Charles University in Prague

Faculty of Social Sciences

Institute of Economic Studies

MASTER THESIS

Forecasting Ability of Confidence Indicators: Evidence for the Czech Republic

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Declaration of Authorship

The author hereby declares that she compiled this thesis independently, using only the listed resources and literature.

The author hereby declares that this thesis has not been used to obtain another university degree.

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Prague, May 18, 2012 ....

Lenka Herrmannová

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Abstract

This thesis assesses the usefulness of confidence indicators for short-term forecasting of the economic activity in the Czech Republic. The predictive power of both the business confidence indicator and the customer confidence indicator is examined using two empirical approaches. First we predict the likelihood of economic downturn defined as a discrete event using logit models, later we estimate GDP growth out-of-sample forecasts in the framework of vector autoregression models.

The results obtained from the downturn probability models confirm the ability of confidence indicators (especially the business confidence indicator) to estimate the current economic situation and to anticipate economic downturn one quarter ahead. Results from the out-of-sample GDP growth value forecasting are ambiguous. Nevertheless the customer confidence indicator significantly improved original forecasts based on a model with standard macroeconomic variables and therefore we conclude in favour of its predictive power. This result was indirectly confirmed by OECD as the Czech customer confidence indicator has been included as a new component in the OECD domestic composite leading indicator since April 2012.

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Keywords	confidence indicators, macroeconomic forecasting, vector autoregression, logistic regression
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Abstrakt

Tato diplomová práce se zabývá užitečností indikátorů důvěry pro krátkodobé předpovědi ekonomické situace v České republice. Dvěma odlišnými empirickými přístupy zkoumáme predikční schopnosti podnikatelského i spotřebitelského indikátoru důvěry. Nejprve pomocí logistické regrese predikujeme pravděpodobnost ekonomického zpomalení, které si definujeme jako nespojitou událost a následně za použití vektorové autoregrese odhadujeme přesné hodnoty reálného růstu HDP.

Výsledky získané z pravděpodobnostních modelů ekonomického zpomalení potvrzují schopnost indikátorů důvěry odhadnout současnou ekonomickou situaci i předjímat ekonomické zpomalení jedno čtvrtletí dopředu. Výsledky modelů predikujících přesné hodnoty HDP jsou víceznačné. Nicméně index spotřebitelské důvěry signifikantně zpřesnil předpovědi základního modelu se standardními makroekonomickými proměnnými, a proto můžeme potvrdit jeho predikční schopnosti. Tento závěr byl nepřímo potvrzen také OECD, když byl indikátor spotřebitelské důvěry od dubna roku 2012 zahrnut do OECD kompozitního indikátoru hospodářského cyklu pro Českou republiku.

Klasifikace JEL	E27, E37, E66
Klíčová slova	indikátory důvěry, makroekonomické predikce, vektorová autoregrese, logistická regrese

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Master Thesis Proposal

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Proposed Topic:

Forecasting ability of confidence indicators

Topic Characteristics:

Our expectations and confidence about the future are influenced by the knowledge of our personal prospects. This thesis will examine whether this information could be captured by the indicators of confidence and used on the aggregate level for empirical models of real economic development. Furthermore we will analyse to what extent the information included in the confidence indicators can enhance the forecasting power of the empirical model of the GDP growth in the Czech Republic.

Hypotheses:

1. There is an interaction between confidence and macroeconomic variables.
2. Confidence indicators improve the forecasting ability of empirical models describing real economic development.
3. There are systematic patterns in the literature related to forecasting abilities of confidence indicators

Methodology:

Meta-analytical techniques will be used as rigorous methods for the survey of related literature. We will compare studies which proved that confidence indicators have some predictive power with cases with no effect on GDP forecast and try to reveal systematic patterns, for example differences in confidence measurement, method of GDP modeling or geopolitical aspects.

Vector Autoregression Methodology (VAR) will be used to examine the forecasting ability of confidence indicators in a time series model of GDP. A model with standard macroeconomic variables which describe the economy best will be compared with a model enhanced by indicators of confidence. Then the additional explanatory and forecasting power of confidence will be analysed.

Outline:

1. Introduction
2. Survey of related literature
    2.1. Confidence in economic theories
    2.2. Qualitative literature review
    2.3. Quantitative literature review (meta-analysis)
3. Measuring confidence
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4. Empirical model of the GDP growth in the Czech economy
    4.1. Methodology (VAR) and data
    4.2. Model with standard economic variables
    4.3. Model enhanced by confidence indicators
    4.4. Comparison of forecasting performance
5. Conclusion

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Acronyms

AIC	Akaike Information Criteria
BCI	Business Confidence Indicator
CCI	Consumer Confidence Indicator
CEPR	Centre for Economic Policy Research
CNB	Czech National Bank
CUSUM	Cumulative sum of residuals
CZSO	Czech Statistical Office
ECRI	European Cycle Research Institute
EU	European Union
GDP	Gross Domestic Product
GNP	Gross National Product
HQIC	Hannah-Quin Information Criteria
IC	Information Criteria
LEAD	Composite Leading Indicator
LR	Likelihood Ratio
MAE	Mean Absolute Error
ME	Mean Error
MSE	Mean Squared Error
NBER	National Bureau of Economic Research
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
PRIBOR	Prague Interbank Offered Rate
Q	Quarter
RMSE	Root Mean Squared Error
SBIC	Schwarz-Bayes Information Criteria
SRC	Survey Research Centre
SUR	Seemingly Unrelated Regression
USA	United States of America
VAR	Vector Autoregression
VMA	Vector Moving Average

1. Introduction

"*Predicting the future is a tricky business*."

Arturo Estrella and Frederic Mishkin (1998)

Confidence indicators seem to be "*the sort of economics anyone can grasp*" (BBC News Online, 2001). Not surprisingly, they have experienced a great deal of attention from both economic analysts and popular business press worldwide. Although confidence indices are broadly used in the context of current economic situation appraisal or future perspectives estimation, their forecasting abilities are still considered as a matter of dispute.

There are two types of confidence measures – the customer confidence indicator and the business confidence indicator. Both are results of regular surveys based on responses of either customers or business agents to their own (or their business) current economic situation evaluation and future perspectives or expectations. Because both confidence indicators include a forward-looking part - personal or business prospects - it is logically questioned whether this information could be used on the aggregate level for macroeconomic forecasting.

Earlier availability of confidence indicators compared to long publication delay of standard macroeconomic variables like gross domestic product (GDP) determines them to be useful instruments not only for economic forecasting but also for models of the current state of the economy, sometimes called nowcasting. Moreover, they could be even potentially used for an early detection of business cycle turning points. All these possible capabilities of confidence indicators are clearly important to policy makers and market participants.

The motivation of this thesis is to shed light on two potential abilities of confidence indicators: GDP value forecasting and business cycle turning point detection. Our research is purely atheoretical; except for two theoretical concepts briefly mentioned in the literature review, all the results and contributions are solely based on the empirical research. Confidence indicators from the Czech Republic and their role in macroeconomic modelling is examined, as they have never been subject to empirical analysis in such an extent, unlike the other confidence indicators from various developed countries. Furthermore, we examine predictive abilities of both Czech customer and business confidence indicators and because the business index has been globally subject to less empirical scrutiny (based on published results), we also compare their performance, which (altogether with Czech data analysis) differentiates us from previous research.

The first part of our empirical analysis focuses on the prediction of the likelihood of economic downturn (defined as a discrete event); a logistic model is applied for turning points modelling. The aim of this approach is to reveal whether the low value of confidence indicators can signalize oncoming economic downturn and how early such a signal could be detected. The second part evaluates predictive power of confidence indicators in the framework of vector autoregression models. Quantitative GDP forecasts from models enhanced by confidence indicators are compared with benchmark models and additional improvement is assessed. The principal criterion of predictive accuracy is set to the out-of-sample performance, i.e. forecast accuracy for the period which follows the initial period used for model estimation. The underlying idea is that unlike in-sample performance that could be always improved by including additional variables to the model, out-of-sample forecasts are not necessarily better, as our results will show.

The thesis is organized as follows. The next chapter provides a review of recent literature with a short historical excursion. Chapter 3 describes the construction of confidence indicators altogether with initial assessment of their leading properties. Methodological background for the empirical models is introduced in chapter 4 and our empirical research follows in chapter 5. Chapter 6 concludes the thesis.

2. Related literature

Twenty years ago, in coincidence with the fortieth birthday of the Michigan index of consumer sentiment, the first index measuring customer confidence, Curtin (1992, p. 22) wrote: "*Consumer sentiment is now the most closely watched and intensely debated indicator of future economic trends*". Ten years ago, on its fiftieth birthday, Gollineli & Parigi (2004, pp. 149) quoted Curtin's statement and wrote "*this statement is still all the more valid and is the central topic of the debate on the usefulness of sentiment indices.*" It is now 2012, the sixties birthday of the consumer sentiment index and we can quote these authors again because the debate is still ongoing. Rich evidence on links between confidence indicators and economic output is available; we provide only selected articles in this chapter. However, an extensive meta-analysis would be necessary for an objective literature, which is behind the scope of this thesis.

2.1 Historical contributions

Preliminary attempts to evaluate the predictive power of confidence indicators date to the second half of the twentieth century and are associated with the academic debate about the usefulness of the first confidence indicator. The research began after the U.S. FED presented its final report on usefulness of U.S. consumer sentiment survey data in anticipating consumption behaviour with broadly negative conclusions (Gollineli & Parigi, 2004 from FED, 1955).

This conclusion was deeply contested by George Katona who designed the first U.S. sentiment index. In Katona (1957) he criticizes the committee's focus on evaluating the predictive abilities of the survey data on an individual level and also the committee's call for re-interviewing individual respondents and subsequent validation of fulfillment of their expectations. To the contrary, Katona argues for assessing predictive power on the aggregate level and against reinterview tests as he considers consecutive surveys with different representative samples to be more satisfactory: "*... aggregative tests may contribute to the understanding of consumer behavior and may indicate that expectations and intentions are relevant and useful, even if a reinterview test is not conclusive.*" (Katona, 1957, pp. 44). Furthermore he emphasizes the importance of surveys of consumer attitudes in revealing turning points in aggregate consumer demand rather than the continuation of prevailing trends.

Tobin (1959) and Okun (1960) contribute largely to the subsequent debate. Tobin (1959, pp. 1) defends the committee's opinion: "*I do not see how the predictive value of these data can be adequately appraised without confronting the attitudes and intentions of individual households with the record of their subsequent behavior*." To support this opinion he carries out a microscopic study of the correlations between attitudes of interviewed households and their subsequent economic behaviour. Tobin (1959, pp. 1) is not afraid to claim: "*The relevance of such a test to the general question of the predictive value of consumer attitude and intentions seems to me self-evident*." and concludes that buying intentions (answers to survey questions regarding planned purchases) have predictive values, while other attitudinal questions do not.

Okun (1960) follows Tobin's ideas and although the name of his paper is *Value of anticipations data in forecasting national product*, he in fact tries to predict only some parts of the gross national product (GNP), among others expenditures on cars with a positive predictive value of consumer survey data and expenditures on durable goods with a negative predictive value. Okun (1960, pp. 427) comments that "*... divergent results cannot yield any conclusive findings ... However cross-section results are relevant and these point uniformly toward a negative evaluation of consumer anticipations data other than plans to buy*."

However, with incoming computer technologies and development of advanced econometric methods, the research of confidence indicators became more extensive. We shall therefore only focus on selected articles published since nineties onwards.

2.2 Key paper by Matsusaka and Sbordone

The paper *Consumer confidence and economic fluctuations* by Matsusaka & Sbordone (1995) could be considered as a pioneer contribution to the field of modern confidence indices research. Since its publication this article has been cited by the majority of researchers examining confidence indicators. Matsusaka and Sbordone are also the first economists who investigated the link between consumer confidence and economic fluctuations using vector autoregression. Part of our empirical research is also inspired by their proposed methodology.

Matsusaka and Sbordone empirically address the relationship between the questioned U.S. index of consumer sentiment and GNP development and found robust evidence that, controlling for effects of other variables, consumer sentiment causes (in the Granger sense[1]) GNP fluctuations. Furthermore, their reported variance decompositions suggest that consumer sentiment accounts for between 13% and 26% of the innovation variance of GNP (depends on model specifications and the ordering of variables).

Moreover, their contribution to that time state of knowledge is exceptional because, apart from other succeeding researchers, they also present a theoretical rationalization for the confidence-GNP causality. This theoretical framework covers multiple (Nash) equilibria models with strategic complementarities.[2] In their multiple equilibria model the output responds to economic fundamentals, but additionally, there can be fluctuations in economic activity as economy shifts between equilibria. This shift is caused by the change in customer sentiment and as Matsusaka & Sbordone (1995, pp. 297) aptly sum up "*if people expect bad times they get them*".

2.3 Cause and consequence

The idea of cause and consequence of consumer confidence and economic output is difficult to disentangle. However, some economists tried to untie this Gordian knot using rationalizations based on economic theory. Potter (1999) provides an alternative theoretical justification for a causal link between confidence and output than Matsusaka & Sbordone (1995). He examines asymmetries over the business cycle during the Great Depression and develops a rational expectations model which reveals that asymmetries are driven by fluctuations in the confidence of investors. Moreover he discusses the role of government during that period and argues that the inept

[1] For the explanation see subchapter 4.2.9 Granger causality.

[2] A game theory term: "Roughly speaking, a model contains strategic complementarities if each agent's optimal action is positively correlated with the action of other agents." (Matsusaka & Sbordone, 1995, pp. 296)

government interventions during the Great Depression which reduced the confidence of investors are the most likely explanation.

Unlike using the rational-expectations model, Chauvet & Guo (2003) empirically verify the interrelations between waves of optimism and pessimism and subsequent fluctuations in economic output in the framework of multiple-equilibria models. They split confidence indicators into fundamental and non-fundamental parts and examine the behaviour of non-fundamental movements as a proxy for consumers' *sunspots* (in case of customer confidence) and investors' *animal spirits* (for business confidence).[3] They reveal that even when the economic fundamentals were strong, a wave of pessimism occurred before various U.S. downturns and played a nontrivial role in deepening economic recessions.

Another stream of research tries to empirically explain determinants of consumer confidence. Their results prove that consumer confidence should not be considered as a completely exogenous variable. Vuchelen (2004) analyses Belgian data and empirically explains about one half of consumer confidence variance using variables representing expected economic conditions (expected income) and uncertainty. Author proxies these variables by the consensus of the forecasted real rate of economic growth and by a measure of the degree of disagreement between forecasters.

In contrast, Ramalho et al. (2011) do not prove any significant link between consumer confidence in Portugal and the major indicators of economic performance in the long-run. However, they find evidence for the short-run relationship between consumer confidence and economic performance, the entrance in the Euro zone and electoral circumstances. Especially the last variable which is related to election dates is interesting and proves that not only economic conditions but also the political situation affects confidence of consumers.[4]

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[3] The term *sunspot* is widely used in literature on the multiple-equilibria model. Both *sunspots* and Keynes' famous *animal spirits* refer to innovations or shocks that are not related to economic fundamentals such as technology and preferences. For more information about links between confidence and sunspots see Harrison (2005).

[4] Further evidence on this topic is provided by Hardouvelis & Thomakos (2007) who revealed interesting finding that consumer confidence increase before dates of elections and falls subsequently both in EU-15 countries and in the U.S.

Furthermore, recent research made by Duch & Kellstedt (2012) indicates that since the world economy has become closely interdependent, even consumer confidence variance is interconnected as they proved on a case of Canada, France, Germany, and the UK. Some part of the confidence index variance still stays unique for each country. This topic was previously examined by Lemmens et al. (2007) with similar conclusions: short-term fluctuations in consumer confidence are country specific, but with longer horizon become much more homogenous and this homogeneity is inversely related to the economic and cultural distance for European countries.

2.4 Literature concerning the predictive power

Majority of the published articles which aimed to evaluate the predictive content of confidence indicators reports improvement in real GDP forecasts by adding some confidence indicator to benchmark GDP models. Researchers use rich variety of empirical methods for their analyses; a purely atheoretical approach assessing the predictive power is common to all of them.

2.4.1 Evidence of forecasts improvement

Howrey (2001) empirically examines the U.S. consumer sentiment index over the long period 1962-2000 and finds evidence for short-term GDP forecasts improvement compared to the forecasts based on the autoregressive process. However, Howrey does not take the advantage of such a long time series and based his conclusions on models that were estimated over the entire sample period. Nowadays, out-of-sample evaluation of the predictive power is preferred, as will be discusses in the methodological part.

Mourougane & Roma (2003) use a similar methodology for investigation of the role of confidence indicators on the European ground. They compare a model enhanced by customer confidence with a benchmark ARIMA model. On the contrary to Howrey (2001), they apply out-of-sample evaluation criteria, namely mean square forecasting error comparison. Their results also robustly confirmed the usefulness of confidence indicators for short-term GDP forecasting in Belgium, Germany, France, Italy and the Netherlands.

Golinelli & Parigi (2004) conducted the broadest research both in terms of countries involved and methodology used. They examined indicators from developed countries all over the world and used both in-sample and out-of-sample analysis in the framework of vector autoregression models (VAR). Their findings robustly confirm the predictive power of customer confidence as a leading or coincident GDP indicator, depending on country: leading in Australia, Canada and examined European countries, coincident in the USA and Japan.

Research made by Taylor & McNabb (2007) methodologically differs from others. Apart from standard VAR forecasts they define economic downturns as discrete events and model probability of future downturn occurrence, firstly with potential leading indicators and then they also include confidence indicators. They conclude that for examined Western European countries either the customer confidence or the business confidence indicator add additional predictive power to the model and therefore could be considered as significant in predicting downturns (based on in-sample evaluation). Their atypical method inspired the first part of our empirical research.

Usage of both types of confidence indicators, business and consumer, in assessing predictive content is rare; economists in most cases focus only on consumer confidence. We can only speculate about reasons for that, maybe because of stronger historical traditions. However, even business confidence indicators may show predictive power, as was proved for example by Santero & Westerlund (1996). In their research the business confidence index even significantly outperforms the customer index.

2.4.2 Evidence against forecast improvement

Finding evidence (in recent literature) against predictive power of confidence indicators is much more difficult. Still, we should avoid imposing premature conclusions like “all researchers confirm predictive ability of confidence”, because we have to consider possible publication bias, i.e. higher chance that research with significant results confirming predictive power will be published. Since we do not have evidence of articles refused by economic journals, we cannot rigorously assess the share of evidence pro and con forecast improvement.

Instead, we look more carefully on results of published papers, because sometimes when authors conclude that they proved predictive power of indicators, it is true only partially - for some models or some countries and the opposite is true for the rest. This stands for example for Mourougane & Roma (2003) who did not confirm improvement in forecasts using confidence index in Spain, Golinelli & Parigi (2004), whose out-of-sample forecasts for Japan were worse after adding confidence or Taylor & McNabb (2007) who fit a large number of models, conclude positively, but in 30 cases out of 63 some confidence indicators were not significant predictors of an economic downturn.

However, some articles with negative results are available. Batchelor & Dua (1998) objectively report that customer confidence would have been helpful in predicting 1991 recession in the USA, but the results do not generalize to other years. Al-Eyd et al. (2009) find the predictive role of confidence indicators for future consumption in the U.S. to be rather weak.[5]

2.4.3 GDP nowcasting and leading indicators

Some relatively new articles are dedicated to recent phenomena called GDP *nowcasting.* Nowcasting refers to forecasting current economic situation, i.e. computing early estimates of current quarter GDP. Nowcasting is necessary because GDP estimates are published only quarterly and with more than six weeks of delay[6] after the end of the particular quarter. Confidence indices are especially appropriate for GDP nowcasting, as they are published regularly on a monthly basis, are available at the end of the particular month and unlike GDP they are not revised afterwards. Evidence on the use of VAR models with confidence indicators for GDP nowcasting can be found for example in Giannone et al. (2009).

Furthermore, there is literature examining the role of leading indicators for GDP nowcasting or short-term GDP forecasting. Another methodology is typically used: large datasets including confidence indicators are employed and various factor models

[5] Other evidence of the use of confidence indicators for consumption forecasting is not discussed, as it is not aim of this thesis. However, positive results could be found for example in Ludvigson (2004).
[6] Source: Angelini et al. (2011)

are used to deliver more precise estimates of the current GDP. The forecasting (nowcasting) power is typically not assessed for individual variables, but for a model as a whole. A typical example is Angelini et al. (2011).

2.4.4 Evidence from the Czech Republic

Finally, review of evidence regarding Czech data remains. Let's digress from the topic at first. Lubomír Mlčoch (2006) in his book *Economics of trust and common good* concerns confidence from the institutional point of view. He specifies the meaning of *confidence* as agents' beliefs in the development of the economy as a whole.

The empirical evidence purely on Czech confidence indicators abilities is limited. In fact, we know only about two authors who examined this issue: Fišer (2010) and Horváth (2012). Fišer (2010) assesses (among others) the link between Czech confidence indicators and Czech GDP using Granger causality in a VAR model. His results regarding Granger causality going from consumer confidence to GDP are ambiguous: causality is proved only for some models. Interestingly, causality from GDP to consumer confidence has been robustly proved as significant.

Contribution of Horváth (2012) is more relevant for our research. In fact one of our empirical parts is based on the Horváth's empirical model and its evaluation. Horváth (2012) examines whether Czech confidence indicators (either customer or business) improve short-term Czech GDP growth forecasts. The evaluation is done by comparison of out-of-sample mean squares forecast errors from a benchmark model and enhanced models. His analysis reveals contemporaneous correlation of confidence indicators and real GDP growth, but the models enhanced by confidence indicators fail to improve GDP forecasts compared to the benchmark VAR model. On the contrary, he proves that adding credit growth significantly improves GDP forecasts.

The stream of Czech literature regarding short-term forecasting of GDP using composite leading indicators, which often consists of confidence indicators, is much richer; however their forecasting results slightly differ. Czesaný and Jeřábková (2009) construct leading, coincident, and lagging composite indicators for the Czech Republic. Confidence indicators are not part of any proposed composite index, but the authors recommend considering incorporation of the Czech composite confidence indicator (composed of both business and customer confidence by the Czech Statistical Office, CZSO) to the coincident composite indicator.

Pošta and Valenta (2011) construct two composite leading indicators with three months and five months leads. Both leading indicators are solely based on the CZSO business confidence indicator; the one with the lead of three months contains information from all business sectors and the one with the lead of five months is based on confidence from the industry sector only. They conclude that both indicators show ability to predict the key turning points in the economic cycle and exhibit high correlation with the relative cyclical component of GDP.

Arnoštová et al. (2011) used CZSO confidence indicators (business, customer and composite) as three of many other monthly series incorporated (using different methods) into six models designed to forecast GDP. Authors consider as the most successful model the model compiled of standard principal components of all monthly series. The forecast accuracy of this model is the best up to three quarters ahead.

Svatoň (2011) constructs leading indicators for the Czech GDP with six months, five months, four months, and three months (respectively) leads. The five months leading indicator contains among others the CZSO business confidence indicator (part from industry confidence) and four and three months leading indicators consist of the composite confidence indicator among others. Compared to Arnoštová et al. (2011) he reports one-quarter-ahead GDP forecasts to be most accurate.

3. Confidence and leading indicators

This chapter familiarises readers with the concept of measuring confidence and outlines the tough beginnings when confidence (or sentiment) indicators were considered useless in contrast to today's time when confidence surveys "*are an important part of the information system used at EU level to monitor economic trends and belong to the priorities for the area of macroeconomic statistics*" (Czech Statistical Office official web page).[7]

Description of confidence indicators construction follows; sources for this part are mostly official methodological web pages of the OECD database and the Czech Statistical Office (CZSO).[8] General properties of economic indicators are introduced and initial exploratory analysis of confidence indicators is consecutively carried out and discussed.

3.1 Brief history of measuring confidence

"*The index of economic sentiment appeared on the economic scene almost by chance*." That is how Golinelli & Parigi (2004, pp. 149) describe the beginnings of confidence measurement. It was in the USA, 1946 and the University of Michigan initialized the economic behavior research, as a part of the post-World War II recovery program. The aim of this research was to reveal how the expectations of consumers form their spending and savings. This task was assigned to George Katona, a Hungarian-born American psychologist and economist at the Survey Research Centre (SRC) and the research was originally funded by the Federal Reserve Board.

As Curtin (2007a) states, Katona's confidence measure was firstly designed to measure the expected changes in income and he named it "consumer confidence indicator". Later, it covered both the expected level and the expected variance of income and Katona rename the index to "consumer sentiment". Since 1952 the index was published regularly on a monthly basis.

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[7] http://www.czso.cz/eng/redakce.nsf/i/business_cycle_surveys
[8] http://stats.oecd.org/ and select Composite Leading indicators – Information; and http://www.czso.cz/eng/redakce.nsf/i/business_cycle_surveys.

In 1955, the Board of Governors appointed a committee (so called Smithies Committee) to evaluate whether the survey's data about consumption behavior are valid. The committee's negative conclusion about usefulness of this survey was deeply contested by Katona (1957, pp. 40): "*Two of the reports contain extensive discussions of survey statistics which call for some comment.*" The debate that followed in the fifties and sixties even more strengthened the general opinion that the survey is useless on the aggregate level. See for example Tobin (1959, pp. 3): "*If Katona believes he has observed that changes in an attitudinal index lead changes in expenditures on durable goods, he has not based this belief on any rigorous statistical test*." Regardless of the negative opinion of mainstream economists the SRC continued to collect data and publish the customer confidence index (up to the present).

