



universität
wien

MAGISTERARBEIT

Titel der Magisterarbeit

„Forecasting Turning Points with Composite
Leading Indicators – the case of Poland”

Verfasser

Krzysztof Zalewski

angestrebter akademischer Grad

Magister der Sozial- und Wirtschaftswissenschaften
(Mag. rer. soc. oec)

Wien, Im Mai 2008

Studienkennzahl lt. Studienblatt:
Studienrichtung lt. Studienblatt:
Betreuer:

A 066 913
Magisterstudium Volkswirtschaftslehre
O. Univ.-Prof. Dr. Dipl. Ing. Robert Mauritius Kunst

Abstract

This master dissertation concerns the problem of short-term forecasting of economic activity. With the use of Composite Leading Indicators the business cycles of Polish economy are forecasted for the years of 1992-2007 and confronted with real data. Results of Composite Leading Indicator analysis for the end of 2007 suggest possible downturn phase at the beginning of 2008.

Zusammenfassung

Die vorliegende Magisterarbeit beschäftigt sich mit dem Problem der kurzfristigen Prognose ökonomischer Aktivität. Mit Hilfe zusammengesetzter vorlaufender Indikatoren werden die Konjunkturzyklen der polnischen Wirtschaft für den Zeitraum 1992-2007 prognostiziert und mit realisierten Daten verglichen. Die Analyse dieser vorlaufenden Indikatoren an Hand von Daten bis Ende 2007 zeigt eine mögliche wirtschaftliche Abschwächung für den Beginn 2008 an.

Keywords

turning points, composite leading indicator, business cycles, short-term forecasting, detrending, smoothing, cross correlation, Granger causality

TABLE OF CONTENTS

1. INTRODUCTION	3
2. LITERATURE REVIEW	6
3. DATA	10
3.1. Reference Series	10
3.2. Component Series	10
3.2. Grouping of Component Series	11
4. PRELIMINARY DATA ANALYSIS.....	15
5. DATA TRANSFORMATIONS	18
5.1. Seasonal Adjustments	18
5.2. Trend Estimation	19
5.3. Moving Average Smoothing and Normalization	21
6. CONSTRUCTION OF COMPOSITE LEADING INDICATORS	23
6.1. Cross Correlation	23
6.2. Granger Causality	25
6.3. Equal Weights	27
6.4. Unequal Weights	28
7. TURNING POINTS ANALYSIS	30
7.1. Turning Points in Reference Series – Comparison with OECD	30
7.2. Turning Points in Composite Leading Indicators	36
8. SUMMARY	42
BIBLIOGRAPHY	44
LIST OF INDEXES	48
APPENDIX	50

1. Introduction

The leading indicator approach to economic and business forecasting was developed by the National Bureau of Economic Research (NBER) of the United States of America more than sixty years ago. Leading indicators became quickly very popular among developed countries. The Organisation for Economic Co-operation and Development (OECD) publishes leading indices for its' member countries on monthly basis. Poland is a member of OECD since the 22nd of November, 1996. However, most of the series for Poland used in this analysis are available in OECD databases from early 90s. The main aim of leading indicator analysis is to signal future turning points in business cycle¹.

From the perspective of policymakers it is crucial to have an idea about future development of the national and regional economy. For the case of Poland a regional economy can mean the whole European Union (65.6% of total imports and 76.4% of total exports – averages for years 2002-2006²), Euro Zone (52.8% of total trade – average for first quarter of 2007 and 2008³), or a group of countries that are the most crucial economic partners, i.e. Germany, Italy, France, UK, China, Russian Federation, and Czech Republic. This group of countries constitutes 56.1% of total exports and 58.5% of total imports in the 2006 year⁴. Forecasts play a key role in formulating fiscal and monetary policy. When a CLI gives a signal of possible (in the near future) turning point, policymakers are given a time necessary to create (or adjust) a countercyclical policy. A popular saying about macroeconomic policy is that it should “lean against the wind”. It means stimulating the economy when it is in recession and trying to slow down in case of booms. (Mankiw, 2005). Unfortunately, it is always a case that a certain time lag is required between realization and identification of a real turning point as well as between implementation of certain policy and the effects of that policy. Analysis done with the use of Composite Leading Indicators can greatly reduce the time between occurrence of turning point and implementation of a policy by giving an early warning sign that possible change from upswing to downswing movement (or reverse) of economic activity is approaching. Besides policymakers also various kind of investors and investment funds are potentially very interested in the future short-term development of a particular economy, especially if they want to invest for speculative rather

¹ The word "cycle" do not imply that there is some regularity in the timing and duration of upswings and downswings in economic activity. Booms and recessions can occur at irregular intervals and last for varying lengths of time.

² Based on data from Central Statistical Office, 2007a.

³ Based on data from Central Statistical Office, 2008.

⁴ Based on data from Central Statistical Office, 2007b.

than strategic purposes. If signals from CLI indicate a possible downturn phase, no rational investor will buy long position on the stock market, as a deterioration in the general economic situation is very likely to cause a fall in share prices and other financial instruments positively related to share prices. Such investors would rather close all long positions and open short ones as they expect prices to decline. These are only two typical examples of economic agents who are interested in the cycle of economy. In general, the business cycle affects everyone because of prices, wages, interest rates, taxes and other variables that are changing due to economic fluctuations or are changed by some authorities as reaction to changes in phases of economy. All these things should make a construction and practical application of Composite Leading Indicator very important topic to everyone.

A Composite Leading Indicator (CLI) is an index that aggregates several component series. This index is supposed to better forecast turning points in business cycle of a given economy than each component separately because aggregation reduces the risk of “false signals”. In other words CLIs are aggregated time series which summarise information contained in a number of key short-term economic indicators known to be linked to GDP. In general, the CLI is intended to give early warning signs of turning points (peaks and troughs) between upswings and downswings in the growth cycle of economic activity. CLI provides qualitative information on short-term economic movements. The main message given by CLI movements over time is the direction down or up in the investigated growth cycle. The major purpose of this thesis is to develop a Composite Leading Indicator of cyclical movements of the Polish economy that can be used to forecast monthly changes in economic activity. Correct analysis and forecast of turning points for Polish economy is the most essential part of this forecasting task. Additional goal of this thesis is to propose one, synthetic indicator that would help National Bank of Poland (NBP) staff to make better prognoses of Polish economy, as, according to my best knowledge, the NBP currently does not use any kind of CLI to forecast future tendencies in the development of the economy. Instead of having one (or few) synthetic Composite Leading Indicators they only observe a set of series.

Unfortunately, there are many approaches to construct a Composite Leading Indicator proposed in the literature – Chapter 2 reviews the methods in detail. The reason why there is no widely accepted methodology is simple – the process of construction of CLI has many degrees of freedom. Starting from seasonal adjustment and detrending methods, going through various smoothers, normalisation schemes, and many others, ending with the problem of selection of components and weights assigned to each of them in the construction of CLI. One cannot use all available methods (so called “brute force” approach) and choose the best one according to some criterion as there is continuum of possibilities – it is enough to look on

Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997) and parameter $\lambda \in \mathbb{R}_+$ chosen by the user. Therefore, each step of construction is somehow subjected to a specific choice done by the researcher. Not only the phase of creation of CLI is ambiguous, but also the most crucial one – identification of turning points. Fortunately, there is significantly less degrees of freedom in this part. The most commonly used technique is the Bry-Boschan routine (Bry and Boschan, 1971). This method, slightly modified, was implemented in this study.

This work adopts a methodology similar to the one currently used by the OECD. Main steps of analysis conducted in this thesis are as follows. First, the general preliminary data analysis is done to familiarize with the data. Secondly, trends are estimated with HP filter and taken away to leave only cyclical components. Thirdly, cyclical components are smoothed with different moving averages and normalized to index form. After that the final selection of component series is conducted within the framework of cross-correlation analysis. As a check of selection a Granger causality test based on final prediction error criterion is performed. Finally, a number of Composite Leading Indicators are constructed as equally (and unequally) weighted averages of component series and each CLI is evaluated according to its ability to forecast turning points.

The remainder of the thesis is organised as follows. Chapter 2 makes a brief literature review on the topic of Composite Leading Indicators. Chapter 3 provides a description of the dataset used in the analysis. Chapter 4 gives results of basic preliminary data analysis. Chapter 5 provides details of data transformations done in this study. Chapter 6 presents the construction of CLI. Chapter 7 focuses on the analysis of turning points, including a comparison with the OECD method. Chapter 8 concludes.

2. Literature Review

Different methods of construction of Composite Leading Indicators were proposed in the literature. The main idea comes from National Bureau of Economic Research and is given in a classic work by Burns and Mitchell (1946). They have used an empirical-inductive approach and analyzed fluctuations in separate sectors of the US economy as the meaningful aspect of economic fluctuation in general. Additionally they have sought uniformities of behaviour in each part, rather than in the whole. Moreover, they have developed a comprehensive picture of the variability and comovement of economic time series and gave a basic definition of the business cycle.

“Business cycle are 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; this sequence of changes is recurrent but not periodic.” (Burns and Mitchell, 1946, p.3)

Their approach was criticized by Koopman (1947) and called “measurement without theory”⁵. Nevertheless, many researchers (including OECD) tried to construct CLIs for different economies using various methods with origins in Burns and Mitchell's (1946) seminal study. Moreover, researchers like de Leeuw (1991) or the European Central Bank (2001) argue that there are some theoretical rationales for the lead of indicators against the business cycles⁶. Most concepts and methods used in this study follow OECD papers.

In general, OECD does not use only one method to calculate CLI. The basic steps of each attempt to construct a good CLI are as follows: estimate and remove the trend to deal only with cyclical components of each series, smooth detrended series to sweep out the independent measurement error as well as other noise in the data, normalize smoothed series to have useful index form, and finally identify turning points in reference series and CLIs. Different concepts have evolved over the years. For example, the method of detrending was changed several times. To estimate and remove trend in the series OECD used: the deviation from long-term trend analysis (OECD, 1998), Phase Average Trend method (PAT) (Nilsson, 2000) developed by the US National Bureau of Economic Research (Bry and Boschan, 1978), 33-term Henderson Weighted Moving Average (HMA) (Nilsson, 2003a), and Hodrick-Prescott filter (Nilsson and Brunet, 2006). Each mentioned method has advantages and disadvantages. Therefore, the choice is not obvious and there is no consensus among researchers. For example, Period to Period Changes (PPC) along with PAT is tried by Brunet

⁵ For detailed historical development of the “theory versus measurement” debate in macroeconomics see Simkins Scott (1999) *Measurement and Theory In Macroeconomics*.

⁶ Section 3.2 presents details of various theories used to explain the leading power of each component series.

(2000), while Zhang and Zhuang (2002) as well as Binner et al.(2005) use the HP method. To sum up the issue of detrending: two alternative methods, i.e. PAT and HP filter, seem to have most followers.

The smoothing method preferred by OECD is called Months of Cyclical Dominance (MCD). However, other researchers use a fixed number of months (Matkowski, 2002; Zhang and Zhuang, 2002) or the Kalman smoother (Fukuda and Onodera, 2001). In this study I have decided to apply 24 different moving average smoothers to each series. Therefore, my analysis does not only cover the MCD concept (usually 1 to 5 months) as well as fixed number of months, but it also considers cases of additional, potentially better, smoothers.

Several methods of normalisation are widely used. A first method is to subtract the mean of the MCD moving average series, then divide by the mean of the absolute values of the differences of the MCD moving average series from its mean (Brunet, 2000). A second method considers period to period changes in series, dividing the series by the mean absolute values of the period to period changes (Brunet, 2000). A third method is to standardise each component series so that their average month-to-month changes are equal. This is done by dividing the month-to-month changes by the average month-to-month change (Nilsson, 2000). Another method used in this analysis is a simple standardization to have sample mean zero and unit standard deviation done by subtracting sample mean and dividing by sample standard deviation (Stock and Watson, 2005; Zhang and Zhuang, 2002).

In all OECD papers selection of turning points is done according to Bry-Boschan routine with the possibility to manually insert a turning point (Nilsson, 2003a). Other researchers sometimes simply accept turning points dated by some authoritative organizations, such as the National Bureau of Economic Research in the US, the Central Statistical Office in the UK, and the OECD for its member countries. In this thesis a modified Bry-Boschan routine inspired by Zhang and Zhuang (2002), who have constructed CLIs for the Malaysian and Philippine economies, has been implemented. These authors follow a method proposed by Artis et al. (1995). The most important difference compared to the Bry-Boschan routine used by OECD is that the turning point is located at the extreme value. In spite of the fact that Bry-Boschan routine is widely accepted and used, not all authors blindly follow turning points given by this algorithm. For example, Zarnowitz and Ozyildirim (2000, p.164) state: “Note that the Bry and Boschan algorithm identifies a peak in March 1998 and a trough in September 1999. We did not use this peak-trough pair in our analysis since it is uncertain whether it qualifies as a growth cycle contraction.”

Main source of predictions of turning points for Poland is still OECD. However, several papers that deal with construction of CLI for Poland have been published. Matkowski (2002)

has proposed a set of composite indicators of economic activity that are based on consumer and business surveys. Bandholz (2005) uses linear and non-linear dynamic factor models for Poland and Hungary. Nevertheless, the method used in his thesis approaches the problem of forecasting turning points from a totally different perspective. The use of non-linear Markov Switching Dynamic Factor Analysis is an alternative to construct CLI as a weighted average of component series and is beyond the scope of this thesis.

Important is the fact that CLI can be constructed not only for growth cycles, but also for many other important macroeconomic indices. One possible usage of Composite Leading Indicator idea is described by Claus and Claus (2002). They construct a composite index of leading indicators of New Zealand employment. Their indicator model in almost 80 percent of the time has correctly predicted (out of sample) the direction of employment evolution in the next period. Therefore, it helps forecasters from various state agencies or Central Banks to improve their forecasts. Having good predictions the formulation of fiscal and monetary policies (by respective authorities) can be done in a more effective way.

More popular than employment forecasts with the use of Composite Leading Indicators are predictions of inflation. For example, there are attempts to forecast Irish inflation (Quinn and Andrew, 1996), Australian inflation (Moosa, 1998), inflation for United Kingdom (Binner and Wattam, 2003) and for the whole Euro area (Binner et al., 2005). Quinn and Andrew apply Principal Component Analysis to reduce the number of component series from twelve to only six and to calculate weights for each of these component series. They have generated two false signals and missed two turning points at the beginning of their sample (1972-1980). Nevertheless, their overall result was quite good – average lead of 1 quarter (1.25 for peaks, 0.75 for troughs) for second part of the sample: 1980-1994. Australian inflation was forecasted with the use of five component series on a quarterly basis. A Composite Leading Indicator was built on the grounds of cointegration analysis. Between 1972 and 1992 five peaks and six troughs were found and successfully led by this indicator. In the case of United Kingdom Binner and Wattam applied Kalman filter to extract signals from component series. Their indicator outperformed the indicator used in the United Kingdom Central Statistical Office. The construction of leading indicator for the whole Euro area by Binner et al. involved Fourier analysis and also a Kalman filter technique. Moreover, they have interpolated all quarterly data to have monthly frequencies. Besides forecasting inflation of the Euro area they have tried to answer the question whether the United Kingdom should join Euro area or not. Their answer is that staying out of Euro area is better for the United Kingdom.

Dua et al. (1999) present an interesting use of CLI in the field of real estate. They examine the usefulness of leading indicators in predicting US home sales with the use of Bayesian vector autoregressive models. Their main finding is that Bayesian VAR model with added leading indicator produces more accurate forecasts than the benchmark model. Another not typical application is presented by Lahiri and Yao (2005) who studied both the growth cycles and the classical business cycles of the US transportation sector with the use of economic indicators. Using their analysis and prognoses the business and transportation planning can be improved. Their CLI provides early signals of the peaks and troughs of the transportation growth cycles – 6 and 12 months, on average, respectively, without missing any cycle and giving a false signal.

All these examples show that Composite Leading Indicators can be used in many ways to conduct various kinds of analysis and policy recommendation. Forecasts based on the CLI are not only constrained to the case of cyclical movements of economic activity but also can be done for any other variable of interest (unemployment, inflation, home sales, etc.). Therefore, the proper construction and inference from signals given by CLI can be very helpful for policymakers when making their policies. Besides policymakers (governments, central bankers) others also can gain. For instance, private investors, investment funds managers, private bankers, and even typical consumers may use additional information on the possible future development of the entire economy (or some interesting parts of it) to improve upon their decisions and plans. Such reasoning is especially visible in the rational expectations school of economics (Muth, 1961). In other words, information provided by CLIs give a quite reliable short-term prediction of what is going to happen with economic activity, unemployment, inflation, home sales, etc., provided that a relevant CLI is constructed. Of course, one should not believe completely the results produced by this short-term analysis: “It should also be emphasised that CLIs complement, but cannot substitute for quantitative or long-term forecasts based on econometric models.” (OECD, 1998, p.1)

3. Data

Most of the series used in this study come from OECD⁷ databases available on-line and free of charge. One series comes from NBP⁸ database, which is also available online and for free.

