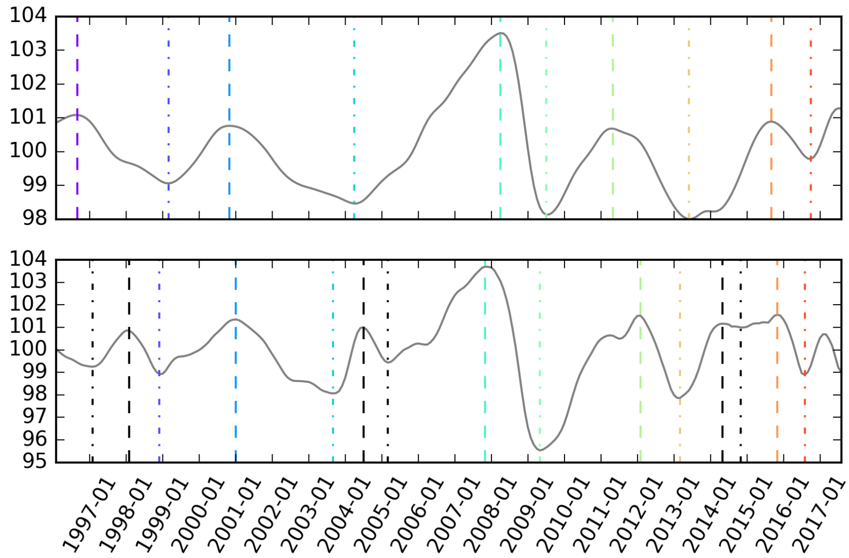


Figure 6.2 – Comparison of turning points of Czech GDP (upper chart) and Czech exports (lower chart) detected by the Bry-Boschan algorithm in the normalised cyclical components of the series. Extra turning points detected in exports are marked in black (6 regular extras).
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

during the time of the last CLI construction Czech exports showed the mean lead time of 8 months. However, after the observations from the last 5 years have been added, the time series shows the mean lead of 1 month only and 6 extra turning points. On the other hand, the imports time series (table 6.6) contains less extra turning points (4) and longer mean lead time (2.67 months). Therefore the CIF CLI prefers the imports indicator.

The inverted consumer price index showed the mean lead of 11 months in 2012 according to OECD (2012). Nowadays the mean lead has dropped to 3.56 months as the last three turning points were rather coincident or lagging (figure 6.3). The actual median lead is 4 months, but it cannot be compared with the original value, as OECD hasn't include medians in their publication. The actual inverted consumer price index reaches the maximal cross correlation 0.61 when lagged by 13 months. The maximal correlation is rather low and the difference between its position and median lead, which serves as a sanity check, is very high (13 - 4 = 9 months). That means, that the relation between the turning points of these two series could be erratic and unstable. Therefore the inverted consumer price index hasn't been included in the CIF CLI.

6.2.2 Other countries

Mexican CLI was published in 1994 and hasn't been revised ever since (OECD, 1997). The last revision of Australian, German, Finnish, Japanese and American CLIs occurred in 2002 (OECD, 2002), New Zealand and South African CLIs were revised in 2006 (OECD, 2006) and the last version of Korean CLI was published in 2010 (OECD, 2010a).

Appendix D contains the structures of CLIs created by OECD and constructed in CIF for each of these countries. Australian and South African datasets provide a very limited number of eligible series: CIF selects only 2 indicators for both of them. This should be considered while interpreting the results in the next section.

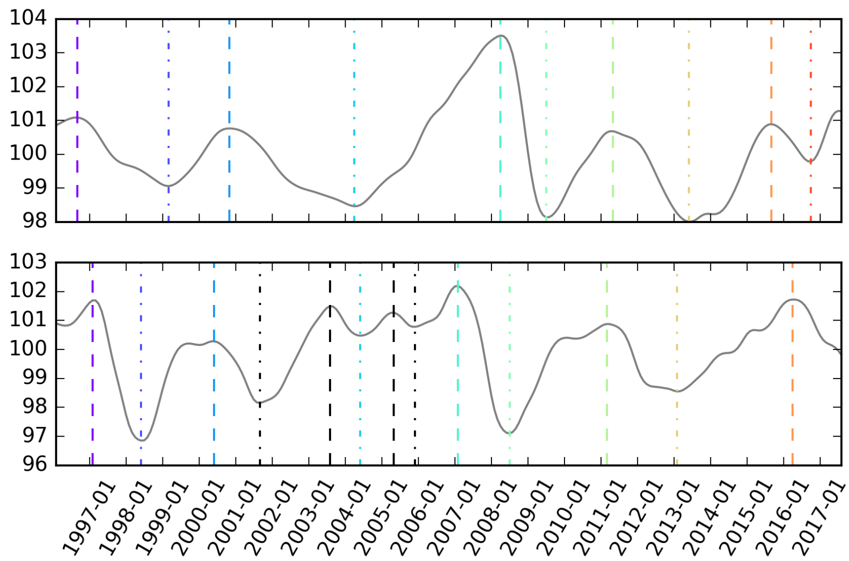


Figure 6.3 – Comparison of turning points of Czech GDP (upper chart) and inverted Czech consumer price index (lower chart) detected by the Bry-Boschan algorithm in the normalised cyclical components of the series. Extra turning points detected in the consumer price index are marked in black (4 regular extras).
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

German OECD CLI (as well as CIF CLI) consists mostly of business tendency surveys indicators. CIF CLIs of both Asian countries (Japan and South Korea) are based mainly on the labour force surveys. New Zealand CLIs are the only one, which include the monetary aggregates M1 among leading component series.

The quality of the leading indicators is discussed in the next section.

6.3 CLI performance

Tables 6.4 and 6.5 show the basic characteristics of CLIs published by OECD and those constructed with the automated approach in CIF, respectively. The tables summarize total number of turning points of the reference series in the observed time period, number of missing and extra turning points, mean and medium lead time of turning points, maximum and location of the peak of the cross correlation function and cross-check (absolute difference between the location of the correlation peak and the median lead) for each national CLI. The texts in the table 6.5 are coloured according to the differences between OECD and CIF CLI results. The green cell means that there is a substantial improvement in the result gained by CIF when compared with the OECD one. The red cell means that the OECD result is substantially better. The black cell means that their values are equal or that there is no significant difference between them. This table also contains a column and row called *comparison*. These values show the overall assessment of the CIF CLIs performance. For more information on the evaluation methodology, see chapter 5.

The lengths of the observed periods need to be the same for OECD CLI and CIF CLI in order to compare them. The composite indicators are published, when at least 60 % of their component series are available, therefore the differences in the structure of the CLIs can affect their lengths. That's why some of the series (usually OECD CLIs) need to be shortened. The shortened indicators are marked as *time adjusted* in the tables. See also the characteristics of the full length series in table D.1.

The function *pipelineEvaluation()* takes parameter *weights* as an input. The following analyses work with the default set of weights, which usually gives the most similar results to the OECD CLIs. The default weights are as follows: number of missing turning points = 0.25, number of early missing turning points = 0.05, number of extra turning points = 0.15, mean lead time = 0.15, standard deviation of lead time = 0.00, coefficient of variation of lead time = 0.10, cross-check = 0.15, maximum of correlation coefficient = 0.15. However, the default settings aren't optimal for some of the analysed countries (Japan, Mexico and South Africa), so altered weights are used. Such indicators are marked as *weights adjusted* in the tables. The new settings are discussed in more detail in subsection 6.3.2.

6.3.1 Czech Republic

Czech OECD and CIF CLIs are compared with Czech GDP. Its cyclical component is depicted in the upper charts in figures 6.1 - 6.5. There have been ten turning points

Table 6.4 – Basic characteristics of OECD CLIs compared to national GDPs (periods are adjusted to enable comparison with CIF CLIs).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check	Comparison
AUS (OECD, time adjusted)	18	5	6	-1.08	1.0	0.29	2	1.0	x
CZE (OECD)	10	2	0	6.13	4.0	0.82	6	2.0	x
DEU (OECD, time adjusted)	13	0	2	2.08	2.0	0.70	6	4.0	x
FIN (OECD)	15	0	4	7.27	7.0	0.61	12	5.0	x
JPN (OECD)	19	3	2	-0.88	-2.0	0.76	3	5.0	x
KOR (OECD, time adjusted)	14	0	2	6.29	6.0	0.52	6	0.0	x
NZL (OECD)	18	6	7	4.42	3.0	0.49	6	3.0	x
MEX (OECD, time adjusted)	10	3	4	4.29	4.0	0.56	7	3.0	x
USA (OECD, time adjusted)	18	2	8	3.44	2.5	0.78	5	2.5	x
ZAF (OECD)	20	2	6	5.61	5.0	0.82	8	3.0	x

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Table 6.5 – Basic characteristics of CIF CLIs compared to national GDPs (the ZAF CLI period is adjusted to enable the comparison with OECD CLI). The colour of the text responds to the difference between the CIF and OECD CLIs performance (green = improvement, red = deterioration, black = no substantial change).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check	Comparison
AUS (CIF)	18	9	5	-1.11	2.0	0.43	8	6.0	4/2
CZE (CIF)	10	0	3	5.20	3.5	0.79	5	1.5	1/2
DEU (CIF)	13	1	1	7.00	6.5	0.78	8	1.5	5/1
FIN (CIF)	15	0	1	7.80	6.0	0.73	8	2.0	3/2
JPN (CIF, weights adjusted)	19	6	0	10.54	10.0	0.66	18	8.0	4/3
KOR (CIF)	14	4	1	6.50	7.0	0.60	10	3.0	4/2
NZL (CIF)	18	3	7	4.53	5.0	0.47	7	2.0	4/0
MEX (CIF, weights adjusted)	10	1	2	4.89	7.0	0.33	9	2.0	5/1
USA (CIF)	18	3	9	5.93	5.0	0.50	19	14.0	3/4
ZAF (CIF, time adjusted, weights adjusted)	20	4	6	3.69	4.5	0.78	5	0.5	1/3
Comparison	x	3/6	6/2	3/1	7/1	3/3	7/3	5/4	x

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

(five peaks and five troughs) during the last 22 years since this indicator has been available in the MEI database (1st quarter of 1996). Hindls et al. (2011) provided the economic reasons for many of these movements, e.g., the recession between 1997 and 1999 was caused by the privatisation and restructuring of the banking sector, the expansion between 2005 and 2006 was drawn by the foreign trade and the drop that started in 2008 was of course caused by the worldwide Great Recession.

Figures 6.4 and 6.5 contain Czech OECD CLI and CIF CLI, respectively. The OECD CLI doesn't show any extra turning points, but it misses 2 of them (in the beginning and at the end of the time series). Its mean lead is 6.13 months and median lead 4 months. On the other hand, the CLI constructed by CIF does not miss any of the turning points, but it shows 3 extra turning points. The false signals in August 2004 (peak) and April 2005 (trough) can be seen also in the Czech imports indicator, which serves as one of the component series (figure 6.1). The CIF CLI has the mean lead of 5.2 months and the medium lead of 3.5 months. These lead times are only slightly shorter than those in OECD CLI.

However, the overall performance of the Czech CIF CLI is worse than the OECD CLI according to the methodology introduced in chapter 5. The CIF CLI substantially improves only the number of missing turning points, but its number of extra turning points and cross correlation peak position are worse.

Table 6.6 presents basic characteristics of the component time series which are included in Czech CIF CLI. These time series were introduced in table 6.3. There are three component times series with better overall performance than the CIF CLI: the inverted volume of stocks from business tendency surveys (BRVSLV02), the confidence indicator from consumer surveys (CSCICP02) and the share prices (SPASTT01). Another four component indicators show inferior performance to the composite indicator: the future production tendency (BSPRFT02), the future tendency of selling prices (BSSPFT02), the tendency of demand evolution (BVDETE02) and the imports (XTIMVA01). CIF CLI, which consists of these time series, does not miss any turning point of the reference series and show the higher value of cross correlation peak than most of its component series. The composite indicators are sometimes connected with the motto ”the whole is greater than the sum of its parts”, which means, that the composite indicators can perform better than any of its component series by itself because the individual faults of each economic time series can be mitigated after the aggregation. The example of the Czech CIF CLI does not confirm this hypothesis – it shows that there are individual economic time series which clearly outperforms the created CIF CLI. However, there are only three of them and predictions based only

Table 6.6 – Basic characteristics of individual economic indicators contained in the Czech CIF CLI compared to Czech GDP. The colour of the text responds to the difference between the performance of the individual economic indicators and Czech CIF CLI (green = improvement, red = deterioration, black = no substantial change).

Indicator	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check	Comparison
CZE_BRVSLV02_STSA_INV	10	0	2	6.10	9	0.43	9	0	4/1
CZE_BSPRFT02_STSA	10	1	6	5.22	6	0.65	7	1	2/3
CZE_BSPRTE02_STSA	10	1	4	6.89	5	0.63	7	2	3/3
CZE_BSSPFT02_STSA	10	1	6	5.22	4	0.42	4	0	1/4
CZE_BVDEFT02_STSA	7	0	0	6.57	3	0.69	4	1	2/2
CZE_BVDETE02_STSA	7	2	2	4.60	3	0.70	3	0	2/3
CZE_CSCICP02_STSA	10	1	2	6.00	5	0.54	7	2	3/2
CZE_SPASTT01_IXOB	10	0	2	5.70	4	0.79	6	2	2/0
CZE_XTIMVA01_NCML	10	1	4	2.67	3	0.78	2	1	0/4

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

on three indicators tend to be rather volatile and adding other series should make them more robust.

6.3.2 Other countries

Table D.1 shows the basic characteristics of the full-length OECD CLIs when compared to the national GDPs. Some of these series needed to be shortened in order to be compared with the CIF CLI as explained above. The *time adjusted* indicators are listed in table 6.4.

Japanese CLI published by OECD is of a poor quality, as it lags instead of leading. Its mean lag is 0.88 months and median lag equals 2 months. Another lagging indicator is the Australian one. The full indicator (which targets 39 turning points of the reference series) shows mean lead of 2.19 months, but the shorter version (which targets the last 18 turning points) is lagging. Other OECD composite indicators are leading, with the mean lead from 2.08 months (Germany) to 7.27 months (Finland). Australian CLI is the only lagging indicator among those created in CIF. Other indicators show leading behaviour with the mean lead from 3.69 months (South Africa) to 10.54 months (Japan).

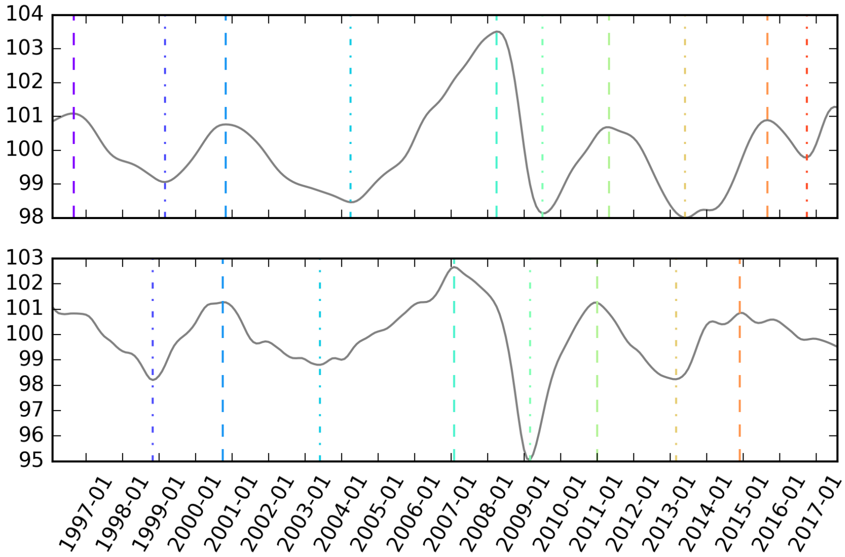


Figure 6.4 – Comparison of turning points of normalised cyclical component of Czech GDP (upper chart) and OECD CLI (lower chart) detected by the Bry-Boschan algorithm.
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

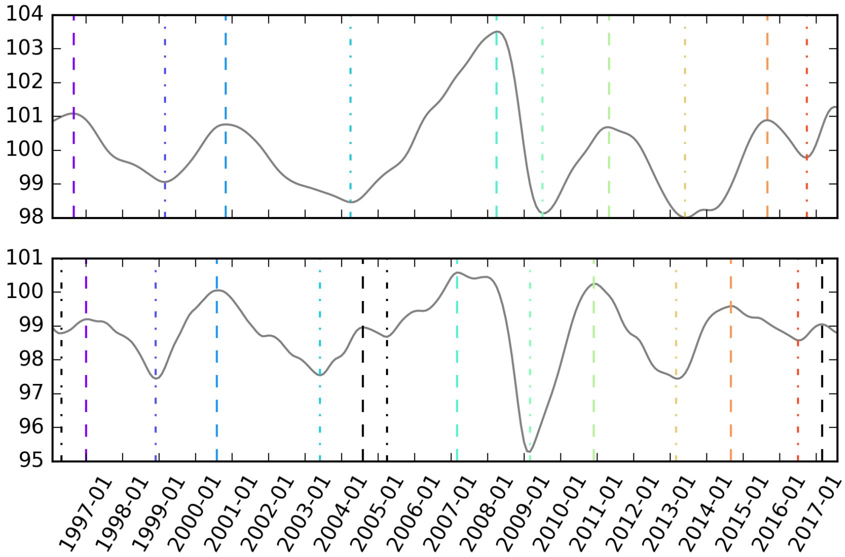


Figure 6.5 – Comparison of turning points of normalised cyclical component of Czech GDP (upper chart) and CIF CLI (lower chart) detected by the Bry-Boschan algorithm. Extra turning points detected in the CIF CLI are marked in black (3 regular extras and one at the end of the series, which could still be matched in the future).
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

When Japanese CLI was constructed in CIF with the default set of weights, the indicator contained too many missing (8) and extra (2) turning points (table 6.7). The different set of weights, which penalizes the missing turning points, was suggested to prevent this[8]. CIF found 15 economical series (see table D.9) that should be included in Japanese CLI with the new settings. The mean lead of the new CIF CLI is 10.54 months and it contains less missing turning points (6). The new version doesn't show any extra turning points. Even though the high value of cross-check needs to be considered, the overall performance of the CIF CLI is better than the performance of the OECD CLI (increase in four areas and decrease in three).

On the other hand, CIF hasn't found almost any eligible series to be included in Australian CLI. The CIF CLI is based on two economic indicators only and it shows the mean lag of 1.11 months. As OECD and CIF CLIs are both lagging, it seems, that there are no proper leading individual economic indicators in Australian data set. Both CLIs also contain a lot of missing end extra turning points. The CIF CLI performance substantially increases when measured by 4 metrics and decreases when measured by 2 of them, therefore its overall performance is considered better than OECD CLI.

The similar change in the overall performance is visible in Korean data: although its CIF CLI misses more turning points it otherwise performs better than OECD CLI.

Mexico is another country with weights adjustments. The CIF CLI, created with the default settings (table 6.8), covered only last 8 reference series turning points, missed 2 of them and gave 4 false signals. When the new set of weights[9] is applied, the series shows less missed and extra extremes and longer mean and median lead. Mexico is (together with Germany) one of the countries, where the CIF helps to improve the quality of the leading indicator in the most significant way: it improves the performance in 5 areas while decreasing only in one (value of cross correlation coefficient).

[8] Number of missing turning points = 0.35, number of early missing turning points = 0.10, number of extra turning points = 0.10, mean lead time = 0.10, coefficient of variation of lead time = 0.10, cross-check = 0.10, maximum of correlation coefficient = 0.15.

[9] Number of missing turning points = 0.20, number of early missing turning points = 0.20, number of extra turning points = 0.15, mean lead time = 0.15, coefficient of variation of lead time = 0.10, cross-check = 0.10, maximum of correlation coefficient = 0.10.

When default weights were applied on South African data, the CIF selected only one indicator to be included in CLI: newly registered passenger cars[10]. Another set of weights[11] ensures that the CLI contains another economical indicator (share prices). None of the tested combinations of weights provided CLI with more than two component series. The structure of South African CIF CLI is by chance exactly the same as the Australian one. The difference between the overall performance of the composite indicators is the worst for South African CIF CLI: only the value of cross-check is better and the values of three other metrics are inferior.

German CIF CLI misses one turning point and gives one false signal. The OECD version misses nothing, but its lead (measured by mean, median or position of maximal cross correlation) is shorter. The improvement of the overall performance of German CIF CLI is one of the best.

New Zealand CIF CLI is the only one which doesn't worsen in any of the observed quality criteria. It gives a lower number of missing turning points and cross-check while it shows a higher median and cross correlation lead time. Its performance in the other areas is equal or similar to the OECD CLI. The New Zealand CIF CLI therefore objectively outperforms the OECD CLI.

Finnish CIF CLI behaves a little bit better than OECD CLI: values of three of the quality metrics are superior and values of another two are inferior.

The lead of the American CIF CLIs is longer, but it misses more turning points and its cross-check value is very high. This may indicate the instability of the lead. United States is one of the three countries, where the CIF CLI quality is lower than the OECD one.

Even though the exact comparison is not possible, because the different input data are used, it is shown that the CIF CLIs tend to behave better than the OECD CLIs

[10] Code: SLRTCR03, full name: Sales > Retail trade > Car registration > Passenger cars.

[11] Number of missing turning points = 0.20, number of early missing turning points = 0.05, number of extra turning points = 0.15, mean lead time = 0.20, coefficient of variation of lead time = 0.05, cross-check = 0.15, maximum of correlation coefficient = 0.20.

Table 6.7 – Basic characteristics of Japanese OECD CLI and CIF CLI (calculated with default weights).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check
JPN (OECD)	19	3	2	-0.88	-2.0	0.76	3	5.0
JPN (CIF)	19	8	2	7.91	10.0	0.59	20	10.0

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Table 6.8 – Basic characteristics of Mexican OECD CLI and CIF CLI (calculated with default weights).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check
MEX (OECD, time adjusted)	8	2	4	3.50	4.0	0.63	6	2.0
MEX (CIF)	8	2	4	1.83	-2.0	0.39	21	23.0

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

– 7 out of 10 analysed countries show increase in performance. This chapter also illustrated how to parametrize the construction process: the performed analyses utilized different sets of weights during the *evaluation* phase. However, other parts of the process could be easily customized as well (e.g., increased expected lengths of phases and cycles, so only longer cycles would be evaluated).

The improved performance and the similar structure of the CIF algorithmic approach when compared with OECD CLIs (which utilizes expert knowledge of OECD researchers) show, that it is possible to automatize the computational process of the composite indicators construction.

CIF already allows its users to limit the maximum number of time series that enter the composite indicator. However, it could also enable users to set the lower limit. The composite indicators would then contain more component series, even though the series wouldn't have passed all the requirements (e.g. minimal median lead). Such adjustments could create composite indicators with shorter, but steadier lead of the turning points. This could help to create better-performing indicators for Australia and South Africa, but it remains as a future work.