Over the years, the opinion on confidence surveys changed and more countries started to measure their own confidence (sentiment) indices. Nowadays, consumer confidence surveys based on Katona's methodology are regularly conducted in at least forty-five countries (Curtin, 2007b) and moreover, the procedure of conducting the surveys and transformations into numeric values has been for many countries harmonized under the patronage of OECD. The harmonization is strongest in the EU; it started even before the EU was established, in January 1985 (for 9 EU countries, while the rest were gradually incorporated up to present).[9]

Although the surveys for all EU Members are still carried out on the national level by local offices, they are now managed by the European Commission. The OECD reports that customer and business confidence indicators in the EU are fully comparable across these countries.[10]

The Czech Republic started to measure business confidence relatively early, in 1993. On the other hand, the poll for customer confidence was not carried out until

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[9] The exact starting dates of availability are as follows: January 1985 for Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Netherlands and UK; January 1986 for Spain and Portugal; November of 1987 for Finland and since nineties also Austria and Sweden, Luxemburg and then the new EU members. Source Hardouvelis & Thomakos (2007)

[10] For more information see http://stats.oecd.org/index.aspx?queryid=306 and look for Information

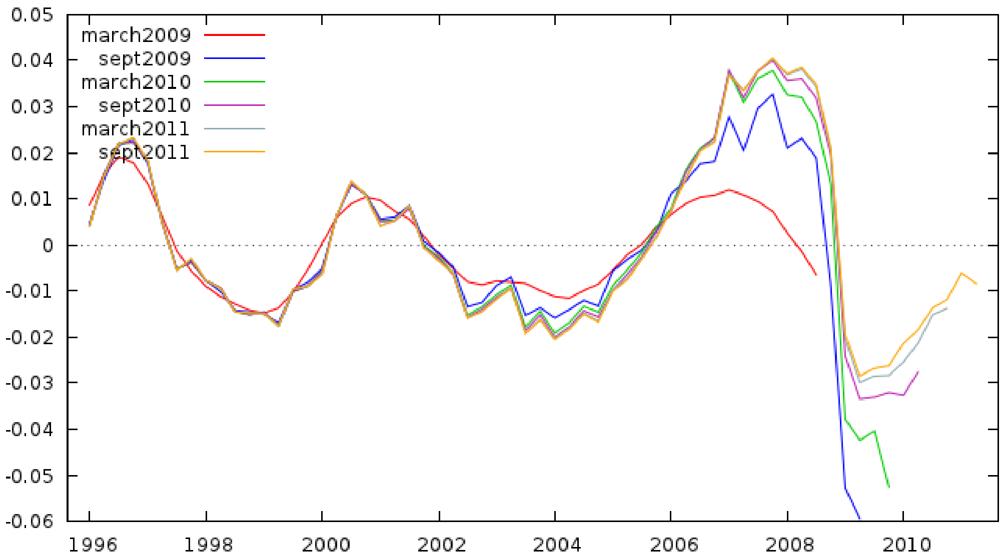
1998. In 2002, the sector of services was added to the business confidence indicator and after some adjustments along the EU lines in 2010, the methodology of indices compilation stays the same up to now.

3.2 Czech confidence indicators compilation

There are three types of confidence indices in the Czech Republic: the business confidence indicator (BCI), the customer confidence indicator (CCI) and the composite confidence indicator, which is a combination of the first two. Because we want not only to assess the predictive power of both business and customer indicators, but also examine the different forecasting properties of these two, we will not use the composite indicator as it does not carry any additional information apart from that contained in BCI and CCI.

Confidence surveys are completed by the Czech Statistical Office and the poll for customer confidence is organised in co-operation with a specialized market research company, Gfk-Praha. Results are published regularly on a monthly basis, usually within the last week of the corresponding month and there are no revisions afterwards. These two facts offer a great advantage over standard measures of economic activity like GDP, which is published only quarterly and with a significant delay and later is subject to significant revisions, see Figure 3.1

Figure 3.1: Revisions matter - GDP gap estimates using Hodrick-Prescott filter



Source: *Baxa (2011)*

3.2.1 The customer confidence indicator by CZSO

The survey is based on a representative random sample of respondents from the whole Czech Republic aged 15-79 years. Every month, the sample of 1000 respondents is created using the telephone register and respondents are contacted via the telephone. The response rate is 33%.

The questionnaire is designed to reveal expectations of respondents about the period of next 12 months. Customers answer four questions regarding:

1. *expected financial situation*
2. *expected overall economic situation*
3. *expected total unemployment* (negative relation)
4. *expected savings*

Respondents are not asked to provide quantitative estimates, but only simple qualitative information. There are six possible answers: *much better*, *slightly better*, *will remain unchanged*, *slightly worse*, *much worse*, *don´t know*.

Answers of "*much better*" and "*much worse*" are assigned double the weight of "*slightly better/worse*". The variant "*will remain unchanged*" and "*don´t know*" have zero weight. The balance is an aggregate characteristic which converts qualitative answers of consumers into quantitative ones.

3.2.2 The business confidence indicator by CZSO

The poll on business confidence reflects opinions of entrepreneurs and company managers regarding expectations in their particular business area. The random sample consists of companies from four sectors: construction (600 enterprises), industry (1100 enterprises), retail trade (600 enterprises) and services (900 enterprises).

The sample is selected using the public phone register and are stratified on the size of the enterprise and sector. The sector coverage in construction and manufacturing represents at least a half of total turnover in the sector and at least one third of total turnover in retail trade and services.[11]

The questions are answered by mail, telephone or email. The questionnaire is designed so that it could be quickly completed by company management - the business respondents choose only from three answers: *increase*, *do not change* or *decrease.* It includes questions on current and expected trends in their business. The questions are specific for each sector:

1. industry: *demand for products, inventory of finished goods* (negative relation), *expected development of production*
2. construction: *total demand*, *expected employment*
3. retail trade: *current economic situation, current level of inventories, expected development of economic situation*
4. services: *current economic situation, demand for services, expected development of demand services*

The confidence indicator for each sector is constructed as an average of seasonally adjusted weighted "business cycle balance" ("konjunkturální saldo" in Czech). This balance is a difference between responses *increase* (+) and *decrease* (-) expressed in percents. The data are weighted: in industry, trade and services the weights are revenues and in the sector of construction the weight is the building production. (For questions regarding employment the weight is the average number of employees.) Finally, the business confidence indicator is a weighted average of seasonally adjusted confidence indicators for all surveyed sectors.

3.2.3 Confidence indicators by OECD

Because the confidence indices have been recognized as an important part of the EU information system used to monitor economic trends, the methodology of national surveys has been harmonized by the European Commission under the patronage of

[11] The survey covers 55% of total employment and 55% of total turnover in the construction sector. In the manufacturing sector it is 55% of total employment and 65% of total turnover. The coverage of the retail sector is 25% of total employment and 33% of total turnover. The survey covers 27% of total employment and 43% of total turnover in the services sector.

OECD. The OECD database now covers confidence indicators from 36 countries all over the world and 6 blocks of countries (for example G7, Major Five Asia or Euro area). CZSO provides the data to OECD database as well; the OECD and CZSO time series slightly differ due to the different method of seasonal adjustment and standardization.

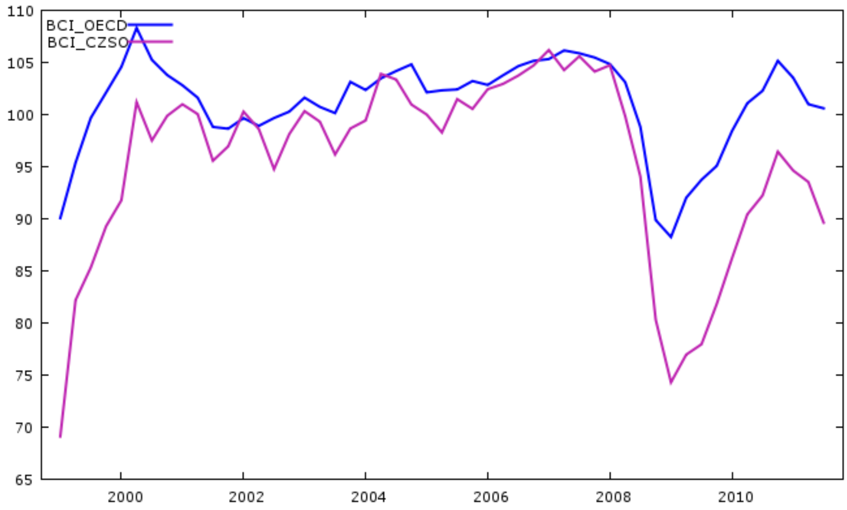
The main advantage of the standardised OECD business and customer confidence indicators is that they are comparable across countries. Comparability has been achieved by survey harmonization, and also by smoothing, centring, and amplitude adjusting of these series.[12] The OECD has decided to fix 100 as the mean of the OECD standardised BCI and CCI. Therefore 100 represent the long-term average, or normal situation, and is not attached to a specific base year, on the contrary to the CZSO methodology, where the base year 2005=100.

The resulting OECD and CZSO time series of BCI and CCI are plotted, in Figure 3.2 and Figure 3.3 we can see that both pairs of time series are comparable; they differ mostly in smoothness and scale. The coefficient of correlation for BCI by CZSO and OECD is 0.87 and for the two CCI time series is even 0.98.

Because both OECD and CZSO confidence time series are results of surveys carried out by CZSO and differs only in adjustments and standardizations, which was confirmed by very strong correlation between them, we have the possibility to choose only one of them for our empirical analysis. We decided to enable easier comparison of our empirical results within other countries and therefore we use only OECD BCI and CCI series for our analysis. Since now by using “BCI” and “CCI” we refer to confidence indicators from the OECD database.

[12] From June 2010, the series are smoothed using the Hodrick-Prescott (HP) filter, with cycles shorter than six months removed (λ=1). Furthermore, the series are normalised by subtracting the mean of the series and then dividing this difference by the standard deviation of the series. After normalisation, they are amplitude-adjusted to the detrended indices of GDP, used as proxy measures of the business cycle, and finally centred around 100. For more information see the document available at http://www.oecd.org/dataoecd/3/22/45430429.pdf

Figure 3.2: Comparison of BCI by OECD and CZSO



Source*: own calculations in the Gretl*[13] *software*

Figure 3.3: Comparison of CCI by OECD and CZSO

Source: *own calculations in the Gretl software*

3.3 Economic indicators

We shall (seemingly) digress from the topic of confidence indicators now and devote following paragraphs to *economic indicators*. Generally speaking, an economic indicator is any economic statistic which indicates state of the economy, for example unemployment rate, industrial production or stock market prices. Each economic

[13] Gretl is an open-source free statistical software available at http://gretl.sourceforge.net/.

indicator purveys specific information and they differ in three important attributes: frequency of the data, relation to business cycle and timing.

Frequency of the data reflects how often figures are released. GDP, one of the most important indicators of the economic activity is published quarterly, while many others indicators are released monthly. Some financial indicators such as interest rates are available on a daily basis and for example the Dow Jones Index is changing every minute. It is important for our hypothesis regarding predictive power of confidence indicators, that confidence indicators are released at the end of the corresponding month, so they may immediately reflect the changes in the economic situation unlike GDP with its quarterly frequency and long publication delay.

According to the relation to the business cycle we divide economic indicators into three categories: *procyclical* (positive correlation with the economic situation or the reference variable), *countercyclical* (negative correlation with the economic situation or the reference variable) and *acyclical* (no relationship). As will be graphically shown soon, confidence indicators clearly belong to the family of procyclical indicators with GDP as a reference series.

Finally, timing of economic indicators is the most important attribute for our research. We recognize three types of indicators: *lagging*, *coincident* and *leading indicators* and this classification reflects the timing of their changes relative to the economic development, which is in this thesis represented and measured by GDP. In this respect, *lagging indicators* are those which change after (with some delay) GDP changes or in other words their current value is related to a past GDP value (GDP lag). A lagging indicator is for example the unemployment rate. *Coincident indicators* move together with GDP development, the example is the index of industrial production. The most interesting regarding our research are *leading indicators* which change before the economy does. In other words they lead the GDP development – signalize oncoming changes. Leading economic indicators are the most important type for policy makers or investors as they help to predict what the economy will be like in the future. Typical examples of leading indicators are stock market returns as the stock market usually begins to decline before the economy declines. Havránek et al. (2011) confirmed leading properties of various financial variables with respect to the Czech GDP.

If we want to examine the leading properties of confidence indicators with respect to the Czech GDP, it will be useful to compare their predictive power with some other leading indicator. For this purpose we choose the only publicly available indicator designed to be the eligible leading indicator for the Czech economy: the *OECD Composite Leading Indicator* for the Czech Republic (instead of "CLI" we will use comprehensible abbreviation "LEAD" for this indicator).

3.3.1 The OECD Composite Leading Indicator

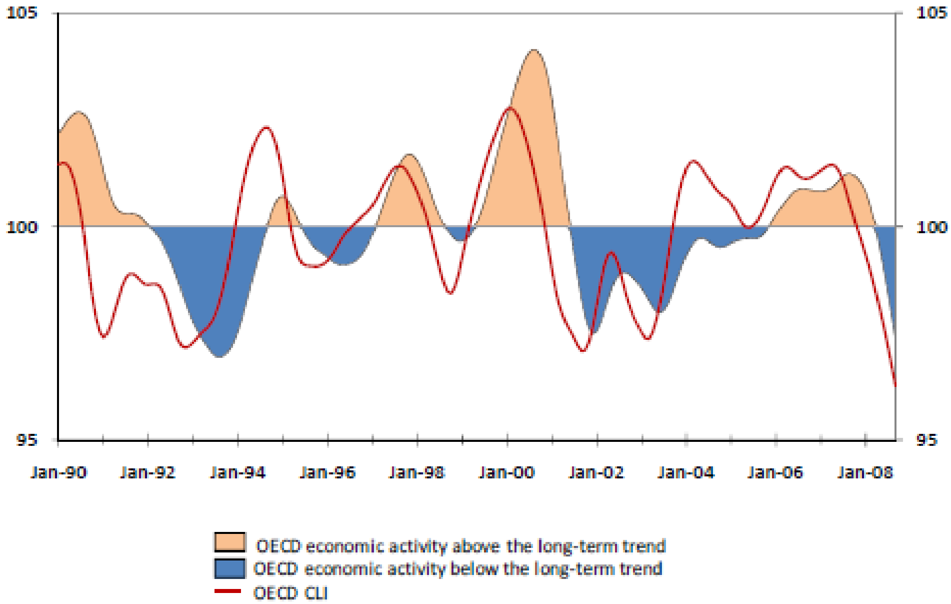
"*The OECD system of composite leading indicators was developed in the 1970's to give early signals of turning points of economic activity. This information is of prime importance for economists, businesses and policy makers to enable timely analysis of the current and short-term economic situation*." (OECD official materials by Gyomai & Guidetti, 2008, pp. 3)

The composite leading indicator is a time series composed[14] (as its name suggests) of variety of economic indicators which, as defined by OECD, "exhibit leading relationship with the reference series at turning points." Industrial production (IIP) up to March 2012 was used as a reference series, since then GDP is the reference series.[15] LEAD is designed to provide qualitative information, especially at the turning points, rather than quantitative estimates. OECD states that turning points in the detrended reference series have been found about 4 to 8 months after the signals of turning points have been detected by LEAD. Figure 3.4 nicely illustrates its leading properties for the OECD area.

[14] The methodology of LEAD composition is complicated and is not discussed here. We recommend the readers interested in details to go through *The OECD Handbook on constructing composite indicators: methodology and user guide*, which is available online at http://www.oecd.org/dataoecd/37/42/42495745.pdf

[15] For reasons and details about this change see www.oecd.org/dataoecd/35/27/49985449.pdf

Figure 3.4: OECD area Composite Leading Indicator and economic activity (long-term trend = 100)



Source*: OECD documents (Gyomai & Guidetti, 2008)*

For the examined period 1999 – 2010[16] the composite leading indicator for the Czech Republic contained the following component series:

1. *finished goods stocks in manufacturing* (% balance)
2. *selling prices in manufacturing: future tendency* (% balance)
3. *consumer prices: future tendency* (%)
4. *share price index PX-50* (2000=100)
5. *total retail sales* (volume, 2000=100)
6. *monetary aggregate M2* (CZK)

The fact that during the desired period LEAD did not consist of either the business confidence indicator or the customer confidence indicator gives us great possibilities for our empirical analysis. We will use the composite leading indicator not only for comparison purposes but also we will include both LEAD and BCI (or CCI) to one GDP model and evaluate the additional predictive power carried by BCI (or CCI) above information contained in the leading indicator. The changes in LEAD composition for the Czech Republic introduced in April 2012 will be provided in the

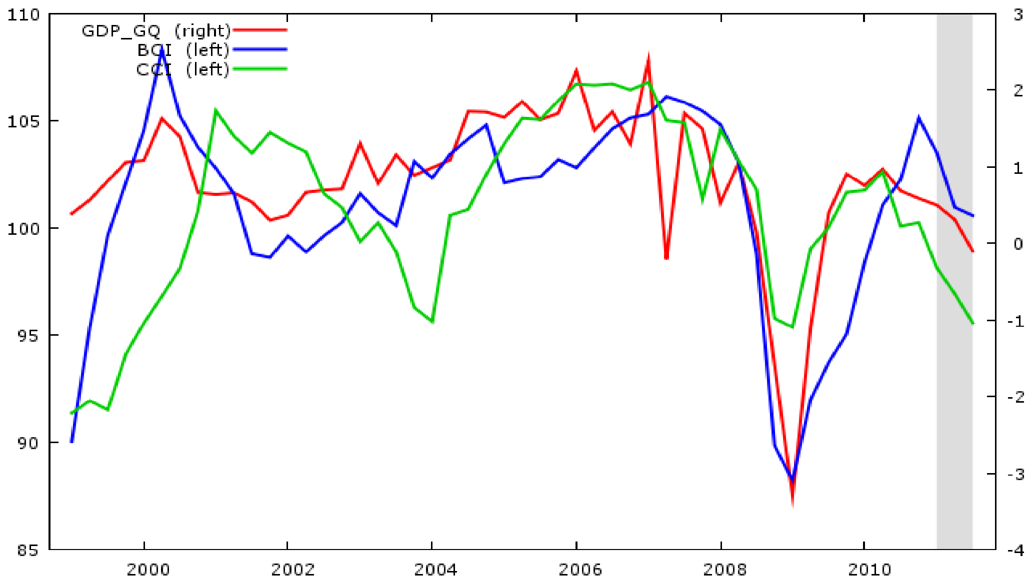
[16] The period 1999-2010 is used for our empirical analysis.

conclusion. However, firstly we have to investigate whether Czech confidence indicators could be considered as leading indicators at all.

3.4 GDP and leading properties of confidence indicators

The simplest way how to examine leading properties of Czech confidence indicators regarding GDP is to compare time series plots and apply descriptive statistics like cross-correlations of confidence indicators and GDP. Data used for empirical analysis will be described in detail in section 5.1; A sufficient information for this exploratory analysis is that we compare data for the Czech Republic: BCI, CCI, LEAD and quarterly GDP growth for the period 1999-2010.

Figure 3.5: BCI, CCI and GDP growth time series



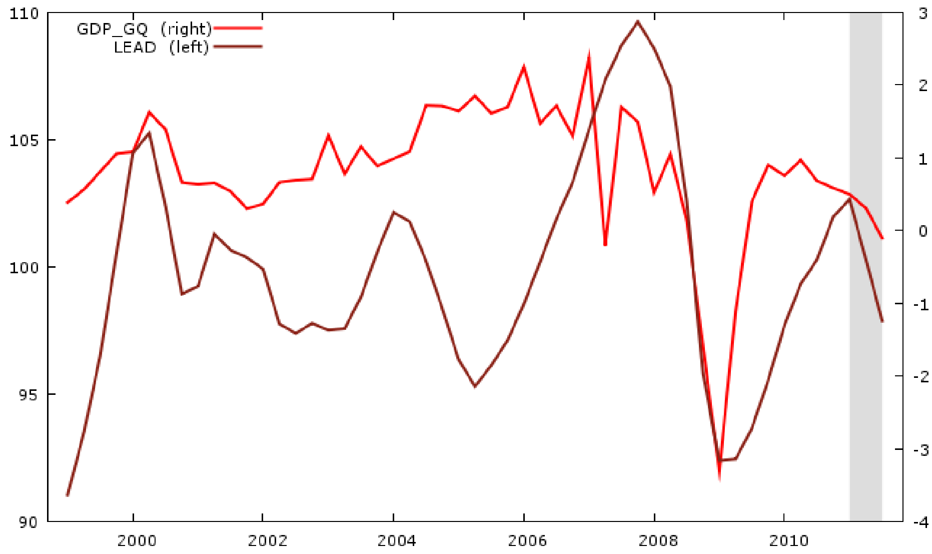
Source: *own calculations in the Gretl software*

Confidence indicators are plotted together with GDP growth in Figure 3.5. The values of both business and customer confidence indicators seem to reflect the economic conditions: low values in 1999 followed by sharp growth and consecutive decline at the beginning of millennium, CIs steady growth in mid-2000s corresponds to solid economic growth experienced in that period. Oncoming depression was foreshadowed by BCI development, which started to slightly decline already in Q2 2007 and significantly fall after Q2 2008. CCI descent started in Q2 2008 as well, still one quarter before a sharp GDP growth fall to red numbers which occurred after Q3 2008.

On the contrary the period of recovery lasted longer for BCI then for GDP. The last development is interesting: business confidence is decreasing but it is still much more optimistic than customer confidence which is in Q3 2011 approximately at the same level as during the financial crisis. We can only speculate whether this lower value of the CCI compared to the BCI could be caused also by the political situation. During the period Q1 2011-Q3 2011 (period for out-of-sample forecasting, grey bar) GDP quarterly growth reached the zero value again.

When we look at Figure 3.6, we can see that the composite leading indicator poorly anticipates GDP development; however, before the depression LEAD sharply fell even before 2008 and correctly signalized the oncoming crisis.

Figure 3.6: LEAD and GDP growth time series



Source: *own calculations in the Gretl software*

Business confidence is slightly more volatile than customer confidence during 1999-2010 (BCI variance is about 14% higher than CCI). This could be interpreted as higher economic perceptiveness of business respondents. Table 3.1 reveals contemporaneous correlation among variables: All indicators are procyclical which means positive correlation with GDP growth. The business confidence indicator exhibits the highest coefficient of correlation with GDP (0.73) and there is even higher correlation between BCI and LEAD (0.76), which may foreshadow common leading properties. Surprisingly, CCI correlation coefficients with other variables are much lower (0.38 with GDP) and even BCI-CCI correlation is not strong (0.44).

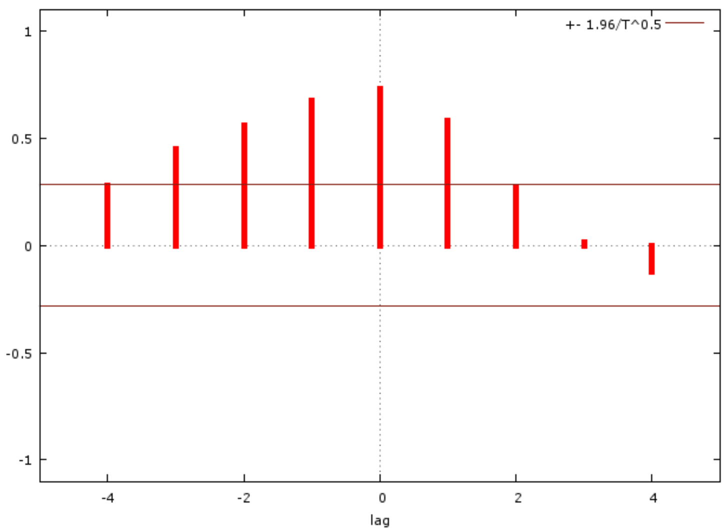
Table 3.1: Correlation matrix

	LEAD	CCI	BCI	GDP_GQ
GDP_GQ	0.3560	0.3848	0.7329	1.0000
BCI	0.7555	0.4418	1.0000	
CCI	0.3417	1.0000		
LEAD	1.0000			

However, cross-correlations of GDP with lagged indicator values which reveal whether GDP is more correlated with lagged, current or lead values of indicator variables are more interesting for our analysis. We define cross-correlations as $corr(GDPgrowth_t, indicator_{t+i})$ and informally assess the indicator as leading GDP growth if its correlations are significant for $i < 0$ (i.e. past values of the indicator are correlated with current GDP or in other time perspective current indicator values are correlated with future GDP values). Logically, the indicator is lagging if the opposite is true - correlations are stronger for $i > 0$ (i.e. significant right part of the cross-correlogram).

Figure 3.7 depicts cross-correlogram for GDP and BCI. Four lags (four past quarters) of BCI are significantly correlated with the current GDP growth value (compared to two significant i=1,2 "lags"), therefore we may consider BCI as a leading indicator. However, the contemporaneous correlation is still the strongest one.