3.1 Reference Series

The monthly index of industrial production (or manufacturing production) is the most commonly used measure of economic activity (Bandholz, 2005). First reason is that, in contrast to GDP, it is available promptly and on monthly basis. Second is that it constitutes the most cyclical subset of the whole economy. Moreover, for many countries it was found that cyclical profiles of GDP and IIP are strongly related (OECD, 2006). An obvious disadvantage of using GDP instead of IIP is that GDP is very often revised by Central Statistical Office and subject to significant changes (OECD, 1998). Therefore, this study uses the monthly index of industrial production (IIP) as a reference series.

3.2 Component Series

As component series I have chosen 14 series that describe as many parts of the Polish economy as possible. The main criteria for series selection were data quality and availability. First of all, the component series had to be on monthly basis as I preferred not to conduct any kind of interpolation to change low frequency data into higher frequency data. Such interpolation was done, for example, by Matkowski (2002) and Nilsson (2003b), while Klein and Ozmuur (2004) are sceptic about the use of interpolation and short cut procedures. Another advantage of using monthly data is that new releases of monthly data are available every month and forecasts of possible turning points can be easily updated by extending the database and running the whole analysis one more time. Additional benefit from having monthly data is that the more data points can be observed the closer the cycle can be captured. As a consequence the possibilities of, for example, dating the turning points are better. Second criterion to choose component series was the period of availability. I have chosen the longest available series as I did not want to constrain the analysis to the time range 1995-2007 only. The period of joint availability of all series is from August 1992 until November 2007, which gives 184 observations. Table 1 presents the variables used in this analysis (name, description, availability period, source, and number of observations). The abbreviation SA stands for

⁷ Organisation for Economic Co-operation and Development (<http://www.oecd.org>)

⁸ National Bank of Poland (<http://www.oecd.org>)

seasonally adjusted series – it means that a series has been seasonally adjusted by OECD before it was downloaded from on-line database.

Table 1. Description of variables

Variable	Description	Availability		Source	Obs
		From	To		
pr_ind_sa	Production of total industry 2000=100 SA	Jan-1990	Dec-2007	OECD ⁹	216
job_vac	Unfilled job vacancies SA	Jan-1990	Dec-2007	OECD ¹⁰	216
unrat	Unemployment Registered rate SA	Jan-1990	Dec-2007	OECD ⁴	216
m1	Narrow Money (M1) Index 2000=100 SA	Jan-1990	Dec-2007	OECD ¹¹	216
exp_inf	Average expected inflation in 12 months	Jan-1992	Dec-2007	NBP ¹²	192
trade	Net trade in goods (value) in billions of US dollars SA	Jan-1991	Nov-2007	OECD ¹³	203
cpi	Consumer Price Index - all items	Jan-1990	Dec-2007	OECD ¹⁴	216
plnusd	Currency exchange rates PLN per USD	Jan-1991	Jan-2008	OECD ⁷	204
share	Share Prices Index 2000=100	Apr-1991	Dec-2007	OECD ⁷	201
r	Short-term interest rates. Per cent per annum	Jun-1991	Jan-2008	OECD ⁷	199
mi_prod_f_t	Manufacturing industry Production Future Tendency	Jul-1992	Mar-2008	OECD ¹⁵	189
mi_fin_goods	Manufacturing industry Finished goods stocks Level	Jul-1992	Mar-2008	OECD ⁹	189
mi_prices_t	Manufacturing industry Selling prices Future tendency	Jul-1992	Mar-2008	OECD ⁹	189
mi_prod_t	Manufacturing industry Production Tendency	Aug-1992	Mar-2008	OECD ⁹	188
mi_empl_f_t	Manufacturing industry Employment Future Tendency	Aug-1992	Mar-2008	OECD ⁹	188

Source: Own elaboration.

3.3 Grouping of Component Series

Different component series cover different parts of economy. Still they can be grouped into several main categories. These aggregated categories help to understand, which segments of economy are covered in this analysis.

A first group of variables that describe conditions on labour market is formed by three variables: *job_vac*, *unrat*, and *mi_empl_f_t*. Unfilled job vacancies as well as registered unemployment give an idea about the current situation on the job market. The future tendency of employment in manufacturing industry is covered by *mi_empl_f_t*. Variables *job_vac* and *unrat* seem to be substitutes rather than complements in their ability to describe the general situation on the job market. The more job vacancies we have the less unemployment should

⁹ Dataset: Production and Sales (MEI)

¹⁰ Dataset: Registered Unemployment and Job Vacancies

¹¹ Dataset: Financial indicators MEI

¹² Dataset: IPSOS survey

¹³ Dataset: International Trade (MEI)

¹⁴ Dataset: MEI Original release data and revisions

¹⁵ Dataset: Business Tendency and Consumer Opinion Surveys (MEI)

be. However, in this reasoning we ignore cases of structural unemployment. Therefore, both variables are considered in the future analysis as potential components of the CLI. The relationship between unemployment and production is straightforward. Less unemployment should correspond to the higher production. However, changes in employment now do not necessary cause instantaneous changes in production, as many branches of industry require some time delay before the production is initiated and finished. This delay may be useful in predicting future tendencies in production. Let us consider a simple example to present the general idea in a clearer way. Suppose that it takes 3 months (1 quarter) for workers to produce a new car. Therefore, if employment increases in April, we can guess an increase in number of newly produced cars in July. As a consequence the index of industrial production should increase (*ceteris paribus*) in July. Having an idea about future tendencies of employment in manufacturing industry is also very useful as manufacturing industry is a significant part of total production of industry. In general, manufacturing industry counts for more than 82.5% of industrial production (84.03% on average). Detailed results for years 2000-2004 are presented in Table 2. All values for Manufacturing and for Industrial Production are presented in current prices in 10^6 PLN.

Table 2. Manufacturing as % of Industrial Production

Year	2000	2001	2002	2003	2004
Manufacturing	435247	437166	440342	493498	604851
Industrial Production	513085	524376	532359	589082	707913
Manufacturing as % of Industrial	84.83	83.37	82.72	83.77	85.44

Source: Central Statistical Office, 2006

A second group of variables that describe the situation on the Polish financial market is formed by three variables: *plnUSD*, *share*, and *r*. They are of much importance on future development of the whole Polish economy and general economic activity as they are said to be influential in determining investors feelings (especially foreign investors). It is obvious that the exchange rate has a big impact on the volume and direction of international trade (for example see: Baum, 2001; Tenreyro, 2006). It also affects inflow and outflow of international and domestic capital (Reuven, 1998). For example, within the standard framework of the Mundell-Fleming model (Mundell, 1963; Fleming, 1962) an appreciation of national currency will make foreign goods cheaper to domestic residents (imports increase) and domestic goods more expensive to foreign residents (exports decrease). As a result net export goes down and so does the GDP. Share prices and interest rates are of much importance for potential and current foreign and domestic investors. On one hand high interest rate gives an incentive for

domestic investors to give their money to bankers rather than invest in local firms. It is widely accepted by economists that investment is negatively related to the interest rate. Moreover, investment is a component of GDP. On the other hand, an increasing share price index is a positive signal for investors. They are more likely to buy shares of Polish companies traded on Warsaw Stock Exchange. When the share price of a particular firm goes up, such a firm is able to invest more. Therefore, in the future, the index of industrial production (as well as GDP) is supposed to increase. Additional argument is that share prices and interest rate reflect expectations of economic agents about future development of economy.

A third group of variables that describes prices evolution and its' future tendency is formed by four variables: *m1*, *exp_inf*, *mi_prices_t*, and *cpi*. Current price development is given by Consumer Price Index (all items). Future tendencies are indicated by expected inflation, future tendency of selling prices in manufacturing industry, and narrow money index. On one hand higher prices for products means higher revenues for firms. On the other hand, higher prices lead, on average, to decrease in demand formed by consumers. If the demand falls sufficiently low, such that the change in revenues is negative, the firm may decide to produce less due to costs connected with production. In general, the final result of changes in prices depends on price elasticity of demand and supply. To have an idea about the future development of prices, it is good to have a look at the survey on Poles' expectations (*exp_inf*) or future tendency of selling prices in manufacturing industry (*mi_prices_t*). Expectation on high inflation in the future can easily result in the increase of inflation now. To understand this relationship, just consider the following situation. Let us suppose that everyone (or sufficiently large fraction of consumers) expect increase in price of sugar in two months. Because 20 kg of sugar can be easily stored in house people rush buying it before (according to their expectations) price goes up. As a result of increase in demand now the price of sugar is increased now, not after 2 months. Crucial is the fact that 20 kg of sugar can be stored for quite a long time and that a typical household does not use 20 kg of sugar in 2 months. It is more or less the amount of sugar that an average household consumes in one year¹⁶. Besides these variables strictly connected with prices, also narrow money (*m1*) is included. There is a simple rule of thumb – the more money is printed the higher inflation we have (Barro and Gordon, 1984; Fischer and Easterly, 1990; Bruno and Fisher, 1991).

A fourth group of variables that describe production is formed by three variables: *mi_prod_f_t*, *mi_fin_goods*, and *mi_prod_t*. All these variables measure production in manufacturing industry, which constitutes more than 82.5% of industrial production – see

¹⁶ Data for years 2003-2005 comes from expertise done by Institute of Agricultural and Food Economics - National Research Institute (IERiGŻ-PIB) for the order of the Ministry of Agriculture and Rural Development.

Table 2 for details. These variables convey an idea about the level of finished goods stock, production tendency and future production tendency. If we can observe an increase in these variables we can be quite sure that the Index of Industrial Production will increase as well, for the reasons described above.

The last variable which is not assigned to any other group is a variable *trade* that measures net trade in goods (value) in billions of US dollars. This variable is very important as it is a part of GDP according to the well-known equation:

$$Y = C + I + G + NX,$$

where Y is GDP, C is consumption, I is investments, G is government expenditures, and NX is net export. The relationship between NX and Y is straightforward – an increase in NX causes an increase in Y. According to theory, when we observe a big increase of net trade in March we should be pretty sure that the initial prognoses for 1st quarter GDP will be corrected upward. Nevertheless, in practice, net export constitutes less than 10% of GDP in Poland¹⁷.

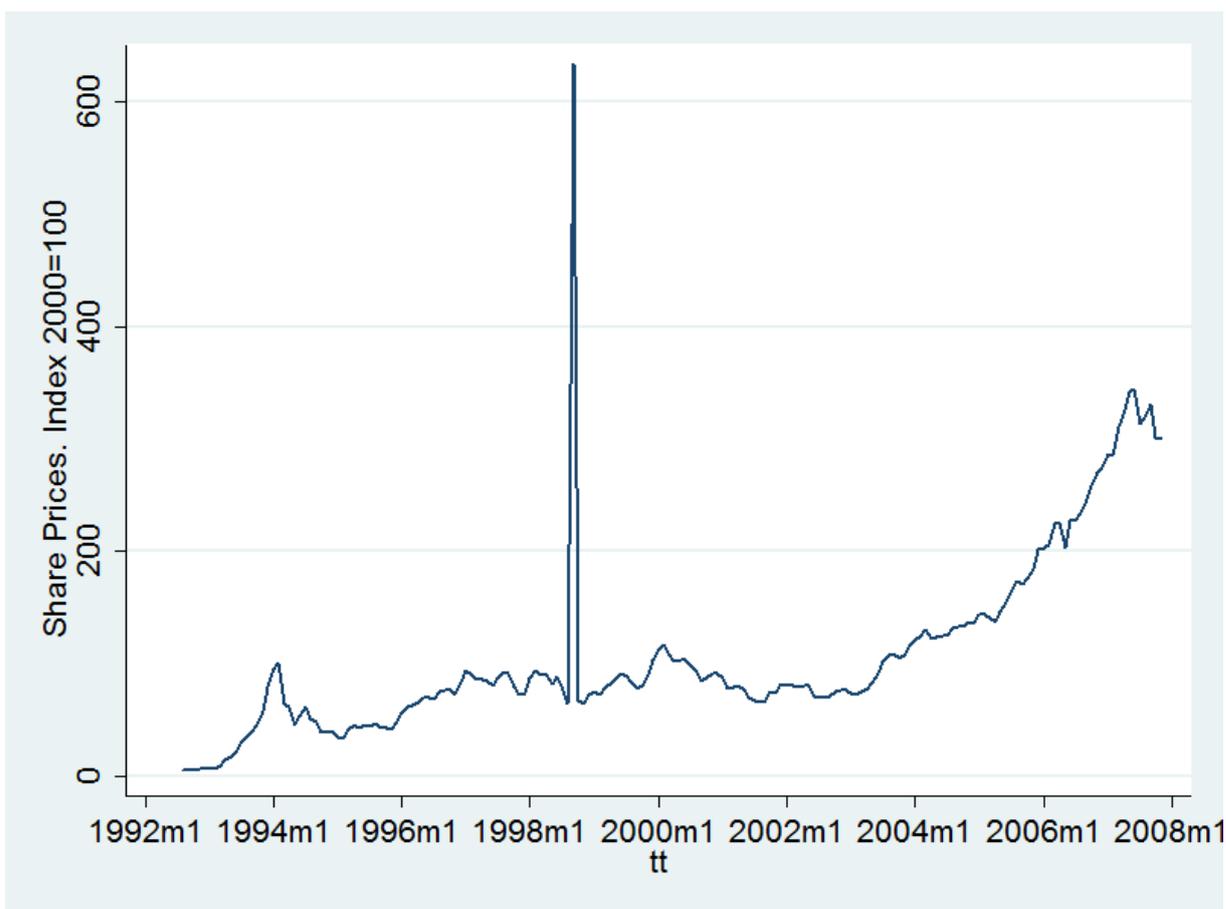
In general, following aspects of Polish economy are covered by component series: labour market conditions, financial (investment) situation, prices, production, and trade. Present situation, tendencies as well as future tendencies are included (if available).

¹⁷ Data comes from Quarterly National Accounts 2000–2006 published by Central Statistical Office.

4. Preliminary Data Analysis

The preliminary data analysis is intended to give some basic idea of the nature of analyzed series¹⁸. According to one famous sentence “anyone who tries to analyse a time series without plotting it first is asking for trouble” (Chatfield, 1996). Therefore I have plotted each series and found that the value of a share price index in September 1998 is extraordinary high and equal to 633.79211 – see Figure 1.

Figure 1. Share price index – original data



Source: Own elaboration.

Such result was extremely unbelievable as the highest value (in June 2007) is equal to 344.536. Moreover, all values of this variable within one year interval (from September 1997 to September 1999) are between 63.37921 and 93.31292. Therefore, I have decided to divide the value of this variable by 10 to get reasonable outcome. The remaining 14 pictures of other variables are presented in the Appendix as Figures A1, A2, and A3.

¹⁸ The deep investigation of univariate and/or multivariate properties of reference and component series is not a purpose of this thesis. Such analysis can be done as an alternative approach to frequency filters method used in this analysis.

In addition to plotting, I have tested the level of integration of each series. To check if a particular series is stationary or trend-stationary (in a weak sense¹⁹) three formal statistical tests were conducted: KPSS²⁰, ADF²¹, and PP²². The significance level was set at 5% in each test for each considered series. Table 3 presents the final results for each series. A column “integration order” indicates the order of integration of a particular series. One can notice that most of the series are integrated of order 1 (it means that they require differencing once to become stationary). Only the future tendency in production of manufacturing industry (*mi_prod_f_t*), level of finished goods stocks in manufacturing industry (*mi_fin_goods*) and future tendency of employment in manufacturing industry (*mi_empl_f_t*) are stationary (in levels). The literature suggests that hardly ever economic series are integrated of order 2. However, results for CPI and M1 indicate that these two variables are such series. This result is in accordance with economic theory and empirical evidence (Awokuse and Yang, 2002). For example, central bank can be interested in keeping constant the rate of growth of money, which is defined as:

$$m_t = \frac{\Delta(M1_t)}{M1_{t-1}} = \frac{M1_t - M1_{t-1}}{M1_{t-1}} = \text{const.}$$

where $M1_k$ is the level of M1 in period k . Such policy produces constant rate of growth of money, which results in second order of integration of M1 as more and more money have to be created to keep this ratio constant²³.

¹⁹ It means that a series has constant mean, finite variance, and autocorrelation that depends only on time distance between two observations.

²⁰ Kwiatkowski, Phillips, Schmidt and Shin test for stationarity.

²¹ Augmented Dickey-Fuller test for unit root.

²² Phillips-Perron test for unit root.

²³ This argument does not hold for logarithms of variable. After taking logs it is enough to difference only once to obtain stationary series. However, it does not change an outcome that levels of M1 are integrated of second order.

Table 3. Integration order of variables

Variable	Integration order
pr_ind_sa	I(1)
job_vac	I(1)
unrat	I(1)
m1	I(2)
exp_inf	I(1)
trade	I(1)
cpi	I(2)
plnUSD	I(1)
share	I(1)
r	I(1)
mi_prod_f_t	I(0)
mi_fin_goods	I(0)
mi_prices_t	I(1)
mi_prod_t	I(0)
mi_empl_f_t	I(1)

Source: Own elaboration.