6.3.3 Comparing the metrics

Table 6.5 contains also the *comparison* row. This row shows the number of countries, where the specific metric was superior/inferior. This can help to assess the performance of the automatized approach of the new CIF package.

CIF gives constantly better results than OECD in almost all areas: especially median and cross correlation lead time and the number of false signals. The only deteriorated metric is the number of missing turning points.

As CIF allows to prioritize between these metrics, users could easily change the weighting scheme during the *evaluation* phase of the computation to minimize the number of missing turning points in the constructed CLI. This would, of course, cause the deterioration of other metrics.

7 Extending the construction of composite indicators by international economic time series

OECD publishes CLIs for most of its 35 member countries and for some partner countries (e.g., Brazil, India or the People's Republic of China). It also compiles the CLIs of the whole G7, NAFTA, Euro area, European OECD and all OECD countries. However, the composition of each country's CLI depends on the national input data only. For example, Czech OECD CLI consists of Czech individual economic indicators. The European economies are nevertheless often small and open and therefore their business cycles relate to the situation in the surrounding countries.

This chapter aims to construct the international CLI based on the input data from multiple countries and assesses

- if considering international data changes the structure (and performance) of CLIs,
- whether international CLIs can be used to analyse the relationships between business cycles of several countries,
- how can be these relationships interpreted and visualized.

This is not the first time when the authors add international data to construct a CLI. For example, the authors of the Czech CLIs sometimes intuitively include few German economic series among their input data, e.g., Svatoň (2011). However, this is the first case, to the best of my knowledge, when the international series are added intentionally to assess their influence on the structure of the constructed composite indicators. This is also the first time when the composition of the international CLIs is used to visualize and interpret the relationships between the countries and their business cycles.

This chapter utilizes CIF library and demonstrates the international CLI construction on data from 5 countries: Austria, the Czech Republic, Germany, Poland and Slovakia. These neighbouring countries were selected to simplify the interpretations and visualizations of the results. However, deploying the proposed library guarantees that the international CLIs can be easily based on all European data or data available all over the world.

This approach was introduced for the first time by Vraná (2018): the paper compares the international CIF CLIs with the state-of-art OECD CLIs. Similar comparison is captured by tables E.1 and E.2 in appendix E. These tables show that the CLI performance of each of the 5 analysed countries is substantially improved by the addition of the international input data. However, it is not clear from these tables, whether this improvement is caused by the new CIF automatic approach or by the extended data set.

Therefore, this chapter is different: the international CIF CLIs are compared with the national CIF CLIs. Thus any change in the structure or performance of the indicators is guaranteed to be caused by the new input data set and not by the differences in the construction method.

7.1 Data

This chapter analyses different countries than the previous chapters. The reason is simple: there should be justified relations between the countries, to include their economic indicators in international CLIs. This is achieved here by considering data from the Czech Republic (CZE) and its neighbouring countries: Austria (AUT), Germany (DEU), Poland (POL) and Slovakia (SVK). All of these countries are members of the European Union and share a lot of common history.

The data for this chapter were downloaded by CIF from OECD MEI and QNA databases in December 2017.

Another important data source for this chapter is GADM (Global Administrative Areas) spatial database, which provides mapping files (Hijmans et al., 2015).

7.2 Extensions to the algorithmic approach

The CIF library didn't require many adjustments to enable the construction of international CLIs.

The function *createDataFrameFromOECD()* can take a list of several countries as an input and the data from multiple countries are thus downloaded from OECD MEI database by one command.

The rest of the process follows the same steps that are described in chapter 4 and that are summarized in the basic pipeline in appendix A. The computation repeats once per each country: with the same individual economic series, but different reference series. Business cycle from each country is compared with all the available economic indicators and the best matching ones are selected as the CLI elements of this country.

The numbers of individual economic indicators which are selected as the component series are counted and these international structures are then visualized in choropleth maps (maps with regions shaded according to specified values).

The next version of CIF will offer a new function *downloadShapefile()* which will automatically download and unzip the mapping files of a specified country from GADM spatial database and therefore minimize the otherwise necessary manual interventions. This function is now available only in the development version of the library.

7.3 National vs. international CLIs

The analysis follows the OECD methodology (chapter 2) with only minor parts of the *pre-selection* and *evaluation* phases altered for this use case:

- the *pre-selection* phase contains input data from multiple countries,
- the number of individual economic indicators selected to be aggregated into CLI is fixed to 15 during *evaluation* phase.

The number of selected individual indicators is fixed to enable the comparison of international influences between several countries. Usually, this kind of prerequisite is not necessary, because the quality of constructed CLI does not depend on the number of selected indicators. However, it is the structure, not the performance quality, which is in the main focus of this chapter. That is caused by two reasons:

- the structure of the indicators is going to be used as the metric of relationship between the countries,
- more than 5 countries should be analysed to decide whether the quality significantly improves.

The CLI constructed by the CIF from national data according to the original methodology is called the *national CLI* and the CLI based on the international data is called the *international CLI* in the following text. Tables 7.1 and 7.2 show basic statistics of these composite indicators.

Table 7.1 – Basic characteristics of national CIF CLIs compared to national GDPs (periods adjusted to enable comparison with international CIF CLIs).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check	Comparison
AUT (CIF, time adjusted)	10	1	0	7.22	5.0	0.80	10	5.0	x
CZE (CIF)	10	0	3	5.20	3.5	0.79	5	1.5	x
DEU (CIF)	13	1	1	7.00	6.5	0.78	8	1.5	x
POL (CIF)	9	1	0	5.88	7.5	0.55	6	1.5	x
SVK (CIF)	8	1	2	9.29	9.0	0.64	6	3.0	x

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Table 7.2 – Basic characteristics of international CIF CLIs compared to national GDPs. The colour of the text responds to the difference between the national and international CIF CLIs performance (green = improvement, red = deterioration, black = no substantial change).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check	Comparison
AUT (CIF, international)	10	0	0	6.4	5.5	0.90	6	0.5	3/1
CZE (CIF, international)	10	1	1	7.89	7.0	0.79	6	1.0	4/1
DEU (CIF, international)	13	1	1	7.92	7.0	0.84	8	1.0	0/0
POL (CIF, international)	9	0	0	8.11	8.0	0.69	8	0.0	5/0
SVK (CIF, international)	8	1	0	7.57	6.0	0.81	4	2.0	3/3
Comparison	x	2/1	2/0	2/1	1/1	3/0	2/2	3/0	x

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

The CLIs are again computed when at least 60 % of their component series are available. The international time series tend to vary in lengths substantially. E.g., OECD provides first German main economic indicators from January 1955 and first Czech ones not sooner than January 1990. That means that if German CLI is composed mainly of Czech economic indicators (which of course is a hypothetical situation), it cannot be calculated sooner than January 1990 (and probably even later, as only a few Czech indicators are available right from the beginning of this timespan). Therefore, the lengths of the national and international CLIs may differ and they are adjusted to the shorter one of the two to enable the comparison: the shortened series are denoted as *time adjusted* in table 7.1.

7.3.1 Czech Republic

Table 7.3 overviews the structure of Czech international CLI. This CLI consists of

Table 7.3 – Structure of Czech international CIF CLI.

Country	Subject	Measure	Inverted	Full name
AUT	BRBUFT02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Future tendency > National indicator
AUT	BRODFT02	STSA	False	Business tendency surveys (retail trade) > Order intentions or Demand > Future tendency > National indicator
CZE	BRVSLV02	STSA	True	Business tendency surveys (retail trade) > Volume of stocks > Level > National indicator
CZE	BVDEFT02	STSA	False	Business tendency surveys (services) > Demand evolution > Future tendency > National indicator
CZE	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total
DEU	BVDETE02	STSA	False	Business tendency surveys (services) > Demand evolution > Tendency > National indicator
DEU	PITGCD01	IXOB	True	Producer Prices Index > Type of goods > Durable consumer goods > Total
DEU	PRMNCG03	IXOB	False	Production > Manufacturing > Consumer goods > Non durable goods
DEU	SLMNCN01	IXOB	False	Sales > Manufacturing > Consumer goods non durable > Volume
DEU	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total
POL	BRCICP02	STSA	False	Business tendency surveys (retail trade) > Confidence indicators > Composite indicators > National indicator
POL	BVCICP02	STSA	False	Business tendency surveys (services) > Confidence Indicators > Composite Indicators > National indicator
POL	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total
SVK	CSCICP03	IXNSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > OECD Indicator
SVK	CSESFT02	STSA	False	Consumer opinion surveys > Economic Situation > Future tendency > National indicator

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

- three Czech indicators (inverted volume of stocks and future demand tendency from surveys and share prices from the financial sector),
- two Austrian indicators (both from business tendency surveys),
- five German indicators (demand tendency from surveys, inverted producer price index, production and sales of non durable goods and share prices from the financial sector),
- three Polish indicators (consumer confidence indicators in retail trade and services and share prices),
- two Slovak indicators (both from consumer opinion surveys).

All the three national component series are also part of Czech national CLI which was presented in table 6.3.

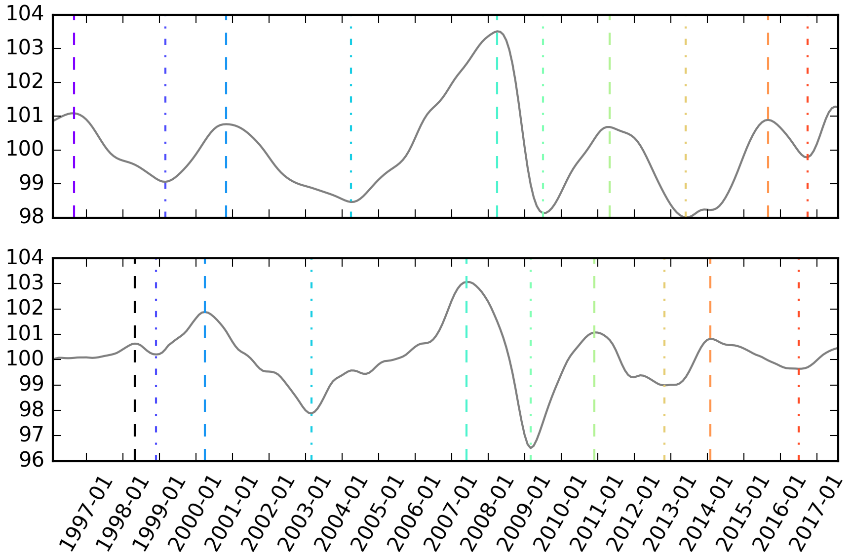


Figure 7.1 – Comparison of turning points of normalised cyclical component of Czech GDP (upper chart) and international CIF CLI (lower chart) detected by the Bry-Boschan algorithm. Extra turning point detected at the beginning of the international CLI is marked in black. Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Figure 7.1 depicts international CLI of Czech business cycle. The national CLI was already displayed in Figure 6.5.

The international CLI misses one turning point (the first peak), that was found by the national CLI. On the other hand, it gives only one false signal (instead of three). It also shows a longer lead (measured by mean, median and cross correlation peak position). The overall performance of the international CLI is substantially better as it is superior in 4 areas while inferior only in one.

7.3.2 Other countries

Tables 7.1 and 7.2 report that Polish international CLI shows longer lead when measured by mean and cross correlation peak position. Moreover, it doesn't miss any of the turning points. Its quality is improved in 5 areas and its overall performance is therefore substantially better.

The Austrian international CLI displays higher conformity with the business cycle (higher maximum of cross correlation) and also has no missing turning points unlike the national CLI. Also, the difference between median and cross correlation peak location of national CLI (cross-check column) is high and therefore the international CLI would probably provide more stable results. Therefore, the overall performance of Austrian CLI is also improved when international data are considered.

The German and Slovak CLIs show neither improvement nor deterioration. None of the quality metrics of the German CLIs differ substantially. The Slovak international CLI displays shorter lead times, but no extra turning points. It also shows higher conformity with the business cycle.

More than 5 countries should be analysed to achieve the proper comparison of the national and international CLIs performance. However, our sample suggests that considering international data tends to improve the overall performance of the CLI. According to the partial metrics, especially the cross correlation maximum is higher and cross-check value is lower, therefore the international CLIs tend to correspond with the business cycle better and to give more stable results.

7.4 Leading influence metric and leading influence maps

This thesis introduces, how to use the international CLIs to analyse the relationships, similarities and differences between the business cycles of selected countries. Table 7.4 summarizes the structure of each constructed CLI (for the complete overview see appendix E). The number of component series was artificially set to 15 as was explained in the previous section, therefore the total equals 15 for each column. The row totals represent the frequencies of the national individual economic indicators in all of the constructed international CLIs. These numbers can serve as a new *leading influence metric*: the higher the number, the more common it is for the individual indicators of this country to appear in the international leading indicators. This could

Table 7.4 – Summary of international CIF CLIs structures.

		Target countries					
		AUT	CZE	DEU	POL	SVK	Total
Input countries	AUT	3	2	4	3	1	13
	CZE	2	3	1	2	1	9
	DEU	7	5	8	7	4	31
	POL	3	3	2	3	9	20
	SVK	0	2	0	0	0	2
	Total	15	15	15	15	15	x

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

also be interpreted as the economic lead or influence the country has compared to the others.

Data from table 7.4 are visualized as choropleth maps to ease the interpretation of the results. Figure 7.2 shows the choropleth map of leading influences of the selected countries on the Czech business cycles. The darker the shade of area in the map, the higher the number of its economic indicators appeared in the constructed CLI. For the maps of the rest of the analysed countries, see figure 7.3.

Germany is the most leading economy according to the leading influence metric – its economic indicators appears in CLIs for 31 times. German CLI also contains the highest ratio of its own national indicators (8 out of 15). The other extreme is Slovakia, whose CLI contains only foreign indicators (almost exclusively Polish and German ones) and whose own national indicators appear only in the Czech CLI.

Poland is the second most leading economy according to the leading influence metric. Its national indicators appear 20 times in the international CLIs. Polish indicators have the majority in Slovak CLI (9 component series).

The influence of Germany on the Czech economy is not surprising as it is Czech key business partner. Tables 7.5 and 7.6 show values of Czech imports and exports

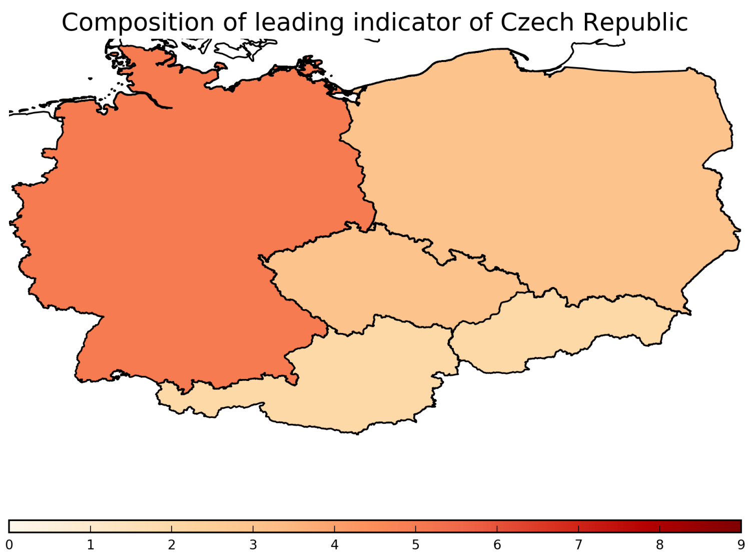


Figure 7.2 – Visualization of leading influences of neighbouring countries on the Czech Republic (top 15 indicators).
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

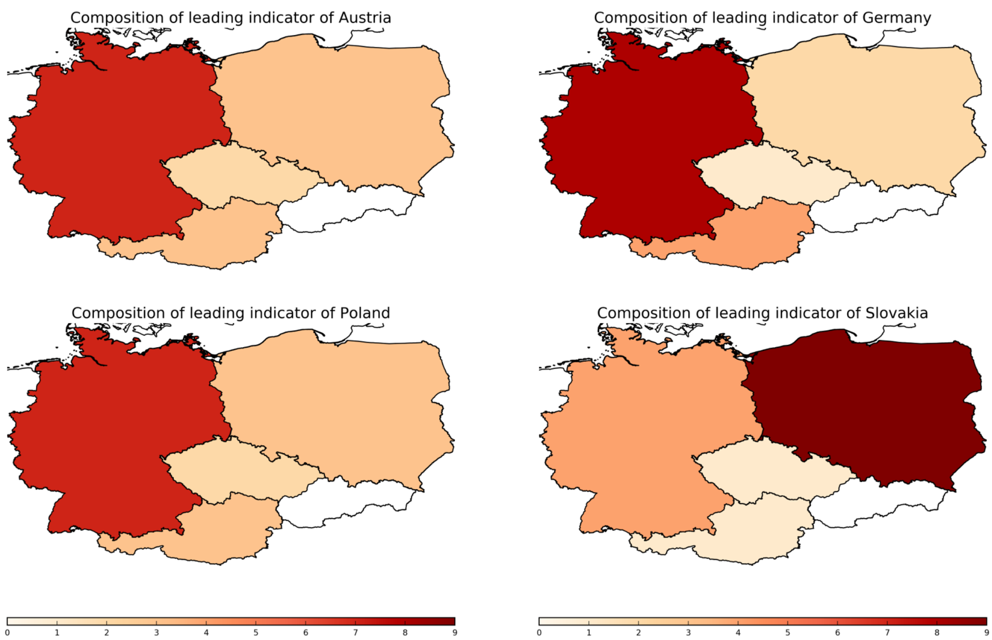


Figure 7.3 – Visualization of leading influences among selected countries (top 15 indicators).
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Table 7.5 – Neighbouring countries by imports into the Czech Republic in 2016.

Country	Rank	Import value (thousands of CZK)	Import ratio (%)
DEU	1	924 082 513	26.40
POL	3	288 884 681	8.30
SVK	4	177 637 683	5.10
AUT	7	101 370 620	2.90

Source: Czech Statistical Office (2017)

Table 7.6 – Neighbouring countries by exports from the Czech Republic in 2016.

Country	Rank	Export value (thousands of CZK)	Export ratio (%)
DEU	1	1 286 717 667	32.40
SVK	2	331 354 077	8.30
POL	3	229 138 114	5.80
AUT	7	168 445 174	4.20

Source: Czech Statistical Office (December 2017)

in 2016 and Germany is number one in both. The role (or the lack of it) of Slovakia is more surprising. Only 2 of its economic indicators occur in the Czech CLI even though Slovakia appears among the top Czech import and export partners. Austria has the same leading influence on the Czech business cycle (measured by the number of its economic series in the Czech CLI), although its share on the Czech international trade is much lower.

Austria business cycle is led mainly by German indicators, which form more than half of its international CLI. The international structure of the Austrian CLI is by chance exactly the same as the Polish one (same counts but different series as can be seen in tables E.4 and E.7 in the appendix).

7.5 Evolution of leading influence maps

The number of selected component series was fixed at 15 in the previous sections. However, there is no reason, why not use 10, 20, 30 or even more series to assess the international relationships between the national business cycles. The structure of the composite indicator could vary significantly for different size limits.

Figure 7.4 depicts the evolution of the influence map of the Czech international CLI with different numbers of contained component indicators: the limit is set from 1 to 25. The two most influential indicators contains data on share prices[1]: the first one comes from Poland and the second one from Germany. The third selected series is from Austria, etc.

Although the first included time series is from Poland, Germany takes over from the fourth component indicator and it is the country with the most powerful leading influence on the Czech business cycle from there on[2].

Figure 7.4 thus indicates, that the international structure of the Czech CLI doesn't depend much on the number of selected component series: Czech business cycle is led mostly by German and least by Slovak economy. There are never more than 2 Slovak economic indicators included in the Czech international CLI. There is often a tie between the number of Polish and Austrian series, but Poland tends to have a greater leading impact on the Czech business cycle than Austria.

[1] Code: SPASTT01, full name: Share Prices > All shares/broad > Total > Total.

[2] With the exception of the 6th and 17th map with a tie between Poland and Germany.

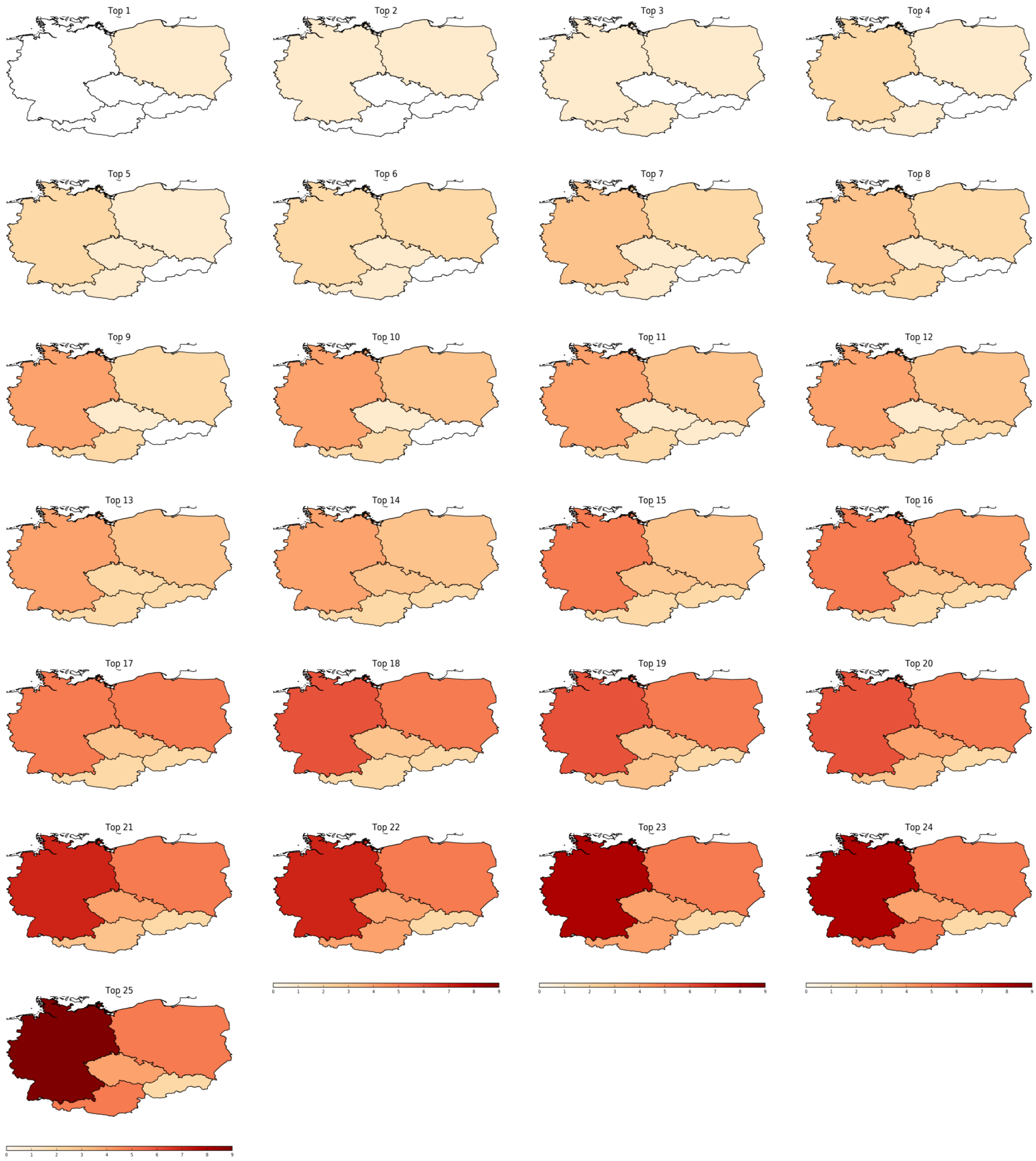


Figure 7.4 – Evolution of leading influences of neighbouring countries on the Czech Republic (top 1 - 25 indicators).
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

7.6 European leading influence maps

The automation of the whole process in CIF enables us to easily construct the influence maps for more than 5 countries, for example, the whole European Union.