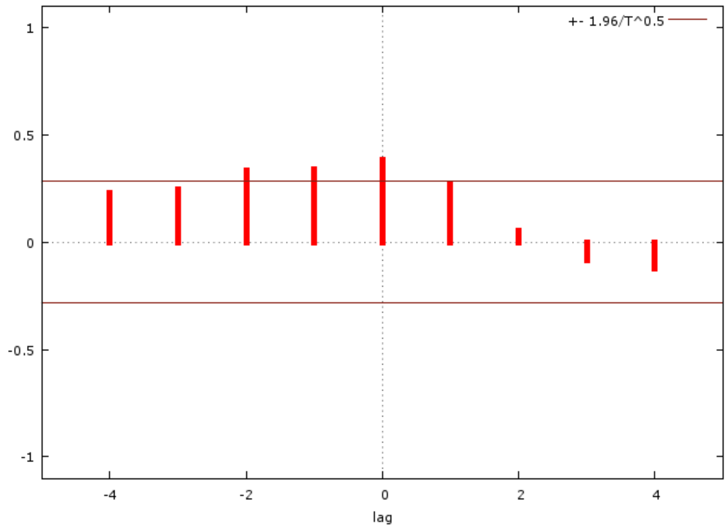
Figure 3.7: Correlations of GDP growth and lagged BCI



Source: *own calculations in the Gretl software*

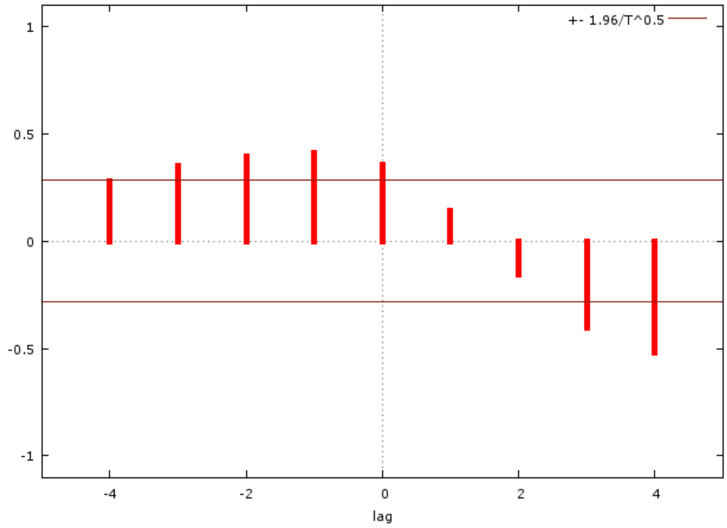
Cross-correlations for CCI and GDP growth are given in Figure 3.8. All cross-correlations are weaker in case of CCI compared to BCI, and only two past lags are significant, but leading attributes still predominate lagging attributes. Again, the strongest is contemporaneous correlation.

Figure 3.8: Correlations of GDP growth and lagged CCI



Source: *own calculations in the Gretl software*

Figure 3.9: Correlations of GDP growth and lagged LEAD



Source: *own calculations in the Gretl software*

Compared to confidence indicators' results, LEAD exhibits apart from leading properties also the ability to lag the GDP growth (Figure 3.9). Interestingly, the correlation of current GDP with future LEAD values is negative. This may signalize not the lagging attributes, but the cyclical structure of the composite leading indicator: it is designed to lead the cycle; therefore negative correlation reflects business cycle development from economic growth to decline.

This simple exploratory analysis confirmed that both confidence indices are contemporaneously correlated with reference GDP growth series and exhibit some leading patterns. For the business confidence indicator the evidence is stronger than for customer confidence indicator. Moreover, we identified cyclical properties of the composite leading indicator. However, the informal assessment of “leading patterns” is only an initial result of our analysis. Construction of formal models, forecasting exercises and predictive power evaluation follow.

4. Methodology

This chapter provides methodological background for the empirical models introduced in the next chapter. We use two methodological approaches for our analysis: logistic regression and vector autoregression. Following paragraphs describe each of them; more emphasis is placed on vector autoregression, as understanding of this comprehensive method is necessary for insight to the empirical analysis. Logistic regression is used in a more straightforward way, therefore only a description of key concepts follows.[17] The last section of this chapter is devoted to forecast evaluation methods. Readers having fair knowledge of logistic regression and vector autoregression are encouraged to skip these two sections to 4.3 Methods for forecasts evaluation, where standard procedures together with one recent concept are introduced.

4.1 Logistic regression

Logistic regression is a type of regression model used for predicting outcome of a dichotomous dependent variable, i.e. variable with only two possible values: 1 or 0, based on one or more predictor variables. Logistic regression is also called the *logistic model* or the *logit model*.[18]

4.1.1 Construction of the logit model

We define a latent variable y_i* which we cannot observe and which determines the value of y_i. What we observe is the value of y_i:

$$y_i = \begin{cases} 1 & \text{if } y_i* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.1}$$

We would like to model this relationship:

$$y_i* = X_i\beta + \varepsilon_i \tag{4.2}$$

[17] The detailed description of the logistic regression could be found in any standard econometric textbook, for example Maddala (2001).
[18] The logit model was firstly introduced by Joseph Berkson in 1944.

Because y_i* is an unobservable variable, we model y_i instead. The way how to model a binary response is to transfer $X\beta$ into a probability. We use a function F such that:

$$prob(y_i = 1) = F(X_i\beta) \qquad \textbf{(4.3)}$$

A natural choice of a function F that transforms $X\beta$ into a number between 0 and 1 is a distribution function or a cumulative density. Using standard normal distribution would lead to the probit model.[19] In the probit model we assume that ε in equation (4.2) follows standard normal distribution. In case of the logit model the logistic distribution Λ is used instead of the normal distribution:

$$P_i = prob(y_i = 1) = \Lambda(X_i\beta) = \frac{\exp(X_i\beta)}{1+\exp(X_i\beta)} \qquad \textbf{(4.4)}$$

Hence

$$\ln\frac{\Lambda(X_i\beta)}{1-\Lambda(X_i\beta)} = X_i\beta \qquad \textbf{(4.5)}$$

And

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \sum_{j=1}^{k}\beta_j x_{ij} \qquad \textbf{(4.6)}$$

where $\frac{P_i}{1-P_i}$ is called the *odds ratio*. The log-odds ratio is a linear function of explanatory variables. We can also compute the odds ratio for one unit increase in x_{ij}; it could be easily proved that it equals $\exp(\hat{\beta}_j)$.

In the logit model the error terms follow what is called an extreme value distribution.[20] The logit and probit functions are shown in Figure 4.1:

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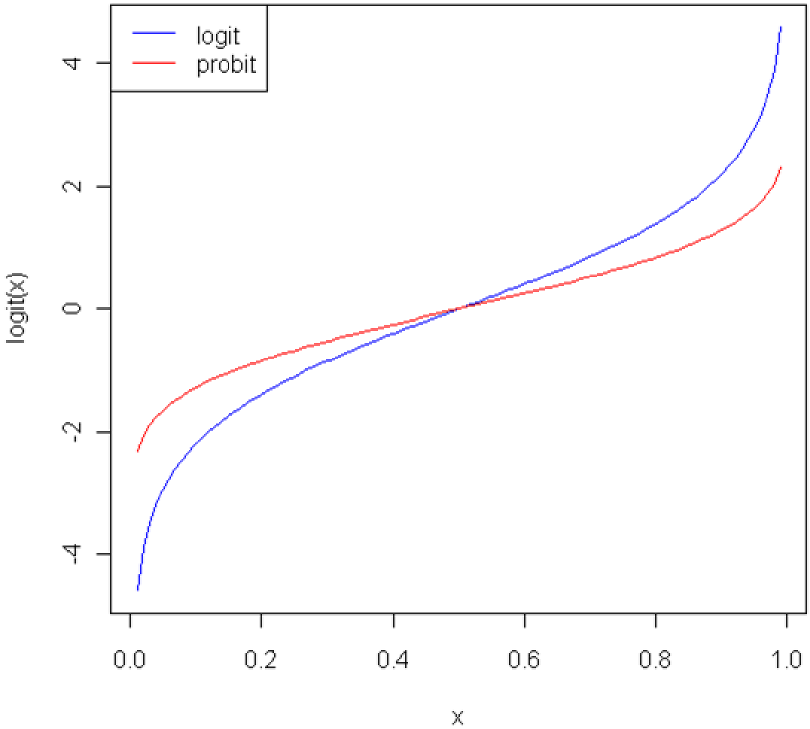
[19] The main difference between the normal distribution and the logistic distribution is that the later has more weight in the tails. Therefore, as stated in Maddala (2001), we are not likely to get very different results using logit or probit method; unless the samples are large (that means enough observations at the tails). However, the estimates of predictors from the two methods are directly comparable only after the certain transformation. For more information see Chapter 8 in Maddala (2001).

[20] For a discussion see Chapter 24 in McFadden (1984).

Figure 4.1: The logit and probit functions



Source*: own calculation in the R software*

The logit model is estimated by the maximum likelihood method and the standard output from statistical software packages includes also the values of the log-likelihood function as it iterates to its maximum.

4.1.2 Logit model accuracy

The likelihood ration test is a general method of testing model assumptions. We will use it as an analogy to joint *F*-test used in standard regressions. The test compares the value of likelihood function for unrestricted and restricted models, where the restricted model has all regression coefficients set to zero. The null hypothesis of this test is that the restricted model is true.

The conventional measure of goodness of fit, R^2, is not appropriate when assessing the performance of logit models, where the response variable y takes only two values. There are several R^2-type measures that have been developed for models with qualitative dependent variables; from this family of tests we will use *McFadden's* R^2:

$$\text{McFadden's } R^2 = 1 - \frac{\ln L_{UR}}{\ln L_R} \tag{4.7}$$

where L_{UR} and L_R correspond to likelihood functions of the unrestricted (full) model and the restricted (only with intercept) model, respectively. If comparing two models on the same data, value of McFadden's[21] would be higher for the model with the greater likelihood.

Another type of model accuracy measure is the proportion of correct predictions. If the predicted probability of an outcome is greater than 0.5, then $y = 1$ and otherwise $y = 0$. *Count R^2* is defined as:

$$\text{count } R^2 = \frac{\text{number of correct predictions}}{\text{total number of observations}} \tag{4.8}$$

Obviously the higher count R^2 the better the fit of the model.

4.2 Vector autoregression

One focus of macroeconomic modelling is to model interactions among different economic variables. Such macroeconomic models often consist of more than one equation and therefore require more complicated analytical method – multivariate econometric models. In this subchapter we introduce a methodological framework called *vector autoregression* (VAR) which is the key modelling approach in multiple time series analysis.

As Enders (2010) states, there are two important difficulties involved in fitting a multivariate model. The first problem is achieving parsimony in model fitting. It is obvious that parsimonious model is preferable to an overparameterized model. As the economic datasets are usually relatively small, estimating an unrestricted model may significantly decrease degrees of freedom and make the forecast useless. Furthermore, when insignificant coefficients are included in the model, the variability of the model's forecasts is higher.

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[21] Daniel L. McFadden is an econometrician, who received the shared Nobel Memorial Prize for Economic Science in 2000 (with James Heckman). McFadden was awarded for "his development of theory and methods for analyzing discrete choice". *Source*: http://www.nobelprize.org.

The second difficulty concerns the assumption of no feedback from one variable time sequence to another. Although certain economic models may assume that policy variables (such as government spending) are exogenous, there still may be feedback such that the policy variables are set with specific reference to the state of the other variables in the system – there may be problem of reverse causality.

Until VAR was firstly introduced by Christopher A. Sims[22] in his paper *Macroeconomics and Reality* (Sims, 1980) macroeconometric hypothesis tests and forecasts were conducted using large-scale macroeconometric models. Usually, ad hoc behavioural assumptions and restrictions were imposed and a complete set of structural equations was estimated, one equation at a time. Then all equations were aggregated in order to form overall macroeconomic forecasts.

Sims (1980, pp. 14) criticized such multiequation models for the ad hoc restrictions needed for identification and for the ad hoc classification of exogenous and endogenous variables in the system. Instead, he suggested VAR models for forecasting macro time-series: "*Because existing large models contain too many incredible restrictions, empirical research aimed at testing competing macroeconomic theories too often proceeds in a single- or few-equation framework. For this reason alone it appears worthwhile to investigate the possibility of building large models in a style which does not tend to accumulate restrictions so haphazardly. ... It should be feasible to estimate large-scale macromodels as unrestricted reduced forms, treating all variables as endogenous.*"

Since publication of the Sims' famous paper in 1980, VAR modelling has become the standard empirical method for evaluating the properties of macroeconomic systems. Nowadays we appreciate VAR as a simple but powerful statistical tool that enables us to describe causalities in data, make forecasts easily, analyse structural inference, reveal the business cycle alignment or perform policy analysis. One of the main criticisms towards the VAR methodology is that, due to degrees of freedom

[22] 31 years later, in 2011, Christopher A. Sims received the shared Nobel Memorial Prize for Economic Science with Thomas J. Sarget. They were awarded jointly "for their empirical research on cause and effect in the macroeconomy". *Source*: http://www.nobelprize.org.

considerations, it allows only a limited number of variables to be included in the model specification.

From a different perspective, we can look at VAR models as multiple extensions of univariate Box-Jenkins time series models; with the difference that instead of being parsimonious, VAR models are (as said by Sims, 1980) "*profligately parameterized*". In the following paragraphs describing VAR models we will use mostly information from Enders (2010) and Kočenda & Černý (2007).

4.2.1 VAR in general

VAR is a linear multivariate system with *n* equations and *n* variables in which each variable is explained by its past values (of pth order) and current and past values of the other variables (of pth order). All variables are treated symmetrically as endogenous but the model may also include exogenous variables like constants, time trends or dummy variables.

4.2.2 Structural and reduced form of VAR

Consider the simplest VAR(1) model, with only two variables interacting with each other:

$$y_t = b_{10} - b_{12} z_t + \gamma_{11} y_{t-1} + \gamma_{12} z_{t-1} + \varepsilon_{yt} \tag{4.9}$$

$$z_t = b_{20} - b_{21} y_t + \gamma_{21} y_{t-1} + \gamma_{22} z_{t-1} + \varepsilon_{zt} \tag{4.10}$$

where the following assumptions hold: y_t and z_t are stationary time series and ε_{yt} and ε_{zt} are mutually uncorrelated white-noise disturbances with variances σ_y^2 and σ_z^2 respectively. Equations (4.9) and (4.10) constitute a first-order vector autoregression, because there is only one lagged value of each variable. The structure of this system includes feedback, because y_t and z_t are allowed to affect each other. ε_{yt} and ε_{zt} are shocks (or innovations) to y_t and z_t respectively, and if b_{12} is not equal to zero, ε_{zt} has an indirect contemporaneous effect on y_t and if b_{21} is not equal to zero, ε_{yt} has an indirect contemporaneous effect on z_t. As there are correlated variables with error terms, because both cov y_t, ε_{zt} and cov z_t, ε_{yt} are not equal to zero, the system is not in a reduced form. However, it is possible to transfer this structural form (also called *primitive form*) to the reduced form VAR (also called *standard form*). The model can be rewritten in a matrix form with current values on the left hand side of both equations:

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{4.11}$$

or simply

$$Bx_t = \Gamma_0 + \Gamma_1 x_{t-1} + \varepsilon_t \tag{4.12}$$

where

$$B = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix},\ x_t = \begin{bmatrix} y_t \\ z_t \end{bmatrix},\ \Gamma_0 = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix},$$

$$\Gamma_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix},\ \varepsilon_t = \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix}.$$

By multiplying (4.12) with B^{-1} we obtain the VAR(1) model in the reduced form:

$$x_t = A_0 + A_1 x_{t-1} + e_t \tag{4.13}$$

where $A_0 = B^{-1}\Gamma_0$, $A_1 = B^{-1}\Gamma_1$, and $e_t = B^{-1}\varepsilon_1$. This model can be rewritten without matrix notation in the equivalent form:

$$y_t = a_{10} + a_{11}y_{t-1} + a_{12}z_{t-1} + e_{1t} \tag{4.14}$$

$$z_t = a_{20} + a_{21}y_{t-1} + a_{22}z_{t-1} + e_{2t} \tag{4.15}$$

Let's focus on error terms e_{1t} and e_{2t} now. These error terms are composed of two shocks ε_{yt} and ε_{zt}. Since $e_t = B^{-1}\varepsilon_t$ we can compute the e_t matrix as:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \frac{1}{1-b_{12}b_{21}}\begin{bmatrix} 1 & b_{12} \\ -b_{21} & 1 \end{bmatrix}\begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{4.16}$$

where $e_{1t} = \dfrac{\varepsilon_{yt} - b_{12}\varepsilon_{zt}}{1 - b_{12}b_{21}}$ and $e_{2t} = \dfrac{\varepsilon_{zt} - b_{21}\varepsilon_{yt}}{1 - b_{12}b_{21}}$. Because ε_{yt} and ε_{zt} are assumed to be white-noise processes, both e_{1t} and e_{2t} have zero mean. The variance of the error term is time independent:

$$\operatorname{var} e_{1t} = E\left(\frac{\varepsilon_{yt} - b_{12}\varepsilon_{zt}}{1 - b_{12}b_{21}}\right)^2 = \frac{E(\varepsilon_{yt}^2 - 2b_{12}\varepsilon_{yt}\varepsilon_{zt} + b_{12}^2\varepsilon_{zt}^2)}{(1 - b_{12}b_{21})^2} = \frac{\sigma_y^2 + b_{12}^2\sigma_z^2}{(1 - b_{12}b_{21})^2} \qquad \textbf{(4.17)}$$

The autocorrelations of e_{1t} and e_{1t-i} are zero:

$$Ee_{1t}e_{1t-i} = E\frac{\left[(\varepsilon_{yt} - b_{12}\varepsilon_{zt})(\varepsilon_{yt-1} - b_{21}\varepsilon_{zt-1})\right]}{(1 - b_{12}b_{21})^2} = 0 \quad \text{for } i \neq 0 \qquad \textbf{(4.18)}$$

Analogically we can prove that e_{2t} is a stationary process with zero mean, constant variance and zero autocorrelation. It is important to mention that reduced forms error terms e_{1t} and e_{2t} are correlated:

$$Ee_{1t}e_{2t} = E\frac{\left[(\varepsilon_{yt} - b_{12}\varepsilon_{zt})(\varepsilon_{zt} - b_{21}\varepsilon_{yt})\right]}{(1 - b_{12}b_{21})^2} = -\frac{b_{21}^2\sigma_y^2 + b_{12}^2\sigma_z^2}{(1 - b_{12}b_{21})^2} \qquad \textbf{(4.19)}$$

Only in the special case when there are no contemporaneous effects between y_t and z_t, i.e. when $b_{12} = b_{21} = 0$ the shocks will be uncorrelated.

4.2.3 Stability (stationarity) of reduced form VAR

For the autoregressive model AR(1) $y_t = a_0 + a_1 y_{t-1} + \varepsilon_t$ it holds that this process is stable if $|a_1| < 1$. Analogically we can derive stability conditions for VAR(1). We can use lag operators *L* and rewrite the equations (4.14) and (4.15) in the following way:

$$y_t = a_{10} + a_{11}Ly_t + a_{12}Lz_t + e_{1t}$$

$$z_t = a_{20} + a_{21}Ly_t + a_{22}Lz_t + e_{2t}$$

It can be proved that after transforming into a stochastic difference equation and explicitly solving for y_t (steps omitted), we get

$$y_t = \frac{a_{10}(1-a_{22}) + a_{12}a_{20} + (1-a_{11}L)e_{1t} + a_{12}e_{2t-1}}{(1-a_{11}L)(1-a_{22}L) - a_{12}a_{21}L^2} \qquad \textbf{(4.20)}$$

The convergence criterion requires that the roots of the polynomial in the denominator must lie outside the unit circle.[23] Because characteristic equations are the same, the same stability conditions hold for z_t .

There is an ongoing debate whether the individual time series employed in a VAR model need to be stationary. From a statistical point of view, all time series should be stationary and free of any deterministic trend. If this is not the case, time series should be differenced and estimated with detrended variables. However, Sims (1980) argued against differencing even if the variables contain a unit root. According to Sims, the main goal of a VAR analysis is to reveal the interrelations among variables and continues with the argument that with differencing we may lose important information concerning comovements in the data. Enders (2010) supports this opinion and notes that the majority view is that the form of variables in the VAR should mimic the true data-generating process.

Kočenda & Černý (2007, pp. 156) mention the argument that VAR models are, after all, designed to describe the dynamic properties of a system and it can be described also with $I(1)$ variables or with deterministically trending variables. However, their own suggestion "*is to estimate VAR models with stationary I(0) variables and to use a VAR in first differences if the variables are trending or contain a unit root. Only if we investigate the cointegration of the I(1) variables then we should leave the variables in levels, because a VAR in first differences would be a specification error in this case*."

The answer to this disputation is not clear. Borys et al. (2009, pp. 431) agree with Sims (1980), do not difference non-stationary variables in their analysis and conclude: "*What matters for the robustness of the VAR results is the overall stationarity of the system. Only if the stability condition is ensured, the impulse responses functions are robust and interpretable*."

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[23] We can derive identical conditions also by iterating (4.14) backwards.

4.2.4 Estimation

The main goal of Box-Jenkins single equation models (autoregressive moving average) is to provide a parsimonious model. Therefore the most accurate short term forecast is done by eliminating all insignificant parameters from the model. On the other hand, Sims (1980) criticized imposing ad hoc identification restrictions on parameter values and for the multiple equations models he suggested an alternative estimation strategy. The variables included in a VAR are selected according to a relevant economic model and the lag length is chosen after considering results from lag length tests (discussed below). There is no attempt to eliminate a number of parameter estimates. Of course, VAR will be overparametrized and some parameters may be insignificant; however, the main goal of this method – revealing important relationship among variables – will be more likely achieved compared with losing information by imposing zero restrictions.

Each equation in the reduced VAR system (see 4.13) can be estimated using ordinary least squares (OLS) method. Even though the errors are correlated across equations, seemingly unrelated regressions (SUR) do not add efficiency to estimation procedure because the right-hand-side variables are identical in all equations. According to Enders (2010) the OLS estimates are preferred as they are consistent and asymptotically efficient.

Structural stability of the model could be examined by the CUSUM test: the cumulative sum of residuals is plotted together with confidence lines (depend on significance level of the test) and if CUSUMs stay within these lines, this is evidence for structural stability of the underlying model.[24]

4.2.5 Lag length

In addition to optimal variable selection it is important to properly choose the lag length. One possibility is to allow for a different lag length for each variable in each equation and estimate so-called *near-VAR*. However, this method is recommended only if there is a good reason to do so.

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[24] For details see the original paper by Brown et al. (1975)

Standard way is to estimate the VAR with identical lag lengths for all variables and equations. The appropriate lag length is critical, because we have to consider loosing degrees of freedom. In a VAR model with *n* variables and *p* lags we estimate $n+pn^2$ parameters. For example in a model with 5 variables and 4 lags we lose 105 degrees of freedom. Therefore it is necessary to consider the number of observations entering the model together with the lag length selection. On the other hand if the lag length is too small the model can be misspecified.

At first we choose the maximum number of lags based on degrees of freedom or the logic behind the model to capture the system dynamics. Then two different tests could be performed:

a) Likelihood ratio test for cross-equations

Because we consider cross-equations restrictions, the *F*-test is not appropriate. The likelihood ratio (LR) test is recommended instead. The LR test statistics is defined as

$$LR = T(\ln|\Sigma_r| - \ln|\Sigma_u|) \qquad \textbf{(4.21)}$$

where:

T is number of observations

Σ_r, Σ_u are variance/covariance matrixes of residuals of the restricted and the unrestricted model, respectively

$\ln|\Sigma|$ is the natural logarithm of the determinant of the variance/covariance matrix

Given the sample sizes usual in economic analysis, Sims (1980) recommended using

$$LR = (T-c)(\ln|\Sigma_r| - \ln|\Sigma_u|) \qquad \textbf{(4.22)}$$

where c is a number of parameters estimated in each equation of the unrestricted system.

Both modifications have a test statistics with an asymptotic $\chi^2_{u-r\ n^2}$ distribution with degrees of freedom equal to the number of restrictions in the system. The null hypothesis is that the restrictions hold. This test can be used not only for lag determination but in general for any type of cross-equation restrictions. Its disadvantage is that the likelihood ratio test is based on asymptotic theory, which may not be very useful for small samples typical for economic time series and requires normally distributed errors in each equation.

b) Tests based on information criteria

Tests based on information criteria (IC) can be used without necessity of pair-wise comparison. The goal is to minimize IC. The multivariate generalizations of IC are given by Akaike information criteria (AIC), Hannah-Quin information criteria (HQIC) or Schwarz-Bayes information criteria (SBIC):

$$AIC = T\ln|\Sigma| + 2N \tag{4.23}$$

$$HQIC = T\ln|\Sigma| + 2N\ \ln(\ln T) \tag{4.24}$$

$$SBIC = T\ln|\Sigma| + N(\ln T) \tag{4.25}$$

where

T is number of observations

N is total number of parameters estimated in all equations

$\ln|\Sigma|$ is the natural logarithm of the determinant of the residuals variance/covariance matrix

4.2.6 Identification

We have to answer the question how to estimate the original structural form (4.9) and (4.10). The structural form of VAR cannot be estimated directly, because standard estimation techniques require that regressors are uncorrelated with error terms. In this case cross-correlations between variables and error terms are present: $\text{cov}(y_t, \varepsilon_{zt}) \neq 0$ and $\text{cov}(z_t, \varepsilon_{yt}) \neq 0$ so the Gauss-Markov theorem is violated. However, the reduced form VAR (4.14) and (4.15) do not exhibit cross-correlation and can be estimated using OLS.

The issue is how to recover the structural form VAR from the reduced form VAR estimates. Because the structural model always contains more parameters than the reduced form, the structural system is not identified. In our case the structural model has ten parameters (two intercepts, four autoregressive coefficients, two feedback coefficients and two residuals variances) whereas the reduced form contains only nine parameters (two intercepts, four feedback coefficients and two residuals variances and one covariance). We can identify such a system only by imposing ex ante restrictions on parameters, in this case one. There are more methods, but the most common is Cholesky decomposition.

Cholesky decomposition means that we impose restrictions on contemporaneous effect of one variable on the second variable. Generally, we have to impose $(n^2-n)/2$ restrictions to identify the system, where n is number of variables in the system. Since the Cholesky decomposition is triangular, it forces exactly $(n^2-n)/2$ values of B matrix to be zero. The VAR system is then called *recursive*. Restrictions should follow logic of the economic model.