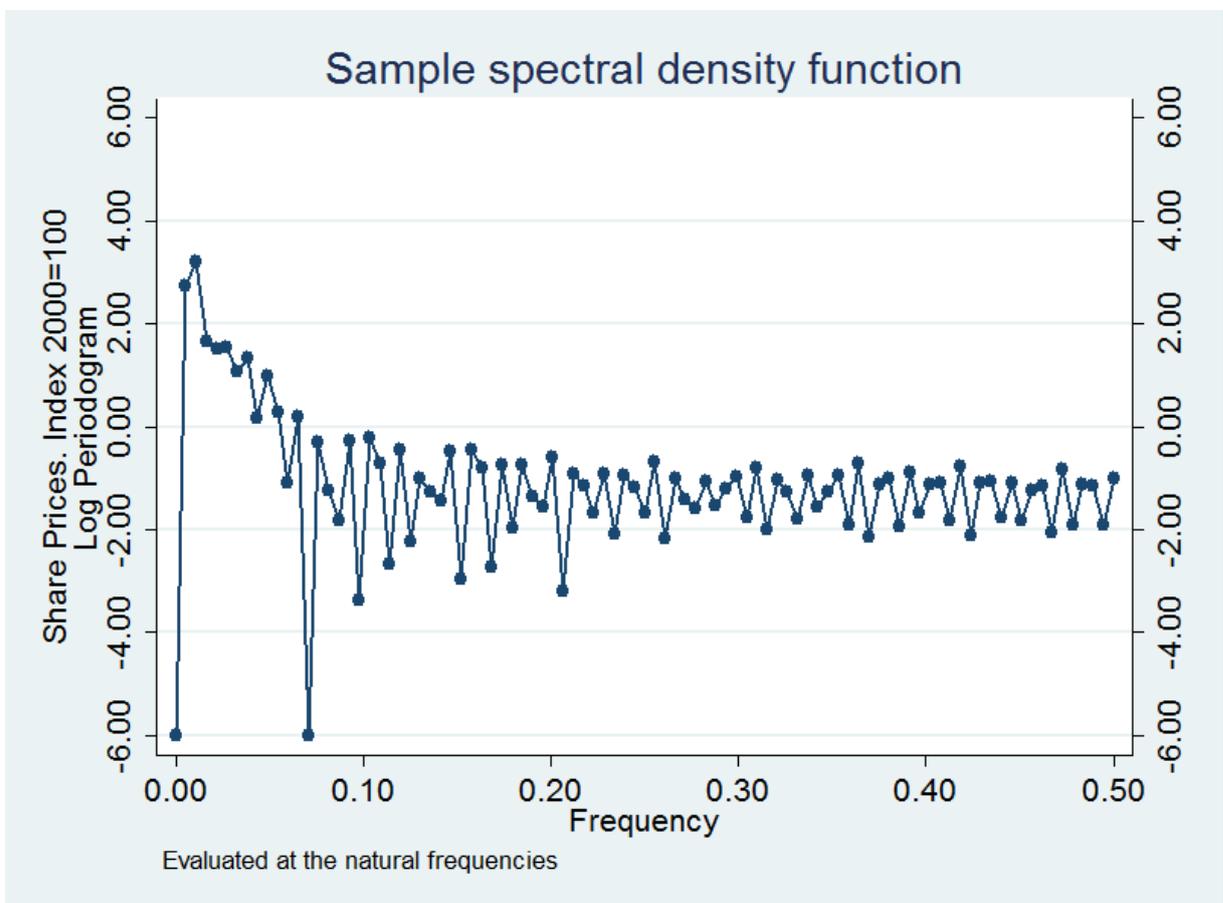
5. Data transformations

Before one starts to construct Composite Leading Indicator some necessary transformations have to be done. These transformations include: seasonal adjustments (only if necessary), decomposition of series into cyclical part and long-run trend (detrending), smoothing, and normalization. The next three sections present these transformations in more details.

5.1. Seasonal Adjustments

Some of the series (exactly 5 out of 15) available in databases have already been seasonally adjusted by OECD – see Table 1 for details. Those which have not been seasonally adjusted did not require any adjustment as they were not seasonal series. The decision if a series is seasonal and requires seasonal adjustment or not was made after looking on the simple plot of the particular variable (Figures A1, A2 and A3 in Appendix) and on its periodogram (Figures A4 and A5 in Appendix). One typical example of a periodogram is presented below as Figure 2.

Figure 2. Example of periodogram – share price index 2000=100



Source: Own elaboration.

The interpretation of the picture is based on visual inspection and is done as follows. If a visible peak can be observed then the seasonality at particular frequency should be deeper investigated. The frequency scale begins with 0.5, which corresponds to a two-month seasonal cycle (the lowest possible in case of monthly data, for quarterly data it is half year). Frequency 0.25 (0.5/2) represents quarterly (4 months) seasonality, 0.1667 (0.5/3) represents half-yearly (6 months) seasonality, etc. Results presented in Figure 2 indicate that no seasonality should be found in the series.

5.2. Trend Estimation

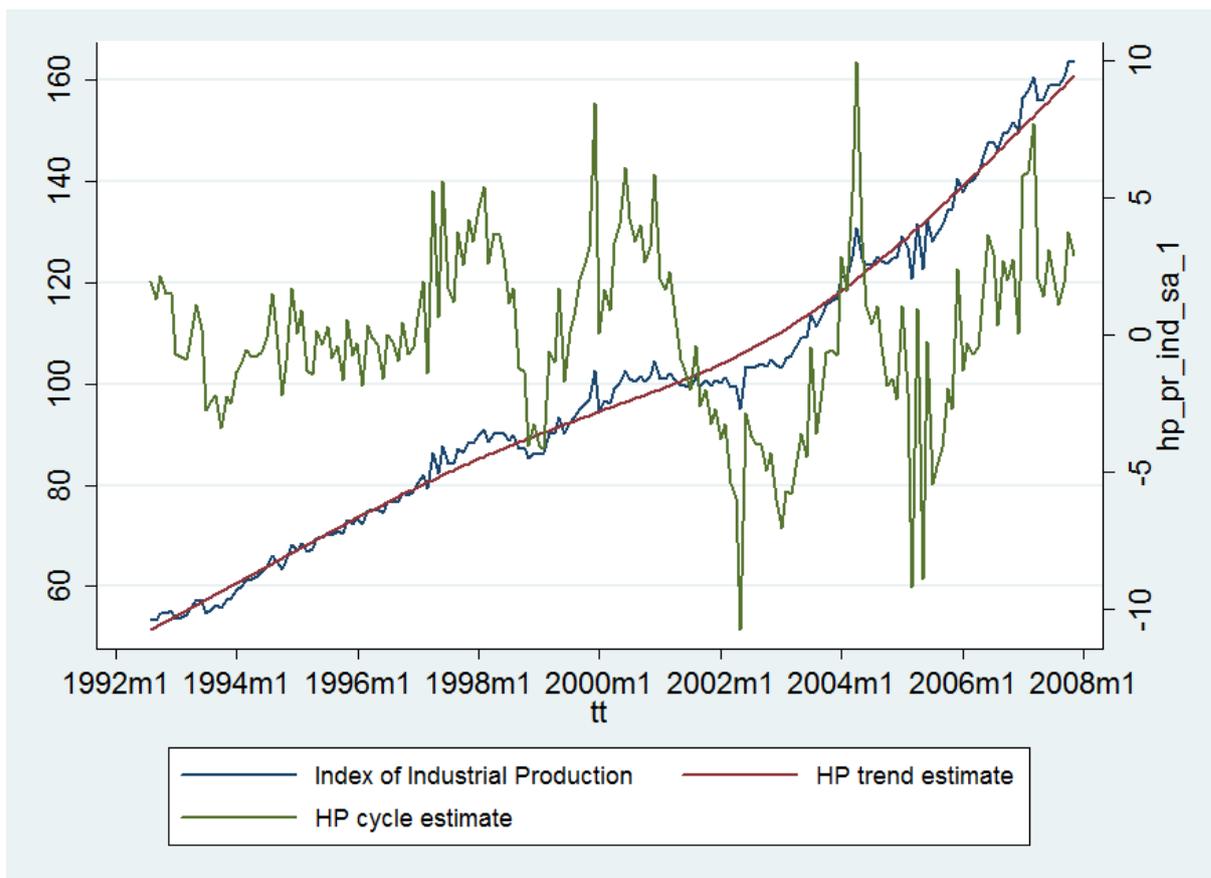
In this study the Hodrick-Prescott (HP) filter has been used to estimate trend in each series. The HP filter is a commonly used tool for detrending. It is a most favourable extractor of a trend, which is stochastic but moves smoothly over time and is uncorrelated with the cycle (OECD, 2006). For $t=1,2,3\dots$ the trend component Y^* is computed, and λ is chosen to minimize:

$$\sum_{t=1}^T (Y_t - Y_t^*)^2 + \lambda \sum_{t=2}^{T-1} [(Y_{t+1}^* - Y_t^*) - (Y_t^* - Y_{t-1}^*)]^2$$

To get optimal results for detrending, it has been suggested to choose $\lambda=1600$ for quarterly data and $\lambda =129600$ for monthly data (Ravn and Uhlig 1999). In this analysis, the value for λ is fixed at 129600 for all time series. Exception is $\lambda = 1600$ for quarterly GDP. An advantage of the HP method is that no restriction on the length of time series is imposed. Nevertheless, there is a requirement that before proceed with HP filter one should seasonally adjusted each series. The trend itself is not very interesting in the analysis of cyclical behaviour. Therefore, the rest of study was done with cyclical components of each series (Nilsson and Brunet, 2006).

As an example, decomposition of reference series (Index of Industrial Production, seasonally adjusted) into trend and cyclical movements is presented in Figure 3.

Figure 3. Results of HP filter for reference series



Source: Own elaboration.

The blue line shows the original series, the dark, red line is the estimated HP trend. From the point of view of this thesis, the most interesting feature is the green line that represents the cyclical component of the original series. Values of cyclical components are shown on the right axis and represent deviations from the estimated trend. It is worth noting that these deviations lie in the interval $[-10;10]$, while the values of reference series are in the interval $[55;160]$. Table 4 shows the time points of largest deviations from the estimated trend, in absolute value, and it gives some summary statistics on the deviations.

Table 4. Summary statistics of trend deviation for IIP

Mean	Std. Dev.	Min (2002m5)	Max (2004m4)
0.00000	3.18332	-10.70446	9.99413

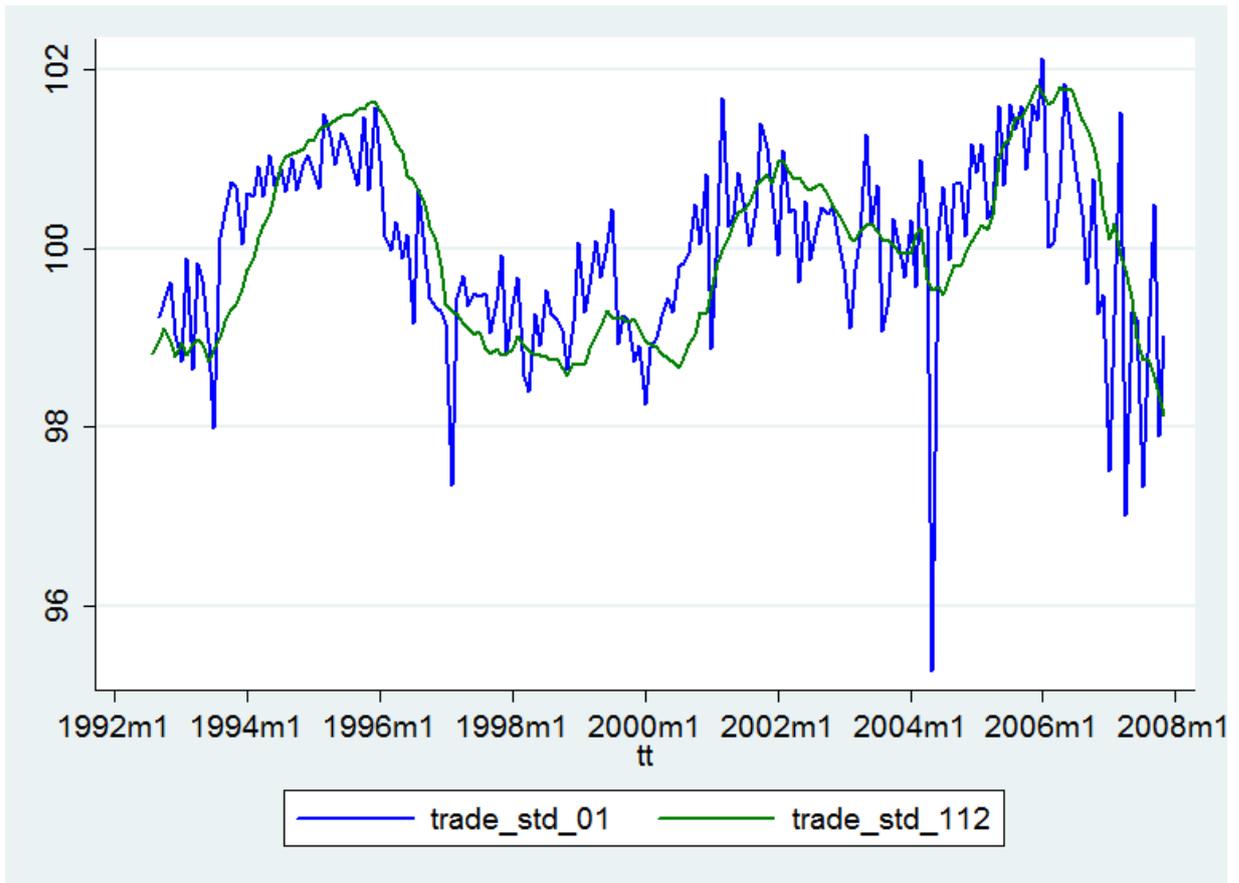
Source: Own elaboration.

Mean deviation, as expected, is equal to zero. Standard deviation is a little bit greater than 3. The maximal negative value of deviation from trend occurred in May 2002, while the maximal positive was observed for April 2004. These extreme values constitute -10.11% and 8.28% of the trend, respectively.

5.3. Moving Average Smoothing and Normalization

After detrending, all series were smoothed with the use of a moving average smoother. A decision what kind of moving average smoother to use was not done in an arbitrary way. I have done smoothing with uniformly weighted moving average by using from 1 up to 12 lagged terms, 0 forward terms, and with or without inclusion of the current observation in the filter. The reason why so many different smoothers were used is that I wanted to cover smoothing with Months of Cyclical Dominance concept and also consider other possibilities of smoothing. For each component variable 24 counterpart variables were generated. Each counterpart variable represents usage of a different smoother. This step of transformation yields 336 new variables (14 variables times 24 versions of different smoothing). Each of these 336 newly created variables was normalized to have a mean of 100 and unit standard deviation (Stock and Watson, 2005). Normalization was conducted according to the following procedure. From each variable its mean was deducted and then it was divided by its standard deviation. To have a convenient index form, 100 was added to every variable. The difference between slightly and severely smoothed series is quite big and easily visible even after normalization to the index form. A typical example is presented in Figure 4.

Figure 4. Comparison of two moving average smoothers



Source: Own elaboration.

The blue, rough line shows how smoothing of trade variable without inclusion of current observation and with use of 1 lagged term looks like. The green, smooth line shows how smoothing of the same variable with inclusion of current observation and with the usage of 12 lagged terms looks like. What strikes is the difference between these two lines that depict two extreme situations. Very important is an idea how to find a good compromise between these two poles of smoothing. This is done in Section 6.1 on the grounds of cross correlation analysis.

6. Construction of Composite Leading Indicator

The number of possibilities to construct a Composite Leading Indicator from more than 300 series is enormous. A method to greatly reduce the number of component series to a more tractable amount is required. I have decided to adopt a technique of cross correlation analysis to choose component series. See Section 6.1 for detailed description of the procedure. To be more confident that chosen variables have some predictive power to explain future behaviour of the IIP the Granger causality test (Granger, 1969) was performed. Section 6.2 brings more details about this method. Once component series were chosen and positively verified, two approaches to construct Composite Leading Indicators have been used. The first variant, with equal weights, is presented in Section 6.3. The second one, with unequal weights determined by absolute values of averages of four extreme cross correlations, is presented in Section 6.4. For both methods I have constructed 10 CLIs. Each CLI was constructed by averaging (with or without weights) different number of component series (from 3 up to 12).

6.1. Cross Correlation

For each of the series produced in latest step (Section 5.3) I have calculated cross correlation between standardized reference series (*pr_ind_100*) and these series, up to 24 lags²⁴. In further analysis I paid little attention to lags larger than 12 (one year), as the first 12 lags are of primary interest. For each bundle²⁵ of 24 respective variables I have calculated the minimum and maximum of the cross correlations. If such value was (in absolute value) smaller than 0.33 then such a bundle was dropped from further analysis. This procedure reduced the number of variables from 14 to 12. Two variables that failed to pass my cross correlation criterion were: unfilled job vacancies (*job_vac*) and manufacturing industry employment future tendency (*mi_empl_f_t*). It is somehow a little bit surprising that future tendencies in employment in manufacturing industry had to be dropped as one may think that future tendencies of employment should be a very good indicator of what is happening with production of total industry. The result for unfilled job vacancies is also surprising, as this variable should be inversely related to production facilities. This result may be caused by the fact that most unfilled job vacancies are in other parts of economy (different from industrial production), such as agriculture or services. Lack of workers in agriculture is well known matter of Polish economy. It results from the fact that a lot of people that used to work in agriculture have migrated to newly opened job markets, for example, to the United Kingdom or to Ireland (Ministry of Economy, 2005). However, in this analysis there is another variable

²⁴ The exact results for all series are not presented here for reasons of brevity.