Table 7.7 – Basic characteristics of international CIF CLIs (input data from the whole European Union). The colour of the text responds to the difference between the national and international CIF CLIs performance (green = improvement, red = deterioration, black = no substantial change).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check	Comparison
CZE (CIF, EU)	10	1	0	8.89	9.0	0.86	9	0.0	5/1

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

European Union nowadays consists of 28 countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom. However, the OECD MEI database doesn't provide any data on Croatia. There are 9 262 economic series available from the 27 selected European countries. The larger size of the input data set doesn't make any difference for the automatized approach of the CIF, the analysis only takes longer time. On the other hand, the solutions, which depend on manual interventions and expert decisions, would probably fail this task, because their users would have to browse through all the partial results to select the best component series.

Figure 7.5 depicts the leading influence map of the European Union countries (without Croatia) on the Czech Republic business cycle. The higher number of indicators is selected in this case (top 100 economic series) so that the map is not sparse.

The most influential countries according to the influence map are Luxembourg and the United Kingdom (both with 8 economic indicators among the top 100). They are followed by Denmark, France, Netherlands, Portugal and Sweden (each with 6 selected economic series).

The CLI composed from all these international series gains even better results than the CLI presented in section 7.3: no extra turning points and mean, median and cross correlation peak lead of 9 months (table 7.7).

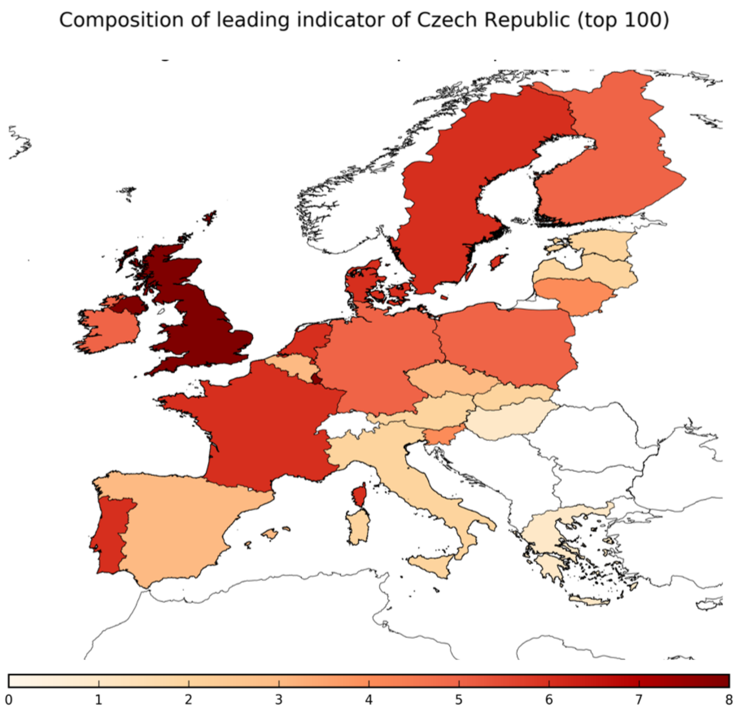


Figure 7.5 – Visualization of leading influences of European Union countries on the Czech Republic (top 100 indicators).
Source: Own construction based on OECD MEI and QNA Databases (December 2017)

This chapter showed how the inclusion of international time series improved the quality of the Czech international CIF CLI. The method could be further extended to analyse the available data from countries all around the world and it could, for example, help to create clusters of regions with similar business cycle movements.

8 Real-time performance of composite indicators

The CLIs are the most frequently constructed type of business cycle composite indicators because of their said predictive powers. However, some authors (e.g., Diebold and Rudebusch (1991)) question these predictive abilities and state, that the CLIs are not in fact able to predict the movements of the business cycle when the constant revisions of the series and the lags before the publishing of the data are considered.

All the previous chapters utilized the *ex-post* evaluation of the results – analysis of a current data edition without the possible effects caused by data revisions. This chapter aims to discover, whether the CLIs can predict the turning points of the economy even in the *real-time* setting, and to describe the modifications of the process automation which are necessary to perform the *real-time* analysis.

8.1 Ex-post vs. real-time evaluations

When Gyomai and Guidetti (2012) describe OECD methodology, the process ends with the *presentation* phase of the construction. They assess the quality of the CLI only by length and consistency of the lead (analysis of the turning points) and cyclical conformity between the CLI and the reference series (cross correlation analysis),

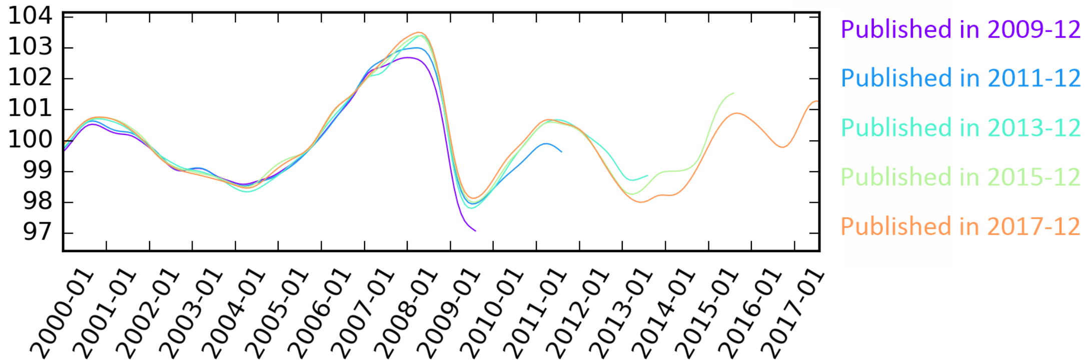


Figure 8.1 – Example of the normalised cyclical component of Czech GDP revisions, data editions published in December 2009, 2011, 2013, 2015 and 2017.
Source: Own construction based on OECD MEI_ARCHIVE Database (December 2017)

as was described in chapter 2. This kind of evaluation, based on the latest data edition[1], is called *ex-post* analysis.

The example of some of the data editions of the Czech GDP normalised cyclical component is depicted in figure 8.1. The *ex-post* analysis works only with the latest data edition (data published in December 2017), but the figure shows, that the results could be slightly different, if the analysis was based on one of the earlier editions. For example, in the data editions published in December 2015 and 2017, there is a peak in May 2011. The corresponding peak could be detected in July 2011 in the data edition published in December 2013. In the previous data editions (published in December 2009 and 2011), the peak could not be detected at all. The data edition published in December 2011 provides data on Czech GDP from the 1st quarter of 1996 to the 3rd quarter of 2011. Therefore there is not enough data to confirm, whether the local peak in the end of the time series is the real turning point or only some minor fluctuation (for more details, see section 4.5.1).

Although the *ex-post* analysis is widespread, this approach is equivalent to testing the model performance on the training data, which can easily lead to overestimation of the model quality. In common machine learning problems, methods like holdout

[1] Editions are called data vintages in some publications.

(i.e., randomly dividing data into training and testing sets), cross-validation or bootstrap are applied to prevent overfitting (Aggarwal, 2015). However, the time series testing is different as observations are not independent and random partitions are out of the question. Temporal data can be also split into training and testing sets, but not at random: all records that occurred before specified date enter the training data set and the rest of them is held in the testing set. This splitting date can be fixed, or a walk forward validation can be used with a sliding or expanding window of training data. Analysis like this would nevertheless be based only on the current data edition (exactly as the *ex-post* analysis) and the results could still overestimate the real performance of the composite indicator. That's because the economic indicators (component indicators as well as reference time series) undergo frequent revisions (Astolfi et al., 2016):

- regular revisions by National Statistical Offices (even though Gyomai and Guidetti (2012) state, that analysts should prefer series that are not subject to significant revisions during the *pre-selection* phase of the CLI construction),
- exceptional revisions caused by the implementation of new methodologies.

Adding new observations to the dataset can also substantially change the results of the analysis as the entire series are detrended at once using Hodrick-Prescott filter and new values at the end of the series can cause the dynamic changes in the whole cyclical component. The proper analysis of CLI performance therefore shouldn't be based on the current data edition only, but should also incorporate the previous data editions. Another factor to consider is the lag between the true date of the event and the publication of the data.

Astolfi et al. (2016) describe the *real-time* analysis, that covers these specifics of CLI performance testing. They analyse CLI editions that OECD publishes in their archive and look at signs of the CLI evolution in the last three months. This approach was originally proposed by Vaccara and Zarnowitz (1978, p. 4) to create forecasts based on CLI values. They "have defined a signal of change in direction as having occurred

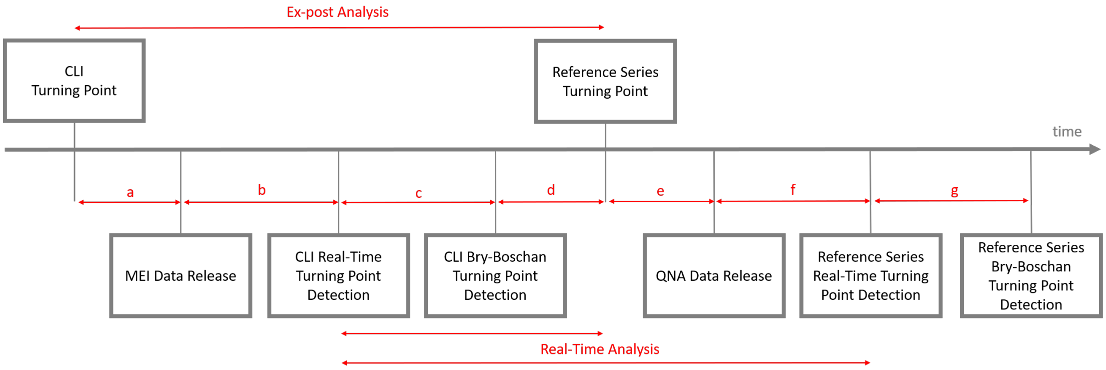


Figure 8.2 – Chronology of events
Source: Own construction based on Astolfi et al. (2016)

when the leading composite index shows a change in direction of movement for at least three consecutive months".

Figure 8.2 depicts the chronology of events connected to the performance analysis. Ideally, the CLI turning point occurs several months before the reference series turning point (which should correspond with the true turning point in the whole economic activity). The data, that cover the date of the CLI turning point, are usually published 2 or 3 months later (period *a*). However, it takes at least another 3 months to be able to detect this turning point by the *real-time* analysis (period *b*). The same applies to the reference series: data have to be published first (period *e*) and then another 3 or more months are necessary to find the turning points by the *real-time* analysis (period *f*). After few more months, the dates of the turning points can be detected by Bry-Boschan algorithm (section 4.5.1), which ignores peaks and troughs in the last 5 months of the series, to prevent false signals. The confirmation of the extremes positions by Bry-Boschan algorithm is therefore substantially delayed (period $a+b+c$ for the CLI and period $e+f+g$ for the reference series). This delay is the main reason, why Bry-Boschan algorithm, which is priceless during the construction of the composite indicators, is not suitable for the *real-time* analysis, which requires the results as soon as possible.

The *ex-post* analysis considers the differences between the locations of the turning points detected by Bry-Boschan algorithm (period $a+b+c+d$). The *real-time* analysis in this thesis focuses on:

- the period between the instance, when the turning point could be detected in the CLI series for the first time, and the true reference series turning point location (period $c+d$),
- the period between the instances, when the CLI and reference series turning points could be detected for the first time (period $c+d+e+f$).

The period $c+d$ can be negative when the CLI turning point is detected after the occurrence of the turning point in the reference series.

Some authors mention another type of evaluation: *simulated real-time* experiment. However, it seems that Bruno et al. (2004) and Nilsson and Gyomai (2011) in fact only apply the walk-forward validation on the latest available data edition and their method is therefore rather like the *ex-post analysis*.

8.2 Data

The OECD MEI database is updated each month, but it contains only the current data edition. OECD provides another database, Main Economic Indicators Revision Database[2] (MEI_ARCHIVE), which can also be downloaded via OECD API. Unfortunately, the MEI_ARCHIVE database is very limited when compared to the MEI database. OECD states, that it provides access to 21 key economic time series, but the CIF *getOECDJSONStructure()* function returns in fact 24 names, therefore the OECD information is probably obsolete. This is unfortunately still just a small fragment of MEI indicators (you can compare it with table 6.1). Moreover, 3 of those 24 series are different versions of GDP (GDP in constant prices, GDP in current prices and implicit price deflator) and 4 of them are versions of OECD CLI. This leaves us

[2] Information available at http://stats.oecd.org/mei/default.asp?rev=1.

with 17 individual economic indicators to use as the input time series for the CLI construction. Unfortunately, the MEI_ARCHIVE doesn't contain most of the series, that are often included in the CLIs, e.g. share prices or any series from business tendency surveys or consumer opinion surveys.

Therefore, the *real-time* evaluation won't be illustrated with the CIF CLIs analysis (which could not be constructed on this limited data set), but with the OECD CLIs, that are available with all their revisions. This shouldn't cause any problems, as this chapter aims to show, that the CLIs in general are able to predict the turning points of the reference series in the *real-time* experiment. The intuition is, that if the OECD CLIs can predict the turning points, then the CIF CLI which exhibited better performance during the *ex-post* evaluation would also be able to pass this test.

This chapter discusses the same countries, that were compared in chapter 6: Australia (AUS), the Czech Republic (CZE), Germany (DEU), Finland (FIN), Japan (JPN), the Republic of Korea (KOR), New Zealand (NZL), Mexico (MEX), United States of America (USA) and the Republic of South Africa (ZAF).

Unlike the MEI database, MEI_ARCHIVE doesn't contain several measures per each indicator. It provides data editions instead: from February 1992 to December 2017[3]. The ambiguities in the OECD naming conventions inside the MEI database were already mentioned in section 6.2. OECD uses another completely different set of codes and names in MEI_ARCHIVE database, which worsen user experience with their API.

8.3 Extensions to the algorithmic approach

Revisions of the OECD CLI and the GDP can be downloaded from OECD API with the standard CIF function *createDataFrameFromOECD()* introduced in figure 4.2, where MEI_ARCHIVE database is set as a data source.

[3] This was an actual state in January 2018, when the data for this thesis were retrieved.

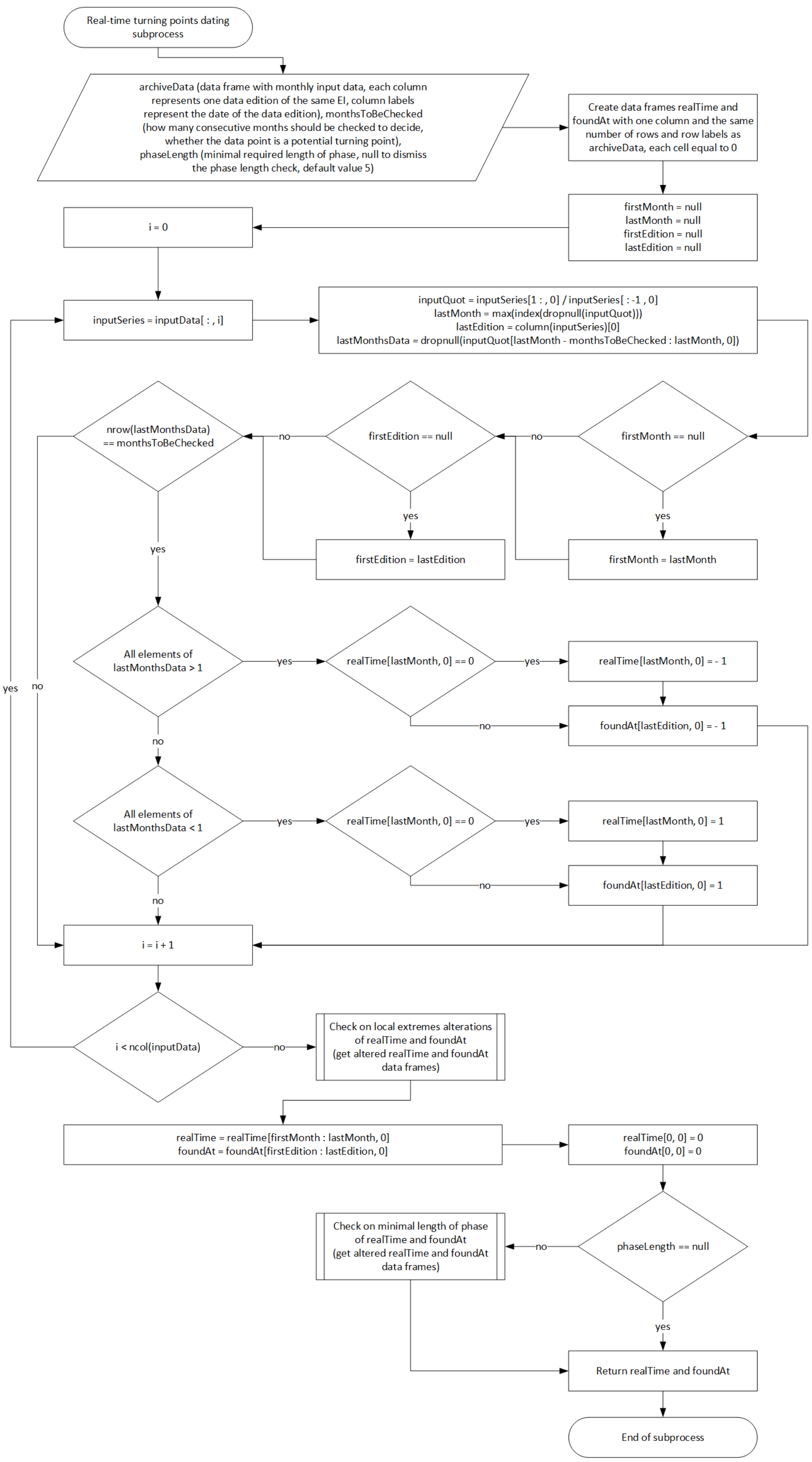


Figure 8.3 – Flowchart of *real-time* turning points detection.
Source: Own construction

Turning points are not detected by Bry-Boschan algorithm, therefore the function *pipelineTPDetection()* (described by a flowchart in figure 4.14) cannot be used and a new function *realTimeTPDetectionFromArchive()* was created instead. This function is explained in figure 8.3: it browses through the revisions of the normalized cyclical components of the time series and evaluates the changes in the last 3 months (3 months is the default value of the *monthsToBeChecked* parameter and can be easily altered).

The flowchart refers to two subprocesses, which were already introduced in section 4.5.1: checking the turning points alterations (figure C.3) and checking the minimal length of the phase (figure C.5). Both of these subprocesses utilize *keepFirst* parameter, which is set to *True* during the *real-time* analysis. For example, if there is a sequence of multiple peaks in the evaluated time series, the *keepFirst* parameter ensures, that only the first of them is kept and the rest is discarded during the alteration check.

The flowchart in figure 8.3 offers another parameter – *phaseLength* – which adds the minimal phase length constraint into the process. The *real-time* method by itself generates many extra turning points. For example, when the *phaseLength* parameter is set to 5 months, the CIF won't highlight another extreme unless there is at least 5-month window from the previous extreme. This relatively simple constraint improves significantly the results of the *real-time* detection as will be shown in the next section.

The CIF returns the turning points with two sets of dates:

- the dates when the turning points were apparent in the behaviour of the series for the first time,
- the dates of the data edition publication when the turning points became apparent for the first time (usually 2 or 3 months later).

For example, the constantly rising series starts decreasing in April (April is therefore the true position of the turning point). After 3 months decrease in June, the turning point could be discovered by the *real-time* analysis, but the June data won't be available till September. The CIF therefore provides both of these dates: June and September, and it lets the researchers decide, which of them is suitable for their analysis. The true date of the turning point would be discovered even later by the Bry-Boschan algorithm which needs at least 5 months of the data history plus time necessary for publication of the time series.

The charts in this chapter use the first type of dates because the visualisations would be chaotic otherwise (there would not be any apparent connection between the behaviour of the series and the turning points). On the other hand, the tables presented in this chapter use the later dates (including the time necessary for publication), as this is the only way how to assess whether the CLIs can really provide some useful information on the turning points of the economic activity before these are visible directly in the GDP movements.

There is another CIF function created specifically for this type of analysis: *plotArchive()*. This function takes the whole archive data frame as an input and compares all the revised data editions in one chart. It enables users to optionally add the detected turning points as vertical dashed lines into the chart. These visualisations are presented in the course of this chapter.

8.4 Real-time analysis

This section shows how to perform the *real-time* analysis of CLI performance. The *real-time* predictions have to be compared with the true positions of the reference series turning points. These are estimated by Bry-Boschan algorithm in the latest data edition (*ex-post* analysis).

Table 8.1 shows the characteristics of the OECD CLI with turning points detected by Bry-Boschan algorithm, i.e., the *ex-post* evaluation. The leads and lags in these tables are equivalent to the periods $a + b + c + d$ from figure 8.2. Similar table was presented in chapter 6, but the periods here are adjusted according to the data editions

Table 8.1 – Basic characteristics of OECD CLIs compared to national GDPs (ex-post evaluation), periods adjusted to enable comparison with the real-time detection.