In our case we assume that $b_{21}=0$, so z_t has contemporaneous effect on y_t, but not vice versa; y_t affects z_t only with one-period lag. We can rewrite (4.11) as

$$\begin{bmatrix} 1 & b_{12} \\ 0 & 1 \end{bmatrix}\begin{bmatrix} y_t \\ z_t \end{bmatrix}=\begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix}+\begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix}+\begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \tag{4.26}$$

B^{-1} is given by:

$$B^{-1}=\frac{1}{1-b_{12}b_{21}}\begin{bmatrix} 1 & b_{12} \\ -b_{21} & 1 \end{bmatrix}=\begin{bmatrix} 1 & -b_{12} \\ 0 & 1 \end{bmatrix} \tag{4.27}$$

Premultiplication of the structural system with B^{-1} yields

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix}=\begin{bmatrix} b_{10}-b_{12}b_{20} \\ b_{20} \end{bmatrix}+\begin{bmatrix} \gamma_{11}-b_{12}\gamma_{21} & \gamma_{12}-b_{12}\gamma_{22} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix}+\begin{bmatrix} \varepsilon_{yt}-b_{12}\varepsilon_{zt} \\ \varepsilon_{zt} \end{bmatrix} \tag{4.28}$$

Estimating the system using OLS yields the parameter estimates from

$$y_t = a_{10} + a_{11} y_{t-1} + a_{12} z_{t-1} + e_{1t}$$

$$z_t = a_{20} + a_{21} y_{t-1} + a_{22} z_{t-1} + e_{2t}$$

Finally, these parameter estimates can be transformed into structural parameters by solving following equations:

$$a_{10} = b_{10} - b_{12} b_{20}$$

$$a_{11} = \gamma_{11} - b_{12} \gamma_{21}$$

$$a_{12} = \gamma_{12} - b_{12} \gamma_{22}$$

$$a_{20} = b_{20}$$

$$a_{21} = \gamma_{21}$$

$$a_{22} = \gamma_{22}$$

Since $b_{21} = 0$, $e_{1t} = \varepsilon_{yt} - b_{12} \varepsilon_{zt}$ and $e_{2t} = \varepsilon_{zt}$. Hence,

$$\mathrm{var}(e_1) = \sigma_y^2 + b_{12}^2 \sigma_z^2$$

$$\mathrm{var}(e_2) = \sigma_z^2$$

$$\mathrm{cov}(e_1, e_2) = -b_{12} \sigma_z^2$$

The restriction means that both shocks ε_{yt} and ε_{zt} affect the current value of y_t, but only the shock ε_{zt} affects the current value of z_t.

4.2.7 The impulse response function

Analogically to the moving-average representation of simple autoregression, a vector autoregression can be expressed as a vector moving average (VMA). VMA representation is the essential part of VAR methodology; it allows tracing out the time series of responses to various shocks on the variables in the VAR model. As

Sims (1980, pp. 21) pointed out: "*The best descriptive device appears to be analysis of the system's response to typical random shocks, ... the resulting system responses are fairly smooth, in contrast to the autoregressive lag structures, and tend to be subject to reasonable economic interpretation*."

We can rewrite our two-variable VAR(1) in a reduced matrix form as a moving average representation in terms of the $\{\varepsilon_{yt}\}$ and $\{\varepsilon_{zt}\}$:

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \bar{y}_t \\ \bar{z}_t \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) \\ \phi_{21}(i) & \phi_{22}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{yt-1} \\ \varepsilon_{zt-1} \end{bmatrix} \tag{4.29}$$

The VMA representation is a useful tool to reveal the interaction between y_t and z_t sequences. The coefficients ϕ_i - impact multipliers - are used to generate the effects of shock ε_{yt} or ε_{zt} on the time paths of y_t and z_t sequences. For example, $\phi_{12}(0)$ is the instantaneous impact of a one-unit change in ε_{zt} on y_t; $\phi_{11}(1)$ and $\phi_{12}(1)$ are the one-period responses of unit changes in ε_{yt-1} and ε_{zt-1} on y_t, respectively.

The four sets of coefficients $\phi_{11}(i)$, $\phi_{12}(i)$, $\phi_{21}(i)$ and $\phi_{22}(i)$ are called the impulse response function. The accumulated effects of unit responses in ε_{yt} or ε_{zt} can be obtained by the summation of appropriate coefficients of the impulse response functions. Plotting the impulse response functions (coefficients of $\phi_{jk}(i)$ against i) is a way how to visualize the behaviour of y_t and z_t sequences in response to unit shocks.

Practically, we cannot compute impulse responses from structural VAR, because the system is not identified. As mentioned before, we must impose some restrictions, e.g. Cholesky decomposition on the system to be identified. The key fact is that the decomposition forces an important asymmetry on the system, because $e_{1t} = \varepsilon_{yt} - b_{12}\varepsilon_{zt}$ and $e_{2t} = \varepsilon_{zt}$ and therefore ordering of variables in the vector autoregression model matters. Another key point is that if the system is stationary, the impulse responses decline to zero.

Impulse responses are constructed using the estimated coefficients. Since the estimates are imperfect, the impulse responses also contain errors. Therefore confidence intervals are constructed around impulse responses that allow for parameter uncertainty inherent in the estimation process.

4.2.8 Variance decomposition

VAR model estimates are often difficult to interpret; another useful tool (apart from impulse responses) is to construct variance decomposition. The forecast error variance decomposition offers a slightly different method of examining VAR models dynamics. We can reveal the relationship among variables in the system by looking at the properties of the forecast error. Variance decomposition gives the proportion of the movement in the dependent variables that are due to their own shocks compared to shocks to other variables. This is done by determining how much of steps ahead a forecast error variance for each variable is explained by shocks to each explanatory variable.

If ε_{zt} shocks do not explain any forecast error variance of the y_t sequence at all forecast horizons, the y_t sequence is said to be exogenous with respect to z_t. In this case, y_t evolves independently of the ε_{zt} shocks and of the z_t sequence. The opposite extreme would be if the ε_{zt} shocks explained almost all of y_t forecast error variance. Then the y_t sequence would be entirely endogenous.

Normally, a variable explains most of its variance at short horizons and a decreasing proportion at longer horizons. We would expect this pattern if ε_{zt} shocks had small contemporaneous effect on y_t, but affect the y_t sequence with a lag.

Again, the identification of the system is needed - restrictions must be applied, therefore ordering of variables in the system matters for variance decomposition.

4.2.9 Granger causality

The concept of Granger causality was firstly introduced by Granger (1969). Even though his definition of causality is formally complicated, the econometric application is simple and Granger causality tests are often used in economic research. The logic behind is straightforward. Under the null hypothesis of y_t not Granger causing

z_t, the lagged values of y_t are assumed to have no explanatory power on the current values of z_t. Or simply saying Granger causality examines whether the lagged values of one variable help to predict another variable.

However, rather than using Granger causality tests, we stay focused on out-of-sample forecast evaluation of VAR models, as Stock and Watson (2003) show that in-sample Granger causality tests provide a poor guide to forecast performance evaluation, which stays our main goal.

4.2.10 VAR forecasting

Once the VAR model has been estimated, it can be easily used as a multiequation forecasting model. Suppose we estimated the simple first-ordered model $x_t = A_0 + A_1 x_{t-1} + e_t$ so we know values of coefficients in A_0 and A_1 matrices. If our data run through the period *T* and we want to obtain one-step-forecast for *T*+1, we will use the relationship

$$E_T x_{T+1} = A_0 + A_1 x_T \tag{4.30}$$

Similarly, a two-steps-forecast is obtained recursively:

$$E_T x_{T+2} = A_0 + A_1 E_T x_{T+1} = A_0 + A_1 (A_0 + A_1 x_T) \tag{4.31}$$

Since the reduced form VAR is used for forecast estimation, the identification by imposing ex ante restrictions on parameters is not necessary. Consequently, even if the restrictions are imposed (for example due to the forecast error variance decomposition) the system of restrictions has no effect on predicted values.

4.3 Methods for forecasts evaluation

Econometric methods for measuring and evaluating predictive content can be divided into two groups: in-sample and out-of-sample methods. Both of them will be used in our empirical analysis. The following paragraphs are mostly based on information from standard econometric textbooks, Stock & Watson (2003) and Clark & West (2007).

4.3.1 In-sample measures of predictive content

Assume that we want to assess whether a time series of a candidate variable *X* is useful for forecasting time series of variable *Y*. A simple framework how to test predictive content is a linear regression model relating the future value of *Y* to the current value of *X*:

$$Y_{t+1} = \beta_0 + \beta_1 X_t + \varepsilon_{t+1} \qquad \textbf{(4.32)}$$

If $\beta_1 \neq 0$ then today's value of *X* can be used for forecasting the value of *Y* in the next period. The t-statistics on β_1 tests the null hypothesis, that *X* has no predictive power. This equation applies to one period ahead forecast, but can be easily modified to forecasts *k*-period ahead:

$$Y_{t+k} = \beta_0 + \beta_1 X_t + \varepsilon_{t+k} \qquad \textbf{(4.33)}$$

The model forecast accuracy is tested on the same data that were used to develop this model (estimate the parameters). The significance of the estimate of parameter β_1 can give us a clue about predictive properties of examined variables, but as a final measure of the forecast accuracy the out-of-sample evaluation methods are preferred. As stated by Stock & Watson (2003, pp. 791): "*Evaluation of predictive content should rely on statistics that are designed to simulate more closely actual real-time forecasting, which we refer to generally as pseudo out-of-sample forecast evaluation*." However, if the out-of-sample period is not sufficiently long for proper evaluation, in-sample measures of predictive accuracy are necessary.

4.3.2 Pseudo out-of-sample measures of predictive content

Pseudo out-of-sample measures of predictive power simulate real-time forecasting. Suppose we have quarterly data and want to make pseudo out-of-sample forecast for 2011 Q1. We estimate the model using data through 2010 Q4 and then use this model to estimate the 2011 Q1 forecast as if we were in 2010 Q4. "Pseudo" refers to the fact that we actually know the true values for 2011 Q1, but we did not use it for model selection and development. The estimation must be done using data available prior to the forecast period. However, the knowledge of the actual value for 2011 Q1 together with our forecasted value for 2011 Q1 gives us a great opportunity to use various forecast evaluation statistics.

Let Y_{T+j} be the value of the variable of interest that actually occurred at time t and let $\hat{Y}_{T+j}$ be a forecasted value of Y_{T+j}, Then we define the forecast error:

$$e_{T+j} = Y_{T+j} - \hat{Y}_{T+j}, \text{ where } j=1,2,..., k \quad \textbf{(4.34)}$$

If we have series of k out-of-sample observations and associated forecasts we can construct several measures of the forecasts accuracy. Some commonly used measures are the Mean Error (ME), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). These are defined as follows:

$$ME = \frac{1}{k}\sum_{j=1}^{k} e_{T+j} \quad \textbf{(4.35)}$$

$$MSE = \frac{1}{k}\sum_{j=1}^{k} e_{T+j}^2 \quad \textbf{(4.36)}$$

$$RMSE = \sqrt{\frac{1}{k}\sum_{j=1}^{k} e_{T+j}^2} \quad \textbf{(4.37)}$$

$$MAE = \frac{1}{k}\sum_{j=1}^{k} e_{T+j} \quad \textbf{(4.38)}$$

Naturally, the smaller the forecast errors the better the forecasts. Following Stock & Watson (2003) and Clark & West (2007)[25] among others, we will focus mostly on the mean squared error measure. Researchers choose this measure because of its familiarity and ease of interpretation. A common way how to quantify the out-of-sample forecast is to compare the MSE of a candidate (enhanced) model relative to the MSE of a benchmark model.

We still have to remember, that although in-sample performance can always be improved by introducing additional variables, in the out-of-sample context more

[25] Clark & West (pp. 291, 2007) claim: “Perhaps the most commonly used statistic for comparisons of predictions from nested model is mean square prediction error.”

predictors do not necessarily mean better forecasts. But if MSE of the candidate model is lower than the MSE of the benchmark model, than the candidate model has better predictive power than the benchmark. However, this could happen simply because of sampling variability, therefore additional statistical test has to be applied to confirm this conclusion.

To determine whether lower MSE of the candidate model comparing to the benchmark model is statistically significant various tests could be used. We will use the forecast evaluation test developed by Clark & West (2007) especially for nested models[26] within the VAR framework. This test was chosen because in our analysis we evaluate forecasting performance of a benchmark VAR model nested within various candidate models.

For nested models, Clark & West (2007) showed that under the null hypothesis, the larger model introduces noise into its forecast by estimating parameters whose population values are zero. They observe that the MSE from the benchmark (parsimonious) model is expected to be smaller than that of the larger models.

Clark & West (2007) suggest that comparison of the MSE must be adjusted for the noise. Let MSE_1 be the evaluation of forecast for the benchmark model (1) and MSE_2 for the larger candidate model (2). Then the adjustment term is defined as

$$adj = \frac{1}{k}\sum_{j=1}^{k}(\hat{y}_{1,T+j} - \hat{y}_{2,T+j})^2 \quad \textbf{(4.39)}$$

Under the null hypothesis of no forecast improvement $MSE_1 - (MSE_2 - adj) = 0$ against the alternative $MSE_1 - (MSE_2 - adj) > 0$ that implies improvement in the forecast accuracy of the larger model compared to the benchmark model.

Authors of this test suggest that the computationally most convenient way how to proceed is to define

$$\hat{f}_{T+j} = (y_{T+j} - \hat{y}_{1,T+j})^2 - \left[(y_{T+j} - \hat{y}_{2,T+j})^2 - (\hat{y}_{1,T+j} - \hat{y}_{2,T+j})^2\right] \quad \forall j = 1, 2, ..., k \quad \textbf{(4.40)}$$

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[26] Nested models could be obtained by restricting one or more parameters in a more complex model to zero.

where $MSE_1 - (MSE_2 - adj)$ is simply the average of $\hat{f}_{T+j}$. So to test the null hypothesis they regress (using the ordinary least squares method) all $\hat{f}_{T+j}$ on a constant and used the *t*-statistic for a zero constant. The null is rejected if the statistic is greater than +1.282 (for a one sided 0.10 test) or +1.645 (for a one sided 0.05 test). The test statistic is designed in a way that increase in its value implies higher probability of rejecting the null hypothesis.

5. Empirical models

The predictive power of confidence indicators is empirically evaluated on data from the Czech Republic. We applied two different approaches. Firstly, using logit models with one of the confidence or leading indicators we analyze and compare the in-sample predictions of an economic situation defined as a discrete event. Secondly, the VAR models enhanced by confidence indicators are developed and the out-of-sample forecasts are compared to the benchmark model and the reality. A detailed description of data precedes the empirical analysis.

5.1 Description of data

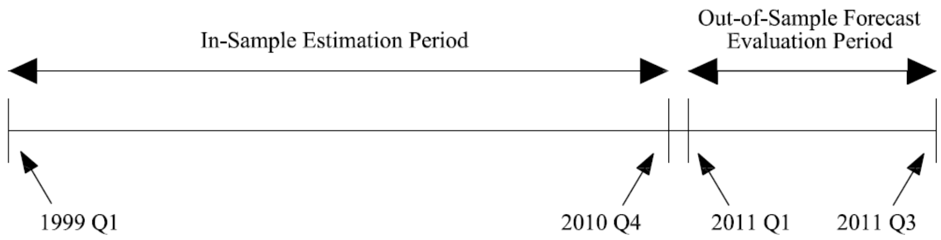
Some macroeconomic time series are subject to data revisions. If we wanted to get closer to forecasting reality, we would construct pseudo out-of-sample forecasts using real-time data, i.e. data before revisions. Data revision is not an issue for confidence indicators; these are not revised retrospectively, nor are the other variables used in the analysis, except for the GDP. Concerning GDP, we decided to use ex-post data, not real-time. Our argument for this choice is perspicuous: we want to know whether confidence indicators can help to predict the actual true economic activity and we suppose that data revisions are made to get the data closer to the reality.[27]

Our dataset is limited by availability of Czech data. The consumer confidence indicator is available since January 1998. However, we will use data including the CZE/EUR exchange rate for our final model of Czech economy and given that the euro area was established in 1999, we decided to restrict the sample to 1999 Q1 onwards and keep this restriction for all models.

The end of the dataset used for estimations of all models is set to 2010 Q4 (included, for maximization of our sample). Furthermore, the data from 2011 Q1 - Q3 are used for pseudo out-of-sample forecast evaluation only. The evaluation for three quarters ahead should be sufficient given that our interest is to assess to the near future economic situation. The sample dataset ranges are depicted on the scheme below:

[27] Apart from that, real-time data for the Czech GDP are not retrospectively easily available.

Figure 5.1: Dataset ranges



Source*: own painting in the AutoCAD software*

The confidence and leading indicators are reported monthly. Since the GDP data are only available at quarterly basis, we use quarterly observations of all data.[28] Therefore the values of confidence and leading indicators in the last month of particular quarter are taken.

In case of the GDP and the consumer price index we followed the empirical strategy of Mourougane & Roma (2003) and Horváth (2012) and employ the quarter-on-quarter growth rates to get closer to cyclical changes and avoid the complicated structure in the regression residuals. According to Horváth (2012) such a structure typically arises when year-on-year growth rates are used. Other variables remain in levels. Although log transformations are widely applied in macroeconomic VAR forecasting, we decided not to transform the data, based on the results of Mayr & Ulbricht (2007) who robustly compared the results of VAR forecasts based on log transformed data and data in levels and conclude that both approaches basically yield the same results.

As a primary source of data we used the OECD Statistics database.[29] The Ifo business climate indicator is received from the Ifo Institute.[30] All these time series are

[28] Another possibility how to deal with mixed frequencies would be to interpolate quarterly data to monthly values using for example quadratic-match average procedure. We found evidence of this transformation in Borys et al. (2009) and Havránek et al. (2011). However, in author's opinion such a transformation can cause a loss of important information in data, creates artificial values of the key variable and produces results, which are in fact not based on real values of some variables. This opinion was supported by PhDr. Jaromír Baxa in the Business Cycles Theory seminar discussion.
[29] Publicly available at http://stats.oecd.org/.
[30] Publicly available at http://www.cesifo-group.de/.

seasonally adjusted from the source. The Czech National Bank ARAD database[31] was used for the CZK/EUR exchange rate and PRIBOR.

The following variables form empirical models:

GDP_GQ	Quarterly growth rate of the real gross domestic product in the Czech Republic (expenditure approach, millions of CZK, chained volume estimates, national reference year)
Inflation_Q	Quarterly growth rate of the consumer price index (CPI) in the CR, originally 2005=100
PRIBOR	3-months Prague interbank offered rate, quarterly average
EXRATE	CZK/EUR exchange rate, quarterly average
BCI	Business confidence indicator for the CR, OECD standardized, amplitude adjusted (long term average=100), see Figure 3.5.
CCI	Customer confidence indicator for the CR, OECD standardized, amplitude adjusted (long term average=100); see Figure 3.5
LEAD	OECD's composite leading indicator for the CR, amplitude adjusted; see Figure 3.6.
IFO	Ifo business climate for German trade and industry - business expectations, index 2005=100
DT1	Dummy variable representing economic downturn, takes the value 1 if the GDP growth is below the sample average (1999-2010) for more than two consecutive quarters, 0 otherwise
DT2	Dummy variable representing economic downturn, takes the value 1 if the GDP growth is below the sample average (1999-2010), 0 otherwise

[31] Publicly available at http://www.cnb.cz/docs/ARADY/HTML/index_en.htm

DT3 Dummy variable representing economic downturn, takes the value 1 if the relevant quarter is identified by OECD as a downturn period for the Czech economy, 0 otherwise

All time series plots can be found in Appendix.

5.2 Economic downturn forecasts using logit models

In the first part of our empirical analysis we focus on the prediction of the likelihood of an economic downturn as a discrete event rather than quantitative forecast. The aim of this approach is to reveal whether the change in values of confidence indicators can signalize oncoming economic downturn. Moreover, we analyze how many quarters before the occurrence of a downturn can be such a signal detected.

We use logistic regression methodology introduced in the previous chapter together with in-sample measures of predictive content. Fitted values of the model are compared with real downturn dates and in-sample forecast evaluation methods are applied in order to provide better measures of model fit - for evaluation of the model with a binary dependent variable three out-of-sample periods are not sufficient. This approach follows the idea of Taylor & McNabb (2007) and empirical strategy of Estrella & Mishkin (1998). Furthermore, we compare the predictive power of confidence indicators with the performance of the leading indicator which should by definition lead the business cycle and confirm its predictive ability.

5.2.1 Empirical strategy

The forecast logit model of the likelihood of an economic downturn is defined by the following relationship:

$$y_{t+k}^{*} = X_t \beta + \varepsilon_t \qquad \textbf{(5.1)}$$

where y_{t+k}^{*} is an unobservable variable, which determines the occurrence of downturn at time t and k is the length (in quarters) of the forecast horizon. X_t is a matrix of independent variables including a constant, β is a vector of coefficients and ε_t is a vector of error terms. The observable downturn indicator D_t is related to this model by:

$$D_t = \begin{cases} 1 & \text{if } y_t^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad \textbf{(5.2)}$$

The form of the estimated equation is:

$$\text{Prob}(D_{t+k} = 1) = \Lambda(X_t \beta) \quad \textbf{(5.3)}$$

where Λ is the logit function as in (4.4); the model is estimated by maximum likelihood.

Various methods and definitions could be used to define the economic downturn.[32] The National Bureau of Economic Research (NBER) reports recessions for the USA and The European Cycle Research Institute (ECRI) provides turning points of business cycle for various countries; unfortunately the Czech Republic and the other countries from Central and Eastern Europe are not included.[33] Finally we discovered that the OECD provides peaks and troughs date for all OECD countries.[34] Another approach is to denote one or more periods of below-sample-average GDP as an economic downturn.

In our empirical analysis we define an economic downturn (i.e. $D_t = 1$) in three alternative ways (similarly as Taylor & McNabb, 2007):

(i) $D_t = 1$ if the real GDP quarterly growth is below the sample average (1999-2010) for more than two consecutive quarters;

(ii) $D_t = 1$ if the real GDP quarterly growth is below the sample average (1999-2010) for at least one quarter;

(iii) $D_t = 1$ if the quarter lies between the peak (excluding) and trough (including) date defined by OECD as turning points for the Czech Republic

[32] Other formalized procedures are developed by Bry & Boschan (1971) or Zellner et al. (1990).
[33] There exists also a specialized "Euro Area Business Cycle Dating Committee" established in 2002 by Centre for Economic Policy Research (CEPR). The Committee's mission is to "establish the chronology of the euro area business cycle, by identifying the recessions and expansions of the 11 original euro area member countries from 1970 to 1998, and of the euro area as a whole since 1999." (http://www.cepr.org/data/dating/) However, the dates are not identified for individual countries.
[34] Available at http://www.oecd.org/document/29/0,3746,en_2649_34349_35725597_1_1_1_1,00.html

For evaluation and comparison of the predictive power of confidence indicators we fit and compare models consisting of only one predictor variable: BCI, CCI or the benchmark LEAD. We fit models predicting economic downturns for *k* quarters ahead, where $k = 0, 1, 2, 3$ respectively. Forecasts were achieved by using indicator's value at time *t* and value of downturn dummy at time $t+k$. For each period we have 9 models with different independent variable and different definition of an economic downturn. On the whole we estimate and compare 36 logit models. The analysis was done in the Gretl software; our dataset and Gretl sessions are available upon request.

5.2.2 Results and discussion

The results of this analysis are shown in Table 5.1 to Table 5.4. Each table corresponds to $k = 0, 1, 2, 3$ respectively. In each table we include the estimated values of intercept and parameter β with corresponding *t*-statistic, log-likelihood value, likelihood test statistic and odds ratio. Forecast accuracy is compared using McFadden's R^2, percentage of correct predicted (0,1) values and percentage of correct downturns predicted. Each table is split into three panels based on the three definitions of an economic downturn and three columns for BCI model, CCI model and LEAD model, respectively.

The first set of models for $k = 0$ is not in fact forecasting, but so called *nowcasting*. Results summarized in Table 5.1 confirm strong contemporaneous relationship between the current economic situation (even if it is defined as a binary variable) and the current value of all examined indicators; except for one CCI model, all others are strongly significant. Values of all betas' estimates are negative; this confirms the common sense that the increasing value of the confidence indicator results in lower probability of an economic downturn.

The highest predictive (nowcasting) power is proved by the business confidence indicator; it outperforms both the consumer confidence indicator and the leading indicator; this fact is robustly confirmed by all evaluation statistics. Using BCI is possible to correctly *nowcast* about 80% of states of the economy (the average of models with *i* and *ii* definitions of downturn) and about 69% of downturn periods. Even the third model with BCI and the OECD downturn definition reached the benchmark value of 50% correct downturn forecasts.

Table 5.1: Results for logit model k = 0 quarters

	BCI		CCI		LEAD	
	estimate	statistic	estimate	statistic	estimate	statistic
(i) D = 1 if the GDP growth is below average for more than two quarters						
Intercept	44.3363	3,039***	12.6736	1,679*	25.3449	2,622***
Beta	-0.4424	-3,078***	-0.1298	-1,735*	-0.2595	-2,657***
Log-likelihood	-22.2799	19,8836***	-30.6110	3,2214**	-27.3035	9,8365***
Odds ratio	0.6425		0.8783		0.7715	
McFadden's R-squared	0.3085		0.0500		0.1526	
Total % of correct forecast	81.30%		60.40%		62.50%	
% of correct downturn forecast	68.42%		26.32%		42.11%	
(ii) D = 1 if the GDP growth is below average for at least one quarter						
Intercept	38.9602	2,897***	8.9184	1,224	15.3183	1,981**
Beta	-0.3846	-2,917***	-0.0890	-1,236	-0.1545	-1,991**
Log-likelihood	-25.1770	16,1048***	-32.4330	1,5928	-30.9451	4,5686**
Odds ratio	0.6807		0.9148		0.8569	
McFadden's R-squared	0.2423		0.0240		0.0687	
Total % of correct forecast	79.20%		52.10%		60.40%	
% of correct downturn forecast	69.57%		34.78%		56.52%	
(iii) D = 1 if the GDP growth coincides with OECD recession dates						
Intercept	36.6893	2,945***	24.1815	2,707***	16.6072	2,006**
Beta	-0.3683	-2,995***	-0.2450	-2,763***	-0.1722	-2,061**
Log-likelihood	-23.3863	16,7374***	-26.9109	9,6884***	-29.2240	5,0621**
Odds ratio	0.6919		0.7827		0.8418	
McFadden's R-squared	0.2635		0.1525		0.0797	
Total % of correct forecast	75.00%		68.80%		62.50%	
% of correct downturn forecast	50%		38.89%		27.78%	

Notes: * Statistical significance at the 10% level. ** Statistical significance at the 5% level. *** Statistical significance at the 1% level.