²⁵ Bundle means a set of all differently smoothed counterpart variables.

strictly connected with the employment issue – unemployment registered rate (*unrat*), which seems to have quite high cross correlation (maximal absolute value equal to 0.45249).

For each of the 12 bundles I have calculated averages of 4 extreme values. It was positive if maximal cross correlation was considerably higher than absolute value of minimal cross correlation. For example, for the production tendency in manufacturing industry, the maximum cross correlation is equal to 0.6161 whereas the minimum equals -0.1424. The average of 4 extreme values is negative if the value of maximal cross correlation is appreciably smaller than absolute value of minimal cross correlation. As an example it is enough to take a look on net trade in goods (value) in billions of US dollars (*trade*) for which maximal cross correlation is equal to -0.0291 while the minimal equals -0.5229. In some cases, the sign of cross correlation is not obvious – for example, the maximum is equal to 0.40684 while the minimum is -0.49508 for currency exchange rates PLN per USD. In such situation I calculated averages of 4 maximal and 4 minimal values. Having calculated averages I take a look at the extremum (positive or negative) and at the lag distribution. For instance, consumer price index (*cpi*) smoothed with moving average with 12 lags and no current observation included and CPI smoothed with the use of moving average with 9 lags and with inclusion of current observation gave the following results. In the former version, the average cross correlation is -0.4361 with 4 extreme values at lags 9, 8, 10, 7 (from the highest absolute value to the lowest), while in the second version the average cross correlation is -0.4375 with extreme lags at 10, 11, 12, 9. The former situation is preferred due to lower lags despite slightly lower, in absolute value, cross correlation. The part of analysis described above is the most subjective one. I have not programmed any kind of automatic rule to select variables used in construction of CLI. Nevertheless, I have eventually chosen 12 variables used to construct various CLIs. The final list of variables used in construction of different Composite Leading Indicators (with number of lags used in moving average smoothing and value of average cross-correlation) is presented in Table 5.

Table 5. Results of cross correlation analysis

Component series	Number of lags	Current observation	Avg cross correlation
unrat_std_11	1	yes	-0.41528
m1_std_09	9	no	0.58070
exp_inf_std_112	12	yes	-0.41216
trade_std_13	3	yes	-0.48819
cpi_std_012	12	no	-0.43610
plnusd_std_05	5	no	0.39485
share_std_112	12	yes	0.36089
r_std_11	1	yes	0.55425
mi_prod_f_t_std_112	12	yes	0.52351
mi_fin_goods_std_012	12	no	0.35742
mi_prices_t_std_11	1	yes	0.57989
mi_prod_t_std_15	5	yes	0.57345

Source: Own elaboration.

6.2. Granger Causality

The Granger causality test checks if lagged values of one variable can improve predictions of another variable. Among others, Zonglu and Maekawa (2001) argue that the Granger causality test should be done only on stationary series. In case of integrated and/or cointegrated series, more sophisticated techniques should be used because simple Granger test can give spurious results. Misleading results given by typical Granger test are due to the incorrect asymptotic distribution of the F-test statistic. In case of non-stationary processes a non-standard asymptotic distributions of F statistics have to be simulated by Monte Carlo experiments. Of course, one can make most series stationary by simply differencing them long enough, but in case of cointegration the long-run relationship described by the cointegrating vector is lost. Nevertheless, in my analysis this problem is not relevant as by construction (detrending, smoothing, and normalization) all series are stationary with a mean of 100 and standard deviation (therefore, variance) equal to one. Another possible complication with Granger causality test is the problem of arbitrary lag length selection (Thornton and Batten, 1984). In the literature different criterions have been suggested, for example: BIC²⁶, AIC²⁷, HQ²⁸, FPE²⁹, etc. In this study the most relevant is the FPE as one would like to predict reference series with the lowest possible error. Therefore, the number of

²⁶ Bayesian Information Criterion

²⁷ Akaike Information Criterion

²⁸ Hannan-Quinn Criterion

²⁹ Final Prediction Error

lags included into test was selected according to the Final Prediction Error criterion. The procedure was as follows. First, optimal number of lags (from 1 up to 48) for reference series was chosen. In this step a series of autoregressive regressions on the dependent variables were conducted. In the first regression, the dependent variable is lagged once. In each succeeding regression, one more lag of the dependent variable is added. The 48 regressions that were estimated are of the form:

$$Y_t = \alpha + \sum_{i=1}^m \beta Y_{t-i} + \varepsilon_{1t}$$

where Y_t is a reference series at time t , α is just a constant term, Y_{t-i} is the value of reference series lagged i months, and ε_{1t} is an error term. The value m^* was chosen to minimize FPE. It turned out that $m^*=29$ and $FPE = 0.029453$, for the reference series. Second, optimal number of lags of component series was chosen. For each component series I have also tried number of lags from 1 up to 48 keeping constant the number of lags of the reference series ($m^*=29$).

$$Y_t = \alpha + \sum_{i=1}^{m^*} \beta Y_{t-i} + \sum_{j=1}^n \gamma X_{t-j} + \varepsilon_{2t}$$

The optimal number of lags n^* was chosen to minimize FPE. Decision if a particular series Granger cause reference series was made on the basis of simple rule. If FPE with optimal number of lags for the case of reference series only $FPE(m^*)$ was higher than FPE with optimal number of lags for the reference series plus one of investigated component series, then the result was in favour of Granger causality. This means that a component series is considered as a Grange cause of the reference series if $FPE(n^*, m^*)$ is lower than $FPE(m^*)$. In other words – if addition of component series reduces the FPE for the reference series then this component series is said to Granger cause the reference series (Aqeel and Butt, 2001). Table 6 summarizes results of Granger causality tests.

Table 6. Results of Granger causality tests

Variable	FPE	Reduction of FPE		Granger cause
		Absolute value	in %	
pr_ind_100	0.029453			
unrat_std_11	0.024857	0.004596	15.60	YES
m1_std_09	0.024579	0.004874	16.55	YES
exp_inf_std_112	0.025373	0.004080	13.85	YES
trade_std_13	0.025242	0.004211	14.30	YES
cpi_std_012	0.024707	0.004746	16.11	YES
plnUSD_std_05	0.025504	0.003949	13.41	YES
share_std_112	0.024274	0.005179	17.58	YES
r_std_11	0.025437	0.004016	13.64	YES
mi_prod_ft_std_112	0.025102	0.004351	14.77	YES
mi_fin_goods_std_012	0.025080	0.004373	14.85	YES
mi_prices_t_std_11	0.024780	0.004673	15.87	YES
mi_prod_t_std_15	0.025514	0.003939	13.37	YES

Source: Own elaboration.

According to results shown in Table 6, all component series Granger cause the reference series. The highest reduction of FPE is obtained for *share_std_112* series with cross correlation equal to 0.36089 (almost the lowest in absolute value!). This result is slightly unexpected, as the variable with the highest cross correlation should have more predictive power. Nevertheless, the reduction of Final Prediction Error is similar for all component series. From 13.37% for *mi_prod_t_std_15* up to 17.58% for *share_std_112*, with mean reduction equal to 14.99% and standard deviation equal to 1.36%. Because it was confirmed that all variables Granger cause the reference series we can proceed with reliable construction of Composite Leading Indicators.

6.3. Equal weights

A starting point was to use all 12 variables to construct equally weighted CLI. Then one series with the lowest cross correlation (in absolute value) was dropped and another CLI was constructed. This procedure was continued until the number of components were reduced to three. General formula for the construction of k^{th} Composite Leading Indicator is as follows:

$$CLI_k = \frac{1}{k} * (variable_1 + variable_2 + \dots + variable_k),$$

where k is the number of component series used in construction. When a variable has negative cross correlation it enters the equation with a negative sign. After each CLI was constructed it was normalized in a way described Section 5.3 to have the same scale for CLIs and reference series. To see that averaging yields better results than simple looking at separate

series, cross correlations were calculated for each CLI. Table 7 presents maximal and average cross correlations of ten, equally weighted, CLIs.

Table 7. Values of cross correlations for equally weighted CLIs

CLI	MAX	AVG
CLI_12	0.71295	0.63093
CLI_11	0.75889	0.68141
CLI_10	0.76206	0.67232
CLI_9	0.75072	0.66709
CLI_8	0.81067	0.74549
CLI_7	0.78382	0.71129
CLI_6	0.83736	0.78852
CLI_5	0.82807	0.78061
CLI_4	0.83142	0.77976
CLI_3	0.74765	0.68749

Source: Own elaboration.

According to the maximal cross correlation criterion, a CLI that consists of 6 components (CLI_6) is the best. Intensity of green colour represents the relative value of cross correlation in each column: darker colours indicate higher cross correlations. It is worth noting that minimal average cross correlation of CLI (0.631) is only a little bit lower than the maximal cross correlation of any single series (0.649). This confirms that construction of Composite Leading Indicator is potentially better than looking on series separately.

6.4. Unequal weights

The procedure for construction of unequally weighted CLI was very similar to the procedure described in Section 6.3. The obvious difference is the weighting scheme. To calculate weights for each component of CLI, I have divided the absolute value of average cross correlation by the sum of all absolute values of average cross correlations of component series used in construction of particular CLI. The formula for the weights is as follows:

$$\omega_i = \frac{\varphi_i}{\sum_{j=1}^k \varphi_j}$$

where i stands for the weight of i^{th} component, φ_i is the absolute value of average cross correlation between component i and the reference series, k is the number of components used in construction. The formula for a particular CLI is as follows:

$$CLI_k = \sum_{i=1}^k \omega_i * variable_i$$

One more time when a variable has negative cross correlation it enters the weighting scheme with negative sign. Moreover, each CLI was normalised to have a mean of 100 and unit standard deviation. Table 8 presents maximal and average cross correlations of 10 unequally weighted CLIs.

Table 8. Values of cross correlations for unequally weighted CLIs

CLI	MAX	AVG
CLI_12w	0.75364	0.67464
CLI_11w	0.78268	0.70768
CLI_10w	0.78328	0.70016
CLI_9w	0.77623	0.69811
CLI_8w	0.81841	0.75528
CLI_7w	0.79652	0.72802
CLI_6w	0.83725	0.78794
CLI_5w	0.82813	0.78002
CLI_4w	0.83008	0.77807
CLI_3w	0.74777	0.68765

Source: Own elaboration.

A small letter “w” at the end of each CLI indicates that an unequal weighting scheme was used in construction. The number shows how many component series were used in the construction. One more time, the starting point was to use all 12 series. The decision which series should be removed from CLI was made on the grounds of the value of weights. Therefore, the variables used in construction of CLI_*k* are the same as used in construction of CLI_*kw* and the difference is only in weights assigned to each component series. According to the maximal cross correlation criterion, a CLI that consist of 6 components (CLI_6w) is again the best. This time the minimal average cross correlation of CLI (0.675) is higher than maximal cross correlation of any separate series (0.649). It turned out that the values of cross correlation do not change a lot between equally and unequally weighted construction schemes. Having 20 different CLI we can proceed with turning points identification in the reference series and in each indicator.

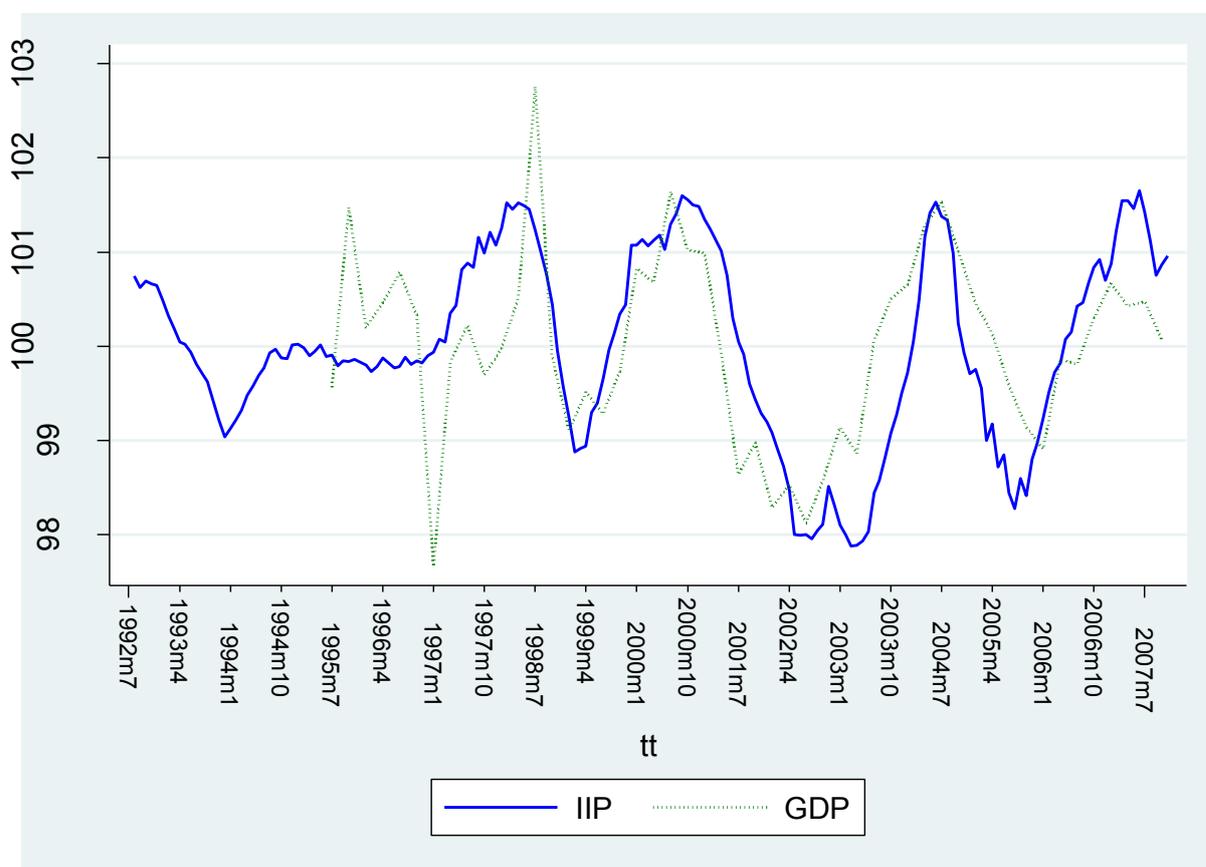
7. Turning Points Analysis

The most important part of cyclical behaviour analysis is the identification of turning points (TP) – peaks (P) and troughs (T). The same method of turning points identification is applied for all series – reference series and Composite Leading Indicators. Details are presented in Section 7.1., where turning points of reference series are discussed.

7.1. Turning Points in Reference Series – comparison with OECD

Figure 5 presents Index of Industrial Production and Gross Domestic Product. Both series were transformed in a way described in Chapter 5 about methodology.