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Comparison
AUS (OECD, time adjusted)	13	3	4	-2.90	-4.0	x
CZE (OECD, time adjusted)	6	1	0	6.80	4.0	x
DEU (OECD, time adjusted)	10	0	2	1.56	2.0	x
FIN (OECD, time adjusted)	10	0	2	6.00	6.0	x
JPN (OECD, time adjusted)	16	3	1	-2.25	-2.0	x
KOR (OECD, time adjusted)	8	0	1	9.00	8.5	x
NZL (OECD, time adjusted)	8	1	1	7.29	3.0	x
MEX (OECD, time adjusted)	10	3	5	4.29	4.0	x
USA (OECD, time adjusted)	9	2	4	2.00	2.0	x
ZAF (OECD, time adjusted)	4	0	4	4.75	4.5	x

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

available in the archive data. This enables us to compare the *real-time* and the *ex-post* performance of OECD CLI.

Tables 8.2 and 8.3 provide basic characteristics of turning points of OECD CLI and GDP detected by the *real-time* analysis. The tables show the lead (or lag) times of the editions, when the turning points were detected. That means, that the leads (lags) in these tables are equivalent to the periods $c + d$ and $e + f$ from figure 8.2, respectively.

Data in table 8.2 are compared with the *ex-post* results using the performance metrics introduced in chapter 5.

None of these tables contain any of the characteristics based on the correlation analysis (cross correlation maximum, cross correlation peak location and cross-check), because the turning points are not based on one series, but on the whole revision archive.

Table 8.2 – Basic characteristics of OECD CLIs compared to national GDPs (real-time evaluation). The colour of the text responds to the difference between the OECD CLIs real-time and ex-post performance (green = improvement, red = deterioration, black = no substantial change).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Comparison
AUS (OECD, real-time)	13	2	4	1.00	-2.0	3/0
CZE (OECD, real-time)	6	0	0	6.67	7.5	2/0
DEU (OECD, real-time)	10	1	4	4.78	5.0	2/2
FIN (OECD, real-time)	10	2	2	4.38	6.0	0/2
JPN (OECD, real-time)	16	5	6	-4.81	-5.0	0/4
KOR (OECD, real-time)	8	3	3	4.60	5.0	0/4
NZL (OECD, real-time)	8	1	3	1.57	3.0	0/2
MEX (OECD, real-time)	10	2	4	1.13	0.5	2/2
USA (OECD, real-time)	9	2	6	4.00	2.0	1/1
ZAF (OECD, real-time)	4	1	3	4.33	1.0	1/2
Comparison	x	3/5	2/5	3/5	3/4	x

Source: Own construction based on OECD MEI_ARCHIVE and QNA Databases (December 2017)

Table 8.3 – Basic characteristics of national GDPs (real-time evaluation).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Comparison
AUS (GDP, real-time)	13	1	2	-8.42	-9.0	x
CZE (GDP, real-time)	6	0	0	-5.00	-6.0	x
DEU (GDP, real-time)	10	2	4	-8.88	-7.5	x
FIN (GDP, real-time)	10	0	2	-9.22	-9.0	x
JPN (GDP, real-time)	16	4	3	-8.67	-9.0	x
KOR (GDP, real-time)	8	0	4	-5.00	-6.0	x
NZL (GDP, real-time)	8	2	1	-10.33	-9.0	x
MEX (GDP, real-time)	10	1	7	-8.22	-8.0	x
USA (GDP, real-time)	9	2	6	-9.43	-7.0	x
ZAF (GDP, real-time)	4	3	8	-8.00	-8.0	x

Source: Own construction based on OECD MEI_ARCHIVE and QNA Databases (December 2017)

8.4.1 Czech Republic

Figure 8.4 depicts the editions of the Czech CLI published by OECD between April 2006 and December 2017. Editions are distinguished by the different line colours in the chart.

There are 2 exceptional revisions visible:

- December 2008: OECD changed the detrending method from phase-average trend to Hodrick-Prescott filter. New versions of CLI started at January 1995 instead of April 1993 and the series were visibly smoother.
- April 2012: Two major changes happened on this date. OECD switched to GDP as the reference series and published a new Czech CLI structure (OECD, 2012).

Figure 8.5 adds turning points detected in the Czech OECD CLI by the *real-time* method described by Astolfi et al. (2016). A turning point occurs when there is a change in direction in the last three consecutive months of CLI edition current at that time. This chart shows the turning points in the months when they became apparent in the time series for the first time (and it took at least another two months before they were published). It is clear, that this approach gives a lot of false signals, especially at the beginning of 2012 (which are probably caused by the instability of HP detrending at the end of the series.

Astolfi et al. (2016) remind that the Bry-Boschan algorithm generates less turning points because it checks the minimal phase and cycle lengths (5 and 15 months, respectively) and discards the peaks and troughs from shorter phase or cycle candidates. This thesis embraces the suggestion to check the minimal length of the phase during the *real-time* analysis and use it as a simple solution to reduce the number of extra turning points. The *real-time* approach needs to process the data as soon as they are available and it cannot change the past values of the signals. The phase restriction therefore means that the new signal won't be issued unless it appears at least 5 months after the previous signal. Figure 8.6 depicts the turning points detected in the Czech OECD CLI by the *real-time* method with applied phase length restriction. The Conference Board (2001) suggests another method, called *The Three D's*. It is not based on the movements of the CLI series itself, as one series can show many brief increases and declines. Their method considers duration, depth and diffusion (hence the name The Three D's) of the CLI and its components series. E.g., the turning point is announced, when the decline is obvious in the most of the CLI component series.

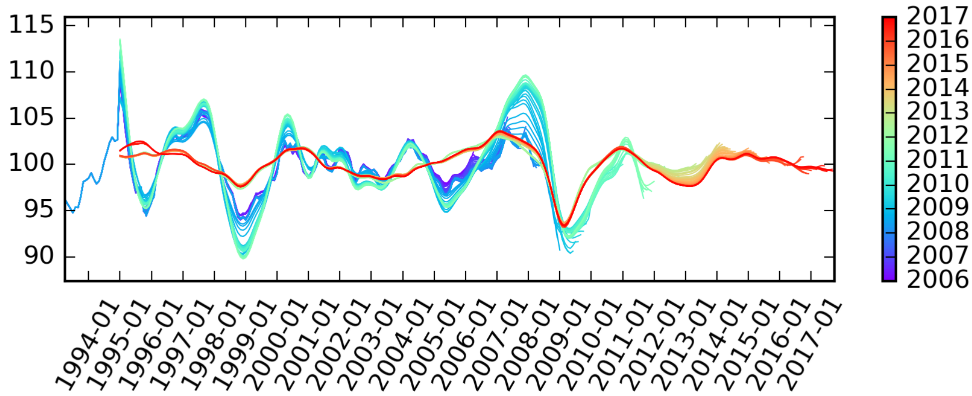


Figure 8.4 – The overview of Czech OECD CLI revisions.
Source: Own construction based on OECD MEI_ARCHIVE Database (December 2017)

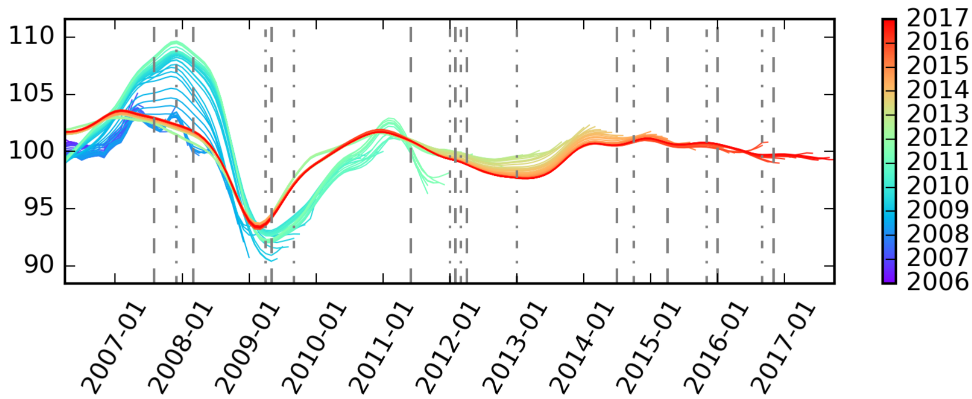


Figure 8.5 – The overview of Czech OECD CLI revisions with turning points detected by the real-time analysis.
Source: Own construction based on OECD MEI_ARCHIVE Database (December 2017)

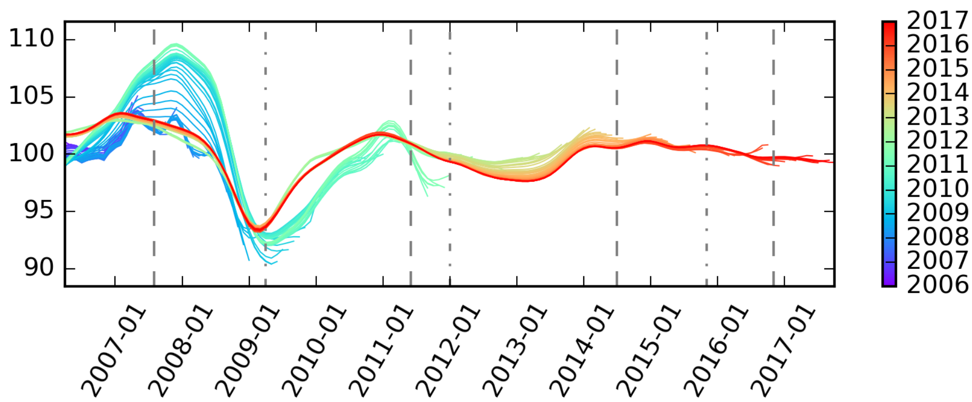


Figure 8.6 – The overview of Czech OECD CLI revisions with turning points detected by the real-time analysis with the minimal phase length of 5 months.
Source: Own construction based on OECD MEI_ARCHIVE Database (December 2017)

This method requires to analyse the behaviour of all the component series of the CLI and it therefore cannot be used with our limited dataset.

Figure 8.7 compares the *real-time* turning points of Czech OECD CLI with the minimal length of phase restriction and the Bry-Boschan turning points of GDP. The CLI doesn't miss any of the 6 covered turning points of the reference series. There is one turning point marked in black at the end of the series, but this one could still be matched in the future and therefore it is not counted as a false signal. The OECD CLI time series shows leading behaviour (mean lead of 6.67 months and median lead of 7.5 months), see table 8.2. This is even better result than the one by ex-post evaluation which has one missing turning point and median lead of 4 months (table 8.1). How is it possible, that the *real-time* results are better than the *ex-post* results when the *real-time* evaluation considers also the time needed for the publication of the series? This can be explained by the revisions of the series during the observed period: the *real-time* turning points were detected in the latest data editions that were available in that time. However, the revisions made to the series seem to shift some of the turning points of the current edition to the later dates (especially the last three matched turning points – trough in January 2012, peak in July 2014 and trough in November 2015). As the *ex-post* analysis uses only the current edition of the data, the overall results may be worse than the *real-time* results, even though it is not common.

The *real-time* evaluation of the reference series plays an important role as well. Even if the CLI signals would be coincident (or slightly lagging) instead of leading, they could still bring a relevant information if they were apparent before the turning points in the reference series. That means, that the *real-time* extremes of the CLI should be compared with the *real-time* extremes of the reference series and if the period $c + d + e + f$ from figure 8.2 is not negative, then the CLI is considered as a useful tool, which is able to indicate the movements of the economy sooner than they are visible in the reference series itself.

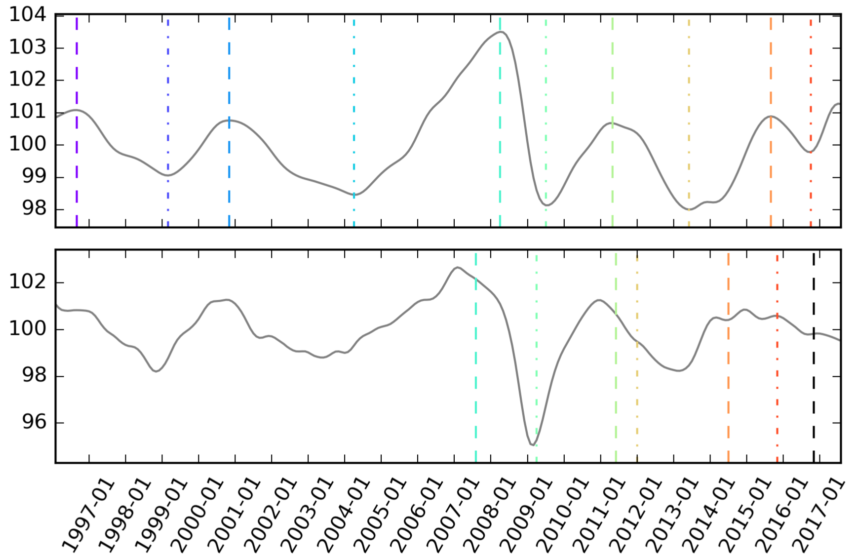


Figure 8.7 – Comparison of turning points of normalised cyclical component of Czech GDP detected by the Bry-Boschan algorithm (upper chart) and OECD CLI detected by the real-time analysis with minimal phase length of 5 months (lower chart). One extra turning point detected in the OECD CLI is marked in black (this one is at the end of the series and it could still be matched in the future).
Source: Own construction based on OECD MEI_ARCHIVE and QNA Databases (December 2017)

Figure 8.8 depicts the editions of Czech GDP in current prices published in MEI_ARCHIVE database between February 1999 and December 2017. The revisions of this series seem rather chaotic because it contains several exceptional revisions[4]:

- July 1999: Base year changed from 1990 = 100 to 1995 = 100 and data were seasonally adjusted.
- October 2000: Data stopped being seasonally adjusted.
- September 2002: Base year changed from 1995 = 100 to 2000 = 100. There is a huge jump in the data, that cannot be explained by the change of the base year and that is not explained by the metadata at all. Therefore, it may be some error in the revision data set.

[4]See the OECD notes in GDP metadata at http://stats.oecd.org/OECDStat_Metadata/ShowMetadata.ashx?Dataset=MEI_ARCHIVE&Lang=en&Coords=[VAR].[101].

- October 2003: Data were seasonally adjusted again.
- October 2004: Series were shortened (they started from 1995 Q1 instead of 1994 Q1).
- July 2006: Series were shortened again (they started from 1996 Q1) and base year changed from 2000 = 100 to 2005 = 100.
- January 2012: Base year changed from 2005 = 100 to 2010 = 100.
- October 2014: Another major revision, but it cannot be matched to any event mentioned in OECD notes on GDP.

Even though the series editions differ in level and some of them lack the seasonal adjustments, none of these aspects should influence their cyclical components, which are displayed in figure 8.9. Then the turning points are detected by the CIF function *realTimeTPDetectionFromArchive()* with the minimal phase length set to 5 months. Figure 8.10 depicts the extremes as if they were discovered in the *real-time*.

Figure 8.11 compares the *ex-post* and *real-time* turning points detected in Czech GDP series. Some of the *real-time* extremes (peak in November 1999 and trough in February 2003) occur before the *ex-post* extremes. This can be explained again by the data revisions.

Table 8.3 summarizes the basic characteristics of the series since April 2006 (last 6 extremes), so it can be compared with the performance of the *real-time* OECD CLI. The data in the table considers also the time necessary for publication of the GDP. The mean and median lags of the *real-time* turning points are 5 and 6 months, respectively. This means, that the Czech OECD CLI managed to give the signals in average almost 1 year sooner (6.67 – (−5.00) = 11.67 months) than the switch of the economy was apparent in the GDP.

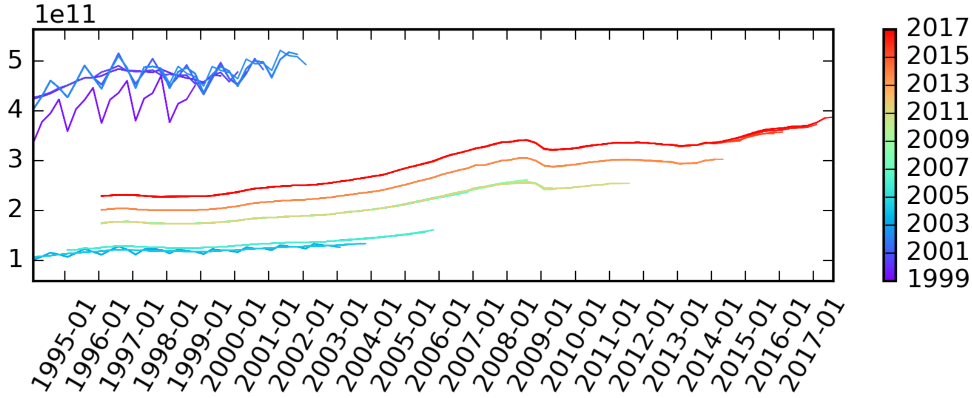


Figure 8.8 – The overview of Czech GDP revisions (monthly estimates, in hundred billions CZK).
Source: Own construction based on OECD MEI_ARCHIVE Database (December 2017)

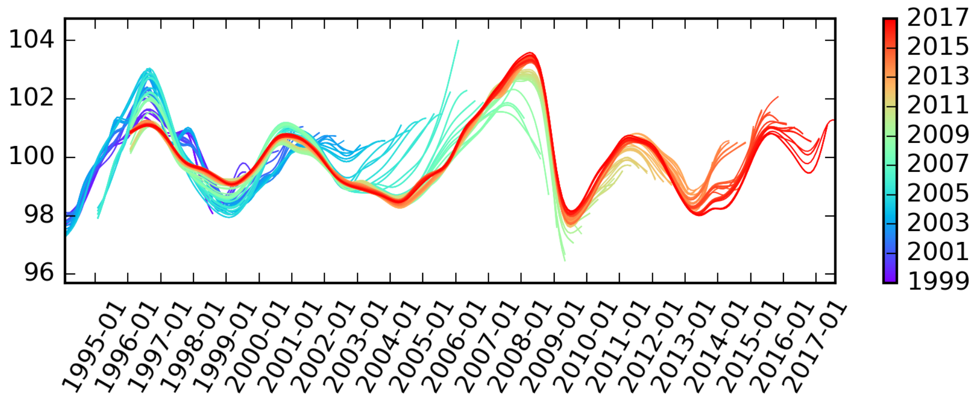


Figure 8.9 – The overview of the normalised cyclical component of Czech GDP revisions.
Source: Own construction based on OECD MEI_ARCHIVE Database (December 2017)

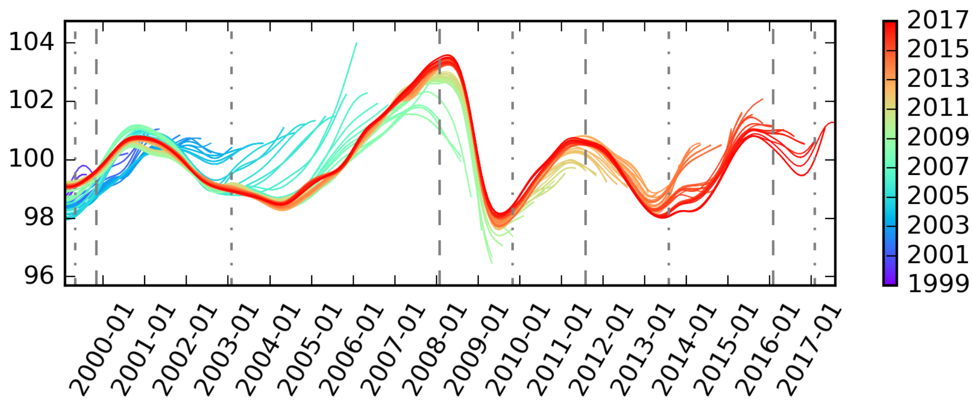


Figure 8.10 – The overview of the normalised cyclical component of Czech GDP revisions with turning points detected by the real-time analysis with the minimal phase length of 5 months.
Source: Own construction based on OECD MEI_ARCHIVE Database (December 2017)

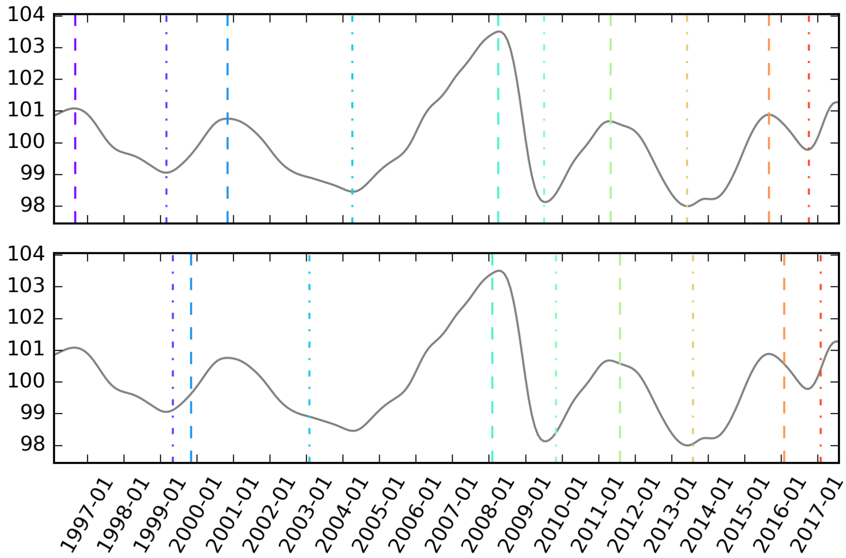


Figure 8.11 – Comparison of turning points of the normalised cyclical component of Czech GDP detected by the Bry-Boschan algorithm (upper chart) and detected by the real-time analysis with the minimal phase length of 5 months (lower chart).
Source: Own construction based on OECD MEI_ARCHIVE and QNA Databases (December 2017)

8.4.2 Other countries

Table 8.2 shows, that the results gained by the *real-time* turning points detection are generally worse than the ones gained by Bry-Boschan algorithm during the *ex-post* evaluation. However, this is not surprising as the *real-time* results are affected by the revisions of the series and by the delay before the data are published. The important question of this chapter is, whether the CLIs can be used to predict the movements of the business cycle in the *real-time* settings and this table implies that they can.

The Austrian and Japanese turning points detected by the *real-time* analysis show lagging behaviour, but such behaviour was apparent also during the *ex-post* evaluation. The Mexican CLI is rather coincident with the movements of the economy (mean lead of 1.13 and median lead 0.5 months). Even though the turning points of these three CLIs appears together with (or after) the extremes of the business cycle, they can indicate these extremes sooner then they could be discovered in the GDP (table 8.3).

That means, that these CLIs are not considered as leading in the period $c+d$ from figure 8.2, but they are leading when the whole period $c+d+e+f$ is examined.

The CLIs of the rest of the observed countries demonstrated their leading abilities even during the stricter evaluation: in period $c+d$. The turning points of these CLIs thus tend to occur before the economy switches from the expansion into the recession or vice versa.