Let's now analyze in detail the best model for nowcasting below-average GDP growth for a longer period (at least three consecutive quarters): the BCI model. If the value of BCI is 85, 100 or 115, respectively, the probability of downturn is 99.9%, 52.3% or 0.1%, respectively. Moreover, if the BCI increases from the long-term average value of 100 only to 103, the probability of downturn decreases by approximately 30 percentage points (ppt.) to 22.6%. If BCI decreases from 100 to 97, the probability of downturn increases by 28.2 ppt. to 80.5%. Probabilities of a downturn for all values of BCI are available at Table A.1 in Appendix. All these findings confirm strong relationship between the current value of the business confidence and actual economic situation.

Table 5.2 depicts results for one-quarter-ahead forecasts (k = 1). Variables CCI and LEAD are not statistically significant predictors at the 5% level; CCI predicting OECD recession dates is significant at the 10% level. On the other hand models with variable BCI are still strongly significant at the 1% level and therefore BCI outperforms LEAD again. However, the forecast accuracy of BCI models declined. McFadden's R^2 for all three models is lower and percentage of correct forecast is less satisfactory: model with the best fit predicted correctly 73% states of the economy, but only 47% downturns. Such a result does not reach the benchmark probability "flip a coin" and although the BCI variable cannot be rejected as significant predictor in the model, we consider the predictive power as unsatisfactory.

Let's discuss BCI model forecasting longer defined downturn (DT1) again. If we want to make forecasts one quarter ahead and BCI is 85, 100 or 115, respectively, the probability of an economic slowdown is 97.8%, 45.3% or 2.3%, respectively. (Precise probabilities for all BCI values could be found in Table A.2, in Appendix.) If BCI increases from 100 to 103, the probability of a downturn decreases to 28.8%. If BCI decreases from 100 to 97, the probability increases to 62.9%. Compared to k = 0 BCI model, even above-the-average values of BCI result in higher probability of a downturn and on the contrary, below-the-average values result in lower probability; logical conclusion is that one-quarter-ahead predictions are less definite than nowcasting.

Table 5.2: Results for logit model k = 1 quarter

	BCI		CCI		LEAD	
	estimate	statistic	estimate	statistic	estimate	statistic
(i) D = 1 if the GDP growth is below average for more than two quarters						
Intercept	23.6795	2.557**	6.6006	0.9173	10.6497	1.429
Beta	-0.2387	-2.610***	-0.0696	-0.9761	-0.1112	-1.484
Log-likelihood	-27.3944	9.6547***	-31.7385	0.9664	-31.0259	2.39157
Odds ratio	0.7877		0.9328		0.8948	
McFadden's R-squared	0.1498		0.0150		0.0371	
Total % of correct forecast	72.90%		60.40%		62.50%	
% of correct downturn forecast	47.37%		10.53%		21.05%	
(ii) D = 1 if the GDP growth is below average for at least one quarter						
Intercept	22.7675	2.410**	4.4011	0.6229	6.0429	0.8786
Beta	-0.2256	-2.429**	-0.0444	-0.6352	-0.0614	-0.8912
Log-likelihood	-29.0421	8.3745***	-33.0257	0.40741	-32.8221	0.814617
Odds ratio	0.7980		0.9566		0.9405	
McFadden's R-squared	0.1260		0.0061		0.0123	
Total % of correct forecast	64.60%		50.00%		50.00%	
% of correct downturn forecast	52.17%		26.09%		39.13%	
(iii) D = 1 if the GDP growth coincides with OECD recession dates						
Intercept	24.8268	2.651***	14.2018	1.838*	7.6738	1.040
Beta	-0.2522	-2.720***	-0.1469	-1.913*	-0.0831	-1.119
Log-likelihood	-25.8927	10.614***	-29.2193	3.9603**	-30.5400	1.31876
Odds ratio	0.7771		0.8634		0.9203	
McFadden's R-squared	0.1701		0.0635		0.0211	
Total % of correct forecast	64.60%		70.80%		66.70%	
% of correct downturn forecast	23.53%		35.29%		5.89%	

Notes: * Statistical significance at the 10% level. ** Statistical significance at the 5% level. *** Statistical significance at the 1% level.

Table 5.3: Results for logit model k = 2 quarters

	BCI		CCI		LEAD	
	estimate	statistic	estimate	statistic	estimate	statistic
(i) D = 1 if the GDP growth is below average for more than two quarters						
Intercept	8.8821	1.286	1.266	0.1776	-3.2343	-0.4712
Beta	-0.0922	-1.348	-0.0167	-0.2371	0.0282	0.4102
Log-likelihood	-31.2697	1.9041	-32.1937	0.0561	-32.1374	0.1686
Odds ratio	0.9119		0.9834		1.0286	
McFadden's R-squared	0.0295		0.0009		0.0026	
Total % of correct forecast	58.30%		60.40%		60.40%	
% of correct downturn forecast	15.79%		0.00%		0.00%	
(ii) D = 1 if the GDP growth is below average for at least one quarter						
Intercept	8.8649	1.263	-2.2894	-0.3255	-4.6957	-0.6914
Beta	-0.0885	-1.277	0.0218	0.3139	0.0462	0.6798
Log-likelihood	-32.3570	1.7448	-33.1799	0.0989	-32.9954	0.4681
Odds ratio	0.9153		1.0221		1.0473	
McFadden's R-squared	0.0263		0.0015		0.0070	
Total % of correct forecast	60.40%		39.60%		54.20%	
% of correct downturn forecast	43.49%		8.70%		34.78%	
(iii) D = 1 if the GDP growth coincides with OECD recession dates						
Intercept	13.4187	1.830*	3.8602	0.5262	-1.7185	-0.2421
Beta	-0.1401	-1.924*	-0.0451	-0.6205	0.0103	0.1446
Log-likelihood	-28.5138	4.0778**	-30.3606	0.3841	30.5422	0.0209
Odds ratio	0.8693		0.9559		1.0103	
McFadden's R-squared	0.0667		0.0063		0.0003	
Total % of correct forecast	64.60%		66.70%		66.70%	
% of correct downturn forecast	18.75%		0.00%		0.00%	

Notes: * Statistical significance at the 10% level. ** Statistical significance at the 5% level.

Results of the predictive performance of logit models two quarters ahead are summarized in the Table 5.3 above. We can see that only one model (again with the BCI predictor) has statistically significant coefficients, but at the 10% level only. The percentage of correct fits is higher for all BCI models then in LEAD models, but none of the models has the successfulness of downturn predictions higher than 50%, some models have even the percentage of correct downturn equal to zero. Therefore we have to conclude that neither confidence indicators, nor leading indicators can predict economic slowdown as a discrete event half a year ahead.

Table 5.4: Results for logit model k = 3 quarters

	BCI		CCI		LEAD	
	estimate	statistic	estimate	statistic	estimate	statistic
(i) D = 1 if the GDP growth is below average for more than two quarters						
Intercept	-3.6177	-0.5237	-2.9289	-0.4046	-18.226	-2.270**
Beta	0.0316	0.4632	0.0248	0.3466	0.1779	2.223**
Log-likelihood	-32.1121	0.2192	-32.1612	0.1212	-29.3194	5.8046**
Odds ratio	1.0321		1.0251		1.1947	
McFadden's R-squared	0.0034		0.0019		0.0901	
Total % of correct forecast	60.40%		60.40%		64.60%	
% of correct downturn forecast	0.00%		0.00%		31.58%	
(ii) D = 1 if the GDP growth is below average for at least one quarter						
Intercept	-2.2961	-0.3468	-6.4247	-0.8930	-17.2434	-2.178**
Beta	0.0219	0.7380	0.0627	0.8826	0.1719	2.168**
Log-likelihood	-33.1731	0.1127	-32.8302	0.7984	-30.4540	5.5507**
Odds ratio	1.0221		1.0647		1.1876	
McFadden's R-squared	0.0017		0.0120		0.0835	
Total % of correct forecast	56.30%		50.00%		64.60%	
% of correct downturn forecast	21.74%		43.48%		56.52%	
(iii) D = 1 if the GDP growth coincides with OECD recession dates						
Intercept	3.4188	0.4969	-6.6875	-0.8411	-11.0686	-1.472
Beta	-0.0417	-0.6113	0.0582	0.7440	0.1027	1.373
Log-likelihood	-29.6275	0.3692	-29.5247	0.5749	-28.8298	1.9647
Odds ratio	0.9592		1.0600		1.1081	
McFadden's R-squared	0.0062		0.0096		0.0330	
Total % of correct forecast	68.80%		68.80%		75.00%	
% of correct downturn forecast	0.00%		0.00%		20.00%	

Notes: ** Statistical significance at the 5% level.

The last set of models - forecasts three quarters ahead - brings interesting results, see Table 5.4. Neither of confidence indicators is a significant economic downturn predictor, regardless the downturn definition. However, at the 5% level we cannot reject the hypothesis that the leading indicator is a significant predictor of below-the-average GDP growth three quarters ahead. The best LEAD model reached 56.5% of correct downturn predictions, slightly above the benchmark.

Interesting finding is that although the significant estimates of beta for LEAD in Table 5.1 (nowcasting) are negative, here the beta for both significant LEAD models is positive, that means higher probability of a downturn with the increase of the LEAD value. This can be logically explained. When comparing performance of the leading indicator, we get the best results for nowcasting. High value of LEAD at k=0 signalizes very low probability of a current downturn – the economy is close to the peak of the business cycle. Three quarters later, it is possible that the economy will move behind the peak and closer to the business cycle through. Therefore high value of LEAD at time k=0 may imply higher probability of an economic downturn at time k=3 as is shown in the results. This finding confirms our results from exploratory cross-correlations, where both positive and negative correlations with GDP occur, based on lag delay or advance.

To conclude the results of the logit analysis, we have revealed strong evidence of predictive power for all three indicators for period k=0 (nowcasting), where the best performance shows the business confidence indicator. BCI also outperformed both CCI and LEAD in one-quarter-ahead forecasts, but the predictive accuracy declined. The satisfactory ability to predict the economic situation two and more quarters ahead was not proved for any of tested indicators; unlike Taylor & McNabb (2007) who proved the predictive power of both confidence indicators even four quarters ahead. On the contrary, the leading indicator model for predictions three quarters ahead is statistically significant and outperforms the confidence indicators.

5.3 GDP growth forecasts using simple VAR models

Having found that confidence indicators play some role in the likelihood of an economic downturn, we would like to reveal whether these are useful for quantitative GDP growth out-of-sample forecasts. For this purpose the VAR methodology is applied and models are estimated using the strategy presented in subchapter 4.2:

$$A(L)y_t = \varepsilon_t \qquad \textbf{(5.4)}$$

where $A(L)$ is a $m\times m$ matrix polynomial in the lag operator, y_t is an $m\times 1$ vector of observations, and ε_t is an $m\times 1$ vector of white-noise disturbances or shocks. All calculations were done in the Gretl and JMulTi[35] software; our dataset and Gretl sessions are available upon request.

Firstly we fit only "simple VAR" models with GDP and confidence indicators and compare them with the VAR model with LEAD. Secondly, VAR models with both

[35] JMulTi is open-source free statistical software available at http://www.jmulti.de/.

the confidence indicator and the leading indicator are analyzed. Finally, forecasting performance of confidence indicators after controlling for the other effects is assessed.

5.3.1 Simple VAR models

Consider the simplest VAR model, with only two variables interacting with each other: the quarterly GDP growth and a confidence, materialized by CCI or BCI. Forecasting accuracy is compared to the performance of a simple VAR model with the leading indicator instead of a confidence indicator. Therefore three models are fitted:

BCI model: $y_t' = (GDP\_GQ_t, BCI_t)$

CCI model: $y_t' = (GDP\_GQ_t, CCI_t)$

LEAD model: $y_t' = (GDP\_GQ_t, LEAD_t)$

The first step is to determine the adequate lag length for all three models respectively. For this purpose we use tests based on information criteria: AIC, HQIC and SBIC (for details see subchapter 4.2.5). When the tests yield different results, the Schwarz-Bayes Information criteria test (SBIC) is favoured, because SBIC is preferred for small sample models as it imposes a heavier penalty on overparametrized models. Because our time series are relatively short, we have to consider loosing degrees of freedom. For all three models the lag length was identically determined as two lags.

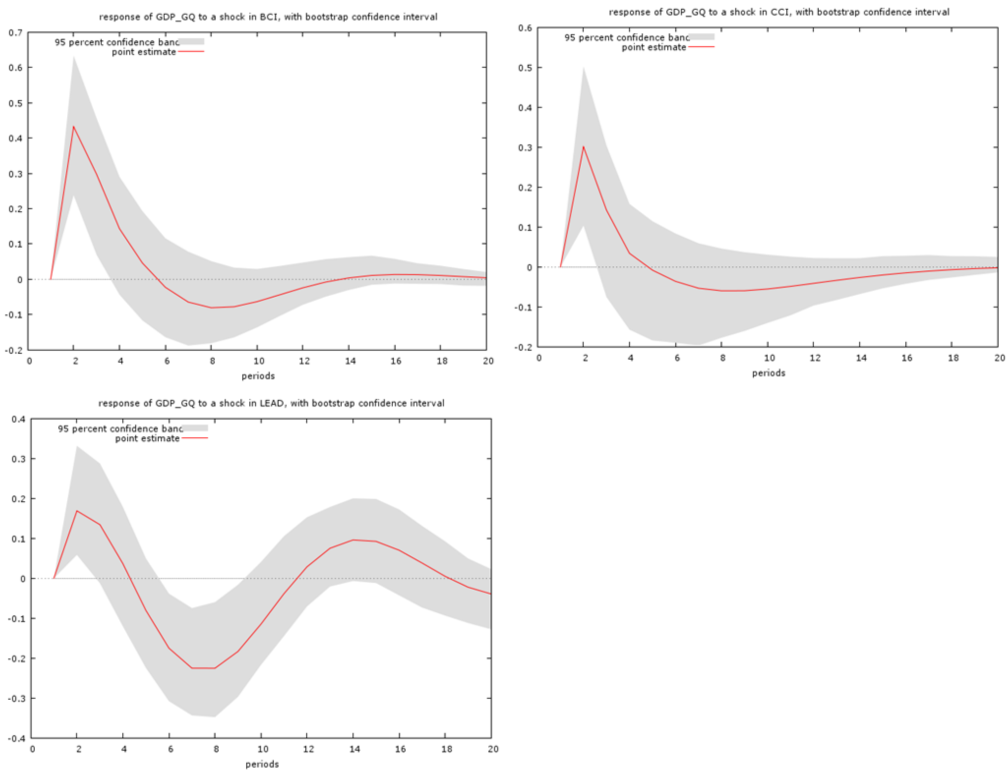
Secondly, models are estimated and the stationarity issues are examined. We considered pros and cons of both approaches mentioned in the previous chapter and decided to follow the ideas of Sims (1980) and strategy of Borys et al. (2009): Do not lose information by detrending variables and consider the stationarity of the system as a whole. Unit root tests of all three models confirmed stability (stationarity) of VAR systems. Stability of parameters is tested using CUSUM test which suggests that the parameters of the models are constant on the 1% significance level.[36]

[36] For graphical presentation of all these tests see Appendix, where also *p*-values of estimated parameters and *F*-tests could be found together with and R-squared for all equations within the VARs.

Because we use models not only for forecasting, but also for impulse responses analysis and variance decomposition, proper identification is necessary. We choose the Cholesky decomposition: we assume that BCI_t, CCI_t or $LEAD_t$ has a contemporaneous effect on GDP_GQ_t, but not vice versa; the economic growth affects indicators only with one and two-period lags, which corresponds to common logic.

Impulse responses show the response of GDP growth to one-unit shock in VAR. Figure 5.2 presents the impulse response functions over time along with 95% confidence intervals. Generally, one-unit shock in either BCI or CCI results in one-shot increase in the GDP growth, which dissipates by around five quarters. The positive response of GDP to shock in BCI compared to CCI is slightly stronger and lasts for one more quarter. On the contrary, the impulse responses to the shock in LEAD show cyclical patterns in GDP response. After about 16 periods, all impulse responses decay to zero, which confirms the stability of the VAR systems.[37]

Figure 5.2: Impulse responses to a shock in BCI, CCI and LEAD, respectively



Source*: own calculations in the Gretl software*

[37] All impulse responses could be seen in Appendix.

The forecasted variance decomposition in Table 5.5 reveals that the attribution of the business confidence indicator to the GDP growth forecast is more than 30% already in the second quarter and slightly increases over time. On the other hand, the consumer confidence indicator explains only about 13% of the future GDP growth and the leading indicator in the first year even less.

Table 5.5: Variance decomposition of GDP and BCI, CCI and LEAD, respectively

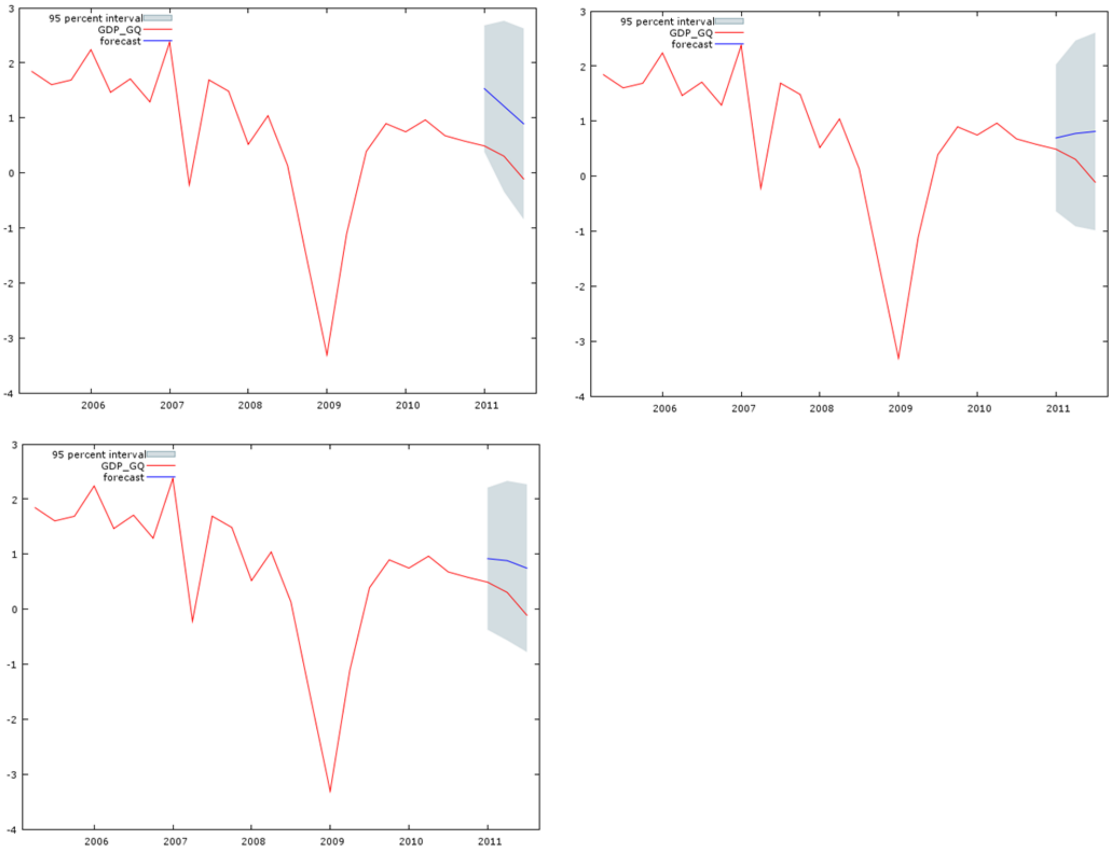
Quarter	GDP		BCI		Quarter	GDP		CCI	
	GDP	BCI	GDP	BCI		GDP	CCI	GDP	CCI
1	100.00	0.00	11.02	88.98	1	100.00	0.00	9.06	90.94
2	68.35	31.65	13.56	86.44	2	87.03	12.97	7.16	92.84
3	62.63	37.37	19.44	80.56	3	85.97	14.03	8.58	91.42
4	63.03	36.97	24.19	75.81	4	86.55	13.45	10.55	89.45

Quarter	GDP		LEAD	
	GDP	LEAD	GDP	LEAD
1	100.00	0.00	0.31	99.69
2	94.44	5.56	0.38	99.62
3	91.81	8.19	0.40	99.60
4	91.84	8.16	0.37	99.63

Notes: The table displays results from the forecast error variance decomposition (in percentage) for all three models and for both GDP and indicator equations.

Finally, three out-of-sample forecasts covering the period Q1-Q3 2011 per each model are calculated and evaluated. Figure 5.3 graphically represents both the true GDP growth and forecasted values with 95% confidence interval. All confidence intervals cover the real GDP value (but the intervals are more than two percentage points of GDP growth wide). However, we cannot speak about the accuracy of the point estimates. There is interesting difference between BCI and CCI: BCI seems to predict the slope (or rate) of decline, but misses the concrete values and CCI almost fit the Q1 2011 true value, but does not reveal the descend trend afterwards. LEAD model forecasts lie somewhere between these two.

Figure 5.3: Out-of-sample GDP growth forecast with BCI, CCI and LEAD respectively



Source*: own calculations in the Gretl software*

Forecasts are formally evaluated using selected (most common in the literature reviewed) measures of accuracy, results are in Table 5.6. CCI model outperformed LEAD in all four statistics and BCI model yields the highest forecast errors.

Table 5.6: Forecast evaluation statistics of the simple VARs

	BCI	CCI	LEAD
Mean Error	-0.9834	-0.5327	-0.6202
Mean Squared Error	0.9702	0.3717	0.4160
Root Mean Squared Error	0.9850	0.6096	0.6450
Mean Absolute Error	0.9834	0.5327	0.6202

Notes: Table reports forecast statistics for BCI, CCI and LEAD model.

Mean squared errors depicted in Table 5.7 represent MSE for the one, two and all three point estimates and will be used for further comparison with other models. CCI confirms the position of the best GDP predictor in this analysis.

Table 5.7: Mean squared errors of forecasts

sample period 1999 Q1 - 2010 Q4

	BCI	CCI	LEAD
2011 Q1	1.0841	0.0415	0.1827
2011 Q2	0.9536	0.1322	0.2584
2011 Q3	0.9702	0.3717	0.4160

Notes: Table reports the value of squared forecast error in Q1 2011 (first row), MSE for the first two estimates (second row) and MSE for all three estimates (last row).

5.3.2 VAR models with both confidence and leading indicator

This analysis will follow the idea of Matsusaka & Sbordone (1995): They suggested evaluating the forecasting ability of confidence indicator (in their case the U.S. index of consumer sentiment) after controlling for fundamentals and other publicly available predictors of an economic output. Because inclusion of a large number of time series consumes degrees of freedom, they chose only one proxy for these forcing variables - the composite leading indicator, which incorporates these effects and is constructed to forecast GDP movements.

We can replicate this method for our analysis of Czech data, because the OECD composite leading indicator for the Czech Republic (unlike OECD composite indicators for Austria, Belgium, Denmark and France among many others) during our sample period did not consist of confidence indicators. Unlike Matsusaka & Sbordone, we will not inspect confidence indicators regarding Granger causality, but stay focused on out-of-sample forecast performance. The analysis is very similar to the previous one; we only increase the number of endogenous variables in the model to three: GDP growth, composite leading indicator and one of confidence indicator, therefore we fit two models, which are then compared to the simple VAR model with LEAD and the predictive value added by BCI or CCI is assessed.

BCI model: $y_t' = (GDP\_GQ_t, BCI_t, LEAD_t)$

CCI model: $y_t' = (GDP\_GQ_t, CCI_t, LEAD_t)$

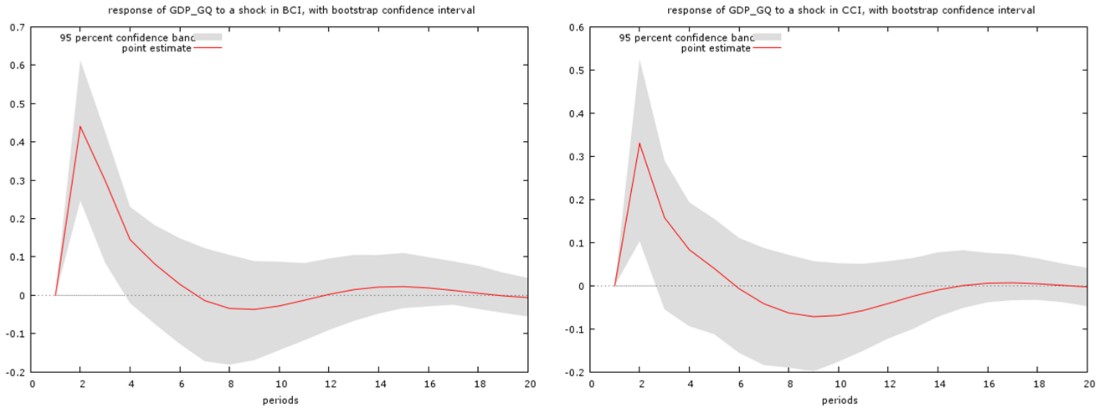
The lag length of both models was set to two lags again, based on information criteria test. Unit root tests of both two models confirmed stability of VAR systems and

CUSUM tests confirmed that the parameters of the models are stable at the 1% significance level.[38]

Identification is needed, so we apply the Cholesky decomposition and assume that BCI_t, or CCI_t and $LEAD_t$ has contemporaneous effect on GDP_GQ_t, but not vice versa. The ordering of CI and LEAD was examined both ways and with almost no changes in variance decomposition or impulse responses.