Figure 5. Comparison of IIP and GDP cycles



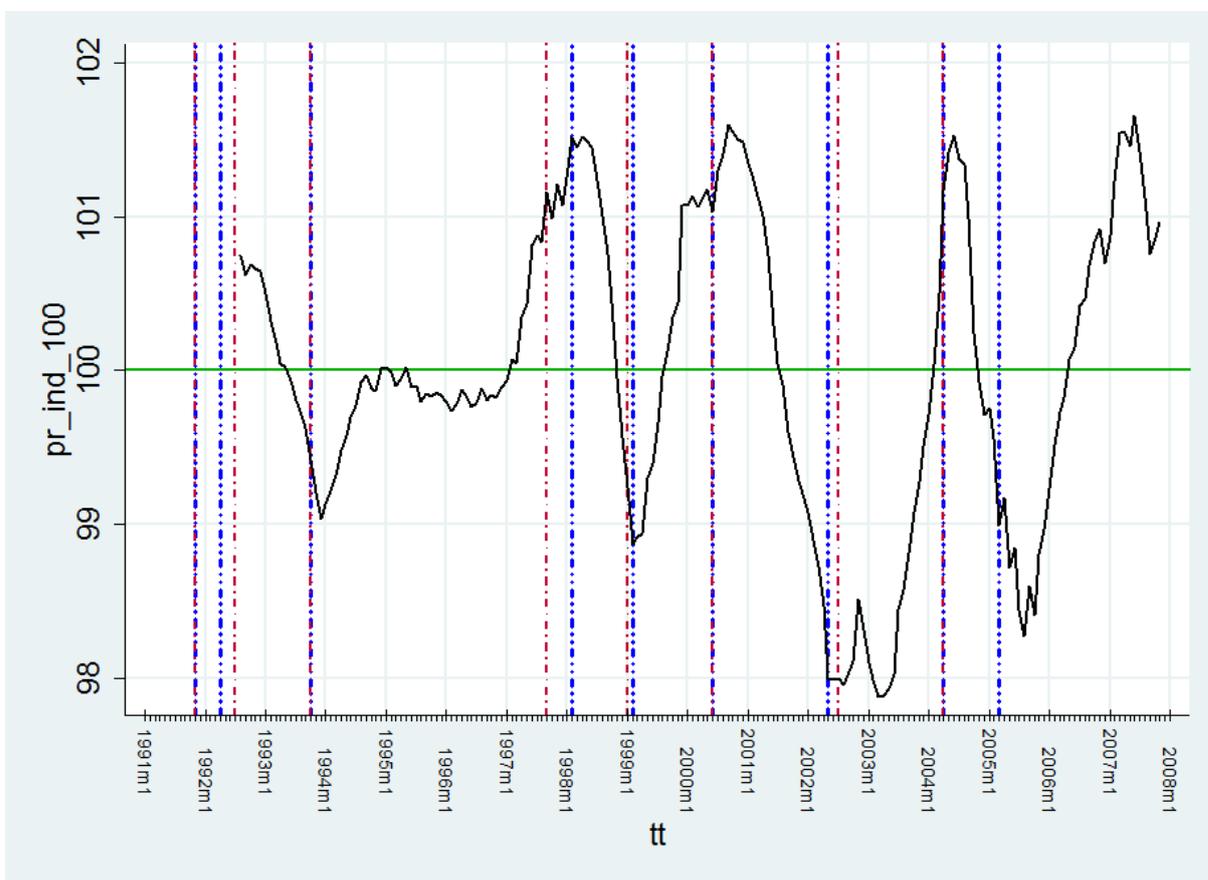
Source: Own elaboration.

It is clearly visible that IIP and GDP are closely related to each other as they present similar cyclical behaviour. Therefore, a good Composite Leading Indicator for IIP can also be used as a leading indicator for changes in GDP cycles.

One major part of the analysis is the identification of turning points. I have compared two different turning points chronologies made by OECD (OECD, 2006; OECD, 2008b) with

a chronology made on my own. Results of the application of chronology proposed by OECD to the Index of Industrial Production are presented on Figure 6.

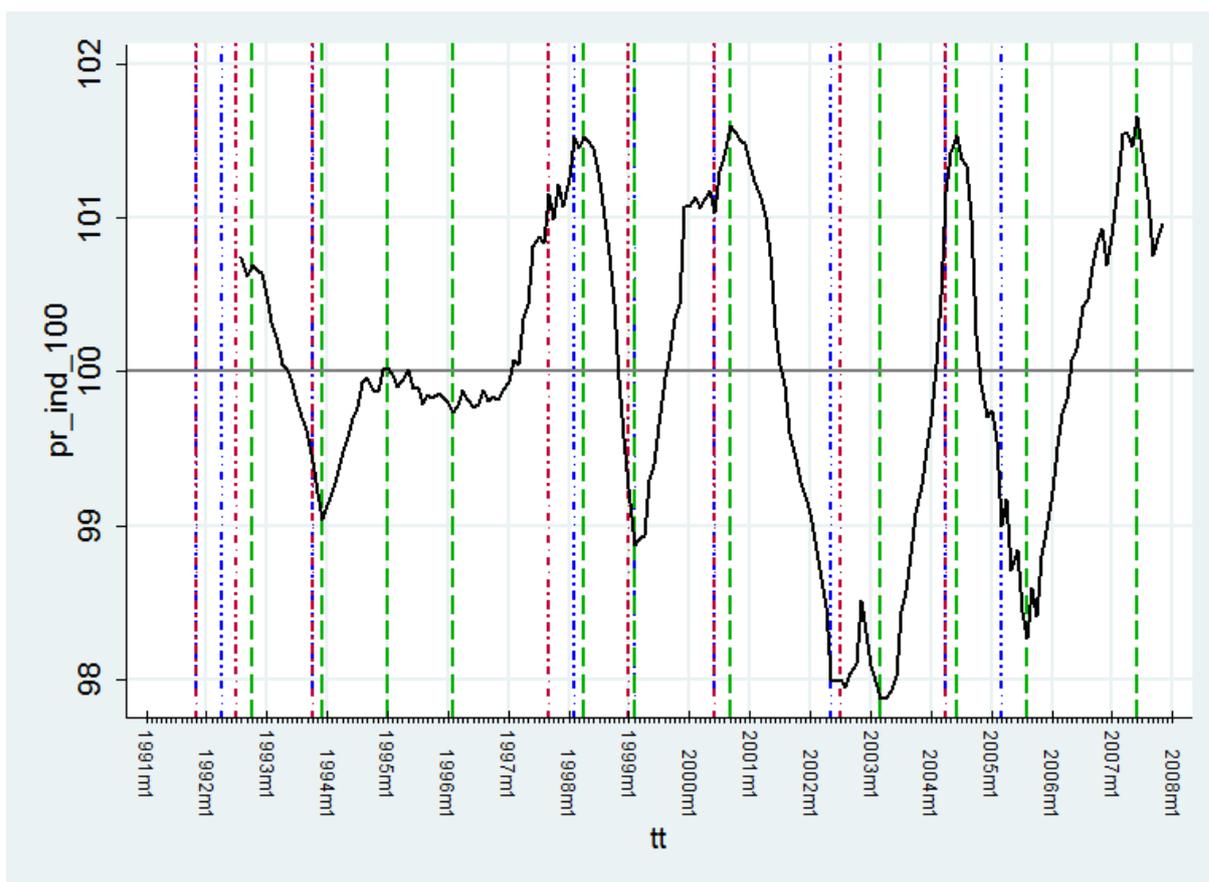
Figure 6. Turning points found by OECD



Source: Own elaboration.

One can easily see that blue, vertical lines (which represent the first OECD chronology) look as if they were better identifiers of turning points than red, vertical lines (which represent the second OECD chronology). Nevertheless, both chronologies are quite similar. It should be mentioned that OECD has identified turning points only to the January 2006 but from January 1991, while I have a slightly different time interval: from August 1992 to November 2007. Turning points that I have identified are presented as green, dashed lines in Figure 7. The last turning point identified by OECD (T in March 2005) may result from data availability. The same is true for all turning points at the end (or beginning) of the sample. It can happen that when new releases of data comes my latest turning point (P in June 2007) will have to be updated and moved further away. However, Composite Leading Indicators can give an idea in which direction things are more likely to develop – recession or expansion.

Figure 7. Comparison of turning points found by OECD and identified in this analysis



Source: Own elaboration.

Green, dashed, vertical lines that represent turning points found in this analysis look a little bit better than those of OECD (red and blue dashed, vertical lines). The biggest difference between OECD and this analysis is that I have found two additional turning points in reference series that were not reported by OECD. The significance of those turning points is a little bit questionable as the reference series did not deviate from the value of 100 a lot. Nevertheless, I have programmed an automatic rule that identify turning points and I did not distinguish between “flat” or “rough” turning points. Another difference is that I have not ignored extreme values of series in question. Similarly to OECD I have adopted the rule that between two peaks (P) it must be one trough (T) and the time distance between two peaks must be at least 15 months. The same rule is applied for two troughs. Minimal time distance between P and T was also set according to OECD standards and was equal to 5 months. It is clearly visible that green lines indicate points that can be intuitively told to be turning points. Table 9 summarizes all three different turning points chronologies and compares them to turning points identified in quarterly GDP (colours of table headers correspond to turning points presented on Figure 7).

Table 9. Comparison of turning points

T or P	OECD 1	OECD 2	MY	OECD GDP	MY GDP
T	1991m11	1991m11			
P	1992m4	1992m7	1992m10		
T	1993m10	1993m10	1993m12		
P			1995m1		
T			1996m2		1995Q4
P	1998m2	1997m9	1998m4	1998Q1	1998Q2
T	1999m2	1999m1	1999m2	1999Q2	1999Q2
P	2000m6	2000m6	2000m9	1999Q4	2000Q2
T	2002m5	2002m7	2003m3	2003Q1	2003Q1
P	2004m4	2004m4	2004m6	2004Q2	2004Q2
T	2005m3		2005m8		2005Q4
P			2007m6		2007Q2

Source: Own elaboration.

“The consistency between turning points from the IIP series and from GDP over the common period since 1995 is not so good at the peak in June 2000 and the trough in May 2002 according to the IIP series, while other turning points are better aligned.” (OECD, 2006, p. 57). This quotation suggests that turning points identified by OECD in the IIP and GDP series occasionally differ. The biggest discrepancy between OECD’s and my turning points in GDP is that according to OECD there was a peak in 4th quarter of 1999 while according to my selection the peak was in the 2nd quarter of 2000. My identification scheme seems to go more with line of the turning points identified in the IIP series. Discrepancies between turning points identified in GDP and in IIP are rather small. The highest difference is for the peak in 2000. According to GDP it was in the 2nd quarter, while according to IIP it occurred in September 2000 – at least 3 months later. However, this results is still better than OECD as they identified a peak in June 2000 in the IIP, while a peak in GDP was in the 4th quarter of 1999 – at least 6 months earlier.

Over the period 1992 – 2007, industrial production registered five growth cycles measured from peak to peak. The length of the cycle (peak-trough-peak) is not very stable with duration of as short as 27 months and as long as 45 months. The longest cycle is 66.67 % longer than the shortest one. The average duration of the cycle is 34.8 months with an average duration of the expansion phase of 18.8 months and an average duration of the slowdown phase of 16 months. The difference between the fact that I have defined a cycle from peak to peak, while OECD uses trough to trough definition, does not cause substantial differences in results of cycles analysis. The average duration of a cycle defined as trough-peak-trough

equals 34.5 months (with averages for slowdowns and expansions periods equal to 16.25 and 18.25, respectively).

Table 10 summarizes findings about the length of slowdowns, expansions and cycles according to the turning points identified for the IIP.

Table 10. Phase and cycle durations in IIP

Phase / Cycle	Turning points (dates)			Duration (months)	
	Peak	Trough	Peak	Phase	Cycle
Slowdown	1992m10	1993m12		14	
Expansion		1993m12	1995m1	13	
Cycle 1	1992m10		1995m1		27
Slowdown	1995m1	1996m2		12	
Expansion		1996m2	1998m4	26	
Cycle 2	1995m1		1998m4		38
Slowdown	1998m4	1999m2		10	
Expansion		1999m2	2000m9	18	
Cycle 3	1998m4		2000m9		28
Slowdown	2000m9	2003m3		30	
Expansion		2003m3	2004m6	15	
Cycle 4	2000m9		2004m6		45
Slowdown	2004m6	2005m8		14	
Expansion		2005m8	2007m6	22	
Cycle 5	2004m6		2007m6		36
	Average	Max	Min		
slowdown	16	30	10		
expansion	18.8	26	13		
cycle	34.8	45	27		

Source: Own elaboration.

The longest slowdown phase was found between September 2000 and March 2003. The length of this recession period is 30 months (2.5 years). The length of the shortest slowdown phase is 10 months, a third of the longest slowdown phase. This short recession period was from April 1998 until February 1999. The longest expansion phase was found between February 1996 and April 1998. The length of this boom period is equal to 26 months (2.167 years). The length of the shortest expansion phase is 13 months, only half of the longest expansion phase. This shortest boom period was from December 1993 until January 1995. This simple comparison yields the ad-hoc conclusion that slowdowns are more volatile and probably may turn out to be more difficult to foreseen.

Similar analysis conducted for quarterly data on GDP yields the results presented in Table 11. Three full cycles were found in GDP and one incomplete cycle that begins in the 4th quarter of 2005. In general, periods of expansions and slowdowns (as well as the whole

cycles) tend to be longer compared to periods calculated for IIP. The average duration for slowdown increased by 5 months, for expansion by 0.2 months, and for the whole cycle by 5.2 months, as compared to results from IIP. If we take into account the incomplete fourth cycle, the results almost do not change – only average duration of expansion drops by 0.25 months.

Table 11. Phase and cycle durations in GDP

Phase / Cycle	Turning points (dates)			Duration (months)	
	Trough	Peak	Trough	Phase	Cycle
Expansion	1995Q4	1998Q2		30	
Slowdown		1998Q2	1999Q2	12	
Cycle 1	1995Q4		1999Q2		42
Expansion	1999Q2	2000Q2		12	
Slowdown		2000Q2	2003Q1	33	
Cycle 2	1999Q2		2003Q1		45
Expansion	2003Q1	2004Q2		15	
Slowdown		2004Q2	2005Q4	18	
Cycle 3	2003Q1		2005Q4		33
Expansion	2005Q4	2007Q2		18	
Slowdown		2007Q2	???	???	
Cycle 4	2005Q4		???		???
full cycles	Average	Max	Min		
slowdown	21	33	12		
expansion	19	30	12		
cycle	40	45	33		
incomplete	Average	Max	Min		
slowdown	21	33	12		
expansion	18.75	30	12		
cycle	40	45	33		

Source: Own elaboration.

The longest slowdown phase of 33 months (2.75 years) was found between the second quarter of 2000 and the first quarter of 2003. The length of the shortest slowdown phase is 2.75 times smaller (equal to 12 months) than the longest slowdown phase. This short recession period was from 2nd quarter of 1998 until 2nd quarter of 1999. The longest expansion phase was found between 4th quarter of 1995 and 2nd quarter of 1998. The length of this boom period is equal to 30 months (2.5 years). The length of the shortest expansion phase is 2.5 times smaller (equal to 12 months) than the longest expansion phase. This shortest boom period was from 2nd quarter of 1999 until 2nd quarter of 2000. Analysis of GDP phases confirms that slowdown phases are slightly more volatile than expansion periods.

7.2. Turning points in Composite Leading Indicators

To obtain turning points for each CLI the same set of rules as for the reference series has been applied. Comparison of turning points identified in the reference series and those from different Composite Leading Indicators is presented in Table 12. The first column contains names of different CLIs. The number at the end of the type of CLI indicates number of variables used in construction (from 3 up to 12), a letter “w” after number indicate that in the construction of CLI unequal weighting scheme (see Section 6.2) was used.

Table 12. Time distance between turning points

IIP	1993 m12	1995 m1	1996 m2	1998 m4	1999 m2	2000 m9	2003 m3	2004 m6	2005 m8	2007 m6
T or P	T	P	T	P	T	P	T	P	T	P*
CLI type	TIME DISTANCE									
CLI_12	2	4	5	0	-1	7	14	-1	0	0
CLI_11	2	3	5	0	-1	7	14	-1	-1	0
CLI_10	2	3	5	0	-1	7	14	-1	-1	0
CLI_9	2	3	5	0	-1	7	14	1	-1	0
CLI_8	-3	3	0	0	-1	4	14	-1	-1	0
CLI_7	2	3	0	0	-1	4	14	-1	-1	0
CLI_6	2	2	0	0	-1	4	14	1	-1	0
CLI_5	2	2	5	0	-1	4	14	1	-1	?
CLI_4	2	2	5	0	-1	1	14	1	-1	-1
CLI_3	-3	2	0	0	-1	4	14	0	-1	-1
CLI_12w	2	3	5	0	-1	7	14	-1	-1	0
CLI_11w	2	3	2	0	-1	7	14	-1	-1	0
CLI_1w	2	3	5	0	-1	7	14	-1	-1	0
CLI_9w	2	3	5	0	-1	7	14	-1	-1	0
CLI_8w	-3	2	0	0	-1	4	14	-1	-1	0
CLI_7w	2	3	0	0	-1	4	14	-1	-1	0
CLI_6w	2	2	0	0	-1	4	14	-1	-1	0
CLI_5w	2	2	5	0	-1	4	14	-1	-1	?
CLI_4w	2	2	5	0	-1	1	14	-1	-1	-1
CLI_3w	-3	2	0	0	-1	4	14	0	-1	-1
Average	1.00	2.60	2.85	0.00	-1.00	4.90	14.00	-0.50	-0.95	-0.22
Median	2.00	3.00	5.00	0.00	-1.00	4.00	14.00	-1.00	-1.00	0.00

* - not certain turning point

Source: Own elaboration.