The Finnish CLI shows the longest mean and median lead, $4.38-(-9.22)=13.60$ months and $6.00-(-9.00)=15.00$ months, respectively. The shortest lead is gained by the Japanese CLI: $-4.82-(-8.67)=3.85$ months mean lead and $-5.00-(-9.00)=4.00$ months median lead.

This chapter demonstrated, that the CLIs really are able to predict the movements of the economy in a short term (usually several months before the switch between the expansion and recession takes place and about one year before this switch is apparent in the movements of the GDP). The CLIs of some countries (Austria, Japan and Mexico) weren't able to confirm the leading behaviour, but even these CLIs could at least indicate the occurrence of the business cycle turning point sooner than it was obvious from the GDP.

Although the CLIs are leading, the analysis shows, that the *real-time* detection of the turning points in fact misses more turning points and generates higher number of false signals. Astolfi et al. (2016, p. 23) state that "despite these (...) drawbacks, looking at the sign of the CLI evolution in the last 3 months remains a very useful practice in order to assess the CLI results in *real-time*, not only for the United States but for all G7 countries."

Huge disadvantage of the *real-time* analysis is that it is very data demanding. The database of all the revisions of every component series is needed. OECD unfortunately doesn't provide the history of each individual economic indicator and therefore the *real-time* analysis in this chapter was illustrated with the OECD CLI and not with the

CIF CLI, which could not be constructed from this limited data set. This is the reason why only the *ex-post* analysis was performed in the previous chapters.

Conclusion

This thesis focused on the automation of the construction of business cycle composite indicators. Three main objectives were defined: (1) to introduce a new algorithmic approach to the construction of composite leading indicator (CLI), (2) to propose a clear set of rules so that the performance of several indicators can be objectively compared, and (3) to suggest the possible ways how to extend the construction with international data.

The history and state of art of the composite indicators were thoroughly described in the first two chapters. Chapter 1 introduced the basic concepts of the business cycle analysis, it compared the differences between classical and deviation business cycles, summarized the history and different approaches to the composite indicators construction and placed emphasis on the situation in the Czech Republic. Chapter 2 described the theory behind the OECD composite indicators, which is the most frequently used composite indicators methodology in the Czech Republic, even though it is built upon many arbitrary steps and subjective choices of the analyst. The OECD approach has been followed during the rest of the thesis.

Although the composite indicators had been known for decades and they had been updated and developed by many authors in recent years, there was no publicly available software program, that could have assisted with the entire process of their construction and that would have offered the automation of the computational process. The most complex available solution was the CACIS program created by OECD, but it was rather obsolete (especially in terms of the user interface and the created visualisations), it accepted limited data sources and didn't allow the users to customize or automatize the computation. There was neither any Python library or R package covering this topic. Therefore I have decided to automate the process by myself and to publish it as a new Python library called CIF (Composite Indicators Framework). CIF was introduced and compared with the existing partial solutions in chapter 3.

Chapter 4 offered the comprehensible visualisation of the whole computation through flowcharts and explained what adjustments were necessary to automate the OECD construction process which was originally based on many subjective expert choices and decisions. The most troublesome part, from the algorithmization point of view, was the *evaluation* phase of the construction. This part included the multicriteria decision problem which was not thoroughly described in any publication. The CIF handled this situation with the weights system to prioritize between the contradictory goals of the *evaluation* phase. The CIF now supports the full automation of the computation process, from downloading data from OECD API to testing and visualising the results. Thanks to the algorithmic approach, the subjectivity of user choices is limited and the results of the calculations are tractable and more objective. The whole analysis can be based on large data files which are processed fast, e.g., around 10 minutes to download and process data, calculate the CLI and evaluate and visualize the results from the complete Czech data available in the OECD database. However, CIF is not a black-box solution and it enables its users to control and alter any part of the process if they decide to intervene. The entire calculation is logged, which increases the tractability of the construction steps and the clarity of the results.

The first of the three objectives – algorithmic approach to the construction – was therefore met.

When the researchers create new composite indicators, they often compare them with some state-of-art CLIs, usually OECD or Conference Board ones. However, they tend to assess the changes in the performance subjectively without previously defined rules. The evaluation is in many cases based on one selected metric (e.g. the number of missed turning points) and ignores the others. Chapter 5 provided the overview of existing comparison methods and then formulated the new set of rules to make the assessment more objective and based on multiple criteria. This chapter therefore covers the second of the three objectives. The newly proposed rules were followed during all the performance evaluations in the rest of this thesis.

Chapter 6 compared the performance of the CLIs constructed with the algorithmic approach in CIF with the CLIs created by OECD experts. This chapter was illustrated with the analysis of data from 10 countries: Australia, the Czech Republic, Germany, Finland, Japan, the Republic of Korea, New Zealand, Mexico, the United States of America and the Republic of South Africa. These countries were selected to cover different types of economies all around the world. These countries are from 5 continents, some of them are G7 countries and some are developing economies. Even though the exact comparison was not possible, because of the slightly different input data set, it was shown, that the CIF CLIs tended to give better results than the OECD CLIs. This implies that the CLIs really can be constructed in the fully automated way.

Chapter 7 proposed a new way how to modify the OECD methodology to improve CLIs results and to fully use their potential. This chapter showed how to enrich the CLIs with international data and how to analyse their structure to discover the relationships between the business cycles of multiple countries. This chapter analysed the different set of countries (Austria, the Czech Republic, Germany, Poland and Slovakia) than the previous chapter because there should have been justified relations among the countries to include their economical series in other nation's CLI. The Czech Republic and all of its neighbours were selected as these countries were European Union members and shared a lot of common history. This chapter proposed the choropleth maps as the tool to visualise the leading influences between the countries. It also showed, on the example of the Czech Republic, that these influences were stable (similar structure was found no matter the number of selected component series) and that they weren't driven solely by the country's international trade. As the construction utilized the algorithmic approach from the CIF, it was possible to easily extend the analysis even more and use input data from the whole European Union.

Not only that the structure of the CLIs was analysed to discover the relationships between the business cycles, but the quality of the CLIs improved with the new data. The third objective – extending the CLI construction – was therefore accomplished.

Although some researchers questioned the predictive powers of the CLIs, chapter 8 confirmed that the CLIs were able to predict the movements of the economy in a short term. This chapter focused on the often neglected *real-time* quality of the OECD CLIs and compared it with the simpler *ex-post* approach, which was utilized in the previous chapters. The *real-time* analysis considered minor and major revisions of economic series to better estimate the true performance of the composite indicators. During the *real-time* evaluation, the CLIs usually indicated the switch between the expansion and recession with a lead of several months. It was usually a year before the same switch became apparent in the movements of the GDP.

All of the analyses presented in this thesis were performed in the automated way with the algorithmic approach in the newly designed CIF library, which is now available as an open-source project on GitHub platform. Most of these analyses could not be performed otherwise, due to a large amount of input data. The researchers from now on don't have to spend their time deploying basic tasks of composite indicators construction, but they are encouraged to participate in the CIF project.

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Glossary

Aggregation phase	Fourth phase of the OECD methodology of composite indicators construction. The selected component series are aggregated into the composite indicator.
Application programming interface, API	Method of communication between two applications.
Beta version	Unstable release of the software application used for community testing.
Bry-Boschan method	Non-parametric method to detect the turning points.
Business cycle	Sequence of expansions (or speedups) and recessions (or slowdowns) in economic activity.
CACIS, Cyclical Analysis and Composite Indicators System	OECD software for composite indicators construction.
Chain linking	Method used during the aggregation of the composite indicators to prevent jumps and discontinuities when new series are added to the dataset.
CIF CLI	Composite leading indicator constructed in CIF.
CIF, Composite Indicators Framework	The newly developed Python library which utilizes the algorithmic approach proposed in this thesis. The only solution, that offers fully automated construction of the composite indicators.

Classical business cycle	Sequence of expansions and recessions in the absolute level of economic activity.
Component indicator	Economic indicator selected to be included in the composite indicator.
Component (time) series	See component indicator.
Composite coincident indicator	Composite indicator whose turning points occur around the same time as the turning points of the whole economy. It is used to confirm the hypothesis about the state the economy is currently in.
Composite indicator	Selected individual economic indicators aggregated into one time series. The turning points of the composite indicator serve to analyse the turning points of the business cycle.
Composite lagging indicator	Composite indicator whose turning points usually occur after the turning points of the whole economy. It is used to certify the cycle behaviour and to correct the dating of the turning points.
Composite leading indicator	Composite indicator whose turning points usually occur before the turning points of the whole economy. It is the most frequently constructed type of composite indicators as it can serve to predict the movements of the economy.
Contraction	See recession.
Cross-check	Absolute difference between the position of the cross correlation peak and the median lead.
Cyclical conformity between two time series	Similarity between the behaviour of the cyclical components of two time series measured by cross correlation analysis.

Data edition	Snapshot of the data set, that was actual on the selected date. Economic series are subject of constant revisions (new observations are added and existing observations are often adjusted). The data editions show the historical states of the database before these revisions.
Data frame	Two-dimensional tabular data structure with observations in rows, features in columns and values in cells. Rows and columns are usually labelled.
Data science	Combination of statistics, mathematics, optimization, programming and other areas necessary to deliver complete analytics solution.
Data vintage	See data edition.
Dating the turning points	Detecting the turning points of the time series.
Depression	Deeper form of recession.
Deviation cycle	Sequence of speedups and slowdowns in the growth rates of economic activity. Obtained by removing the trend from the reference series (usually GDP). Deviation cycle can be interpreted as the output gap (the difference between the actual and potential economy output). The OECD methodology works with deviation cycles and treats the speedups as expansions and the slowdowns as recessions.
Early missing turning point	Turning point of the reference series which is not matched with any turning point in the economic (or composite) indicator and which occurs before the beginning of the analysed economic (or composite) indicator.
Economic (time) series	See economic indicator.
Economic indicator	Time series with data on different areas of the economy: e.g., business tendency and consumer opinion surveys, real sector, financial sector or labour market statistics.

Evaluation phase	Third phase of the OECD methodology of composite indicators construction. The turning points of the economic series are detected, compared with the reference series and component series are selected.
EViews	Commercial software for time series analyses and forecasting.
Expansion	Phase of the business cycle when the absolute level of economic activity tends to increase. In the context of deviation cycles, the speedups are sometimes also referred to as expansions.
Ex-post evaluation	Evaluation based only on the latest data edition.
Extra turning point	Turning point of the economic (or composite) indicator which is not matched with any turning point in the reference series, but which overlaps with the time period of the analysed reference series.
Extreme	See turning point.
False signal	See extra turning point.
Filtering phase	Second phase of the OECD methodology of composite indicators construction. The series are decomposed and their cyclical components are found.
Flowchart	Diagram that visualises an algorithm or process.
GitHub	Version control system with a web-based repository, which enables developers to publish their open-source solutions, cooperate on software projects, track reported issues, etc.
Gross domestic product, GDP	Monetary value of products and services generated in a selected time period (usually a quarter or a year). It often serves as a reference series during the composite indicators construction, because it corresponds with the movements of the whole economy well.
Growth cycle	See deviation cycle.

Hodrick-Prescott filter, HP filter	Method of the time series decomposition.
Individual (economic) indicator	See economic indicator.
Individual (economic) time series	See economic indicator.
Integrated development environment, IDE	Application with enhanced functions to simplify the process of writing code (source code editor, autocompletion, debugging, help, etc.). E.g., R Studio for R or Spyder for Python.
International CLI	Composite leading indicator constructed using data from multiple countries.
Interpolation of quarterly data	Method of estimation of monthly time series from quarterly data.
Lead time	Time between the turning point of the economic (or composite) indicator and the corresponding turning point of the reference series (positive if leading, negative if lagging).
Leading influence maps	Visualisation of the structure of international CLI on the choropleth map.
Leading influence metric	Measurement of how common it is for the individual indicators of the analysed country to appear in the international CLIs of other countries. This can also be interpreted as the economic lead or influence the country has when compared to the others.
Measure	Unit of size, amount, currency, etc.
Missed signal	See missing turning point.
Missing turning point	Turning point of the reference series which is not matched with any turning point in the economic (or composite) indicator, but which overlaps with the time period of the analysed economic (or composite) indicator, and therefore could have been matched. See also early missing turning point.

National CLI	Composite leading indicator constructed using data from the analysed country only (e.g., national CLI for the Czech Republic is based only on the Czech economic indicators).
OECD CLI	Composite leading indicator published by OECD.
Overall performance metric	The newly proposed metric to objectively compare the results of two composite indicators.
Peak	Switch between the expansion and the recession phase of the business cycle.
Performance of the economic (or composite) indicator	The economic (or composite) indicator is compared with the reference series and its performance is measured by several quality criteria: number of missing turning points, number of early missing turning points, number of extra turning points, mean lead time, median lead time, standard deviation of lead time, coefficient of variation of lead time, maximum value of cross correlation coefficient between the normalised cyclical components, location of the peak of cross correlation coefficient or cross-check.
Phase of the business cycle	Time period between the peak and trough (or trough and peak) of the business cycle.
Pre-selection phase	First phase of the OECD methodology of composite indicators construction. Selection of eligible individual economic indicators.
Python	High-level general-purpose programming language.
Quality of the economic (or composite) indicator	See performance of the economic (or composite) indicator.
R	Software environment very popular for statistics, data analytics and data mining.
Real sector of the economy	The sector producing goods and services.

Real-time evaluation	Evaluation based on many data editions, i.e., on the true historical states of the data before the revisions were made. Unlike the ex-post analysis, this method does not overestimate the performance of the composite indicator.
Real-time turning point detection	Non-parametric method to detect the turning points, which can be used to get the early signals of the change in the movements of the economy (switch between the expansion and recession or vice versa).
Recession	Phase of the business cycle when the absolute level of economic activity tends to decline. In the context of deviation cycles, the slowdowns are sometimes also referred to as recessions.
Reference series	Economic indicator which approximates the movements of the whole economy, usually GDP or IIP. All the individual economic indicators are compared with the reference series and only the best performing ones are selected as the component series for the composite indicator.
Slowdown	Phase of the business cycle when the growth rates of economic activity tends to decline. In the context of deviation cycles, the slowdowns are sometimes referred to as recessions.
Software library	Collection of programming code often used to extend the capabilities of a existing solution. This term is often used in connection with Python programming language.
Software package	Collection of programming code often used to extend the capabilities of a existing solution. This term is often used in connection with R programming language.
Speedup	Phase of the business cycle when the growth rates of economic activity tends to increase. In the context of deviation cycles, the speedups are sometimes referred to as expansions.

Stabilizing forecast	Short horizon forecast used before applying Hodrick-Prescott filter (or other band pass filters) to minimize the undesirable dynamic changes in the obtained cyclical component.
Structure of the composite indicators	Composition of the composite indicators, e.g., how many component series are from the financial and real sectors, how many component series are from specified country, etc.
TRAMO/SEATS	Program for automated analysis (outlier detection, seasonal adjustment, detrending, etc.) of time series developed by Bank of Spain.
Trough	Switch between the recession and the expansion phase of the business cycle.
Turning point	Peak or trough of the cyclical component of the time series.
Turning points of the economy, turning points of the business cycle	Peaks and troughs of the business cycle when the economy switches from expansion (resp., speedup) phase into recession (resp., slowdown) phase, or vice versa. Turning points of the business cycle are estimated as the turning points of the normalised cyclical component of the reference series.
X-13ARIMA-SEATS	Program for automated analysis (outlier detection, seasonal adjustment, detrending, etc.) of time series developed by U.S. Census Bureau.

Appendices

A Minimal pipeline in CIF

```python
# COMPOSITE INDICATORS
# MINIMAL PIPELINE

import os
from cif import cif
import pandas as pd
import re
import datetime


# CHECK AVAILABILITY

print(os.environ['X13PATH']) # Check the availability of X-13ARIMA-SEATS model (downloaded from https://www.census.gov/srd/www/x13as/)


# SETTINGS

os.chdir('C:/path/') # Set path to output folder

bw = False # True for black and white visualisations

country = 'CZE' # Select target country


# OUTPUT DIRECTORY

strDate = datetime.datetime.now().strftime("%Y-%m-%d-%H-%M")

outputDir = os.path.join('plots_' + country + '_' + strDate)
os.makedirs(outputDir, exist_ok = True)


# 1) DATA LOAD (loading data from OECD API)

data_all, subjects_all, measures_all = cif.createDataFrameFromOECD(countries = [country], dsname = 'MEI', frequency = 'M')
data_rs, subjects_rs, measures_rs = cif.createDataFrameFromOECD(countries = [country], dsname = 'QNA',
```

```
                                    subject = ['B1_GE'], frequency = 'Q')


# 1a) leading indicators: Component series

colMultiInd = data_all.columns.names.index('subject')

ind_LOCO = subjects_all['id'].apply(lambda x: re.search(r'\bLOCO', x) != None)
subjects_LOCO = subjects_all[ind_LOCO]

# 1b) Leading indicators: Reference series

ind_LORS = subjects_all['id'].apply(lambda x: re.search(r'\bLORS', x) != None)
subjects_LORS = subjects_all[ind_LORS]


# 1c) Leading indicators: CLI

ind_LOLI = subjects_all['id'].apply(lambda x: re.search(r'\bLOLI', x) != None)
subjects_LOLI = subjects_all[ind_LOLI]

# 1d) Candidate time series

subjects_adj = subjects_all[-(ind_LOCO | ind_LORS | ind_LOLI)]
data_adj = data_all.loc[ : , [x for x in data_all.columns if x[colMultiInd] in list(subjects_adj['id'])]].copy()


# 2) DATA TRANSFORMATIONS

# 2.1) REFERENCE SERIES

# 2.1a) Priority list of reference series (GDP) and frequency conversion

rsPriorityList = [ 'LNBQRSA' # Best fit with OECD reference series
                 , 'CQR'
                 , 'LNBQR'
                 , 'DNBSA'
                 , 'DOBSA'
                 , 'CQRSA'
                 , 'CARSA'
                 , 'GPSA'
                 , 'GYSA'
                 , 'CPCARSA'
                 , 'VIXOBSA'
                 , 'VOBARSA'
                 , 'VPVOBARSA'
                 , 'HCPCARSA'
                 , 'HVPVOBARSA'
                 ]

if (data_rs.shape[0] > 0):
```

```
    rsq = cif.getOnlyBestMeasure(df = data_rs, priorityList = rsPriorityList)
    rsq = cif.getRidOfMultiindex(df = rsq)
    rsq = cif.renameQuarterlyIndex(df = rsq)
    rsq = cif.getIndexAsDate(df = rsq)
    rs = cif.createMonthlySeries(df = rsq)
    rs.dropna(inplace = True)


# 2.1b) Seasonal adjustment, outlier filtering and short-term prediction
#   & Cycle identification (Hodrick-Prescott filter)
#   & Normalisation

fileLogs = open(os.path.join(outputDir, country + '_fileLogs_rsTransformation.txt'), 'w')
rs_SA_HP_norm = cif.pipelineTransformations(rs, savePlots = outputDir, saveLogs = fileLogs)
fileLogs.close()


# 2.2) INDIVIDUAL INDICATORS

# 2.2a) Priority list of OECD available measures

priorityList = ['NCML'
                , 'ML'
                , 'CXML'
                , 'ST'
                , 'NCCU'
                , 'CXCU'
                , 'IXOB'
                , 'NCMLSA'
                , 'MLSA'
                , 'CXMLSA'
                , 'STSA'
                , 'NCCUSA'
                , 'CXCUSA'
                , 'IXOBSA'
                , 'IXNSA'
                , 'GP'
                , 'GY']

if data_adj.shape[0] > 0:

    data = cif.getOnlyBestMeasure(df = data_adj, priorityList = priorityList)
    data = cif.getRidOfMultiindex(df = data)
    data = cif.getIndexAsDate(data)


# 2.2b) Seasonal adjustment, outlier filtering and short-term prediction
#   & Cycle identification (Hodrick-Prescott filter)
#   & Normalisation

```

```
fileLogs = open(os.path.join(outputDir, 'fileLogs_dataTransformation.txt'), 'w')
data_SA_HP_norm = cif.pipelineTransformations(df = data, savePlots = outputDir, saveLogs = fileLogs, createInverse = True)
fileLogs.close()


# 3) TURNING-POINT DETECTION (Bry-Boschan algorithm)

# 3.1) REFERENCE SERIES

fileLogs = open(os.path.join(outputDir, country + '_fileLogs_rsEvaluation.txt'), 'w')
rs_ind_turningPoints = cif.pipelineTPDetection(df = rs_SA_HP_norm, savePlots = outputDir, saveLogs = fileLogs)
fileLogs.close()


# 3.2) INDIVIDUAL INDICATORS

fileLogs = open(os.path.join(outputDir, country + '_fileLogs_dataEvaluation.txt'), 'w')
data_ind_turningPoints = cif.pipelineTPDetection(df = data_SA_HP_norm, origColumns = list(data.columns), showPlots = False, savePlots = outputDir, saveLogs = fileLogs)
fileLogs.close()


# 4) TURNING-POINTS MATCHING

fileLogs = open(os.path.join(outputDir, country + '_fileLogs_tpMatching.txt'), 'w')
data_ind_extOrd, data_ind_time, data_ind_missing, data_ind_missingEarly, data_ind_extra = cif.pipelineTPMatching(df1 = rs_SA_HP_norm, df2 = data_SA_HP_norm, ind1 = rs_ind_turningPoints, ind2 = data_ind_turningPoints, savePlots = outputDir, saveLogs = fileLogs, nameSuffix = '_06_matching' + '_rs' + country)
fileLogs.close()


# 5) EVALUATION

data_totalEval, data_selectedEval, data_selectedCol = cif.pipelineEvaluation(df1 = rs_SA_HP_norm, df2 = data_SA_HP_norm, missing = data_ind_missing, missingEarly = data_ind_missingEarly, extra = data_ind_extra, time = data_ind_time, maxInd = 15)

```

```

# 6) AGGREGATION & FINAL EVALUATION

# 6a) CLI construction

agg_cMat = data_SA_HP_norm.loc[:, data_selectedCol] # value of the de-trended, smoothed and normalised component

CLI = cif.pipelineCreateCLI(agg_cMat).rename(columns = {'CLI': country + '_CLI'})

cif.compareTwoSeries(CLI, rs_SA_HP_norm)


# 6b) CLI turning points

fileLogs = open(os.path.join(outputDir, country + '_fileLogs_CLIEvaluation.txt'), 'w')
CLI_ind_turningPoints = cif.pipelineTPDetection(CLI, savePlots = outputDir, saveLogs = fileLogs)
fileLogs.close()


# 6c) Match turning points

CLI_ind_extOrd, CLI_ind_time, CLI_ind_missing, CLI_ind_missingEarly, CLI_ind_extra = cif.pipelineTPMatching(df1 = rs_SA_HP_norm, df2 = CLI, ind1 = rs_ind_turningPoints, ind2 = CLI_ind_turningPoints, savePlots = outputDir, nameSuffix = '_06_matching' + '_rs' + country, bw = bw)


# 6d) Basic characteristics

CLI_eval = cif.pipelineEvaluation(df1 = rs_SA_HP_norm, df2 = CLI, missing = CLI_ind_missing, missingEarly = CLI_ind_missingEarly, extra = CLI_ind_extra, time = CLI_ind_time, evalOnly = True)
```

B Overview of CIF functions

This Appendix overviews the functions currently provided in CIF. See these functions directly in CIF for the full descriptions of their parameters.