The impulse responses of the GDP for the ordering GDP, CI, LEAD are reported, see Figure 5.4. One-unit shock in either BCI or CCI results in one-shot increase in the GDP growth, which dissipates by around six quarters, similarly to the simple VAR models. The response to BCI shock is slightly stronger again. Responses decay in time, the stability of both VAR systems is confirmed.[39]

Figure 5.4: Impulse responses of GDP to a shock in BCI and CCI respectively



Source*: own calculations in the Gretl software*

The forecasted variance decomposition in Table 5.8 shows that the BCI accounts for between 34% and 44% of the variance of GDP in the second quarter (depends on ordering of variables) and between 44% and 54% in the fourth quarter. In the CCI model (Table 5.9), the share of CCI in the GDP variance decomposition is significantly lower: only 17% - 21% in the second quarter and 18% - 23% in the fourth quarter. The contribution of LEAD varies based on ordering between 0% and 12% for both models.

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[38] For graphical presentation of all these tests see Appendix, where also *p*-values of estimated parameters and *F*-tests could be found together with and R-squared for all equations within the VARs.
[39] All impulse responses could be seen in Appendix Appendix

Table 5.8: Variance decomposition of GDP – BCI model

Quarter	GDP			GDP		
	GDP	BCI	LEAD	GDP	LEAD	BCI
1	100.00	0.00	0.00	100.00	0.00	0.00
2	56.12	43.80	0.07	56.12	9.44	34.44
3	46.69	53.25	0.07	46.69	12.29	41.02
4	44.83	54.32	0.85	44.83	11.71	43.46

Notes: The table displays results from the forecast error variance decomposition (in percentage) for two types of identification (order of BCI and LEAD)

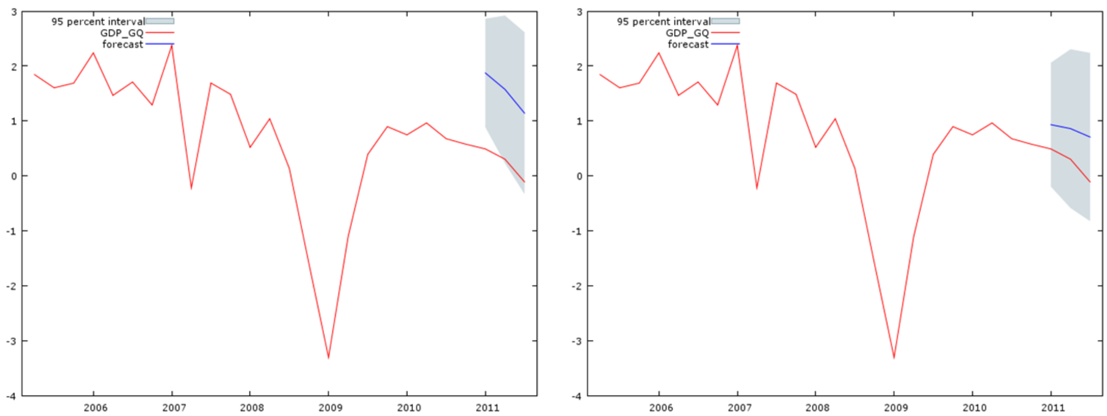
Table 5.9: Variance decomposition of GDP – CCI model

Quarter	GDP			GDP		
	GDP	CCI	LEAD	GDP	LEAD	CCI
1	100.00	0.00	0.00	100.00	0.00	0.00
2	73.03	21.29	5.68	73.03	9.84	17.13
3	69.61	23.25	7.14	69.61	11.91	18.48
4	69.83	23.34	6.83	69.83	11.45	18.72

Notes: The table displays results from the forecast error variance decomposition (in percentage) for two types of identification (order of CCI and LEAD)

Again, three out-of-sample forecasts for period Q1-Q3 2011 for both models are calculated and evaluated, for graphical outcome see Figure 5.5. Adding BCI to the simple VAR model with GDP and LEAD even deteriorates forecast accuracy – although the model perceives decline, the GDP estimates are too optimistic. On the other hand CCI enhanced the baseline simple LEAD model – adds additional information and slightly improves forecast errors, see Table 5.10.

Figure 5.5: Out-of-sample GDP growth forecast using BCI and CCI model, respectively



Source*: own calculations in the Gretl software*

Table 5.10: VARs forecast evaluation statistics

	Baseline	BCI	CCI
Mean Error	-0.6202	-1.3008	-0.6047
Mean Squared Error	0.4160	1.6953	0.3905
Root Mean Squared Error	0.6450	1.3020	0.6249
Mean Absolute Error	0.6202	1.3008	0.6047

Notes: Table reports statistics for BCI and CCI model and baseline LEAD model.

Table 5.11: Mean squared errors of forecasts

sample period 1999 Q1 - 2010 Q4

	Baseline	BCI	CCI
2011 Q1	0.1827	1.9083	0.1945
2011 Q2	0.2584	1.7609	0.2519
2011 Q3	0.4160	1.6953	0.3905

Notes: Table reports value of squared forecast error in Q1 2011 (first row), MSE for the first two estimates (second row) and MSE for all three estimates (last row).

Although the statistics for the three forecasts altogether report moderate improvement for the CCI model, from Table 5.11 it is evident, that the first point forecast is less precise and the enhancement comes with the Q2 and Q3 forecasts. Because we want to statistically evaluate the performance of BCI and CCI after controlling for LEAD, these models are compared to the simple LEAD model and the Clark-West forecast evaluation test for nested models is applied.[40]

Table 5.12: Clark-West test

out-of-sample period 2011 Q1 - 2011 Q3

Model enhanced by:	t-statistic
Business confidence indicator	-17.370
Customer confidence indicator	1.188

Notes: Critical values for one sided test are +1.282 (10% significance) and +1.645 (5% significance)

The null hypothesis - no forecast improvement - cannot be statistically rejected for both models at the 10% significance level. (However, for CCI model it was tight, the null would be rejected at the 12% significance level.)

[40] For details see subchapter 4.3.2 Pseudo out-of-sample measures of predictive content.

5.3.3 Discussion of results

Our simple VAR models confirm that GDP growth increase in response to positive shock in confidence (either customer or business) and this increase last for at least one year. Moreover, BCI accounts for more than one third of GDP variation compared to only much smaller share of CCI in GDP forecasted variance.

However, out-of-sample point estimates of future GDP growth using these simple VAR models cannot be considered as sufficient. Two-variable VARs reveal interesting findings: business confidence missed the real GDP growth but correctly predicted the declining trend and customer confidence missed the trend but gives the most precise forecast for the first quarter (even compared to models with three variables). When assessing the predictive power of BCI and CCI after controlling for LEAD we can conclude that the business confidence indicator does not enhance GDP growth forecasts. The customer confidence index contributes with some additional information and slightly improves GDP forecasts, but this forecasting ability is not statistically confirmed by the Clark-West test.

5.4 VAR models of the Czech economy

OECD composite leading indicator served as a proxy for economic fundamentals in the previous analysis, now we examine a different approach. In the first stage of our final empirical analysis we model the Czech economy using true macroeconomic variables within the framework of standard vector autoregression.[41] This benchmark model is subsequently enhanced by confidence indicators, one at a time. Finally, we statistically evaluate to what extent the confidence indicators improve the out-of-sample GDP growth forecasts. We mostly follow the empirical strategy of Havránek et al. (2011) and Horváth (2012). Robustness check and results discussion conclude our empirical research.

[41] We choose the standard VAR, with reference to Borys et al. (2009), who tested various VAR types of models (factor-augmented VAR, structural VAR, Bayesian sign-restricted VAR and standard VAR) on the Czech data and conclude that in terms of impulse responses all models give similar results.

5.4.1 VAR model with standard economic variables

Our benchmark macroeconomic model of the Czech economy consists of the following variables: real GDP growth (GDP_QG), quarterly growth rate of CPI (Inflation_Q), interest rate (PRIBOR) and CZK/EUR exchange rate (EXRATE). This model corresponds to small open economies, when it covers a measure of the economic activity (GDP), a measure of economic conditions (price level), variable representing financial sector conditions (interest rate) and the international influence (exchange rate). Furthermore, this model has been frequently used in the Czech context (Borys et al., 2009, apart from the above mentioned).

The lag length is set according to Schwarz-Bayes Information criteria to one lag. Unit root test verified stability of the VAR system and CUSUM tests confirmed that the parameters of the models are stable at the 1% significance level.[42]

The system is identified by the Cholesky decomposition: output reacts immediately to all other variables, price level reflects the current values of interest and exchange rate and interest rate is influenced by present exchange rate. All variables interact with each other with one-period lag. This identification system is applied for example in Mojon, B. & G. Peersman (2001) or Havránek et al. (2011).

Benchmark model: $y_t' = (GDP\_GQ_t, Inflation\_Q_t, PRIBOR_t, EXRATE_t)$

Impulse responses of this model correspond to expected reactions that could be found in literature. The common effect of "price puzzle" occurred (i.e. the empirical finding in the VAR literature that prices rise after the interest rate tightening).[43] Both impulse responses plots and variance decomposition could be found in Appendix.

We follow the same forecasting strategy; three out-of-sample forecasts are estimated (period Q1-Q3 2011), for graphical outcome see Figure 5.6. The first point estimate of GDP is close to the reality, but the others are too optimistic. However, when we compare for example the mean square error of GDP predictions, this

[42] For graphical presentation of all these tests see Appendix, where also *p*-values of estimated parameters and *F*-tests could be found together with and R-squared for all equations within the VARs.
[43] See for example Sims (1992). For possible explanations see Coricelli et al. (2006), pp. 41-42.

macroeconomic VAR model ("Macro") outperforms all previous VAR models only with confidence, leading indicator or both. The comparison is reported in Table 5.13.

Figure 5.6: Out-of-sample GDP growth forecast – macroeconomic model

Source*: own calculations in the Gretl software*

Table 5.13: Forecast evaluation for macroeconomic model and all other previously fit

	Macro	BCI	CCI	LEAD	BCI+LEAD	CCI+LEAD
ME	-0.3933	-0.9834	-0.5327	-0.6202	-1.3008	-0.6047
MSE	0.2412	0.9702	0.3717	0.4160	1.6953	0.3905
RMSE	0.4911	0.9850	0.6096	0.6450	1.3020	0.6249
MAE	0.3933	0.9834	0.5327	0.6202	1.3008	0.6047

Notes: mean error, mean square error, root mean square error and mean absolute square error are reported for all models, respectively

5.4.2 Models enhanced by confidence indicators

Next, the benchmark macroeconomic VAR model is enhanced by the business confidence indicator and the customer confidence indicator, one after the other (we must consider the degrees of freedom issue). In addition, we follow Horváth (2012) and test the predictive power of a German confidence (represented by the Ifo business climate index for German trade and industry - business expectations) regarding Czech GDP. This is motivated by the fact that as a small open economy, the Czech Republic is highly dependent on the German economy - the share of goods exports to Germany has been 32% on average.[44] The leading indicator is also added for comparison purposes (although one its composite is consumer price index which already appears in the base model as inflation). Altogether we fit four models:

BCI model: $y_t' = (GDP\_GQ_t, Inflation\_Q_t, PRIBOR_t, EXRATE_t, BCI_t)$

CCI model: $y_t' = (GDP\_GQ_t, Inflation\_Q_t, PRIBOR_t, EXRATE_t, CCI_t)$

IFO model: $y_t' = (GDP\_GQ_t, Inflation\_Q_t, PRIBOR_t, EXRATE_t, IFO_t)$

LEAD model: $y_t' = (GDP\_GQ_t, Inflation\_Q_t, PRIBOR_t, EXRATE_t, LEAD_t)$

Tests based on Schwarz-Bayes information criteria suggest the appropriate lag length as one lag, identically for all models. All VAR systems are stable – do not contain the unit root and CUSUM test confirms stability of parameters at the 1% significance level.[45] All the systems are identified by the Cholesky decomposition, the strategy is the same as for the benchmark model and indicators are in the variable ordering put on the last place.[46]

The impulse responses of the GDP value to one-unit shock in BCI, CCI, IFO and LEAD are reported, see Figure 5.7. The other impulse responses are similar to that reported for the base model. One-unit shock in the indicator variable results in one-shot increase in the GDP growth, which dissipates after one year or more, turns into decline and then all effects vanishes. The highest GDP increase comes after the IFO shock and lasts for about 6 periods. The second highest GDP response is after BCI shock, followed by CCI and then LEAD. Compared to previous models, the both BCI and CCI effect is lower now.

The forecasted variance decomposition in Table 5.14 - Table 5.17 shows that after four quarters, BCI accounts only for 2.4% of the forecast GDP variance, and CCI's

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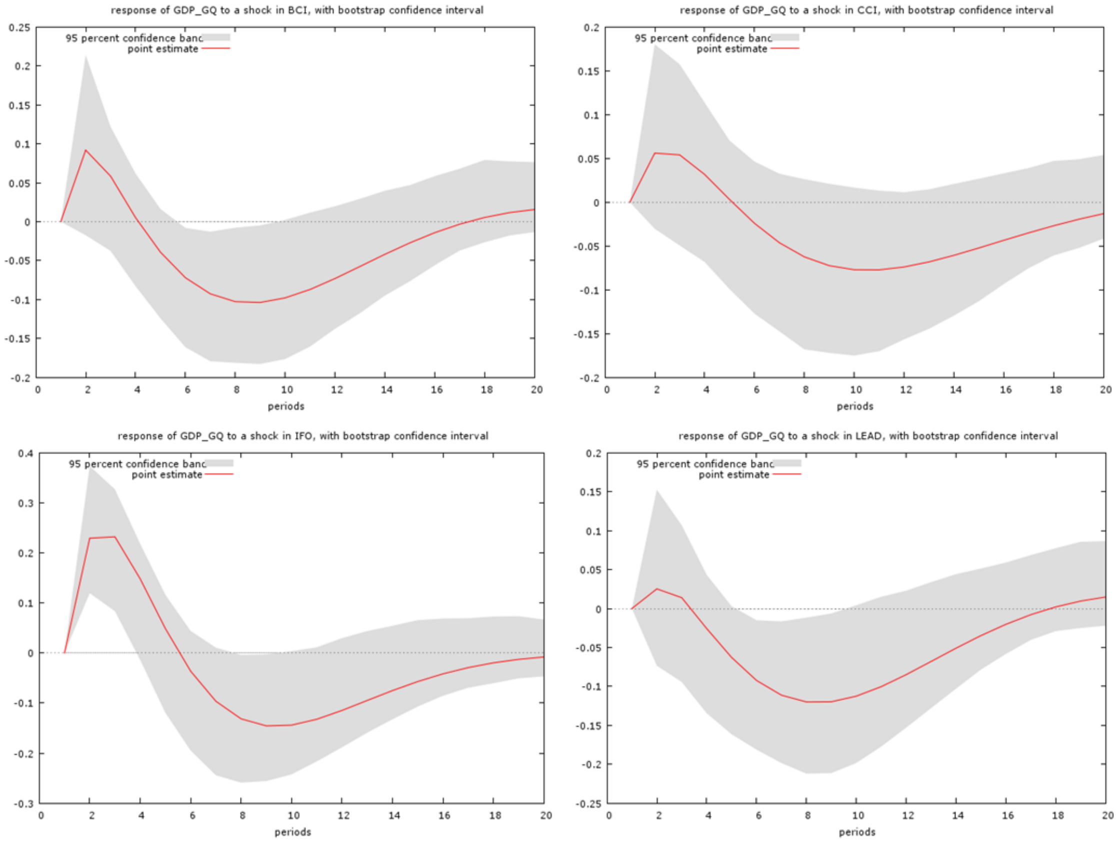
[44] Germany is the Czech Republic's main trading partner, for more detailed information and numbers see http://www.cnb.cz/en/monetary_policy/inflation_reports/2011/2011_IV/boxes_and_annexes/zoi_2011_IV_box_3.html.
[45] For graphical presentation of all these tests see Appendix, where also *p*-values of estimated parameters and *F*-tests could be found together with and R-squared for all equations within the VARs.
[46] We tested even the positions on the fourth and third place, but the change in impulse responses or variance decomposition is not significant.

share is even lower: 1.31%. IFO contributes to the GDP variance with 23.3% after one year and LEAD 0.28% only. The share on variance after two quarters is negligible for all tested variables except for IFO, which accounts for 14.3% of GDP. Only IFO significantly explains GDP variance, but it must be said that in all other models the GDP is mostly self explained; the other macroeconomic variables contribute only between 1% and 7%. Therefore according to this analysis results we could consider German business confidence as a significant source of Czech GDP growth forecast variance.

Figure 5.7: Impulse responses of GDP to a shock in BCI, CCI, IFO and LEAD, respectively



Source*: own calculations in the Gretl software*

Table 5.14: Variance decomposition of GDP: BCI model

Quarter	GDP_GQ				
	GDP_GQ	Inflation	PRIBOR	EXRATE	BCI
1	100.00	0.00	0.00	0.00	0.00
2	95.56	0.04	1.12	1.36	1.92
4	84.66	1.43	4.84	6.69	2.38
8	66.54	7.54	7.89	12.50	5.53

Notes: Values are percentage points

Table 5.15: Variance decomposition of GDP: CCI model

Quarter	GDP_GQ				
	GDP_GQ	Inflation	PRIBOR	EXRATE	CCI
1	100.00	0.00	0.00	0.00	0.00
2	95.71	0.40	1.91	1.30	0.68
4	82.99	2.69	6.68	6.33	1.31
8	67.82	11.20	7.87	11.25	1.86

Notes: Values are percentage points

Table 5.16: Variance decomposition of GDP: IFO model

Quarter	GDP_GQ				
	GDP_GQ	Inflation	PRIBOR	EXRATE	IFO
1	100.00	0.00	0.00	0.00	0.00
2	83.48	0.03	2.44	0.02	14.03
4	60.47	7.74	7.52	0.96	23.30
8	47.97	12.84	9.59	8.87	20.73

Notes: Values are percentages points

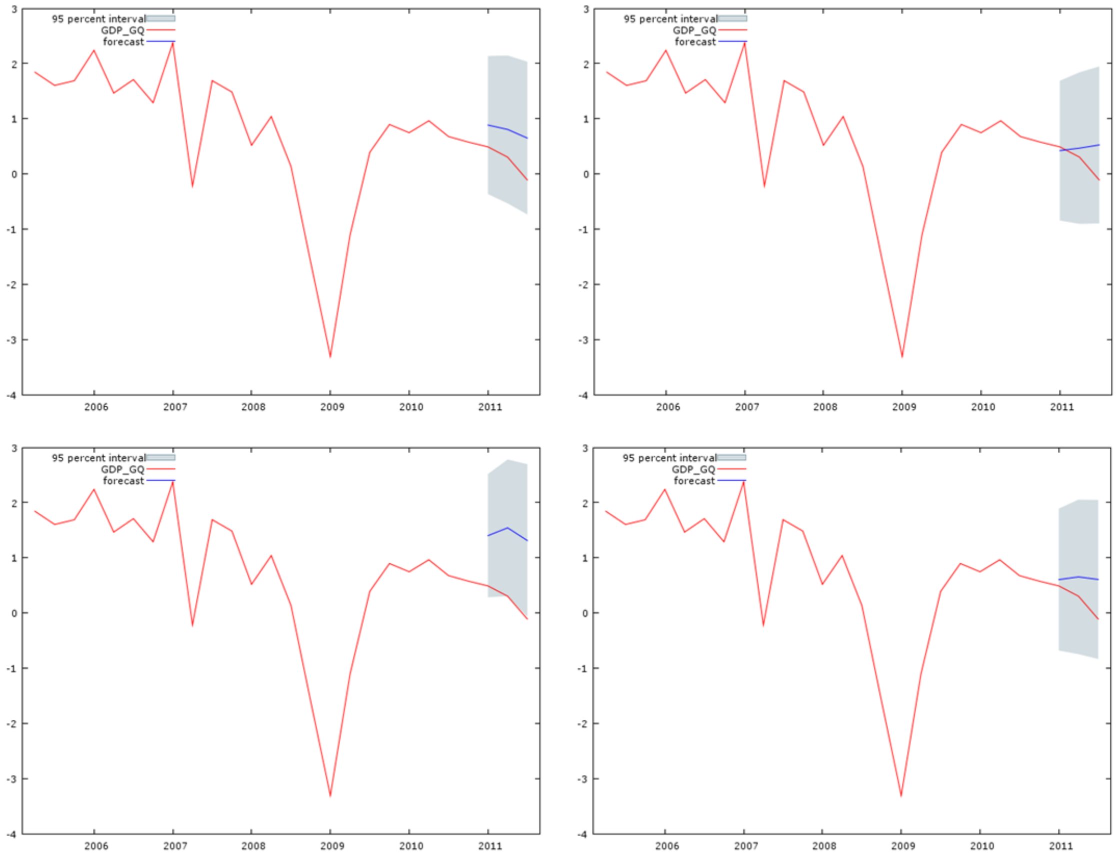
Table 5.17: Variance decomposition of GDP: LEAD model

Quarter	GDP_GQ				
	GDP_GQ	Inflation	PRIBOR	EXRATE	LEAD
1	100.00	0.00	0.00	0.00	0.00
2	96.91	0.36	1.01	1.59	0.13
4	87.44	1.69	4.16	6.42	0.28
8	74.07	5.86	6.13	8.10	5.84

Notes: Values are percentage points

GDP growth for the period Q1-Q3 2011 is estimated using all models and the forecasts confront reality, see Figure 5.8. Table 5.18 summarize precise values of evaluation statistics: adding BCI or IFO to the macroeconomic VAR model even deteriorates its forecast accuracy. IFO’s bad performance could be explained by excessive optimism in Germany since Q4 2009 compared to Czech confidence (see Figure A.4 in Appendix). Only CCI upgrades the benchmark model’s forecasts (lower all “error” statistics) and LEAD reaches similar results as the base model.

Figure 5.8: Out-of-sample GDP growth forecast: BCI, CCI, IFO and LEAD model, respectively



Source*: own calculations in the Gretl software*

Table 5.18: Forecast evaluation statistics

	Macro	BCI	CCI	IFO	LEAD
Mean Error	-0.3933	-0.5520	-0.2437	-1.1898	-0.3942
Mean Squared Error	0.2412	0.3281	0.1452	1.4605	0.2169
Root Mean Squared Error	0.4911	0.5728	0.3810	1.2085	0.4657
Mean Absolute Error	0.3933	0.5520	0.2894	1.1898	0.3941

Notes: Macro models serves as a benchmark for performance of the other enhanced models

Although CCI improves the forecasts, from the Table 5.19 it is obvious that the first forecast (Q1 2011) is less precise and the enhancement comes with the Q2 and Q3 forecasts. Because we want to statistically evaluate the performance of BCI, CCI, IFO and LEAD after controlling for macro variables, we employ Clark-West forecast evaluation test for nested models again (Table 5.20).

Table 5.19: Mean squared errors of forecasts

	sample period 1999 Q1 - 2010 Q4				
	Macro	BCI	CCI	IFO	LEAD
2011 Q1	0.0042	0.1554	0.0047	0.8272	0.0132
2011 Q2	0.0586	0.2040	0.0158	1.1799	0.0679
2011 Q3	0.2412	0.3281	0.1452	1.4605	0.2169

Notes: Table reports value of squared forecast error in Q1 2011 (first row), MSE for the first two estimates (second row) and MSE for all three estimates (last row).

Table 5.20: Clark-West test

out-of-sample period 2011 Q1 - 2011 Q3	
Model enhanced by:	t-statistic
Business confidence indicator	-1.006
Customer confidence indicator	1.999**
Ifo business climate indicator	-2.219
Composite leading indicator	0.770

Notes: Critical values for one sided test are +1.282 (10% significance) and +1.645 (5% significance)

We can reject the null hypothesis and therefore conclude that the forecast improvement is statistically significant only in the case of CCI model, at the 5% significance level. The null of "no forecast improvement" cannot be statistically rejected for all other tested indicators: BCI, IFO and LEAD.

5.4.3 Robustness check

In order to check these results robustly, we carry out the identical analysis again, but at different forecast dates. Unfortunately the robustness check is limited by data availability, time series are not sufficiently long for more robust checks. Now the in-sample period for model development is one and two quarters shorted and the out-of-sample forecast periods start in Q4 2010 and Q3 2010, i.e. one or two quarters earlier, respectively. Again, we assess predicted values for three quarters ahead. First set of results is reported in Table 5.21 and Table 5.22; the second set of results follows (Table 5.23 and Table 5.24).

Table 5.21: Mean squared errors of forecasts

sample period 1999 Q1 - 2010 Q3

	Macro	BCI	CCI	IFO	LEAD
2010 Q4	0.0056	0.0481	0.0084	0.6461	0.0083
2011 Q1	0.0230	0.0540	0.0042	0.7556	0.0238
2011 Q2	0.0667	0.0769	0.0220	0.7540	0.0603

Notes: Table reports value of squared forecast error in Q4 2010 (first row), MSE for the first two estimates (second row) and MSE for all three estimates (last row).

Table 5.22: Clark-West test

out-of-sample period 2010 Q4 - 2011 Q2

Model enhanced by:	t-statistic
Business confidence indicator	-0.109
Customer confidence indicator	2.704**
Ifo business climate indicator	-3.310
Composite leading indicator	0.900

Notes: Critical values for one sided test are +1.282 (10% significance) and +1.645 (5% significance)

Table 5.23 Mean squared errors of forecasts

sample period 1999 Q1 - 2010 Q2

	Macro	BCI	CCI	IFO	LEAD
2010 Q3	0.0658	0.0567	0.0281	0.6055	0.0579
2010 Q4	0.0782	0.0668	0.0356	0.6272	0.0712
2011 Q1	0.0908	0.0773	0.0481	0.5577	0.0888

Notes: Table reports value of squared forecast error in Q3 2010 (first row), MSE for the first two estimates (second row) and MSE for all three estimates (last row).