Table 12 presents in detail the performance of each Composite Leading Indicator in predicting turning points in the Index of Industrial Production. The trough in February 1992 was most difficult to forecast – each CLI has a lead of -1, which means that each CLI has a trough 1 month after a trough in IIP occurred. Relatively difficult to forecast was also a trough in August 2005 – all but one CLIs have forecasted it with 1 month lag, only CLI_12 has 0

lead. Problematic seems to be also a peak in June 2004 – only 4 CLIs managed to forecast it with a lead of 1 month, 2 other CLIs has a 0 month lead, while 14 has 1 month lag in prediction. Results for peak in April 1998 are also of poor quality – all CLIs has 0 month lead. The strangest outcome was for trough in March 2003, which was foreseen with 14 month lead! The result is impressive, but a little bit doubtful. One possible explanation is that in the IIP we observe two troughs – one in August 2002 and one in March 2003. However, the value of the IIP for March 2003 was lower than the value for August 2002 (97.88 compared to 97.95). Therefore, the automated rule has chosen March 2003 as a turning point. The best result was obtained for a peak in September 2000 – average lead of CLI was equal to 4.9 month (median lead equal 4 months) with maximal lead of 7 months given by 8 CLIs. Results for trough in December 1993 and in February 1992 as well as for peak in January 1995 are quite plausible. Maximal lead was equal to 2, 4, and 5 months respectively, while an average was 1, 2.85, and 2.6 months, respectively. Results for peak in June 2007 should not be used in a too much rigorous way as peak identified in the IIP is not necessary the final peak. It can happen that after new releases of data arrive the peak would move forward (also can happen in CLI). Nevertheless, the results from turning points analysis in the IIP and CLIs are good advices for policymakers. They should be aware of the fact, that it was possibly a real peak in June 2007, therefore period of slowdown is quite probable. As a result, policymakers can make a decision about changes in fiscal policy to stimulate economy. To reduce a number of potential CLIs from 20 to something more tractable one can take a look on Table 13 that presents some statistics about predictive power of each CLI.

Table 13. Lead statistics

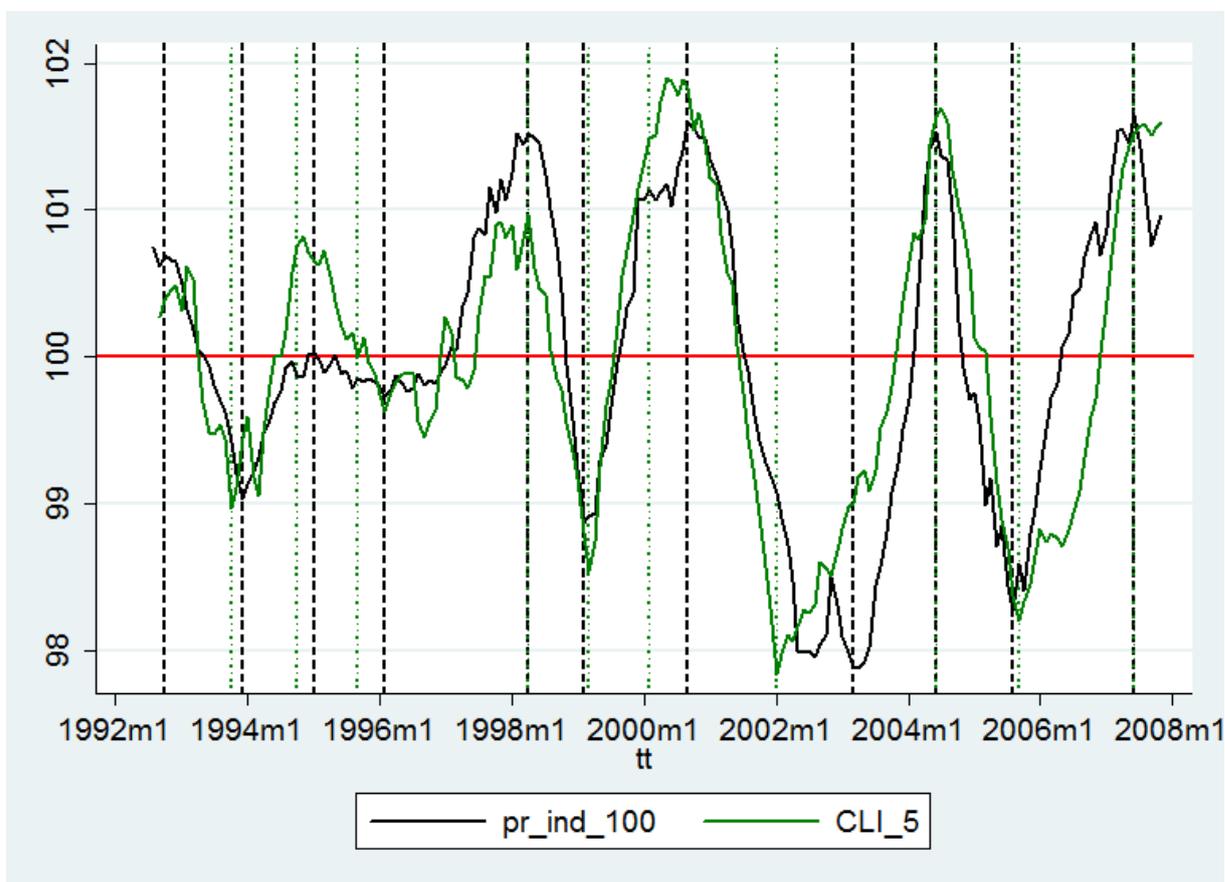
CLI type	LEAD (MONTHS)					
	Avg	Me	Avg P	Avg T	Me P	Me T
CLI 12	3.00	1.00	2.00	4.00	0.00	2.00
CLI 11	2.80	1.00	1.80	3.80	0.00	2.00
CLI 10	2.80	1.00	1.80	3.80	0.00	2.00
CLI 9	3.00	1.50	2.20	3.80	1.00	2.00
CLI 8	1.50	0.00	1.20	1.80	0.00	-1.00
CLI 7	2.00	0.00	1.20	2.80	0.00	0.00
CLI 6	2.10	0.50	1.40	2.80	1.00	0.00
CLI 5	2.89	2.00	1.75	3.80	1.50	2.00
CLI 4	2.20	1.00	0.60	3.80	1.00	2.00
CLI 3	1.40	0.00	1.00	1.80	0.00	-1.00
CLI 12w	2.80	1.00	1.80	3.80	0.00	2.00
CLI 11w	2.50	1.00	1.80	3.20	0.00	2.00
CLI 1w	2.80	1.00	1.80	3.80	0.00	2.00
CLI 9w	2.80	1.00	1.80	3.80	0.00	2.00
CLI 8w	1.40	0.00	1.00	1.80	0.00	-1.00
CLI 7w	2.00	0.00	1.20	2.80	0.00	0.00
CLI 6w	1.90	0.00	1.00	2.80	0.00	0.00
CLI 5w	2.67	2.00	1.25	3.80	1.00	2.00
CLI 4w	2.00	0.50	0.20	3.80	0.00	2.00
CLI 3w	1.40	0.00	1.00	1.80	0.00	-1.00
Average	2.30	0.73	1.36	3.18	0.00	1.00
Median	2.35	1.00	1.20	3.80	0.00	2.00

Source: Own elaboration.

The first two columns show the average (Avg) and median (Me) lead of each CLI, columns three and four show average lead for peaks (P) and troughs (T), while the last two columns contain the median lead for peaks and troughs, respectively. Boldfaced values in green indicate that the lead of particular CLI was higher than average for all 20 CLIs. If a name of CLI is in green it means that such CLI has outperformed average lead of 20 CLIs in all aspects – peaks, trough, and all turning points (for averages and medians). It is only a case of two Composite Leading Indicators: CLI_9 and CLI_5. It means that these two CLIs constructed from 9 and 5 variables, which had the highest cross correlation with reference series (equal weighting scheme), are better than average CLI in predicting turning points, regardless which measure we use (average or median) and regardless what kind of analysis we want to conduct – look for peaks, troughs or both. If a name of CLI is on gray area it means that it has the highest cross correlation with reference series according to analysis performed in Section 6.3 and 6.4. It is only the case of CLI_5 that it is in green and on gray area. Therefore, this CLI can be chosen as the best Composite Leading Indicator to predict turning points in the Index of Industrial Production. Figure 8 illustrates this CLI (green, solid

line) with turning points (green, dotted lines) and compares it to the reference series (black, solid line) and its turning points (black, dashed lines).

Figure 8. Comparison of CLI_5 and reference series

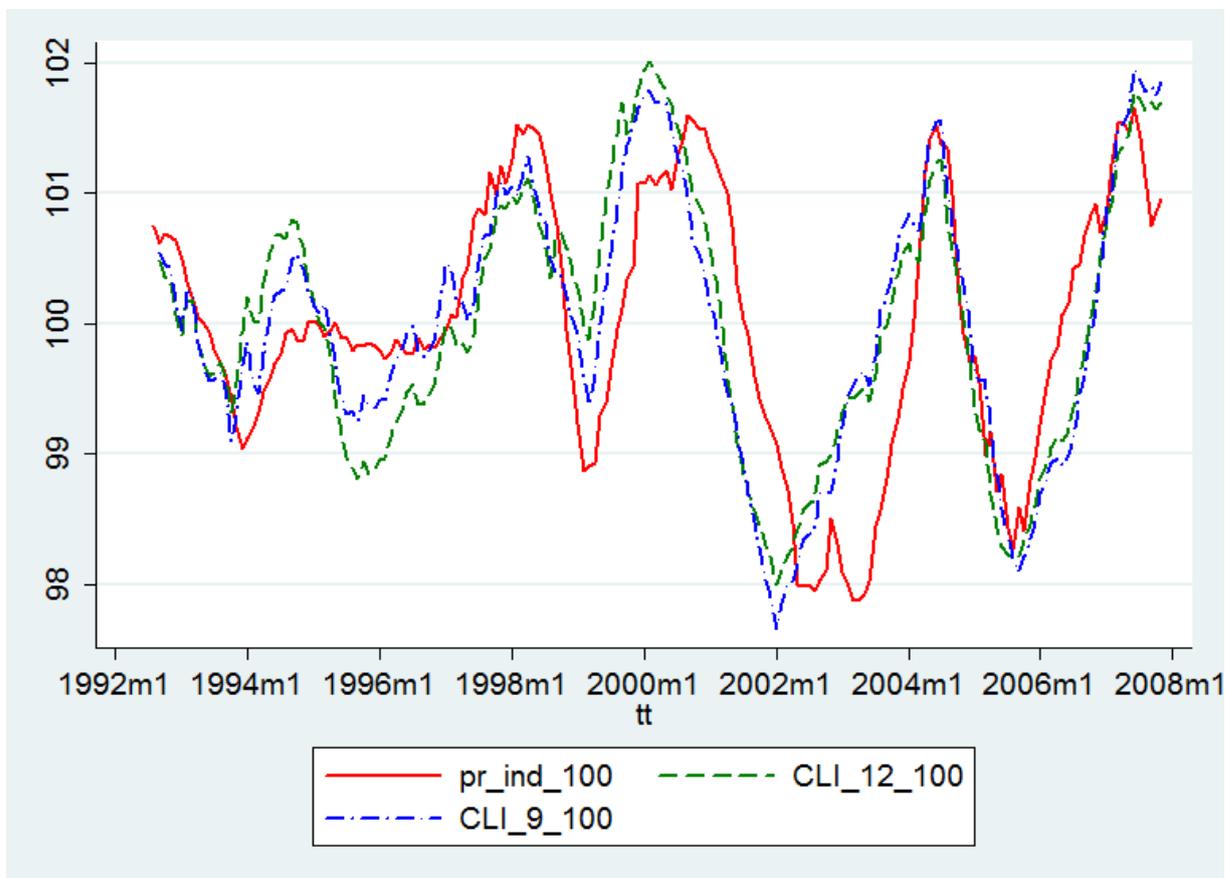


Source: Own elaboration.

Visual inspection yields plausible results. Profiles of CLI_5 and IIP are quite similar and turning points from CLI_5 occur before turning points from IIP almost always. Red, horizontal line indicates the value of 100. It is useful for qualitative analysis. We can define 4 different qualitative signals from CLI's movements over time. If the CLI is increasing and is above 100, then it indicates an expansion. When CLI is increasing but below 100 we have a recovery period, which can change into expansion if the line of 100 is crossed. Opposite situation is when CLI is decreasing and below 100. We then have a slowdown phase. If CLI is decreasing but above 100 then downturn phase is present, which can change into slowdown if the line of 100 is crossed. According to this terminology the CLI_5 indicates possible downturn period for the beginning of the year of 2008. Moreover, talking about recession is far too early as the CLI is relatively faraway from 100 (around 101.5). However, policymakers should be aware that it is high time to think about some policies to prevent change of possible downturn into slowdown.

In terms of average lead CLI_9 as well as CLI_12 have the best predicting power (3 months). Therefore, their performance is also analysed and compared. On Figure 9 these two more Composite Leading Indicators are shown.

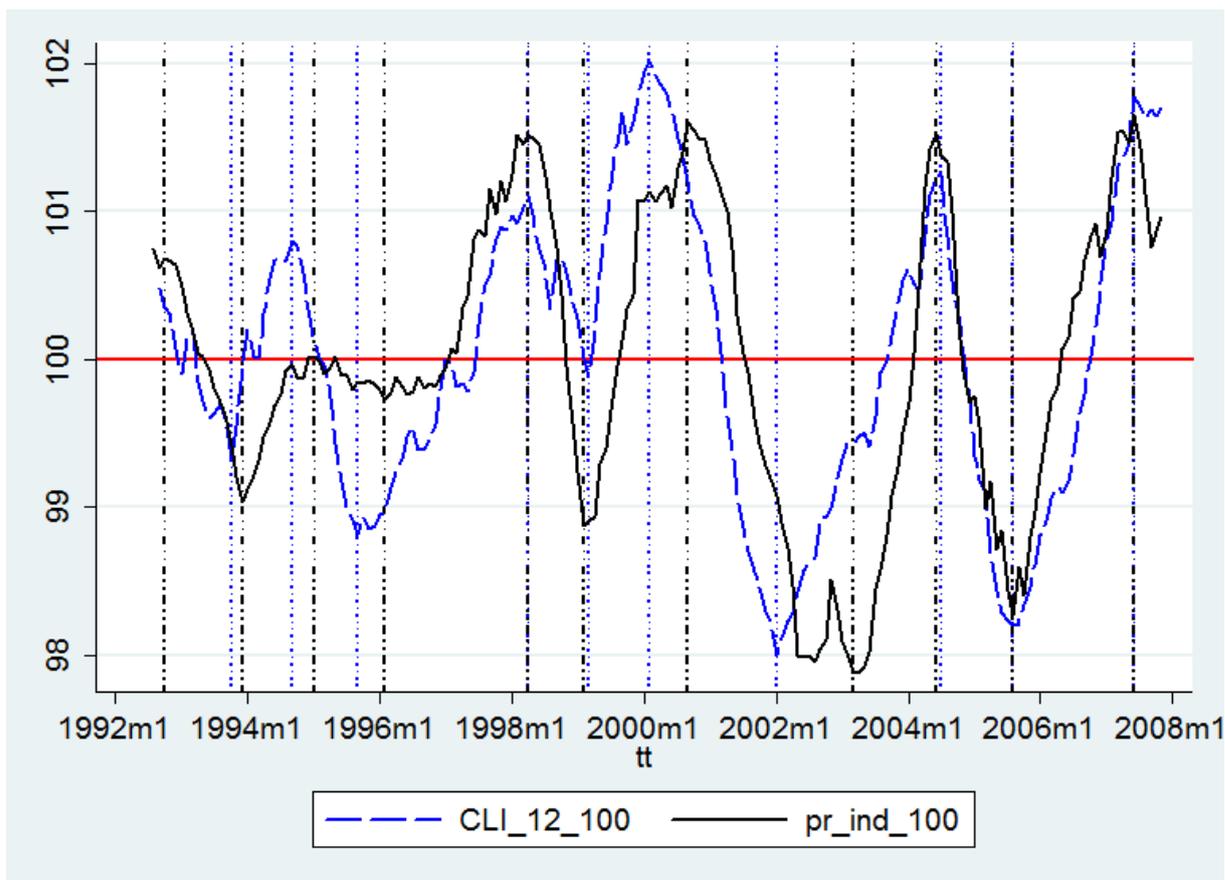
Figure 9. Comparison of CLI_9, CLI_12 and reference series



Source: Own elaboration.

CLI_12 (green, dashed line) has, in general, higher deviations from the value of 100 in the neighbourhood of turning points of IIP than CLI_9 (blue, dashed line). Therefore, signals from this CLI are easier to recognise. Comparison of turning points for CLI_12 and reference series is shown on Figure 10. Blue, dashed line shows CLI_12, while black solid line represents reference series. Colours of vertical lines at turning points correspond to series – blue for CLI and black for IIP. For this CLI the whole profile does not correspond closely to the profile of IIP. Nevertheless, at turning points signals from CLI_12 are clear and almost always precede turning points in the Index of Industrial Production.

Figure 10. Comparison of turning points from CLI_12 and reference series



Source: Own elaboration.

Signal from this CLI is the same as from CLI_5 – beginning of the 2008 year will be a downturn phase. This downturn phase can change into slowdown if the tendency persist too long. With the means of Composite Leading Indicator policymakers can prepare some stimulus packages (for example: decrease in CIT – Corporate Income Tax, subsidies to newly opened firms, increase in investment financed by decrease in unproductive government spending, etc.) to revitalize Polish economy. Hopefully, necessary preparation of infrastructure required by UEFA before EURO 2012 will boost and prolong the expansion phase.

8. Summary

The main aim of this thesis, which was to develop a Composite Leading Indicator of cyclical movements of the Polish economy, was entirely completed. With the help of CLI constructed in this analysis one can easily forecast monthly changes in economic activity. What is more, the second goal of this thesis was also completed. I have offered several synthetic indicators that are able to assist NBP staff in conducting projections of the development of Polish economy. In addition, proposed methodology can be adopted to build indicators for other variables of interest like inflation or unemployment.