B.1 Downloading data

- makeOECDRequest(dsname, dimensions, params = None, root_dir = 'http://stats.oecd.org/SDMX-JSON/data'): Make URL for the OECD API and return a response.
- getOECDJSONStructure(dsname, root_dir = 'http://stats.oecd.org/SDMX-JSON/dataflow', showValues = [], returnValues = False): Check structure of OECD dataset.
- createOneCountryDataFrameFromOECD(country = 'CZE', dsname = 'MEI', subject = [], measure = [], frequency = 'M', startDate = None, endDate = None): Request data from OECD API and return pandas DataFrame. This works with OECD datasets where the first dimension is location (check the structure with getOECDJSONStructure() function).
- createDataFrameFromOECD(countries = ['CZE', 'AUT', 'DEU', 'POL', 'SVK'], dsname = 'MEI', subject = [], measure = [], frequency = 'M', startDate = None, endDate = None): Request data from OECD API and return pandas DataFrame. This works with OECD datasets where the first dimension is location (check the structure with getOECDJSONStructure() function).

B.2 Data transformations

- getOnlyBestMeasure(df, priorityList, countryColName = 'country', subjectColName = 'subject', measureColName = 'measure'): Select only one measure per subject.
- getRidOfMultiindex(df): Rename the series from multiindex to index.
- renameQuarters(x): Rename quarters from YYYY-QQ to YYYY-MM format.
- renameQuarterlyIndex(df): Change index of pandas DataFrame with quarterly time series, so it matches monthly DataFrames.
- createMonthlySeries(df, divide = True): Take quarterly time series from pandas DataFrame and convert their frequency to months (linear interpolation, aligning with the middle month). Return pandas DataFrame with the same number of columns as original DataFrame and index in date format.

- getIndexAsDate(df): Take string date index in format YYYY-MM and transform it to date in format YYYY-MM-DD.

B.3 Filtering

- getSAForecasts(series, forecastSteps = 6, showPlots = True, savePlots = None, saveLogs = None): Get seasonally adjusted time series with forecasts.
- applyHPTwice(series, dateMax = None, lambda1 = 133107.94, lambda2 = 13.93, showPlots = True, savePlots = None, saveAllPlots = False, returnTrend = False): Apply Hodrick-Prescott filter twice: first time to remove the trend, second time to get rid of seasonality and irregularities.
- normaliseSeries(series, createInverse = False, showPlots = True, savePlots = None): Normalise and rescale series. Optionally create inverted time series to analyse counter-cyclical series.

B.4 Turning points detection

- getLocalExtremes(df, showPlots = True, savePlots = None, nameSuffix = ”): Find local maxima/minima in df. Mark all point which are higher/lower than their 5 nearest neighbours.
- checkAlterations(df, indicator, keepFirst = False, showPlots = True, savePlots = None, nameSuffix = ”, saveLogs = None): Check the alterations of the turning points, otherwise delete repeating turning points and keep only the first one (if keepFirst = True) or the highest max or lowest min (if keepFirst = False, default).
- checkNeighbourhood(df, indicator, showPlots = True, savePlots = None, nameSuffix = ”, saveLogs = None): Check the consistency of values between two turning points, otherwise delete turning points that aren’t the lowest/highest of neighbouring values.
- checkCycleLength(df, indicator, cycleLength = 15, showPlots = True, savePlots = None, nameSuffix = ”, saveLogs = None): Check the minimal length of cycle, otherwise delete one of the turning point (the lower/higher one for peaks/troughs).
- checkPhaseLength(df, indicator, keepFirst = False, phaseLength = 5, meanVal = 100, printDetails = True, showPlots = True, savePlots = None, nameSuffix = ”, saveLogs = None): Check the minimal length of phase, otherwise delete one of the turning points and keep only the first one (if keepFirst = True) or the one which is less different from the mean (if keepFirst = False, default).
- realTimeTPDetectionFromArchive(df, monthsToBeChecked = 3, phaseLength = None, indName = ’ind’): Detect turning points from archive values of the series in real time.

B.5 Turning points matching and evaluation

- matchTurningPoints(ind1, ind2, lagFrom = -9, lagTo = 24): Compare turning points of reference and individual time series.
- crossCorrelation(df1, df2, lagFrom = -9, lagTo = 24): Compute cross correlations and returns the highest one and its position.

B.6 Visualisations

- plotHP(data, phase = 1): Plot outputs from statsmodels Hodrick-Prescott filter.

- compareTwoSeries(df1, df2): Plot two series in one plot, first on left axis, second on right axis.
- plotIndicator(df1, df2, savePlots = None, namePrefix = ", nameSuffix = "): Plot series and vertical lines for not null indicator values.
- compareTwoIndicators(df1, df2, ind1, ind2, ord2, savePlots = None, namePrefix = ", nameSuffix = ", bw = False): Plot the reference series with turning points and compare it with turning points of the second time series.
- plotArchive(df, ind = None, savePlots = None, namePlot = 'archiveChanges', colorMap = 'rainbow'): Visualize data revisions.
- downloadShapefile(country = 'CZE', outputDir = "): Download Shapefile from GADM website (https://gadm.org/) and unzip it into specified directory.

B.7 Pipelines

- pipelineOneColumnTransformations(col, showPlots = True, savePlots = None, saveLogs = None, createInverse = False): Pipeline connecting transformation functions (forecasting, HP filter and normalising the series).
- pipelineTransformations(df, showPlots = True, savePlots = None, saveLogs = None, createInverse = False): Pipeline connecting transformation functions (forecasting, HP filter and normalising the series) for multiple column data frames. If createInverse option is True, then 2 data frames are returned: the first one contains all the series (original and inverted), the second one contains original series only, which is useful to shorten time needed for turning points detection.
- pipelineOneColumnTPDetection(col, savePlots = None, saveLogs = None, createInverse = False): Pipeline connecting functions to detect turning points (local extremes, checking for alterations, checking for cycle and phase length).
- pipelineTPDetection(df, origColumns = None, showPlots = True, savePlots = None, saveLogs = None): Pipeline connecting functions to detect turning points (local extremes, checking for alterations, checking for cycle and phase length) for multiple column data frames.
- pipelineTPMatching(df1, df2, ind1, ind2, showPlots = True, savePlots = None, nameSuffix = '_06_matching', saveLogs = None, bw = False, lagFrom = -9, lagTo = 24): Pipeline to compare turning points of reference and individual time series.
- pipelineEvaluation(df1, df2, missing, missingEarly, extra, time, checkCorr = True, maxInd = None, evalOnly = False, weights = [0.25, 0.05, 0.15, 0.15, 0.00, 0.10, 0.15, 0.15]): Pipeline to choose the best individual series for composite leading indicator (computing number of missing turning points (regular and early), number of extra turning points, mean lead time, median lead time, standard deviation of lead time, coefficient of variation of lead time, maximum of correlation coefficient, position of maximum of correlation coefficient, sanity check (= difference between position of maximum of correlation coefficient and median lead time)). With evalOnly = False, the weights are added to each of these criteria to rank the individual series and select the best.
- pipelineCreateCLI(df): Pipeline to compute composite indicator from selected individual time series.

C Flowcharts

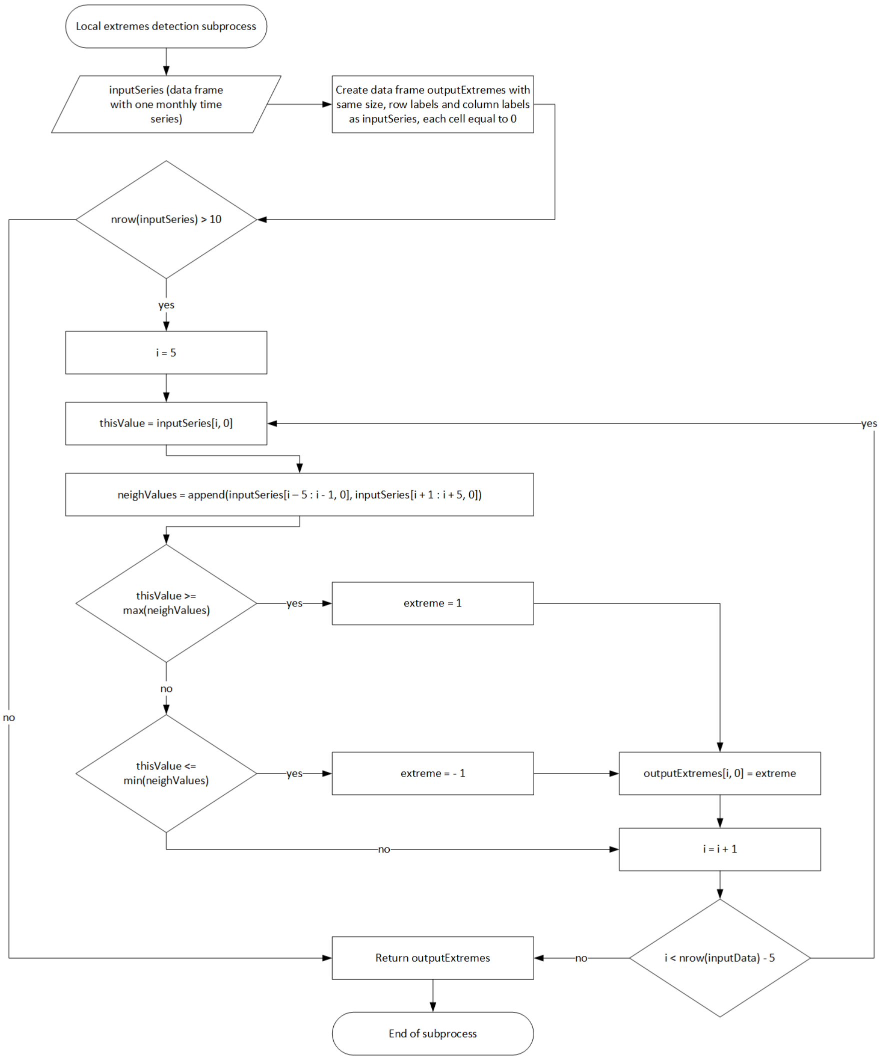

Figure C.1 – Flowchart of local extremes detection.
Source: Own construction

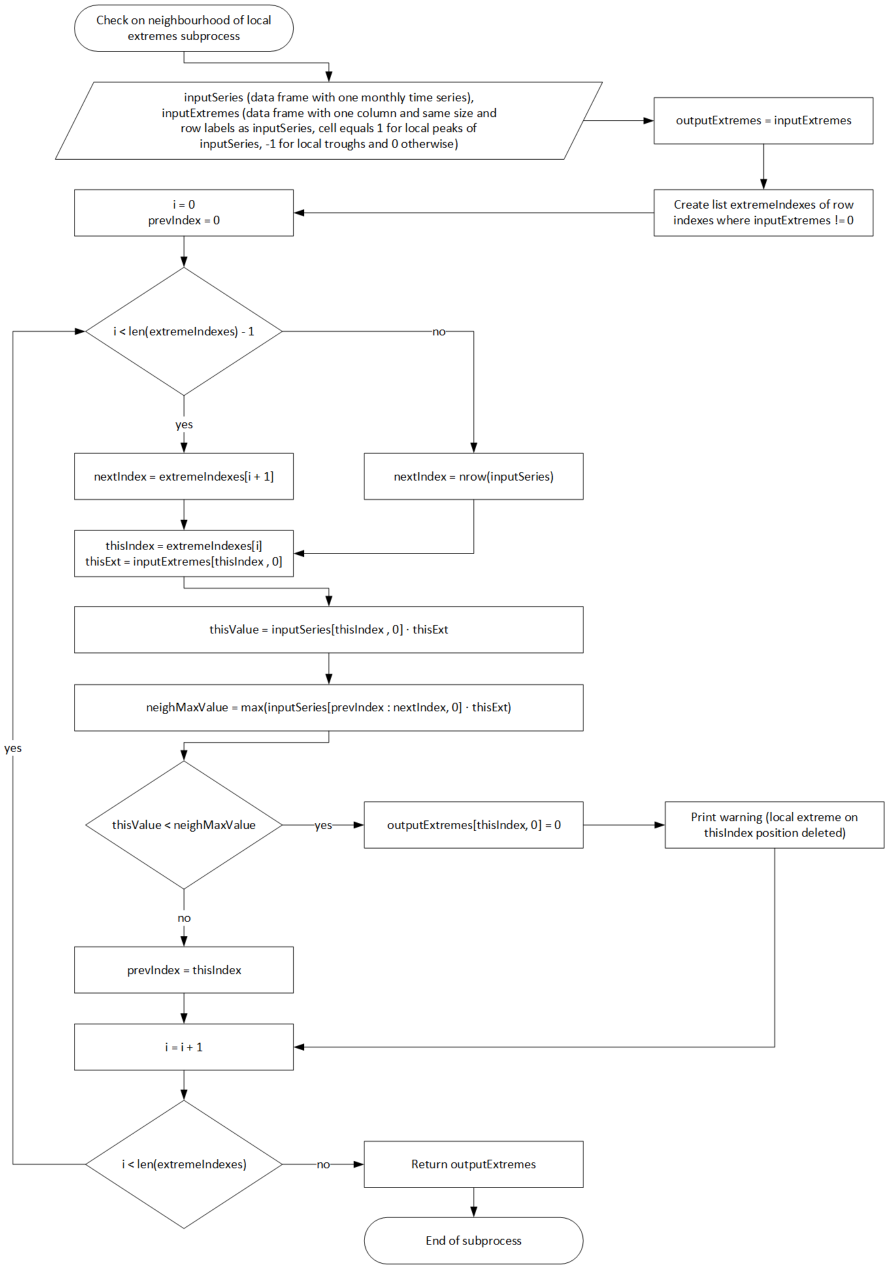

Figure C.2 – Flowchart of check on neighbourhood of local extremes.
Source: Own construction

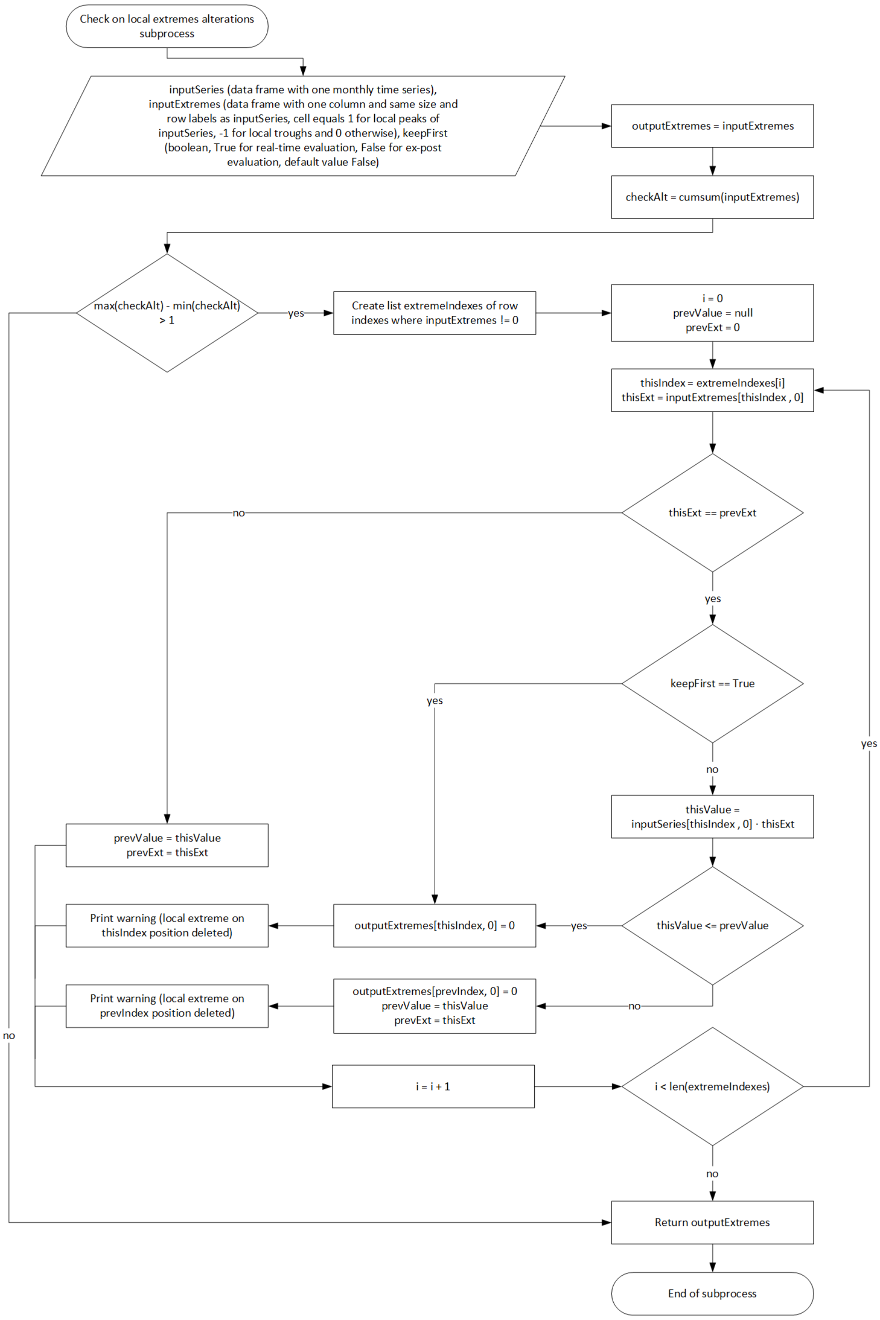

Figure C.3 – Flowchart of check on local extremes alterations.
Source: Own construction

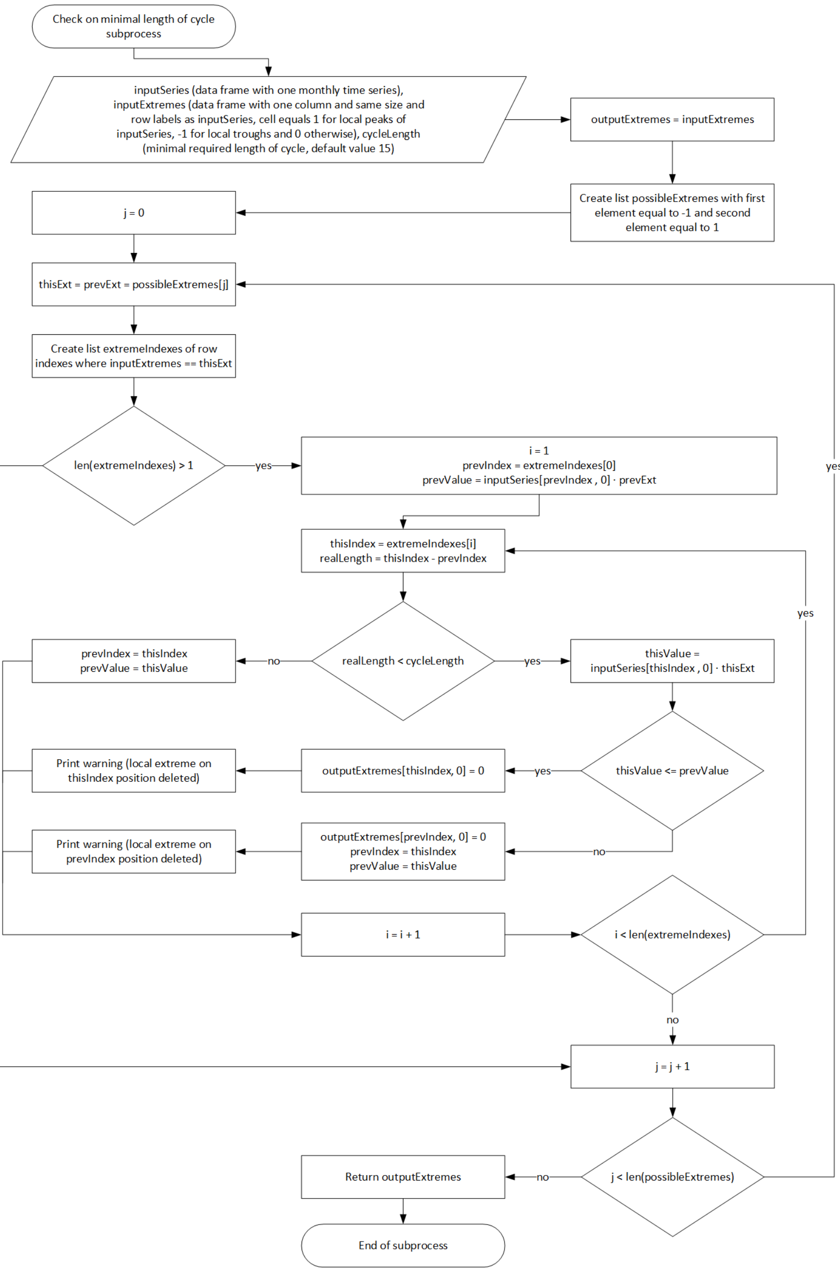

Figure C.4 – Flowchart of check on minimal length of a cycle.
Source: Own construction