Table 5.24: Clark-West test

out-of-sample period 2010 Q3 - 2011 Q1

Model enhanced by:	t-statistic
Business confidence indicator	5.485**
Customer confidence indicator	15.13**
Ifo business climate indicator	-9.398
Composite leading indicator	0.406

Notes: Critical values for one sided test are +1.282 (10% significance) and +1.645 (5% significance)

The robustness checks confirm that the models enhanced by the customer confidence indicator forecast the GDP growth more accurately then the pure macroeconomic model. It is also robustly verified that IFO and the leading indicator do not enhance the VAR model forecasts significantly. The business confidence indicator brings mixed results: two tested sets of forecasts are worse than the macro model, but forecasts for the period 2010 Q3-2011 Q1 significantly overcome the benchmark.

5.4.4 Discussion of results

Our final VAR models with macroeconomic variables and confidence indicators bring mixed results. Although business confidence again correctly predicts the decreasing GDP growth trend, the quantitative forecasts are too optimistic and miss the real GDP growth values. Customer confidence is robustly proved as a variable improving GDP growth forecasts in the model with standard macroeconomic variables. This result accords with Mourougane & Roma (2003) or Golinelli & Parigi (2004). Forecasts are improved, because the first quarter estimate is relatively precise and the two others are “less wrong” compared to the benchmark model; but in fact the CCI is not able to model GDP growth descend trend in 2011.

Interactions between Czech GDP growth and German business confidence index have promising results regarding impulse responses and variance decomposition, but when it comes to out-of-sample forecasting, predictions miss reality. Unfortunately, German optimism mirrored by relatively high values of the Ifo business climate index was not transferred to Czech economic productivity in 2011.

6. Conclusion

"*The appraisal of the predictive value of data is inherently a risky business. Any evaluation should be advanced, and interpreted, as tentative and resting on a pragmatic foundation*."

Arthur Okun (1960)

Our expectations and confidence about the future are influenced by the knowledge of our personal prospects. This thesis assesses whether this information could be captured by confidence indicators and used on the aggregate level for predicting economic activity in the Czech Republic. The role of the business confidence indicator (BCI) and the customer confidence indicator (CCI) in macroeconomic forecasting is examined; our findings are based on empirical research.

During the initial exploratory analysis we revealed significant contemporaneous correlations between both types of domestic confidence indicators and real GDP growth. Cross-correlations of the current GDP growth value and past confidence indicator values are slightly smaller, but still significant and confirm leading properties of both confidence indices.

The consecutive analysis focused on the performance of confidence indicators, first in predicting the likelihood of economic downturn defined as discrete event using logit models and second in GDP growth out-of-sample forecasting using various vector autoregression models.

The results obtained from the downturn probability models with confidence indicators are encouraging for nowcasting (current economic situation estimation) and one-quarter-ahead forecasting, while no significant relationship was apparent for further prospects. We can conclude that both confidence indicators are significant predictors of the likelihood that the economy currently experiences downturn. This information could be useful for policy-makers, because it is almost instantly available. The current GDP value, on the other hand, is published with a long delay. In particular the model with the business indicator included as the predictor variable proved its qualities; it was able to correctly nowcast 80% states of economy and 68% of downturns. Only the BCI is significant for one-quarter-ahead forecasting, but the forecast accuracy declined. Still, we can claim that if the BCI increases from the long-term-average only by three percentage points, the probability of a downturn in the next quarter decreases by 16.5 percentage points (to 28.8% from the basic level of 45.3%). If the BCI decreases by three percentage points, the downturn probability increases to 62.9%. Moreover, we compared the results for individual confidence indicators with the composite leading indicator, which is designed to anticipate business cycle turning points, and we can conclude that the CCI exhibits similar qualities and the BCI significantly outperforms the composite leading indicator in turning points forecast accuracy.

In terms of forecasting quantitative point estimates of GDP growth, the predictive power of confidence indicators is ambiguous. The out-of-sample forecasts using simple VAR models containing only GDP growth and BCI or CCI cannot be considered as sufficient, but they revealed interesting findings: BCI missed the real GDP growth but correctly predicted the declining trend and CCI missed the trend but provided the most precise forecast for the first quarter; this was true for all our models.

When we assess the additional predictive power of confidence indicators above the information provided by the composite leading indicator, the improvement in forecasts was not significant. Finally, we fitted a model of the Czech economy with standard macroeconomic variables only and then enhanced this benchmark model by BCI, CCI and by the German confidence indicator, respectively. From these three, only the customer confidence indicator significantly reduced the forecast error, which was also robustly confirmed.

We can conclude that based on our findings the business confidence indicator is a significant predictor of the likelihood of economic downturns for the current period and a period one-quarter-ahead. Furthermore, the BCI was able to forecast the GDP growth slowdown in 2011, but did not deliver precise values or improve benchmark forecasts. On the contrary, forecasts with the customer confidence indicator one-quarter-ahead are closer to the reality. This index was not able to model GDP decline, but neither did benchmark macroeconomic model. Still, adding CCI to the model with macroeconomic variables significantly confirmed CCI’s predictive power.

This result was indirectly confirmed by OECD; as the Czech customer confidence indicator has been included as a new component in the OECD domestic composite leading indicator since April 2012.

In our opinion, future research on confidence indicators should focus on nowcasting quantitative GDP values, since our downturn nowcasting exercise provides promising results. Furthermore, the predictive power of confidence indicators have not be assessed for some Central and Eastern European countries and the potential cross-country comparison may bring interesting results. Finally, since the research examining the predictive power of confidence indicators in various countries brings mixed results, a meta-analysis of this phenomenon could shed light on this issue.

At the very end, let me identify the last paragraph of this thesis with the last paragraph of Tobin (1959), since these words are even more truthful now than they were fifty-three years ago:

> "*I would not conclude without stressing the very considerable debt the profession owes George Katona and his colleagues at the Survey Research Center for their imaginative and pioneering work in the collection and interpretation of buying intentions and attitudinal data. Without their leadership, we might still be talking about the importance of consumer psychology for short-term business fluctuations and bemoaning our inability to observe and measure it. Thanks to the experience they are accumulating, we can investigate the questions which attitudes are the most important ones to investigate in periodic surveys and what is the best way to use these data in combination with other economic information.*"

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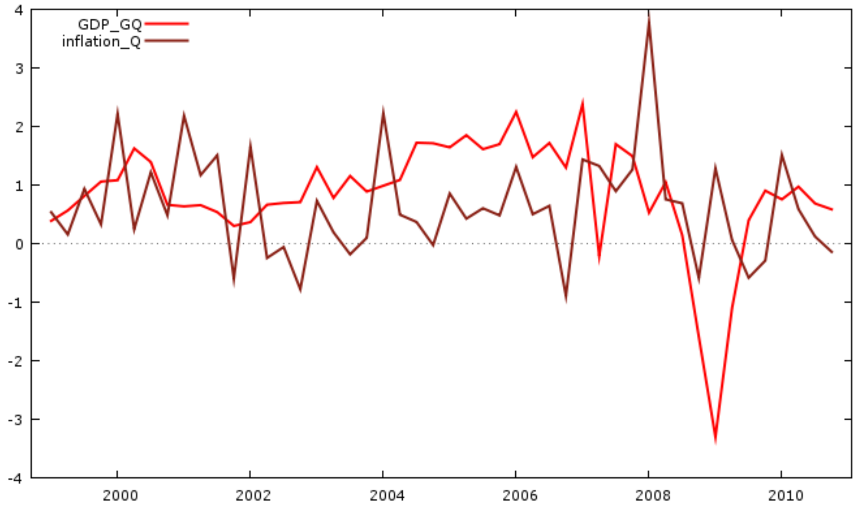
IFO database, available at http://www.cesifo-group.de/
OECD database, available at http://stats.oecd.org/

Gretl software, available at http://gretl.sourceforge.net/
JMulTi software, available at http://www.jmulti.de/.

Appendix

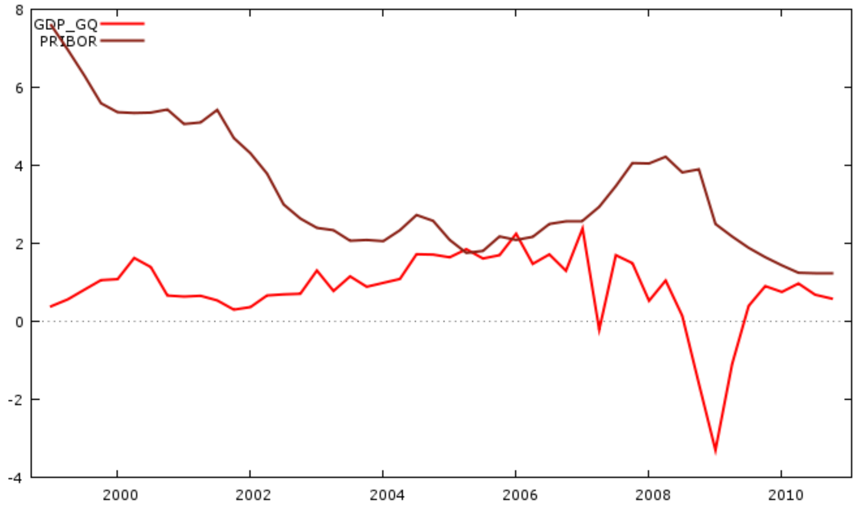
Time series plots

Figure A.1: Inflation and GDP growth



Source*: own calculations in the Gretl software*

Figure A.2: PRIBOR and GDP growth

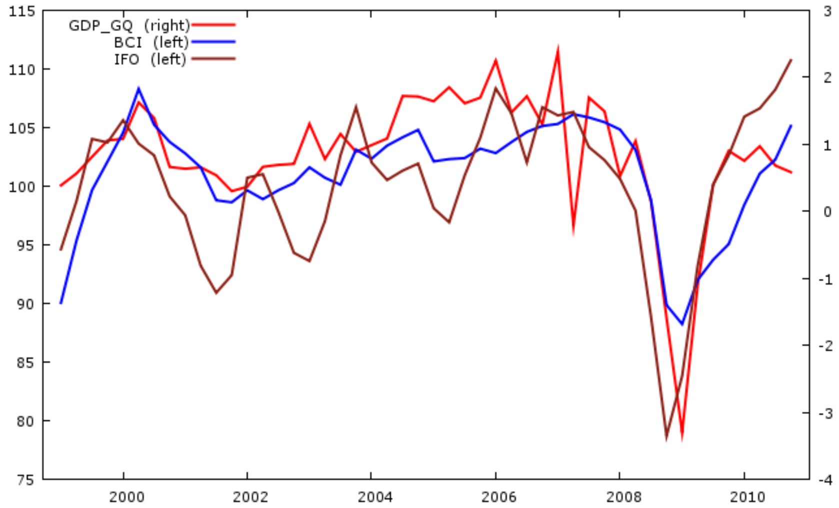


Source*: own calculations in the Gretl software*

Figure A.3: CZK/EUR exchange rate and GDP growth

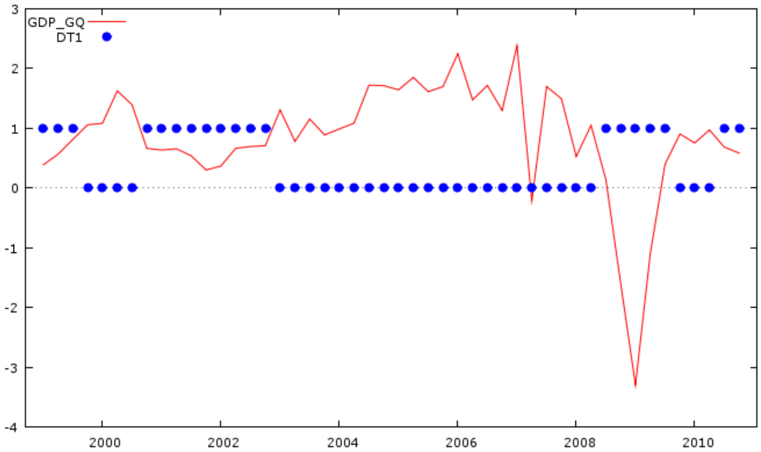
Source*: own calculations in the Gretl software*

Figure A.4: Ifo business climate index, BCI and GDP growth



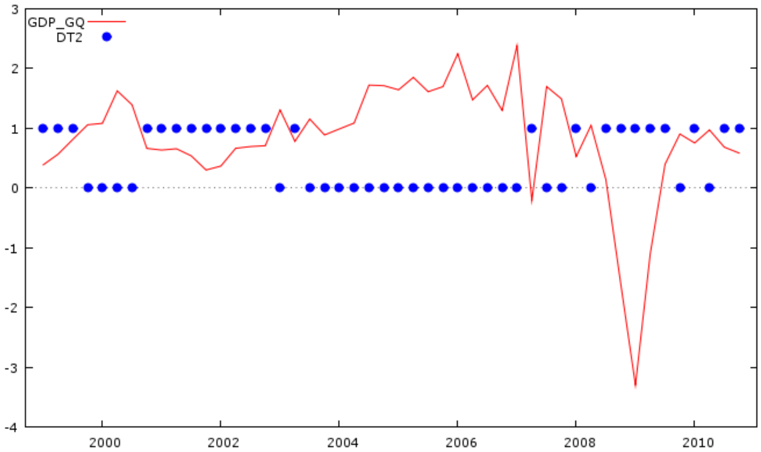
Source*: own calculations in the Gretl software*

Figure A.5: Downturn as a discrete event, first definition



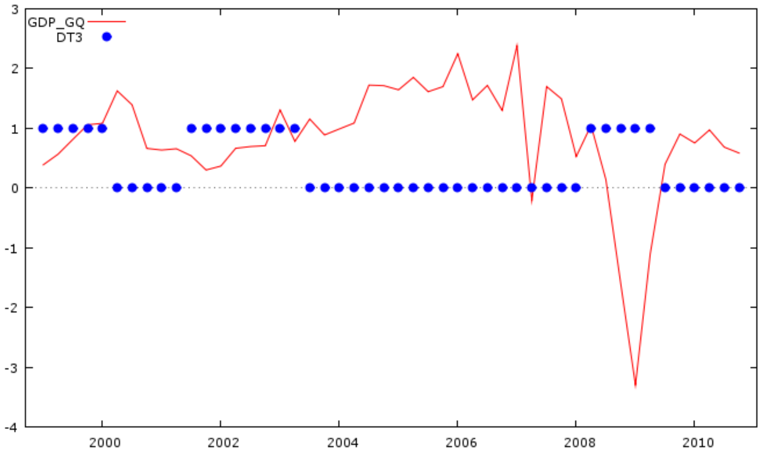
Source*: own calculations in the Gretl software*

Figure A.6: Downturn as a discrete event, second definition



Source*: own calculations in the Gretl software*

Figure A.7: Downturn as a discrete event, OECD definition



Source*: own calculations in the Gretl software*

Logit models results

Table A.1: Logit model of BCI for k = 0 and (i) definition of downturn

BCI value	probability of downturn	difference (ppt.)	difference x=100 (ppt.)
85	99.88%		47.55
86	99.81%	-0.07	47.48
87	99.71%	-0.10	47.38
88	99.55%	-0.16	47.22
89	99.30%	-0.25	46.97
90	98.92%	-0.38	46.59
91	98.33%	-0.59	46.00
92	97.42%	-0.91	45.09
93	96.05%	-1.38	43.72
94	93.98%	-2.07	41.65
95	90.93%	-3.05	38.60
96	86.56%	-4.37	34.23
97	80.54%	-6.02	28.21
98	72.67%	-7.87	20.34
99	63.08%	-9.59	10.75
100	52.33%	-10.75	0.00
101	41.36%	-10.97	-10.97
102	31.18%	-10.18	-21.15
103	22.55%	-8.63	-29.78
104	15.76%	-6.79	-36.57
105	10.73%	-5.03	-41.60
106	7.17%	-3.56	-45.16
107	4.73%	-2.44	-47.60
108	3.09%	-1.64	-49.24
109	2.01%	-1.08	-50.32
110	1.30%	-0.71	-51.03
111	0.84%	-0.46	-51.49
112	0.54%	-0.30	-51.79
113	0.35%	-0.19	-51.98
114	0.22%	-0.12	-52.11
115	0.14%	-0.08	-52.19

Notes: ppt. stands for percentage points

Table A.2: Logit model of BCI for k = 1 and (i) definition of downturn

BCI	probability of downturn	difference (ppt.)	difference x=100 (ppt.)
85	96.75%		51.41
86	95.91%	-0.84	50.57
87	94.86%	-1.05	49.52
88	93.56%	-1.30	48.23
89	91.97%	-1.60	46.63
90	90.02%	-1.95	44.68
91	87.66%	-2.36	42.33
92	84.84%	-2.82	39.51
93	81.51%	-3.33	36.17
94	77.64%	-3.87	32.31
95	73.23%	-4.41	27.89
96	68.30%	-4.93	22.96
97	62.92%	-5.38	17.59
98	57.21%	-5.72	11.87
99	51.29%	-5.92	5.95
100	45.34%	-5.95	0.00
101	39.51%	-5.82	-5.82
102	33.97%	-5.54	-11.36
103	28.84%	-5.13	-16.49
104	24.20%	-4.64	-21.14
105	20.09%	-4.11	-25.24
106	16.53%	-3.56	-28.80
107	13.50%	-3.04	-31.84
108	10.94%	-2.55	-34.39
109	8.83%	-2.12	-36.51
110	7.08%	-1.74	-38.25
111	5.67%	-1.42	-39.67
112	4.52%	-1.15	-40.82
113	3.59%	-0.92	-41.74
114	2.85%	-0.74	-42.48
115	2.26%	-0.59	-43.08

Notes: ppt. stands for percentage points

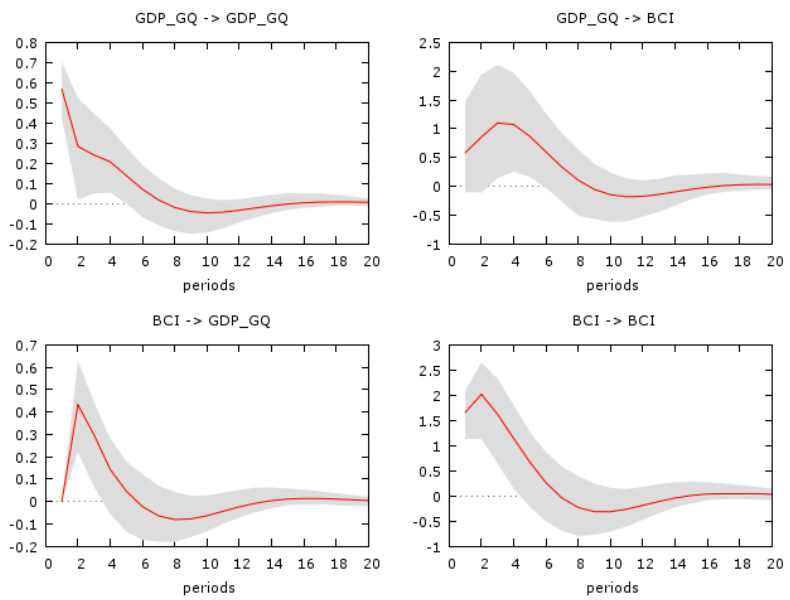
Simple VAR models results and evaluations

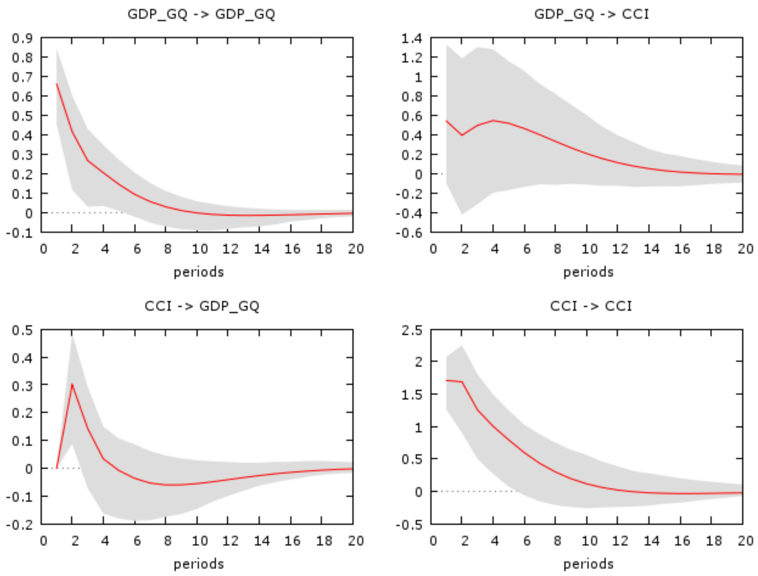
Table A.3: Results for VAR models with GDP and one indicator variable

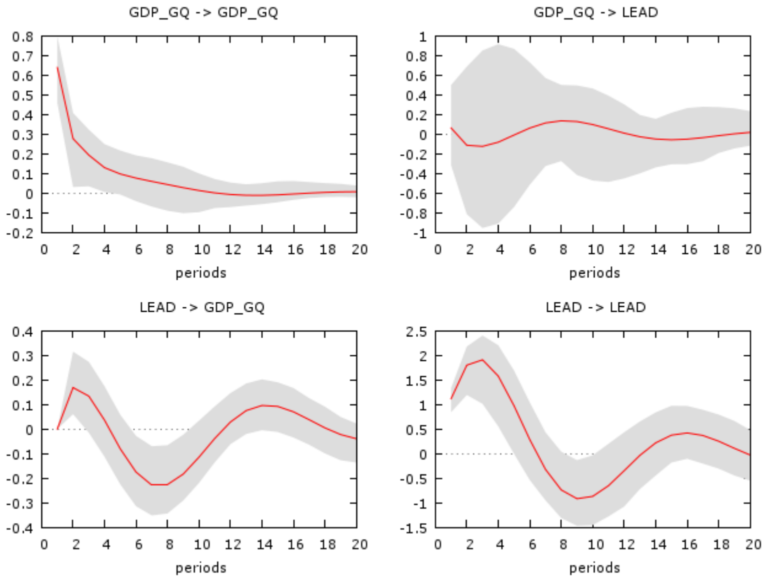
	Dependent		Dependent		Dependent	
	GDP	BCI	GDP	CCI	GDP	LEAD
GDP lag 1	0.1400	0.5967	0.0023	0.6021	0.0083	0.2094
GDP lag 2	0.4290	0.2292	0.3563	0.2549	0.2567	0.2142
Indicator lag 1	0.0000	0.0000	0.0049	0.0000	0.0111	0.0000
Indicator lag 2	0.0000	0.0001	0.0027	0.1786	0.0009	0.0000
GDP all lags	0.1682	0.3371	0.0001	0.5051	0.0003	0.3751
Indicator all lags	0.0000	0.0000	0.0099	0.0000	0.0027	0.0000
F-test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.6494	0.8198	0.5273	0.7721	0.5568	0.9250

Notes: There are three models and two equations per model (represented by six columns). All numbers except R-squared are *p*-values of test with H_0 of a zero coefficient (or jointly zero coefficients in case of "... all lags" and *F*-test)

Figure A.8: Impulse responses for simple BCI, CCI and lead model, respectively

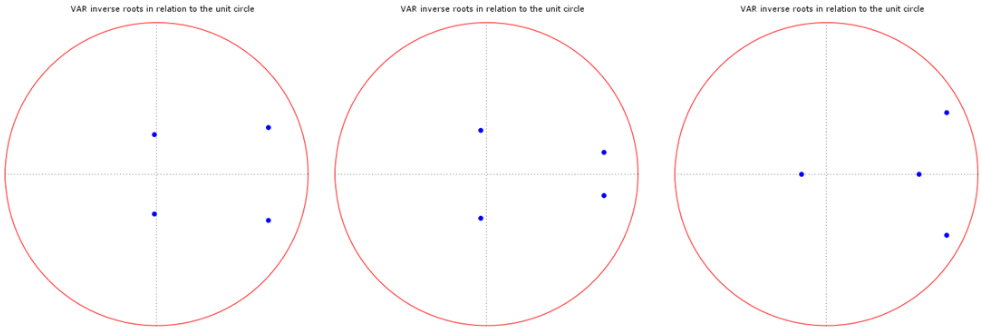






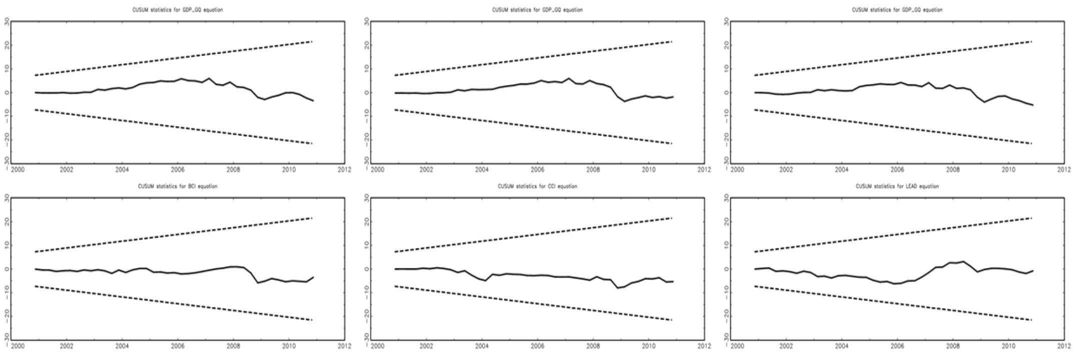
Source*: own calculations in the Gretl software*

Figure A.9: Unit root test for BCI, CCI and LEAD model, respectively (points inside the unit circle mean no unit root)