The Composite Leading Indicator analysis presented in this thesis was designed to provide early warning signals of possible turning points (troughs and peaks) between expansions and slowdowns in the growth cycle of economic activity in the case of Poland. The analysis provided in this thesis offers qualitative information about short-term economic fluctuations and should be supported by quantitative analysis coming from long-term forecasts derived from econometric models of the whole economy. In the case of Poland such a model is an ECMOD model used by NBP (Fic et al., 2005). This model is used for making projections of GDP growth, inflation and other variables of interest (NBP, 2008). However, ECMOD is a quarterly model, so it cannot be properly used in short-term analysis of cyclical movements, for instance, due to data availability constraint. Moreover, making short-term predictions is not a task that large-scale structural models are designed for as they concentrate on the medium-term dynamics of the economy. Therefore, it seems reasonable to supplement projections of NBP by Composite Leading Indicator analysis. The main reason is that a composite formula has an advantage over separate series (currently used by NBP) as much of the independent measurement error as well as other noise in the component series is smoothed out in a weighted index.

This thesis offers a plausible and sometimes even superior results as compared to outcomes given by other researchers. For example, Matkowski (2002, p.15) state that: “all the CSO-based³⁰ ESIs³¹ indicate a continuous fall of economic climate while some RIED-based³² ESIs suggest an improvement towards the end of 2001.” Confronting his results with real data and my CLIs from the end of 2001 and beginning of 2002 one can make an interesting observation. RIED-based Economic Sentiment Indicators have signalled the possible beginning of recovery period around the turn of 2001 and 2002. Very similar outcome was

³⁰ Based on data from Central Statistical Office.

³¹ Economic Sentiment Indicator - reflects the opinion of economic agents on current economic conditions and the tendency of business.

³² Based on data from Research Institute of Economic Development at the Warsaw School of Economics.

produced by all CLIs constructed in my analysis. Such results may be caused by small, apparent “peak” between two troughs in August 2002 and March 2003 in the Index of Industrial Production. However, as mentioned in Section 7.2, only trough in March 2003 is classified as a real trough. The question arise if CSO-based ESIs were so good to foresee this false peak. Unfortunately, this question remains without the answer since it may turn out that these ESIs would miss the cycle, identify a trough after it happened, or predict it with very small lead. The most probable seems to be the case of predicting a trough after it happened as one of main findings by Matkowski (2002, p.15) is that: “the RIED-based ESIs tend to provide a better indication of the current course of the economy as compared with the similar indicators filled with the CSO data.”

Bandholz (2005), who has used linear and non-linear dynamic factor analysis with Markov-switching, has obtained the maximum cross-correlation between reference series and composite index equal to 0.75. As mentioned in Section 6.3 and 6.4 only equally weighted CLI consisting of 12 component series has maximal cross-correlation smaller than 0.75. The highest cross-correlation was equal to 0.84 and was obtained by two CLIs: equally and unequally weighted indicators constructed from six component series. The most remarkable difference between Bandholz and this work is the chronology of slowdowns and expansions in the GDP series. According to Bandholz two slowdowns periods were between 1994 and 2003. First, from 4th quarter of 1997 to 4th quarter of 1998, and second from 4th quarter of 1999 to 3rd quarter of 2001. According to my results there were also two slowdowns periods between 1994 and 2003. However, slowdowns occurred from 2nd quarter of 1998 to 2nd quarter of 1999, and from 2nd quarter of 2000 to 1st quarter of 2003. Moreover, as described in section 7.1, my results are confirmed by OECD analysis. As a result of this discrepancy the expected duration of phases also differ. According to my results an average length of recession and expansion is equal to 7 and 6.3 quarters, respectively. Bandoldz has the expected durations for recession and expansion equal 3.1 and 10.3 quarters respectively.

The main outcome of this thesis is that downturn in economic activity is almost certain and that the phase of expansion has finished (by the end of 2007). With the help of CLI a policymakers can overcome the intrinsic lag of stabilization policy that is defined as “the time between a shock to the economy and the policy action responding to that shock” (Mankiw, 2002, p.382). This intrinsic lag results from the fact that it takes some time for policymakers to realize that a particular shock has happened and apply suitable policies. Composite Leading Indicator is able to decrease this intrinsic lag since it signals with some lead a possibility of change from upswing to downswing (and *vice versa*) in the growth cycle of economic activity. Therefore, policymakers can prepare some actions to stabilize the economy.

Unfortunately, the legislative process in Poland is quite long and complicated. It takes more than two months to fully implement a certain legislation act (CASE, 2004; Goetz and Zubek, 2005). Fortunately, as mentioned in previous paragraphs, policymakers are not the only one group that can benefit from using forecasts of turning points done with the use of Composite Leading Indicators.

This thesis indicated the possible usage of CLI concept. Other researchers should be encouraged to conduct their own studies about forecasting turning with CLIs. There is a lot of possibilities to extend this thesis. For example, it will be interesting to update the database used in this analysis for new data releases and check if prognoses were correct. However, this could not have been done in this analysis since all detailed results (i.e. HP filtering, MA smoothing, cross correlation analysis, etc.) presented in various tables or figures and described in previous sections would have to be changed. Keeping results up to date continuously is possible, but the main purpose of this thesis was to show that the employment of CLI in predicting the behaviour of Polish economy is useful. Another possible extension is to try different detrending, smoothing, normalization, and turning point identification schemes to conduct the real sensitivity check of the methodology proposed in this thesis. Nevertheless, the most interesting extension of this thesis is to provide an analysis based on linear and non-linear Markov Switching Dynamic Factor Analysis. However, a detailed description and implementation of this concept was kept for the sake of my future PhD dissertation.

Bibliography

- Akaike H. and Nakagawa T. 1988. *Statistical Analysis and Control of Dynamic Systems*. Kluwer Academic publishers.
- Anderson H. Gerald and Erceg J. John. 1989. *Forecasting Turning Points With Leading Indicators*. Economic Commentary. Federal Reserve Bank of Cleveland.
- Aqeel Anjum and Butt Sabihuddin Mohammad. 2001. *The Relationship Between Energy Consumption and Economic Growth in Pakistan*. Asia-Pacific Development Journal Vol. 8.
- Arnaud Benoit and Eun-Pyo Hong. 2001. *Comparison of compilation methodologies for the Composite Leading Indicators of Euro area*. OECD.
- Artis M. J., Bladen-Hovell R.C, and Zhang W. 1995. *Turning Points in the International Business Cycle: An Ex post Analysis of the OECD Leading Indicators Series for the G-7 Countries*. OECD Economic Studies.
- Awokuse O. Titus and Yang Jian. 2002. *The informational role of commodity prices in formulating monetary policy: A reexamination*. FREC Staff Paper.
- Bandholz Harm. 2005. *New Composite Leading Indicators for Hungary and Poland*. Ifo Working Paper No. 3.
- Barro J. Robert and Gordon B. David . 1984. *Rules, Discretion and Reputation in a Model of Monetary Policy*. NBER Working Papers 1079. National Bureau of Economic Research.
- Baum F. Christopher, Caglayan Mustafa, and Ozkan Neslihan. 2001. *Exchange Rate Effects on the Volume of Trade Flows: An Empirical Analysis Employing High-Frequency Data*. Computing in Economics and Finance 2001 85. Society for Computational Economics.
- Brunet Olivier. 2000. *Calculation Of Composite Leading Indicators: A Comparison Of Two Different Methods*. Paper for presentation at the CIRET Conference in Paris.
- Bruno Michael and Fischer Stanley. 1991. *Seigniorage, Operating Rules and the High Inflation Trap*. NBER Working Papers 2413. National Bureau of Economic Research.
- Bry Gerhard and Charlotte Boschan. 1971. *Programmed Turning Point Determination*. National Bureau of Economic Research (NBER). Cyclical Analysis of Time Series: Selected Procedures and Computed Programs. NBER Technical Paper 20.
- Bry Gerhard and Charlotte Boschan. 1978. *The Phase Average Trend: A New Way of Measuring Economic Growth*. National Bureau of Economic Research.
- Burns A. F. and Mitchell W. C. 1946. *Measuring Business Cycles*. New York: National Bureau of Economic Research.
- CASE. 2004. *Reforma procesu stanowienia prawa*. Zeszyty BRE Bank – CASE. no. 72.

- Central Statistical Office. 2006. *National Accounts by Institutional Sectors and Sub-Sectors 2000-2004*. Statistical Publishing Establishment.
- Central Statistical Office. 2007a. *Yearbook of Foreign Trade Statistics*. Branch Yearbooks.
- Central Statistical Office. 2007b. *Foreign Trade: January – December 2006*. Economic Statistics Division.
- Central Statistical Office. 2008. *Obroty handlu zagranicznego ogółem i według krajów*. Departament Handlu i Usług – Wydział Handlu Zagranicznego.
- Chatfield C. 1996. *The analysis of time series – an introduction*. 5th ed. Chapman and Hall. London. United Kingdom.
- De Leeuw F. 1991. *Toward a Theory of Leading Indicators*. Cambridge University Press
- European Central Bank. 2001. *The Information Content of Composite Indicators of the Euro Area Business Cycle*. Monthly Bulletin. Frankfurt
- Fic Tatiana (ed.) 2005. *ECMOD – Model of the Polish Economy*. Materiały i Studia Paper no.36. National Bank of Poland.
- Fischer Stanley and Easterly William. 1990. *The Economic of the Government Budget Constraint*. World Bank Research Observer. Oxford University Press.
- Fleming J. M. 1962. *Domestic financial policies under fixed and under floating exchange rates*. IMF Staff Papers 9.
- Fukuda Shin-ichi and Onodera Takashi. 2001. *A new composite index of coincident economic indicators in Japan: how can we improve forecast performances?* International Journal of Forecasting 17.
- Goetz H. Klaus and Zubek Radosław. 2005. *Stanowienie prawa w Polsce - reguły legislacyjne a jakość ustawodawstwa*. Ernst & Young S.A. Poland.
- Granger C.W.J. 1969. *Investigating Causal Relations by Econometric Methods and Cross-Spectral Methods*. Econometrica 34.
- Hannan E. J. and Quinn B.G. 1978. *The determination of the lag length of an autoregression*. Journal of Royal Statistical Society 41.
- Hodrick R. and Prescott E. 1997. *Post-war U.S. business cycles: An empirical investigation*. Journal of Money, Credit and Banking.
- Klein R. Lawrence and Ozmucur Suleyman. 2004. *Models for High-Frequency Macroeconomic Modeling*. The University of Pennsylvania.
- Koopmans T. C. 1947. *Measurement without Theory*. The Review of Economics and Statistics.
- Lahiri Kajal and Wenxiong Yao Vincent. 2006. *Economic indicators for the US transportation sector*. Transportation Research Part A 40.

- Mankiw N. Gregor. 2002. *Macroeconomics*. Worth Publishing - 5th Edition.
- Matkowski Zbigniew. 2002. *Composite Indicators Of Business Activity For Poland Based On Survey Data*. Warsaw School of Economics.
- Ministry of Economy. 2005. *Zatrudnienie Polaków w innych krajach UE/EOG oraz obywateli UE/EOG w Polsce*. Press Office. http://www.mg.gov.pl/NR/rdonlyres/ECC91CAF-075B-4B1D-AF97-9A80FE8518B1/10274/zatrudnienie_1.doc (accessed 14 March 2008)
- Mundell Robert. 1963. *Capital Mobility and Stabilization Policy under Fixed and Flexible Exchange Rates*. Canadian Journal of Economic and Political Science.
- Muth F. John. 1961. *Rational Expectations and the Theory of Price Movements*. Reprinted in *The New Classical Macroeconomics*. Volume 1. 1992.
- NBP. 2008. *Inflation projection of the National Bank of Poland based on the ECMOD model*. Economic Institute. http://www.nbp.pl/en/publikacje/raport_inflacja/ecmodfebruary2008.pdf (accessed 3 March 2008)
- Neville Hill. 2001. *A Guide To Leading Indicators In The Euro Area* Credit Suisse First Boston (Europe) LTD.
- Nilsson Ronny. 2000. *Macroeconomic Analysis and Forecasting B (CLI), Confidence Indicators and Composite Indicators*. Paper for presentation at the CIRET Conference in Paris.
- Nilsson Ronny. 2003a. *OECD System Of Leading Indicators*. OECD/ESCAP Workshop on Composite Leading Indicators and Business Tendency Surveys.
- Nilsson Ronny. 2003b. *System of Leading Indicators Practices and Tools*. OECD/ESCAP Workshop on Composite Leading Indicators and Business Tendency Surveys.
- Nilsson Ronny and Brunet Olivier. 2006. *Composite Leading Indicators for Major OECD Non-Member Economies: Brazil, China, India, Indonesia, Russian Federation, South Africa*. OECD Statistics Working Papers. OECD Publishing.
- OECD. 1998. *OECD Composite Leading Indicators – a tool for short-term analysis*. OECD Statistics Directorate.
- OECD. 2001. *OECD CLI Falls in September – Deterioration in all G7 Countries*. PAC COM NEWS 94.
- OECD. 2006. *Composite Leading Indicators for Major OECD Non-Member Economies: Brazil, China, India, Indonesia, Russian federation, South Africa and Recently New OECD Member Countries: Korea, New Zealand, Czech Republic, Hungary, Poland, Slovak Republic*. OECD: Short-Term Economic Statistics Division – Statistics Directorate.
- OECD. 2008a. *Composite Leading Indicators signal a downswing in all major OECD economies*.

- OECD. 2008b. *Poland - CLI Component Series & Turning Points*. http://www.oecd.org/document/32/0,3343,en_2825_495677_36410848_1_1_1_1,00.html (accessed 25 February 2008)
- Quinn Terry and Mawdsley Andrew. 1996. *Forecasting Irish Inflation: A Composite Leading Indicator*. Economic Analysis: Research and Publications Department. Central Bank of Ireland.
- Ravn O. M. and Uhling H. 1999. *On Adjusting the Hodrick-Prescott filter for the Frequency of Observations*. London Business School. Mimeo.
- Reuven Glick. 1998. *Managing Capital Flows and Exchange Rates: Perspectives from the Pacific Basin*. Cambridge University Press.
- Sargent, T. J. and Sims C. A. 1977. *Business Cycle Modeling without Pretending to Have Too Much A-Priori Economic Theory*. New Methods in Business Cycle Research. Federal Reserve Bank of Minneapolis.
- Seabra Fernando and Flach Lisandra. 2005. *Foreign Direct Investment and Profit Outflows: A Causality Analysis For The Brazilian Economy*. Economics Bulletin. Vol. 6.
- Simkins Scott. 1999. *Measurement and Theory In Macroeconomics*. North Carolina A&T State University
- Sims Christopher. 1972. *Money, Income and Causality*. American Economic Review 62.
- Smoleński Zygmunt, Chudoba Łucja and Szajner Piotr. 2006. *Ocena Skutków Reformy Wspólnej Organizacji Rynków w Sektorze Cukru w Unii Europejskiej dla Polskich Plantatorów Buraków Cukrowych, Producentów i Konsumentów Cukru – Ekspertyza Wykonana Na Zlecenie Ministerstwa Rolnictwa i Rozwoju Wsi*.
- Stock H. James and Watson W. Mark. 2005. *Implications of Dynamic Factor Models for VAR Analysis*. National Bureau of Economic Research. Cambridge.
- Tenreyro Silvana. 2006. *On the Trade Impact of Nominal Exchange Rate Volatility*. London School of Economics.
- Thornton L. Daniel and Batten S. Dallas. 1984. *Lag Length Selection and Granger Causality*. Federal Reserve Bank of St. Louis – Working Paper 1984-001A.
- Zarnowitz Victor and Ozyildirim Ataman. 2000. *Time Series Decomposition and Measurement of Business Cycles, Trends and Growth Cycles*. The Conference Board Business Cycle Indicators Program Advisory Panel.
- Zhang Wenda and Zhuang Juzhong. 2002. *Leading Indicators of Business Cycles in Malaysia and the Philippines*. Asian Development Bank – Economics and Research Department. ERD Working Paper Series no. 32.
- Zonglu Hea and Maekawa Koichi. 2001. *On spurious Granger causality*. Economics Letters. Volume 73. Issue 3.