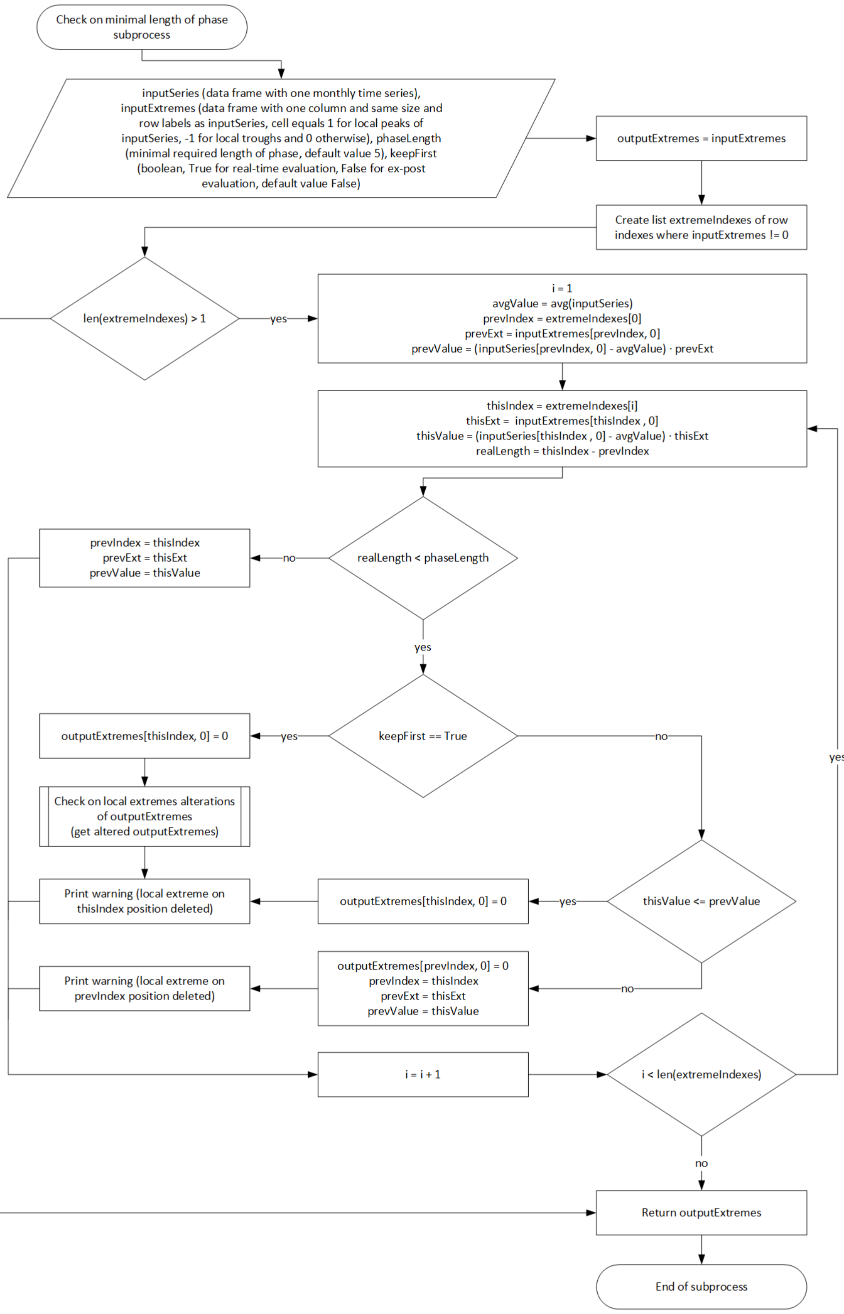

Figure C.5 – Flowchart of check on minimal length of a cycle phase.
Source: Own construction

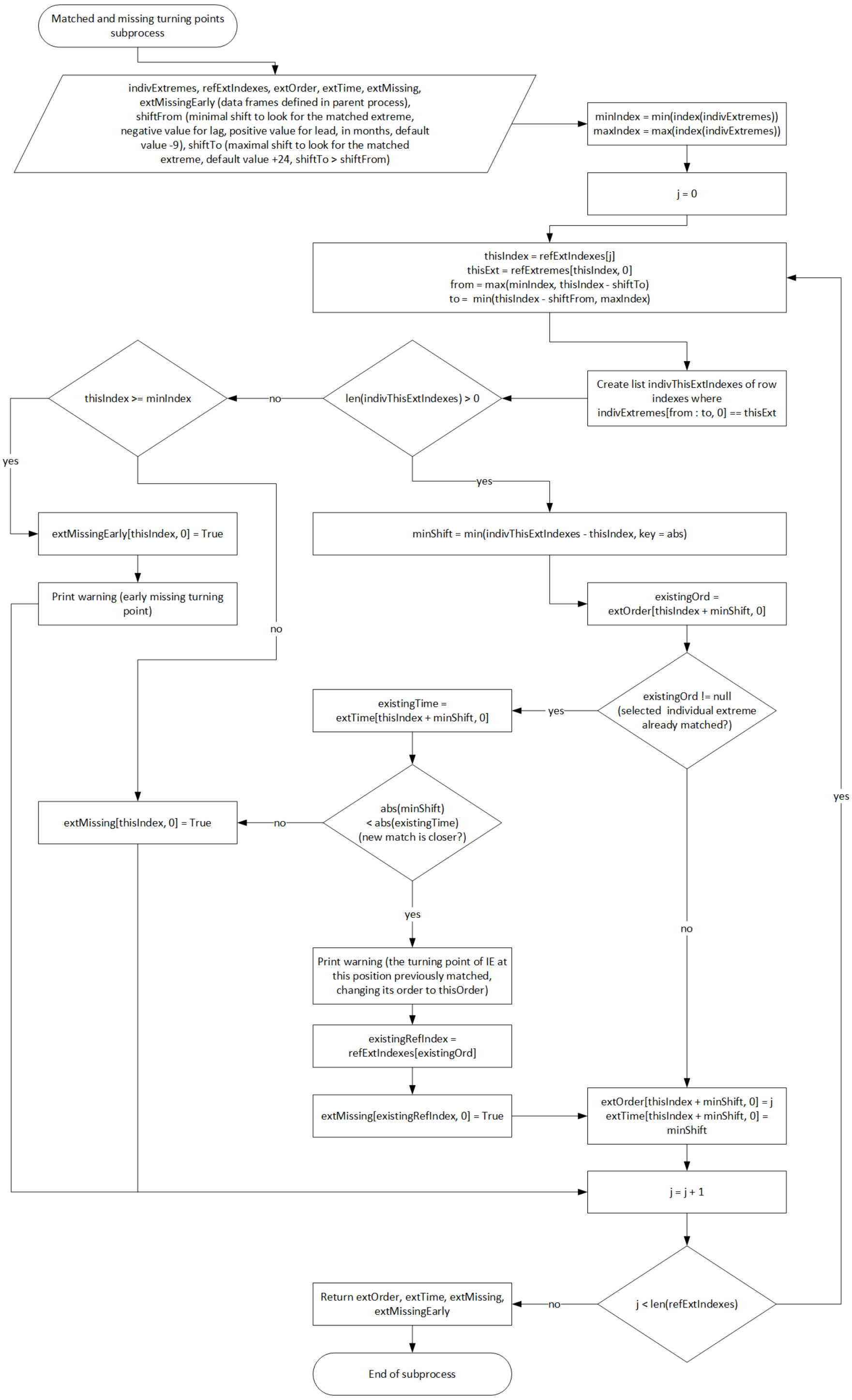

Figure C.6 – Flowchart of locating matched and missing turning points.
Source: Own construction

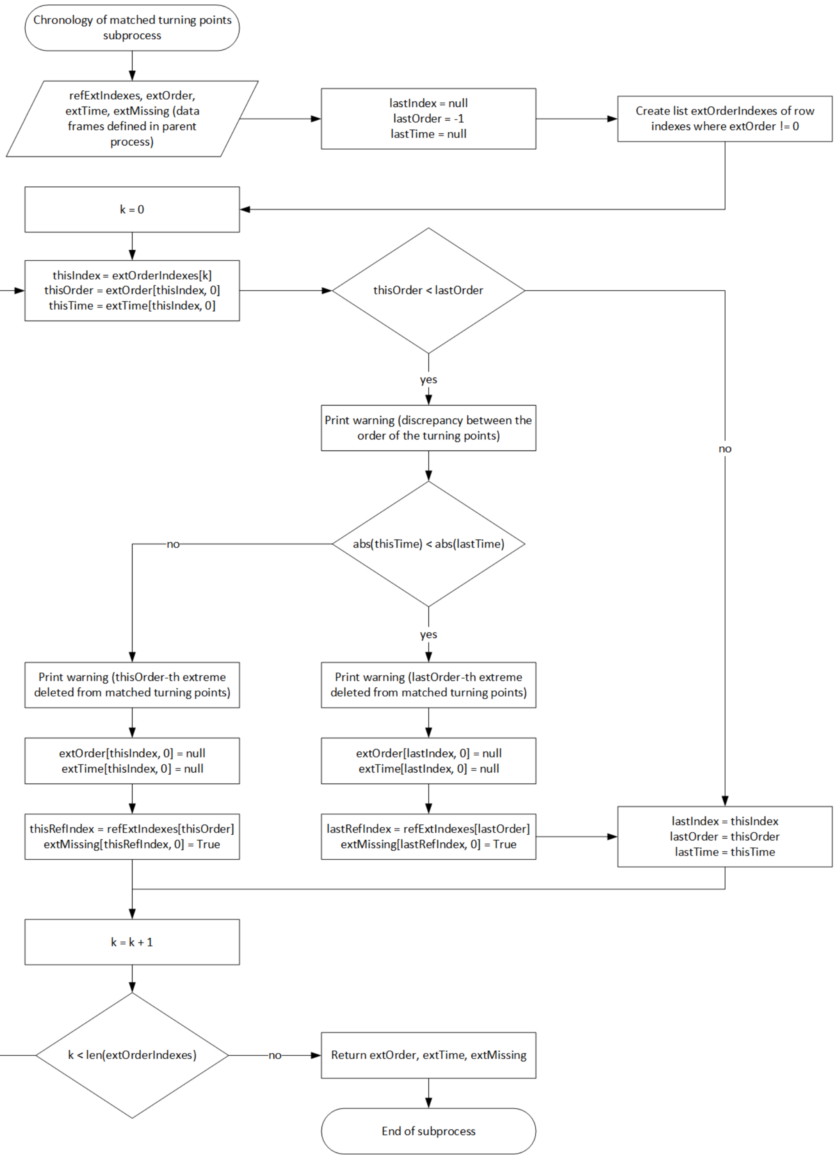

Figure C.7 – Flowchart of check on chronology of matched turning points.
Source: Own construction

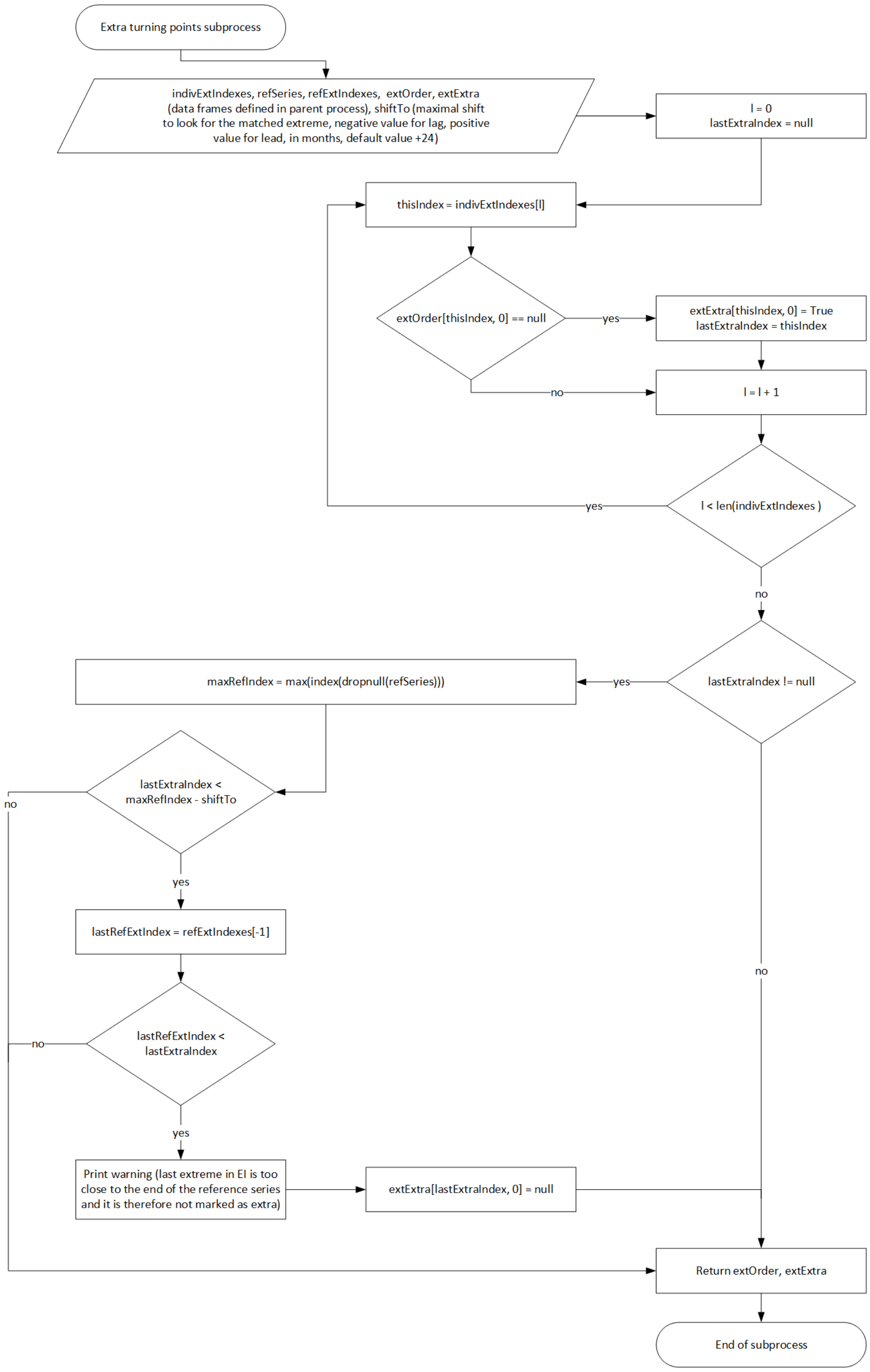

Figure C.8 – Flowchart of locating extra turning points.
Source: Own construction

D Structure and characteristics of leading indicators

D.1 Performance of OECD CLIs

Table D.1 – Basic characteristics of OECD CLIs compared to national GDPs (full length of published series).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check
AUS (OECD)	39	12	6	2.19	4.0	0.55	8	4.0
CZE (OECD)	10	2	0	6.13	4.0	0.82	6	2.0
DEU (OECD)	17	2	2	2.47	2.0	0.68	6	4.0
FIN (OECD)	15	0	4	7.27	7.0	0.61	12	5.0
JPN (OECD)	19	3	2	-0.88	-2.0	0.76	3	5.0
KOR (OECD)	18	0	5	5.72	5.0	0.56	7	2.0
NZL (OECD)	18	6	7	4.42	3.0	0.49	6	3.0
MEX (OECD)	23	3	7	5.65	4.50	0.65	6	1.5
USA (OECD)	40	8	8	3.63	3.5	0.75	5	1.5
ZAF (OECD)	20	2	6	5.61	5.0	0.82	8	3.0

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

D.2 Australia

Table D.2 – Structure of Australian OECD CLI.

Country	Subject	Measure	Inverted	Full name
AUS	LOCOBDNO	STSA	False	Leading Indicators OECD > Component series > BTS - Demand or orders inflow > Normalised
AUS	LOCOBENO	STSA	False	Leading Indicators OECD > Component series > BTS - Employment > Normalised
AUS	LOCOBPNO	STSA	False	Leading Indicators OECD > Component series > BTS - Production > Normalised
AUS	LOCODWNO	STSA	False	Leading Indicators OECD > Component series > Construction > Normalised
AUS	LOCOLTNO	STSA	False	Leading Indicators OECD > Component series > Long-term interest rate > Normalised
AUS	LOCOSPNO	STSA	False	Leading Indicators OECD > Component series > Share prices > Normalised
AUS	LOCOTTNO	STSA	False	Leading Indicators OECD > Component series > Terms of trade > Normalised

Source: OECD MEI Database (December 2017)

Table D.3 – Structure of Australian CIF CLI.

Country	Subject	Measure	Inverted	Full name
AUS	SLRTCR03	ML	False	Sales > Retail trade > Car registration > Passenger cars
AUS	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

D.3 Germany

Table D.4 – Structure of German CLI published by OECD.

Country	Subject	Measure	Inverted	Full name
DEU	LOCOBDNO	STSA	False	Leading Indicators OECD > Component series > BTS - Demand or orders inflow > Normalised
DEU	LOCOBFNO	STSA	False	Leading Indicators OECD > Component series > BTS - Finished goods stocks > Normalised
DEU	LOCOBSNO	STSA	False	Leading Indicators OECD > Component series > BTS - Business situation > Normalised
DEU	LOCOBXNO	STSA	False	Leading Indicators OECD > Component series > BTS - Export orders > Normalised
DEU	LOCOODNO	STSA	False	Leading Indicators OECD > Component series > Orders > Normalised
DEU	LOCOSINO	STSA	False	Leading Indicators OECD > Component series > Interest rate spread > Normalised

Source: OECD MEI Database (December 2017)

Table D.5 – Structure of German CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
DEU	BCOBLV02	STSA	False	Business tendency surveys (construction) > Order books > Level > National indicator
DEU	BRBUFT02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Future tendency > National indicator
DEU	BRBUTE02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Tendency > National indicator
DEU	BRCICP02	STSA	False	Business tendency surveys (retail trade) > Confidence indicators > Composite indicators > National indicator
DEU	BRODFT02	STSA	False	Business tendency surveys (retail trade) > Order intentions or Demand > Future tendency > National indicator
DEU	BVDETE02	STSA	False	Business tendency surveys (services) > Demand evolution > Tendency > National indicator
DEU	LFHUADMA	ST	False	Labour Force Survey - quarterly levels > Harmonised unemployment - monthly levels > Aged 25 and over > Males
DEU	LFHUADTT	ST	False	Labour Force Survey - quarterly levels > Harmonised unemployment - monthly levels > Aged 25 and over > All persons
DEU	LRHUADFE	ST	False	Labour Force Survey - quarterly rates > Harmonised unemployment - monthly rates > Aged 25 and over > Females

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

D.4 Finland

Table D.6 – Structure of Finnish CLI published by OECD.

Country	Subject	Measure	Inverted	Full name
FIN	LOCOBFNO	STSA	False	Leading Indicators OECD > Component series > BTS - Finished goods stocks > Normalised
FIN	LOCOBPNO	STSA	False	Leading Indicators OECD > Component series > BTS - Production > Normalised
FIN	LOCOCINO	STSA	False	Leading Indicators OECD > Component series > CS - Confidence indicator > Normalised
FIN	LOCOPCNO	STSA	False	Leading Indicators OECD > Component series > Consumer prices > Normalised
FIN	LOCOPPNO	STSA	False	Leading Indicators OECD > Component series > Producer prices > Normalised
FIN	LOCOSINO	STSA	False	Leading Indicators OECD > Component series > Interest rate spread > Normalised
FIN	LOCOSPNO	STSA	False	Leading Indicators OECD > Component series > Share prices > Normalised

Source: OECD MEI Database (December 2017)

Table D.7 – Structure of Finnish CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
FIN	BCBUTE02	STSA	False	Business tendency surveys (construction) > Business situation - Activity > Tendency > National indicator
FIN	BCCICP02	STSA	False	Business tendency surveys (construction) > Confidence indicators > Composite indicators > National indicator
FIN	BCEMFT02	STSA	False	Business tendency surveys (construction) > Employment > Future tendency > National indicator
FIN	BCSPFT02	STSA	False	Business tendency surveys (construction) > Selling prices > Future tendency > National indicator
FIN	BSCICP03	IXNSA	False	Business tendency surveys (manufacturing) > Confidence indicators > Composite indicators > OECD Indicator
FIN	BSFGLV02	STSA	True	Business tendency surveys (manufacturing) > Finished goods stocks > Level > National indicator
FIN	BSPRFT02	STSA	False	Business tendency surveys (manufacturing) > Production > Future Tendency > National indicator
FIN	BVDEFT02	STSA	False	Business tendency surveys (services) > Demand evolution > Future tendency > National indicator
FIN	CPGRLE01	IXOB	True	Consumer Price Index > OECD Groups > All items non-food non-energy > Total
FIN	IRSTCB01	ST	True	Interest Rates > Immediate rates (< 24 hrs) > Central bank rates > Total
FIN	PRMNIG01	IXOB	False	Production > Manufacturing > Intermediate goods > Total
FIN	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

D.5 Japan

Table D.8 – Structure of Japanese CLI published by OECD.

Country	Subject	Measure	Inverted	Full name
JPN	LOCOABNO	STSA	False	Leading Indicators OECD > Component series > Bank activity > Normalised
JPN	LOCOBCNO	STSA	False	Leading Indicators OECD > Component series > BTS - Sales expectations > Normalised
JPN	LOCODWNO	STSA	False	Leading Indicators OECD > Component series > Construction > Normalised
JPN	LOCOHSNO	STSA	False	Leading Indicators OECD > Component series > Hours >
JPN	LOCONTNO	STSA	False	Leading Indicators OECD > Component series > Net trade > Normalised
JPN	LOCOSINO	STSA	False	Leading Indicators OECD > Component series > Interest rate spread > Normalised
JPN	LOCOSKNO	STSA	False	Leading Indicators OECD > Component series > Stocks > Normalised
JPN	LOCOSPNO	STSA	False	Leading Indicators OECD > Component series > Share prices > Normalised

Source: OECD MEI Database (December 2017)

Table D.9 – Structure of Japanese CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
JPN	CPGDFD02	IXOB	True	Consumer Price Index > Goods > Food > Food (excl restaurants)
JPN	CSCICP02	STSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > National indicator
JPN	LFAC64MA	ST	True	Labour Force Survey - quarterly levels > Active population > Aged 15-64 > Males
JPN	LFACTTMA	ST	True	Labour Force Survey - quarterly levels > Active population > Aged 15 and over > Males
JPN	LFEM74TT	ST	True	Labour Force Survey - quarterly levels > Employed population > Aged 15-74 > All persons
JPN	LFEMTTMA	ST	True	Labour Force Survey - quarterly levels > Employed population > Aged 15 and over > Males
JPN	LFEMTTTT	ST	True	Labour Force Survey - quarterly levels > Employed population > Aged 15 and over > All persons
JPN	LFESEETT	ST	True	Labour Force Survey - quarterly levels > Employment - by professional status > Employees > Total
JPN	LFWATTFE	ST	True	Labour Force Survey - quarterly levels > Working age population > Aged 15 and over > Females
JPN	LFWATTMA	ST	True	Labour Force Survey - quarterly levels > Working age population > Aged 15 and over > Males
JPN	LFWATTTT	ST	True	Labour Force Survey - quarterly levels > Working age population > Aged 15 and over > All persons
JPN	LREM64TT	ST	True	Labour Force Survey - quarterly rates > Employment rate > Aged 15-64 > All persons
JPN	LREM74TT	ST	True	Labour Force Survey - quarterly rates > Employment rate > Aged 15-74 > All persons
JPN	LRIN25MA	ST	False	Labour Force Survey - quarterly rates > Inactivity rate > Aged 25-54 > Males
JPN	PISPPR02	IXOB	True	Producer Prices Index > Stage of processing > Primary products > Domestic

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

D.6 Republic of Korea

Table D.10 – Structure of Korean CLI published by OECD.