Source*: own calculations in Gretl software*

Figure A.10: CUSUM tests for BCI, CCI and LEAD model, respectively



Source*: own calculations in the JMulTi software*

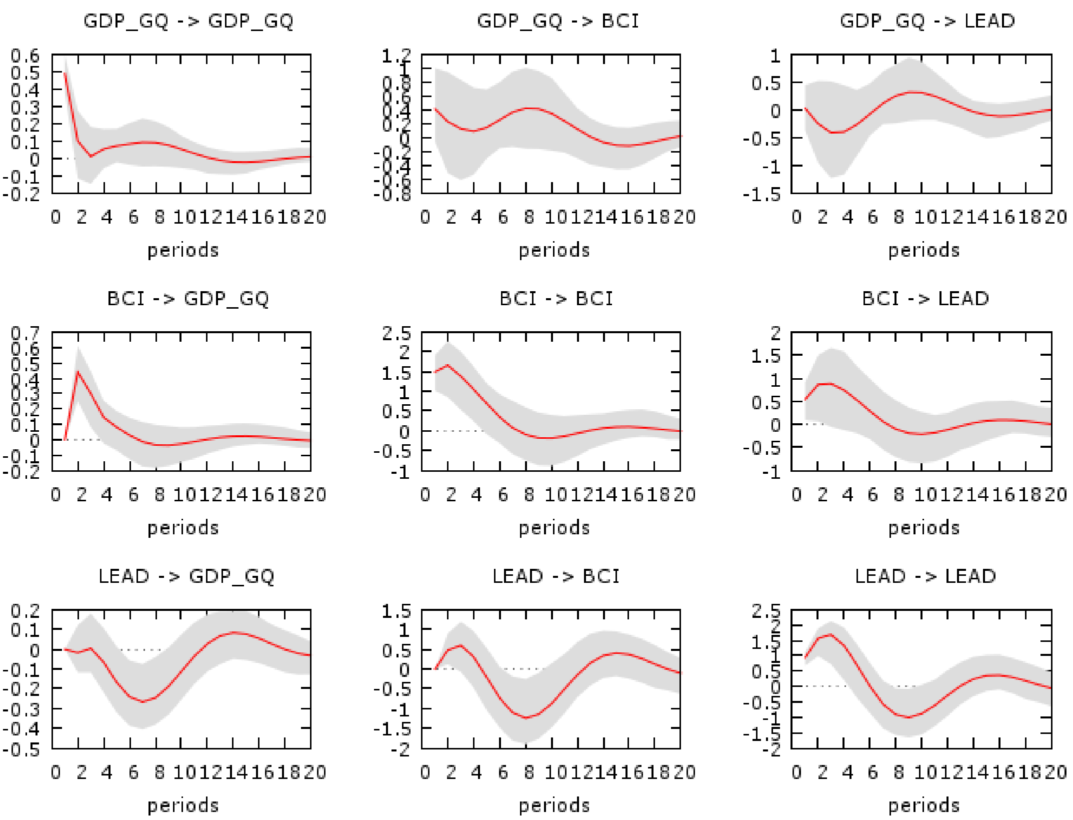
LEAD VAR models results and evaluations

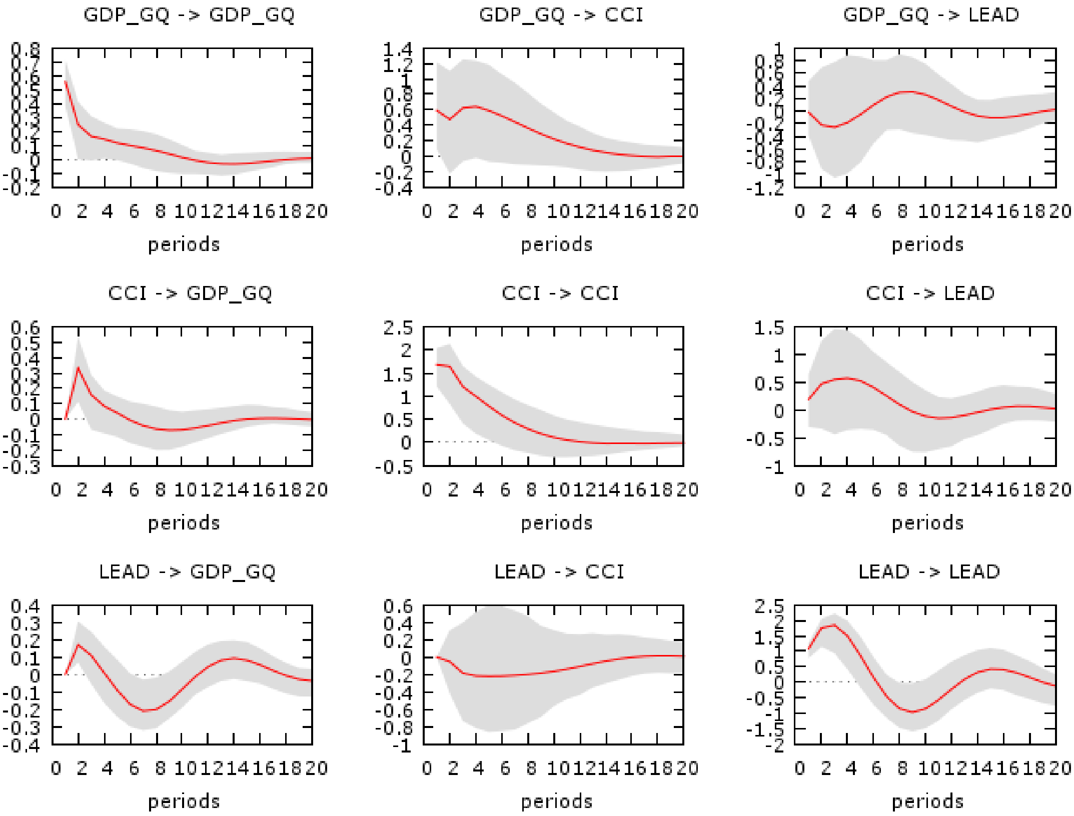
Table A.4: Results for VAR models with GDP, LEAD and one confidence indicator

	Dependent			Dependent		
	GDP	BCI	LEAD	GDP	CCI	LEAD
GDP lag 1	0.7516	0.5005	0.1011	0.0804	0.6754	0.1149
GDP lag 2	0.6619	0.6100	0.8923	0.0689	0.2036	0.2282
Indicator lag 1	0.0000	0.0000	0.8244	0.0012	0.0000	0.3351
Indicator lag 2	0.2887	0.7988	0.1702	0.0027	0.2306	0.6697
LEAD lag 1	0.7529	0.0120	0.0000	0.0039	0.7709	0.0000
LEAD lag 2	0.0811	0.0019	0.0000	0.0004	0.9171	0.0000
GDP all lags	0.8593	0.7046	0.2554	0.0012	0.4083	0.2677
Indicator all lags	0.0000	0.0000	0.3075	0.0049	0.0000	0.4382
LEAD all lags	0.0026	0.0073	0.0000	0.0014	0.7138	0.0000
F-test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.7419	0.8599	0.9294	0.6627	0.7760	0.9281

Notes: There are three models and two equations per model (represented by six columns). All numbers except R-squared are *p*-values of test with H_0 of a zero coefficient (or jointly zero coefficients in case of "... all lags" and *F*-test)

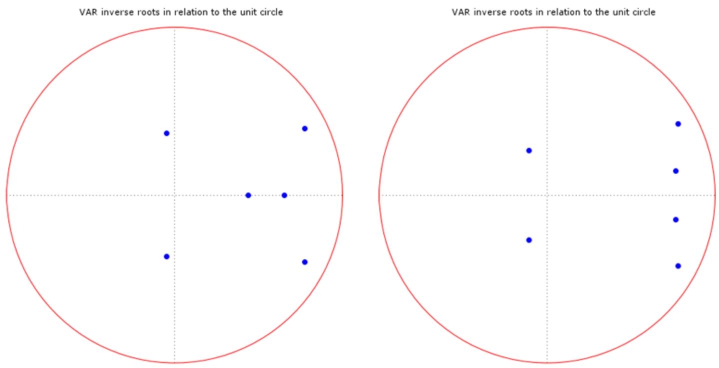
Figure A.11: Impulse responses for BCI and CCI model, respectively





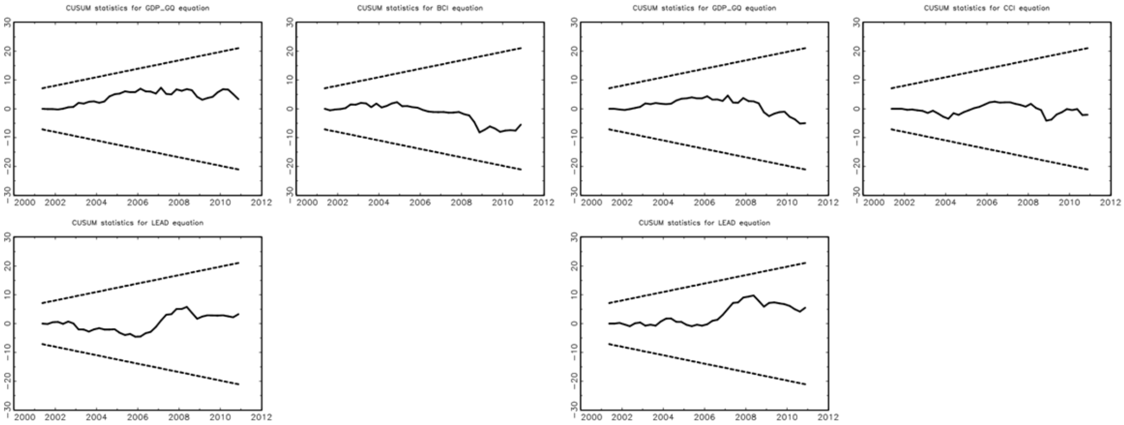
Source*: own calculations in the Gretl software*

Figure A.12: Unit root test for BCI and CCI model, respectively (points inside the unit circle mean no unit root)



Source*: own calculations in the Gretl software*

Figure A.13: CUSUM tests for BCI and CCI model, respectively



Source*: own calculations in the JMulTi software*

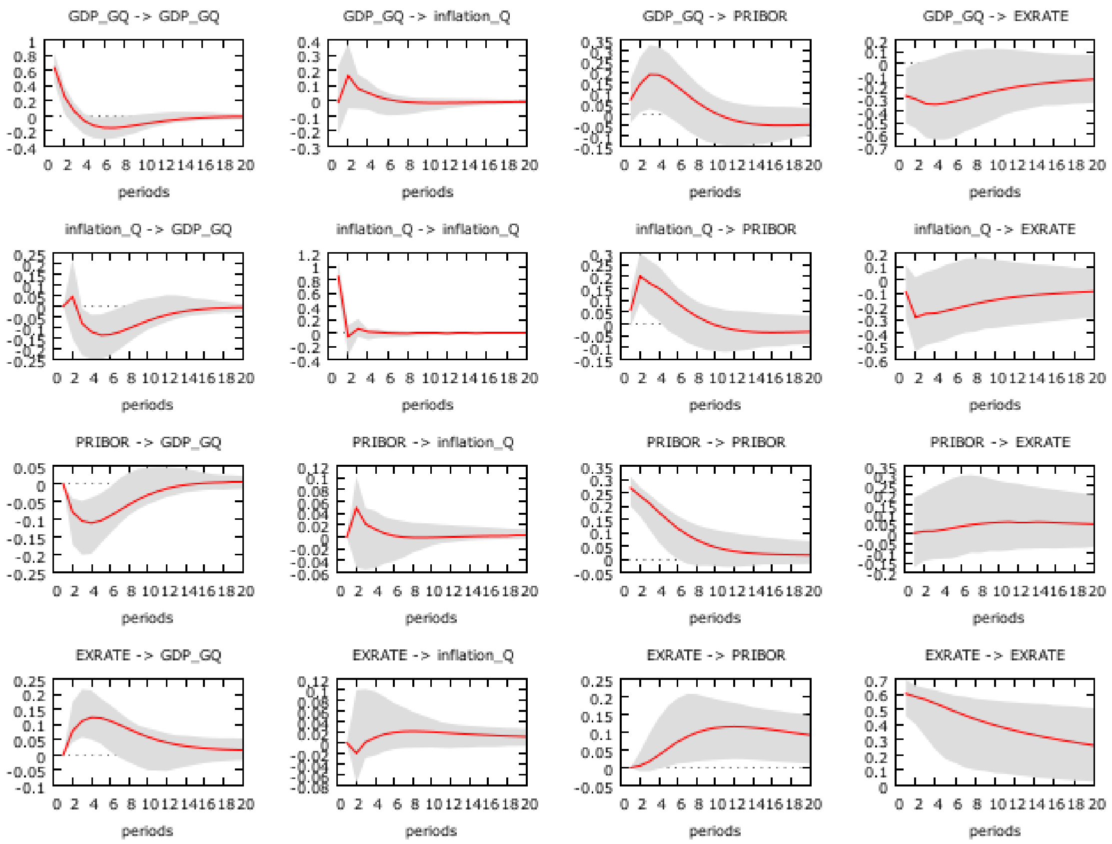
Base VAR model results and evaluations

Table A.5: Results for macroeconomic VAR model

	Dependent			
	GDP	inflation	int. rate	ex. rate
GDP lag 1	0.0001	0.1366	0.0100	0.5963
inflation lag 1	0.4508	0.5944	0.0012	0.0616
interest rate lag 1	0.0021	0.1367	0.0000	0.7484
exchange rate lag 1	0.0014	0.5317	0.5827	0.0000
F-test	0.0000	0.3952	0.0000	0.0000
R-squared	0.5499	0.0906	0.9640	0.9674

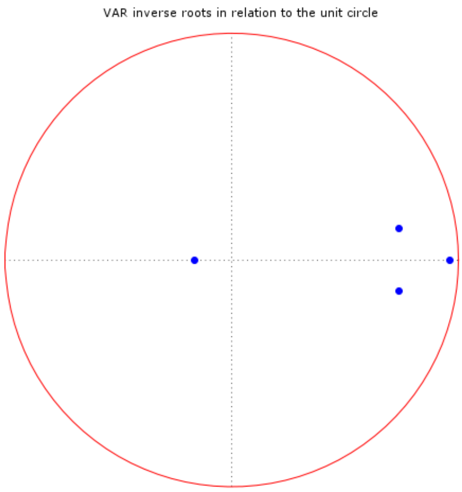
Notes: All numbers except R-squared are *p*-values of test with H_0 of a zero coefficient (or jointly zero coefficients in case *F*-test)

Figure A.14: Impulse responses for the macroeconomic model



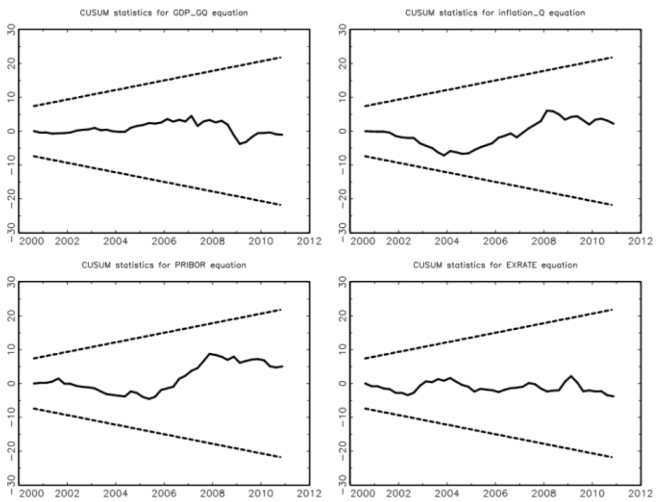
source*: own calculations in the Gretl software*

Figure A.15: Unit root test for macroeconomic model (points inside the unit circle mean no unit root)



source: *own calculations in the Gretl software*

Figure A.16: CUSUM tests for macroeconomic model



source: *own calculations in the JMulTi software*

Enhanced VAR models results and evaluations

Table A.6: Results for BCI enhanced VAR model

	Dependent				
	GDP_GQ	Inflation	PRIBOR	EXRATE	BCI
GDP lag 1	0.0649	0.6403	0.7294	0.7993	0.1896
inflation lag 1	0.9122	0.1990	0.0249	0.1539	0.3132
interest rate lag 1	0.0025	0.0926	0.0000	0.7957	0.0123
exchange rate lag 1	0.0014	0.4810	0.6029	0.0000	0.0023
BCI lag 1	0.1192	0.0442	0.0027	0.4103	0.0000
F-test	0.0000	0.1418	0.0000	0.0000	0.0000
R-squared	0.5761	0.1771	0.9711	0.9680	0.7955

Notes: All numbers except R-squared are *p*-values of test with H_0 of a zero coefficient (or jointly zero coefficients in case *F*-test)

Table A.7: Results for CCI enhanced VAR model

	Dependent				
	GDP_GQ	Inflation	PRIBOR	EXRATE	CCI
GDP lag 1	0.0018	0.1916	0.0761	0.7862	0.5420
inflation lag 1	0.5850	0.6084	0.0023	0.1028	0.1486
interest rate lag 1	0.0028	0.1440	0.0000	0.8515	0.0617
exchange rate lag 1	0.0008	0.5621	0.3421	0.0000	0.0411
CCI lag 1	0.2266	0.9697	0.2721	0.1334	0.0000
F-test	0.0000	0.5446	0.0000	0.0000	0.0000
R-squared	0.5659	0.0906	0.9650	0.9692	0.8145

Notes: All numbers except R-squared are *p*-values of test with H_0 of a zero coefficient (or jointly zero coefficients in case *F*-test)

Table A.8: Results for CCI enhanced IFO model

	Dependent				
	GDP_GQ	Inflation	PRIBOR	EXRATE	IFO
GDP lag 1	0.1198	0.5903	0.2286	0.6845	0.0589
inflation lag 1	0.9145	0.4733	0.0030	0.1094	0.1775
interest rate lag 1	0.0073	0.0968	0.0000	0.9793	0.0210
exchange rate lag 1	0.0009	0.4833	0.6573	0.0000	0.0198
IFO lag 1	0.0006	0.3293	0.1729	0.2022	0.0000
F-test	0.0000	0.4123	0.0000	0.0000	0.0000
R-squared	0.6625	0.1117	0.9656	0.9687	0.7139

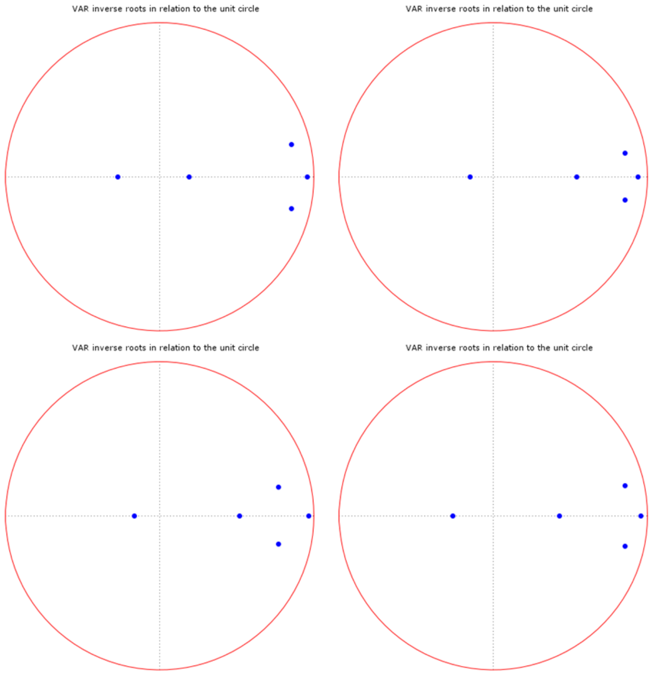
Notes: All numbers except R-squared are *p*-values of test with H_0 of a zero coefficient (or jointly zero coefficients in case *F*-test)

Table A.9: Results for CCI enhanced LEAD model

	Dependent				
	GDP_GQ	Inflation	PRIBOR	EXRATE	LEAD
GDP lag 1	0.0010	0.8983	0.4406	0.9424	0.3427
inflation lag 1	0.6365	0.1333	0.0434	0.1609	0.6257
interest rate lag 1	0.0025	0.5457	0.0000	0.5708	0.2978
exchange rate lag 1	0.0022	0.6426	0.0375	0.0000	0.1913
LEAD lag 1	0.6141	0.0186	0.0008	0.4567	0.0000
F-test	0.0000	0.0802	0.0000	0.0000	0.0000
R-squared	0.5528	0.2067	0.9728	0.9679	0.7936

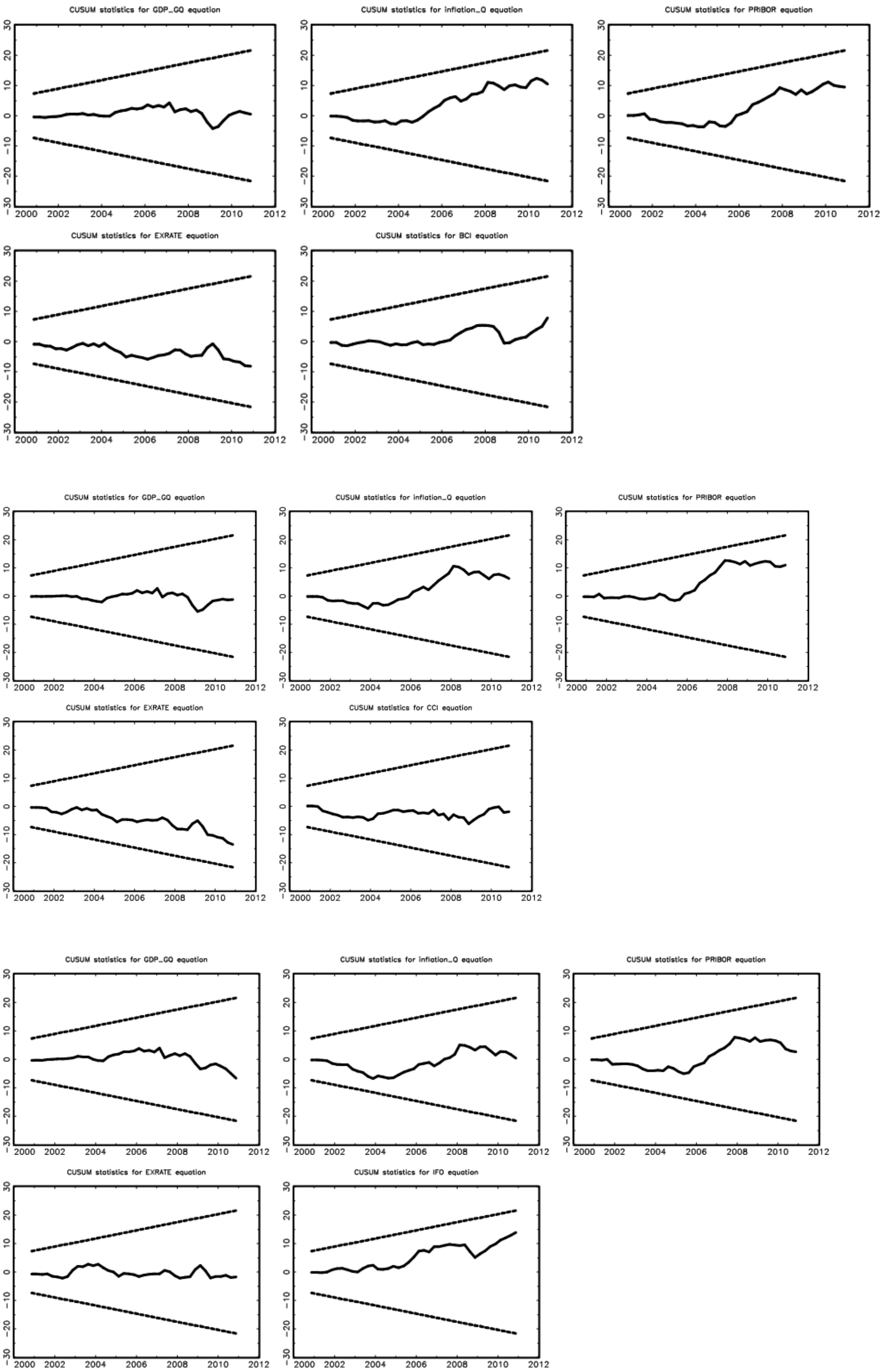
Notes: All numbers except R-squared are *p*-values of test with H_0 of a zero coefficient (or jointly zero coefficients in case *F*-test)

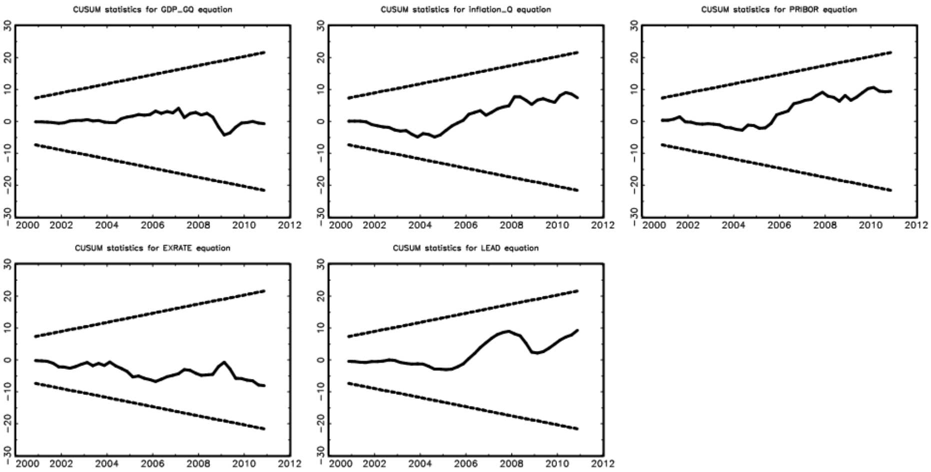
Figure A.17: Unit root test for enhanced models: BCI, CCI, IFO and LEAD, respectively



Source: *own calculations in the JMulTi software*

Figure A.18: CUSUM tests for enhanced models





Source: *own calculations in the JMulTi software*