Index of Tables

- Table 1. Description of variables
- Table 2. Manufacturing as % of Industrial Production
- Table 3. Integration order of variables
- Table 4. Summary statistics of trend deviation for IIP
- Table 5. Results of cross correlation analysis
- Table 6. Results of Granger causality tests
- Table 7. Values of cross correlations for equally weighted CLIs
- Table 8. Values of cross correlations for unequally weighted CLIs
- Table 9. Comparison of turning points
- Table 10. Phase and cycle durations in IIP
- Table 11. Phase and cycle durations in GDP
- Table 12. Time distance between turning points
- Table 13. Lead statistics

Index of Figures

- Figure 1. Share price index – original data
- Figure 2. Example of periodogram – share price index 2000=100
- Figure 3. Results of HP filter for reference series
- Figure 4. Comparison of two moving average smoothers
- Figure 5. Comparison of IIP and GDP cycles
- Figure 6. Turning points found by OECD
- Figure 7. Comparison of turning points found by OECD and identified in this analysis
- Figure 8. Comparison of CLI_5 and reference series
- Figure 9. Comparison of CLI_9, CLI_12 and reference series
- Figure 10. Comparison of turning points from CLI_12 and reference series
- Figure A1. Plots of data: Production of total industry, Unfilled job vacancies, Unemployment Registered rate, Narrow Money, Average expected inflation, and Net trade
- Figure A2. Plots of data: Consumer Price Index, Exchange rate, Short-term interest rates, M.I. Production Future Tendency, M.I. Finished goods stocks Level, M.I. Selling prices Future tendency
- Figure A3. Plots of data: M.I. Production Tendency and M.I. Employment Future Tendency
- Figure A4. Periodograms of not seasonally adjusted series: Average expected inflation, Consumer Price Index, Exchange rate, and Interest rate
- Figure A5. Periodograms of not seasonally adjusted series: M.I. Production Future Tendency, M.I. Finished goods stocks Level, M.I. Manufacturing industry Selling prices Future tendency, M.I. Manufacturing industry Production Tendency, M.I. Manufacturing industry Employment Future Tendency

Index of Abbreviations

AIC	- Aikake Information Criterion
ADF	- Augmented Dickey-Fuller test for unit root,
AVG	- Average
BIC	- Bayesian Information Criterion
C	- Consumption,
CASE	- Centrum Analiz Społeczno–Ekonomicznych (Center for Social and Economic Research)
CLI	- Composite Leading Indicator
CPI	- Consumer Price Index
CSO	- Central Statistical Office
ESI	- Economic Sentiment Indicator
FPE	- Final Prediction Error
G	- Government Expenditures
GDP	- Gross Domestic Product
HMA	- Henderson Moving Average
HP	- Hodrick-Prescott Filter
HQ	- Hannah-Quinn Criterion
IERiGŻ-PIB	- Instytut Ekonomiki Rolnictwa i Gospodarki Żywnościowej - Państwowy Instytut Badawczy
I	- Investment
$I(k)$	- Integration of order k
IIP	- Index of Industrial Production
KPSS	- Kwiatkowski, Phillips, Schmidt and Shin test for stationarity
M1	- Narrow Money
Max	- Maximum
MCD	- Months of Cyclical Dominance
Me	- Median
MEI	- Monthly Economic Indicator
M.I.	- Manufacturing Industry
Min	- Minimum
NBER	- National Bureau of Economic Research
NBP	- National Bank of Poland
NX	- Nett Export
OECD	- Organisation for Economic Co-operation and Development
P	- Peak
PAT	- Phase Average Trend
PLN	- Polish New Zloty
PP	- Phillips-Perron test for unit root
PPC	- Period to Period Changes
RIED	- Research Institute of Economic Development
SA	- Seasonally Adjusted
Std. Dev.	- Standard Deviation
T	- Trough
TP	- Turning Point
UEFA	- Union of European Football Associations
UK	- United Kingdom
US	- United States
USD	- United States Dollar
VAR	- Vector Autoregression
Y	- Production

Appendix

Figure A1. Plots of data: Production of total industry, Unfilled job vacancies, Unemployment Registered rate, Narrow Money, Average expected inflation, and Net trade

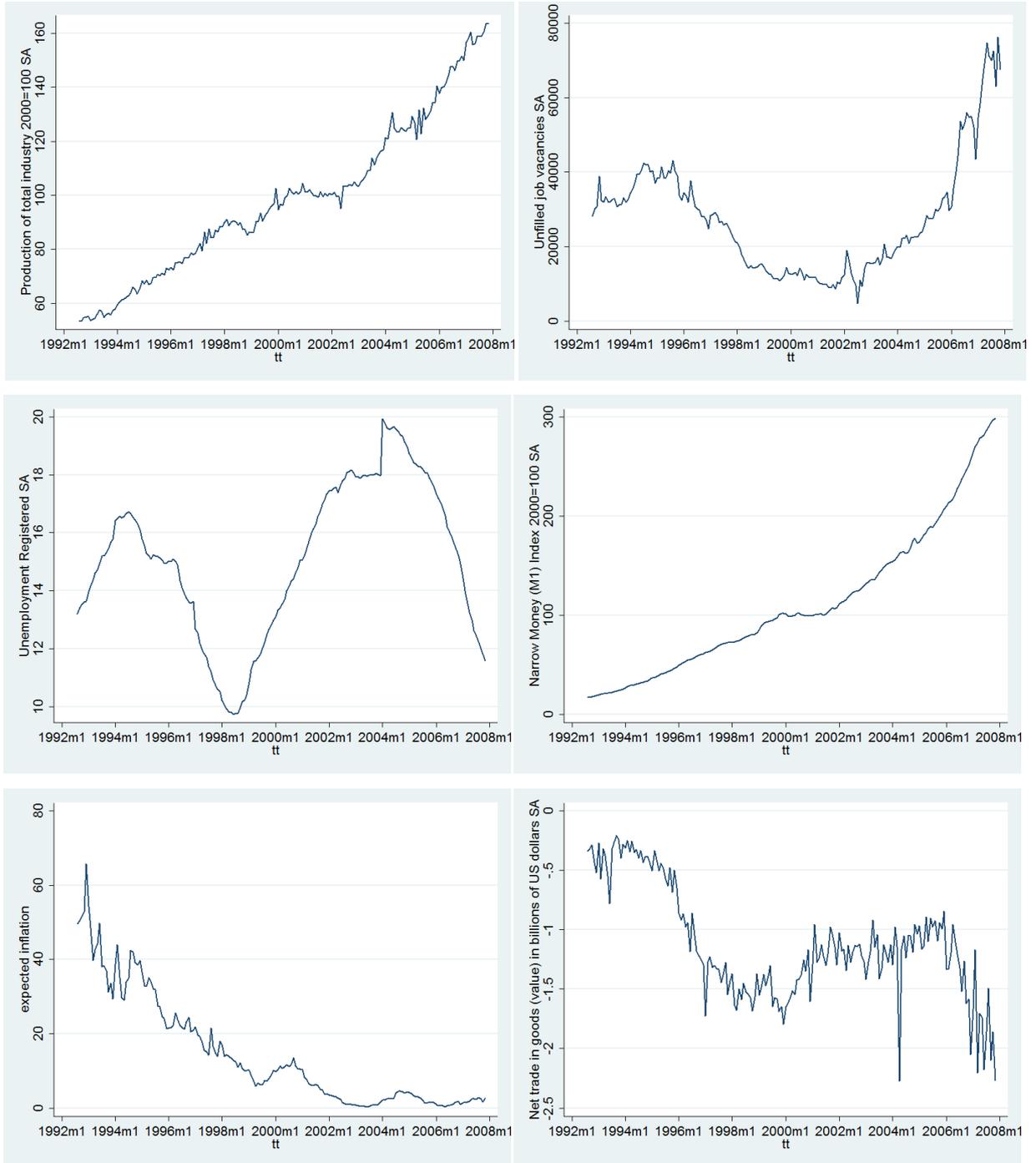


Figure A2. Plots of data: Consumer Price Index, Exchange rate, Short-term interest rates, M.I. Production Future Tendency, M.I. Finished goods stocks Level, M.I. Selling prices Future tendency

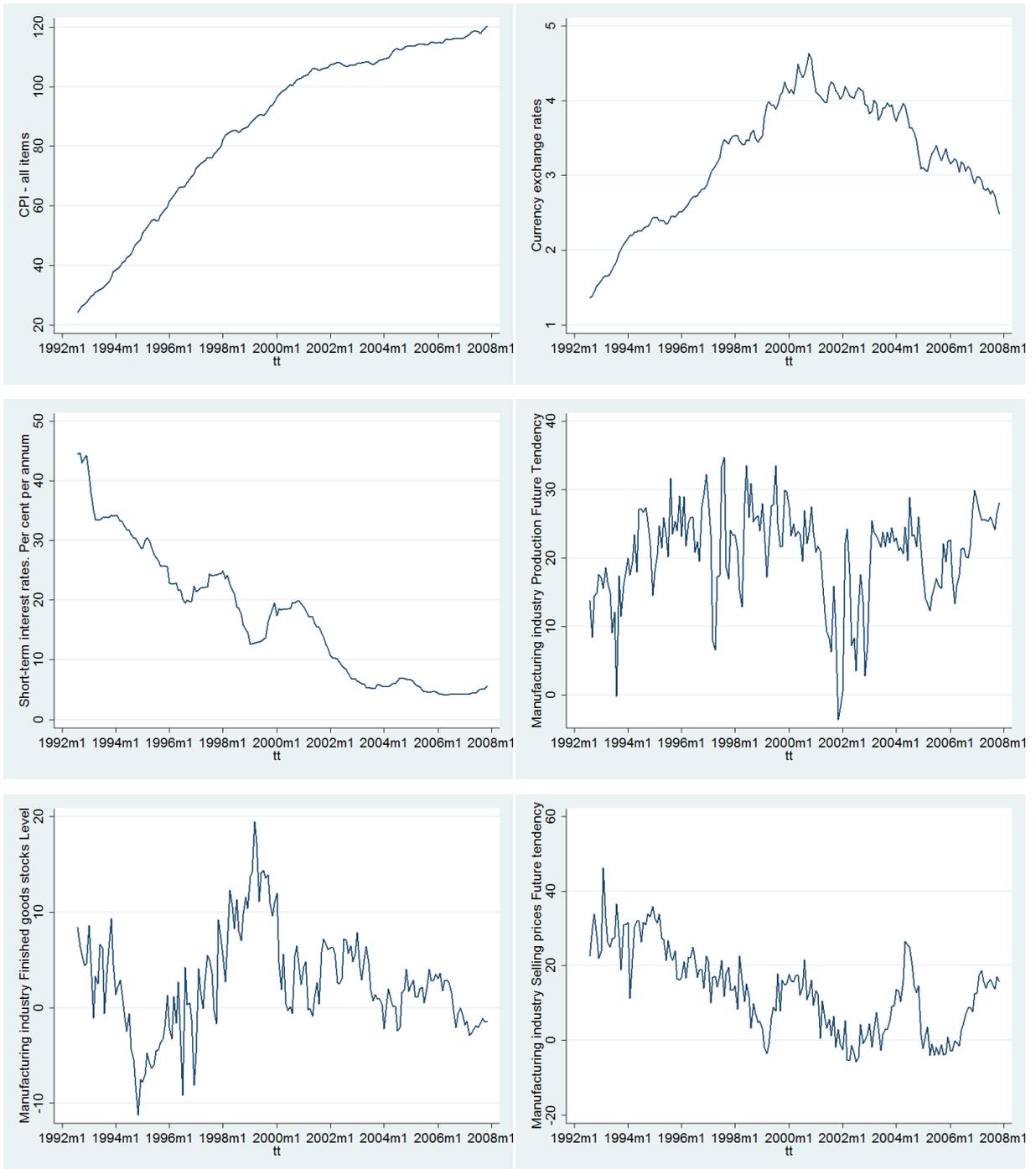


Figure A3. Plots of data: M.I. Production Tendency and M.I. Employment Future Tendency

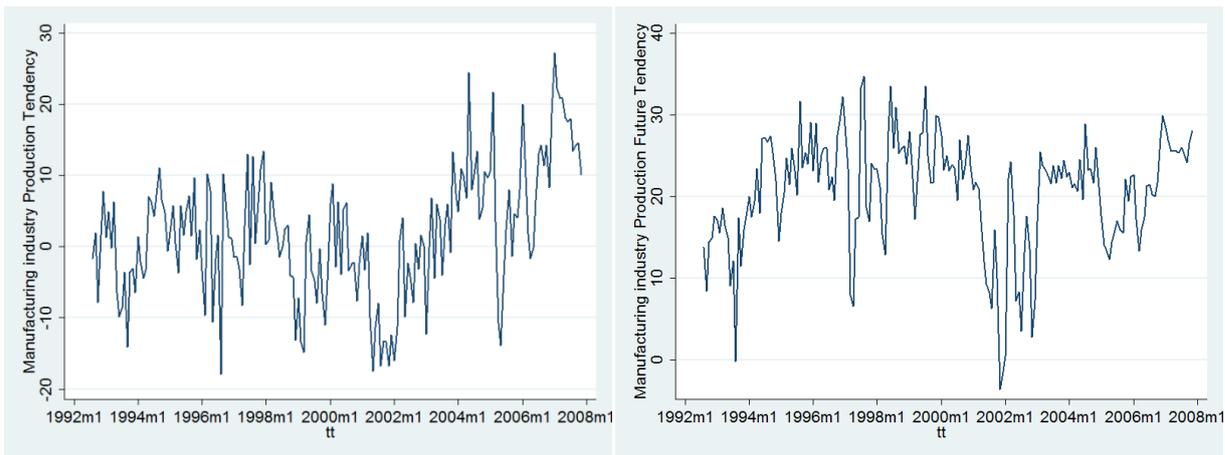


Figure A4. Periodograms of not seasonally adjusted series: Average expected inflation, Consumer Price Index, Exchange rate, and Interest rate

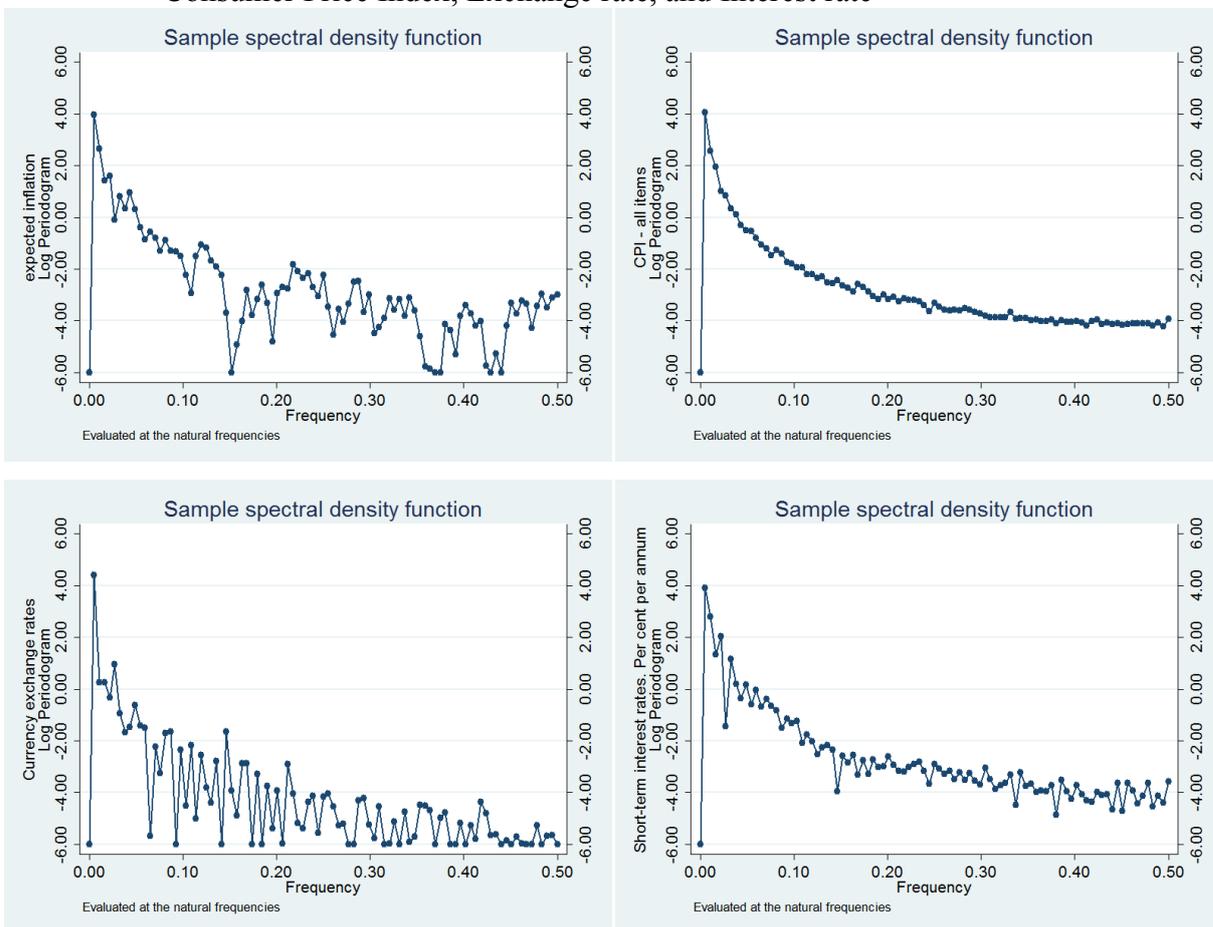


Figure A5. Periodograms of not seasonally adjusted series: M.I. Production Future Tendency, M.I. Finished goods stocks Level, M.I. Manufacturing industry Selling prices Future tendency, M.I. Manufacturing industry Production Tendency, M.I. Manufacturing industry Employment Future Tendency