Country	Subject	Measure	Inverted	Full name
KOR	LOCOBSNO	STSA	False	Leading Indicators OECD > Component series > BTS - Business situation > Normalised
KOR	LOCOISNO	STSA	False	Leading Indicators OECD > Component series > Inventories to shipments > Normalised
KOR	LOCOSINO	STSA	False	Leading Indicators OECD > Component series > Interest rate spread > Normalised
KOR	LOCOSKNO	STSA	True	Leading Indicators OECD > Component series > Stocks > Normalised
KOR	LOCOSPNO	STSA	False	Leading Indicators OECD > Component series > Share prices > Normalised
KOR	LOCOTTNO	STSA	False	Leading Indicators OECD > Component series > Terms of trade > Normalised

Source: OECD MEI Database (December 2017)

Table D.11 – Structure of Korean CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
KOR	BNBUCT02	STSA	False	Business tendency surveys (non-manufacturing) > Business situation > Current > National indicator
KOR	BSBUFT02	STSA	False	Business tendency surveys (manufacturing) > Business situation > Future tendency > National indicator
KOR	BSOITE02	STSA	False	Business tendency surveys (manufacturing) > Orders inflow > Tendency > National indicator
KOR	CPSELR01	IXOB	True	Consumer Price Index > Services > Services less housing > Total
KOR	CSCICP03	IXNSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > OECD Indicator
KOR	IR3TCD01	ST	True	Interest Rates > 3-month or 90-day rates and yields > Certificates of deposit > Total
KOR	LFAC25MA	ST	True	Labour Force Survey - quarterly levels > Active population > Aged 25-54 > Males
KOR	LFEM64MA	ST	True	Labour Force Survey - quarterly levels > Employed population > Aged 15-64 > Males
KOR	LFEM64TT	ST	True	Labour Force Survey - quarterly levels > Employed population > Aged 15-64 > All persons
KOR	LFIN25FE	ST	False	Labour Force Survey - quarterly levels > Inactive population > Aged 25-54 > Females
KOR	LFWA64FE	ST	False	Labour Force Survey - quarterly levels > Working age population > Aged 15-64 > Females
KOR	LREM55MA	ST	True	Labour Force Survey - quarterly rates > Employment rate > Aged 55-64 > Males
KOR	LREM64MA	ST	True	Labour Force Survey - quarterly rates > Employment rate > Aged 15-64 > Males
KOR	LRIN55MA	ST	False	Labour Force Survey - quarterly rates > Inactivity rate > Aged 55-64 > Males
KOR	PISPIG02	IXOB	True	Producer Prices Index > Stage of processing > Intermediate goods > Domestic

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

D.7 New Zealand

Table D.12 – Structure of New Zealand CLI published by OECD.

Country	Subject	Measure	Inverted	Full name
NZL	LOCOBSNO	STSA	False	Leading Indicators OECD > Component series > BTS - Business situation > Normalised
NZL	LOCOCINO	STSA	False	Leading Indicators OECD > Component series > CS - Confidence indicator > Normalised
NZL	LOCOEMNO	STSA	True	Leading Indicators OECD > Component series > Employment - Unemployment > Normalised
NZL	LOCOMANO	STSA	False	Leading Indicators OECD > Component series > Monetary Aggregates > Normalised
NZL	LOCOSLNO	STSA	False	Leading Indicators OECD > Component series > Sales > Normalised
NZL	LOCOSTNO	STSA	False	Leading Indicators OECD > Component series > Short-term interest rate > Normalised

Source: OECD MEI Database (December 2017)

Table D.13 – Structure of New Zealand CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
NZL	CCUSSP01	ST	True	Currency Conversions > US$ exchange rate > Spot, end of period > USD:national currency
NZL	CSCICP03	IXNSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > OECD Indicator
NZL	IRLTLT01	ST	True	Interest Rates > Long-term government bond yields > 10-year > Main (including benchmark)
NZL	MANMM101	STSA	False	Monetary aggregates and their components > Narrow money and components > M1 and components > M1
NZL	XTEXVA01	NCML	True	International Trade > Exports > Value (goods) > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

D.8 Mexico

Table D.14 – Structure of Mexican CLI published by OECD.

Country	Subject	Measure	Inverted	Full name
MEX	LOCOBENO	STSA	False	Leading Indicators OECD > Component series > BTS - Employment > Normalised
MEX	LOCOBFNO	STSA	True	Leading Indicators OECD > Component series > BTS - Finished goods stocks > Normalised
MEX	LOCOBPNO	STSA	False	Leading Indicators OECD > Component series > BTS - Production > Normalised
MEX	LOCOEMNO	STSA	False	Leading Indicators OECD > Component series > Employment - Unemployment > Normalised
MEX	LOCOEXNO	STSA	False	Leading Indicators OECD > Component series > Currency conversion > Normalised
MEX	LOCOLTNO	STSA	True	Leading Indicators OECD > Component series > Long-term interest rate > Normalised
MEX	LOCOSTNO	STSA	True	Leading Indicators OECD > Component series > Short-term interest rate > Normalised

Source: OECD MEI Database (December 2017)

Table D.15 – Structure of Mexican CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
MEX	BSPRTE02	STSA	False	Business tendency surveys (manufacturing) > Production > Tendency > National indicator
MEX	IR3TTS01	ST	True	Interest Rates > 3-month or 90-day rates and yields > Treasury securities > Total
MEX	IRLTLT01	ST	True	Interest Rates > Long-term government bond yields > 10-year > Main (including benchmark)
MEX	LCEAMN04	IXOB	True	Labour Compensation > Earnings > Manufacturing > Real monthly earnings
MEX	LFHU24MA	ST	False	Labour Force Survey - quarterly levels > Harmonised unemployment - monthly levels > Aged 15-24 > Males
MEX	LRHU24MA	ST	False	Labour Force Survey - quarterly rates > Harmonised unemployment - monthly rates > Aged 15-24 > Males
MEX	LRHU24TT	ST	False	Labour Force Survey - quarterly rates > Harmonised unemployment - monthly rates > Aged 15-24 > All persons
MEX	PIEAFD02	IXOB	False	Producer Prices Index > Economic activities > Manufacture of food products > Domestic
MEX	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

D.9 United States of America

Table D.16 – Structure of American CLI published by OECD.

Country	Subject	Measure	Inverted	Full name
USA	LOCOBSNO	STSA	False	Leading Indicators OECD > Component series > BTS - Business situation > Normalised
USA	LOCOCINO	STSA	False	Leading Indicators OECD > Component series > CS - Confidence indicator > Normalised
USA	LOCODWNO	STSA	False	Leading Indicators OECD > Component series > Construction > Normalised
USA	LOCOHSNO	STSA	False	Leading Indicators OECD > Component series > Hours > Normalised
USA	LOCOODNO	STSA	False	Leading Indicators OECD > Component series > Orders > Normalised
USA	LOCOSINO	STSA	False	Leading Indicators OECD > Component series > Interest rate spread > Normalised
USA	LOCOSPNO	STSA	False	Leading Indicators OECD > Component series > Share prices > Normalised

Source: OECD MEI Database (December 2017)

Table D.17 – Structure of American CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
USA	BNEMTE02	STSA	False	Business tendency surveys (non-manufacturing) > Employment > Tendency > National indicator
USA	BNRMTE02	STSA	False	Business tendency surveys (non-manufacturing) > Raw Material Stocks > Tendency > National indicator
USA	BSCICP03	IXNSA	False	Business tendency surveys (manufacturing) > Confidence indicators > Composite indicators > OECD Indicator
USA	BSEMFT02	STSA	False	Business tendency surveys (manufacturing) > Employment > Future Tendency > National indicator
USA	BSOBLV02	STSA	False	Business tendency surveys (manufacturing) > Order books > Level > National indicator
USA	BSOITE02	STSA	False	Business tendency surveys (manufacturing) > Orders inflow > Tendency > National indicator
USA	CPHPTT01	IXOB	True	Consumer Price Index > Harmonised prices > All items > Total
USA	CPSEHO01	IXOB	True	Consumer Price Index > Services > Rent, imputed rent, repairs & maintenance > Total
USA	IR3TIB01	ST	True	Interest Rates > 3-month or 90-day rates and yields > Interbank rates > Total
USA	LFEM74MA	ST	True	Labour Force Survey - quarterly levels > Employed population > Aged 15-74 > Males
USA	LFEM74TT	ST	True	Labour Force Survey - quarterly levels > Employed population > Aged 15-74 > All persons
USA	LFIN55FE	ST	False	Labour Force Survey - quarterly levels > Inactive population > Aged 55-64 > Females
USA	LFWA74MA	ST	True	Labour Force Survey - quarterly levels > Working age population > Aged 15-74 > Males
USA	LFWA74TT	ST	True	Labour Force Survey - quarterly levels > Working age population > Aged 15-74 > All persons
USA	LMJVTTUV	ST	True	Labour - other labour market measures > Job vacancies > Total > Unfilled vacancies (stock)

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

D.10 Republic of South Africa

Table D.18 – Structure of South African CLI published by OECD.

Country	Subject	Measure	Inverted	Full name
ZAF	LOCOBDNO	STSA	False	Leading Indicators OECD > Component series > BTS - Demand or orders inflow > Normalised
ZAF	LOCOBSNO	STSA	False	Leading Indicators OECD > Component series > BTS - Business situation > Normalised
ZAF	LOCODWNO	STSA	False	Leading Indicators OECD > Component series > Construction > Normalised
ZAF	LOCOSINO	STSA	False	Leading Indicators OECD > Component series > Interest rate spread > Normalised
ZAF	LOCOSPNO	STSA	False	Leading Indicators OECD > Component series > Share prices > Normalised
ZAF	LOCOVRNO	STSA	False	Leading Indicators OECD > Component series > Car registration - sales > Normalised

Source: OECD MEI Database (December 2017)

Table D.19 – Structure of South African CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
ZAF	SLRTCR03	IXOBSA	False	Sales > Retail trade > Car registration > Passenger cars
ZAF	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

E Structure and characteristics of international leading indicators

E.1 Performance of OECD CLIs

Table E.1 – Basic characteristics of OECD CLIs compared to national GDPs (periods adjusted to enable comparison with international CIF CLIs).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check	Comparison
AUT (OECD, time adjusted)	10	0	2	4.80	5.0	0.79	6	1.0	x
CZE (OECD)	10	2	0	6.13	4.0	0.82	6	2.0	x
DEU (OECD, time adjusted)	13	0	2	2.07	2.0	0.70	6	4.0	x
POL (OECD)	9	2	0	7.86	11.0	0.16	10	1.0	x
SVK (OECD)	8	2	2	7.16	6.5	0.74	2	4.5	x

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Table E.2 – Basic characteristics of international CIF CLIs. The colour of the text responds to the difference between the international CIF CLIs and OECD CLIs performance (green = improvement, red = deterioration, black = no substantial change).

Country	Number of actual turning points	Missing	Extra	Mean lead time	Median lead time	Cross correlation maximum	Cross correlation peak location	Cross-check	Comparison
AUT (CIF, international)	10	0	0	6.4	5.5	0.90	6	0.5	3/0
CZE (CIF, international)	10	1	1	7.89	7.0	0.79	6	1.0	4/1
DEU (CIF, international)	13	1	1	7.92	7.0	0.84	8	1.0	6/1
POL (CIF, international)	9	0	0	8.11	8.0	0.69	8	0.0	3/2
SVK (CIF, international)	8	1	0	7.57	6.0	0.81	4	2.0	4/0
Comparison	x	3/1	3/1	3/0	2/1	3/0	2/1	4/0	x

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

E.2 Austria

Table E.3 – Structure of national Austrian CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
AUT	BCCICP02	STSA	False	Business tendency surveys (construction) > Confidence indicators > Composite indicators > National indicator
AUT	BRBUFT02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Future tendency > National indicator
AUT	BRODFT02	STSA	False	Business tendency surveys (retail trade) > Order intentions or Demand > Future tendency > National indicator
AUT	BSEMFT02	STSA	False	Business tendency surveys (manufacturing) > Employment > Future Tendency > National indicator
AUT	BSFGLV02	STSA	True	Business tendency surveys (manufacturing) > Finished goods stocks > Level > National indicator
AUT	BSPRTE02	STSA	False	Business tendency surveys (manufacturing) > Production > Tendency > National indicator
AUT	BVEMFT02	STSA	False	Business tendency surveys (services) > Employment > Future tendency > National indicator
AUT	CSCICP03	IXNSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > OECD Indicator
AUT	CSESFT02	STSA	False	Consumer opinion surveys > Economic Situation > Future tendency > National indicator
AUT	PIEAFD01	IXOB	True	Producer Prices Index > Economic activities > Manufacture of food products > Total
AUT	PIEAFD02	IXOB	True	Producer Prices Index > Economic activities > Manufacture of food products > Domestic
AUT	PITGCD02	IXOB	True	Producer Prices Index > Type of goods > Durable consumer goods > Domestic
AUT	PITGCG01	IXOB	True	Producer Prices Index > Type of goods > Consumer goods > Total
AUT	PITGCG02	IXOB	True	Producer Prices Index > Type of goods > Consumer goods > Domestic
AUT	PITGND02	IXOB	True	Producer Prices Index > Type of goods > Non durable consumer goods > Domestic

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Table E.4 – Structure of international Austrian CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
AUT	BSEMFT02	STSA	False	Business tendency surveys (manufacturing) > Employment > Future Tendency > National indicator
AUT	CSCICP03	IXNSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > OECD Indicator
AUT	PIEAFD02	IXOB	True	Producer Prices Index > Economic activities > Manufacture of food products > Domestic
CZE	BVBUTE02	STSA	False	Business tendency surveys (services) > Business situation - Activity > Tendency > National indicator
CZE	BVCICP02	STSA	False	Business tendency surveys (services) > Confidence Indicators > Composite Indicators > National indicator
DEU	BCCICP02	STSA	False	Business tendency surveys (construction) > Confidence indicators > Composite indicators > National indicator
DEU	BRBUFT02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Future tendency > National indicator
DEU	BRBUTE02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Tendency > National indicator
DEU	BRCICP02	STSA	False	Business tendency surveys (retail trade) > Confidence indicators > Composite indicators > National indicator
DEU	BRODFT02	STSA	False	Business tendency surveys (retail trade) > Order intentions or Demand > Future tendency > National indicator
DEU	PITGCD01	IXOB	True	Producer Prices Index > Type of goods > Durable consumer goods > Total
DEU	PITGCD02	IXOB	True	Producer Prices Index > Type of goods > Durable consumer goods > Domestic
POL	BSPRTE02	STSA	False	Business tendency surveys (manufacturing) > Production > Tendency > National indicator
POL	LMJVTTUV	ST	False	Labour - other labour market measures > Job vacancies > Total > Unfilled vacancies (stock)
POL	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

E.3 Germany

See table D.5 for structure of national German indicator.

Table E.5 – Structure of international German CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
AUT	BCBUTE02	STSA	False	Business tendency surveys (construction) > Business situation - Activity > Tendency > National indicator
AUT	PIEAFD01	IXOB	True	Producer Prices Index > Economic activities > Manufacture of food products > Total
AUT	PIEAFD02	IXOB	True	Producer Prices Index > Economic activities > Manufacture of food products > Domestic
AUT	PRMNCG03	IXOB	False	Production > Manufacturing > Consumer goods > Non durable goods
CZE	PITGND01	IXOB	True	Producer Prices Index > Type of goods > Non durable consumer goods > Total
DEU	BCOBLV02	STSA	False	Business tendency surveys (construction) > Order books > Level > National indicator
DEU	BRBUFT02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Future tendency > National indicator
DEU	BRBUTE02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Tendency > National indicator
DEU	BRCICP02	STSA	False	Business tendency surveys (retail trade) > Confidence indicators > Composite indicators > National indicator
DEU	BRODFT02	STSA	False	Business tendency surveys (retail trade) > Order intentions or Demand > Future tendency > National indicator
DEU	BVDETE02	STSA	False	Business tendency surveys (services) > Demand evolution > Tendency > National indicator
DEU	LFHUADTT	ST	False	Labour Force Survey - quarterly levels > Harmonised unemployment - monthly levels > Aged 25 and over > All persons
DEU	LRHUADFE	ST	False	Labour Force Survey - quarterly rates > Harmonised unemployment - monthly rates > Aged 25 and over > Females
POL	BCBUTE02	STSA	False	Business tendency surveys (construction) > Business situation - Activity > Tendency > National indicator
POL	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

E.4 Poland

Table E.6 – Structure of national Polish CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
POL	BCBUTE02	STSA	False	Business tendency surveys (construction) > Business situation - Activity > Tendency > National indicator
POL	BRCICP02	STSA	False	Business tendency surveys (retail trade) > Confidence indicators > Composite indicators > National indicator
POL	BRODFT02	STSA	False	Business tendency surveys (retail trade) > Order intentions or Demand > Future tendency > National indicator
POL	BSPRFT02	STSA	False	Business tendency surveys (manufacturing) > Production > Future Tendency > National indicator
POL	BSPRTE02	STSA	False	Business tendency surveys (manufacturing) > Production > Tendency > National indicator
POL	BVBUTE02	STSA	False	Business tendency surveys (services) > Business situation - Activity > Tendency > National indicator
POL	BVCICP02	STSA	False	Business tendency surveys (services) > Confidence Indicators > Composite Indicators > National indicator
POL	BVDEFT02	STSA	False	Business tendency surveys (services) > Demand evolution > Future tendency > National indicator
POL	BVDETE02	STSA	False	Business tendency surveys (services) > Demand evolution > Tendency > National indicator
POL	LMJVTTUV	ST	False	Labour - other labour market measures > Job vacancies > Total > Unfilled vacancies (stock)
POL	PIEAFD01	IXOB	True	Producer Prices Index > Economic activities > Manufacture of food products > Total
POL	PIEAMP02	IXOB	True	Producer Prices Index > Economic activities > Manufacturing > Domestic
POL	PIEATI02	IXOB	True	Producer Prices Index > Economic activities > Industrial activities > Domestic
POL	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total
POL	XTIMVA01	NCML	False	International Trade > Imports > Value (goods) > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Table E.7 – Structure of international Polish CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
AUT	BRODFT02	STSA	False	Business tendency surveys (retail trade) > Order intentions or Demand > Future tendency > National indicator
AUT	CSCICP03	IXNSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > OECD Indicator
AUT	PITGCD02	IXOB	True	Producer Prices Index > Type of goods > Durable consumer goods > Domestic
CZE	BSPRTE02	STSA	False	Business tendency surveys (manufacturing) > Production > Tendency > National indicator
CZE	BVCICP02	STSA	False	Business tendency surveys (services) > Confidence Indicators > Composite Indicators > National indicator
DEU	BCBUTE02	STSA	False	Business tendency surveys (construction) > Business situation - Activity > Tendency > National indicator
DEU	BRBUTE02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Tendency > National indicator
DEU	BREMFT02	STSA	False	Business tendency surveys (retail trade) > Employment > Future tendency > National indicator
DEU	BRODFT02	STSA	False	Business tendency surveys (retail trade) > Order intentions or Demand > Future tendency > National indicator
DEU	BSOITE02	STSA	False	Business tendency surveys (manufacturing) > Orders inflow > Tendency > National indicator
DEU	CSESFT02	STSA	False	Consumer opinion surveys > Economic Situation > Future tendency > National indicator
DEU	PRMNCG03	IXOB	False	Production > Manufacturing > Consumer goods > Non durable goods
POL	BVBUTE02	STSA	False	Business tendency surveys (services) > Business situation - Activity > Tendency > National indicator
POL	BVCICP02	STSA	False	Business tendency surveys (services) > Confidence Indicators > Composite Indicators > National indicator
POL	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

E.5 Slovakia

Table E.8 – Structure of national Slovak CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
SVK	BRBUFT02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Future tendency > National indicator
SVK	BSCICP03	IXNSA	False	Business tendency surveys (manufacturing) > Confidence indicators > Composite indicators > OECD Indicator
SVK	BSFGLV02	STSA	True	Business tendency surveys (manufacturing) > Finished goods stocks > Level > National indicator
SVK	BSPRFT02	STSA	False	Business tendency surveys (manufacturing) > Production > Future Tendency > National indicator
SVK	BVBUTE02	STSA	False	Business tendency surveys (services) > Business situation - Activity > Tendency > National indicator
SVK	BVCICP02	STSA	False	Business tendency surveys (services) > Confidence Indicators > Composite Indicators > National indicator
SVK	BVDEFT02	STSA	False	Business tendency surveys (services) > Demand evolution > Future tendency > National indicator
SVK	BVDETE02	STSA	False	Business tendency surveys (services) > Demand evolution > Tendency > National indicator
SVK	CSCICP03	IXNSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > OECD Indicator
SVK	CSESFT02	STSA	False	Consumer opinion surveys > Economic Situation > Future tendency > National indicator
SVK	PIEAEN01	IXOB	True	Producer Prices Index > Economic activities > Energy > Total
SVK	PITGND02	IXOB	True	Producer Prices Index > Type of goods > Non durable consumer goods > Domestic
SVK	XTIMVA01	NCML	False	International Trade > Imports > Value (goods) > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)

Table E.9 – Structure of international Slovak CLI constructed in CIF.

Country	Subject	Measure	Inverted	Full name
AUT	BVDEFT02	STSA	False	Business tendency surveys (services) > Demand evolution > Future tendency > National indicator
CZE	BVDEFT02	STSA	False	Business tendency surveys (services) > Demand evolution > Future tendency > National indicator
DEU	BVEMTE02	STSA	False	Business tendency surveys (services) > Employment > Tendency > National indicator
DEU	CSCICP02	STSA	False	Consumer opinion surveys > Confidence indicators > Composite indicators > National indicator
DEU	CSESFT02	STSA	False	Consumer opinion surveys > Economic Situation > Future tendency > National indicator
DEU	SPASTT01	IXOB	False	Share Prices > All shares/broad > Total > Total
POL	BCEMFT02	STSA	False	Business tendency surveys (construction) > Employment > Future tendency > National indicator
POL	BRBUFT02	STSA	False	Business tendency surveys (retail trade) > Business situation - Activity > Future tendency > National indicator
POL	BSPRFT02	STSA	False	Business tendency surveys (manufacturing) > Production > Future Tendency > National indicator
POL	BVBUTE02	STSA	False	Business tendency surveys (services) > Business situation - Activity > Tendency > National indicator
POL	BVCICP02	STSA	False	Business tendency surveys (services) > Confidence Indicators > Composite Indicators > National indicator
POL	BVDETE02	STSA	False	Business tendency surveys (services) > Demand evolution > Tendency > National indicator
POL	BVEMFT02	STSA	False	Business tendency surveys (services) > Employment > Future tendency > National indicator
POL	PITGND02	IXOB	True	Producer Prices Index > Type of goods > Non durable consumer goods > Domestic
POL	PITGVG01	IXOB	True	Producer Prices Index > Type of goods > Investments goods > Total

Source: Own construction based on OECD MEI and QNA Databases (December 2017)