JEL Classification: E23, E37, E51 Keywords: confidence, GDP, vector autoregression, forecasting

Do Confidence Indicators Help Predict Economic Activity? The Case of the Czech Republic^{*}

Roman HORVATH—Institute of Economic Studies, Faculty of Social Sciences, Charles University, Prague (roman.horvath@gmail.com)

Abstract

We examine whether confidence indicators—and their underlying components—improve the forecasts of future economic activity. Using quarterly data from the Czech Republic in 1999–2011, we estimate a vector autoregression model of the Czech economy (consisting of several commonly used macroeconomic variables) and compare its forecasting performance with models that additionally contain domestic and foreign confidence indicators. Our results suggest that although confidence indicators are contemporaneously well correlated with GDP, they fail to improve the GDP forecasts vis-à-vis the model based on macroeconomic variables only or vis-à-vis autoregressive models.

1. Introduction

Consumer and business sector confidence indicators have fallen dramatically during the current global financial crisis, further deepening the economic slowdown. It has been investigated whether the government is able to affect confidence and thus help mitigate the crisis (Bachmann and Sims, 2012; Barsky and Sims, 2012). This stream of research finds a rather limited role for the government to influence confidence and to coordinate the expectations of economic agents. Despite these pessimistic findings about the ability of the government to manipulate private sector confidence, an interesting question for market participants as well as for policy makers is whether these confidence indicators at least contain some useful information about future economic activity or whether they merely reflect past economic fluctuations. More specifically, are confidence indicators able to deliver more precise (out-of-sample) forecasts of economic activity than other commonly followed indicators? Comparing the precision of out-of-sample forecasts differentiates us from the previous literature focused largely on in-sample forecast evaluation, which is known to provide a poor assessment of forecast performance (Stock and Watson, 2003).¹

For this reason, we collect data on confidence indicators in the Czech Republic and examine their forecasting performance. To do so, we first estimate a canonical vector autoregression model (VAR) of the Czech economy consisting of the following variables: real GDP growth, consumer prices, the interest rate, and the exchange rate.²

^{*} The author thanks two anonymous referees and seminar participants at the Austrian central bank for helpful comments. Support from Grant Agency of the Czech Republic Research Grant No. P402/12/G097 is gratefully acknowledged.

¹ Arnoštová et al. (2011) conduct an extensive forecasting exercise focusing on Czech GDP. However, their primary interest lies in examining which methods rather than specific variables are helpful for GDP forecasting.

We label this as the macroeconomic model for convenience. We use the forecasts from this commonly used model as a benchmark against which we compare the forecasting accuracy of confidence indicators. More specifically, we include business sector and consumer confidence indicators one after the other in the macroeconomic model and use the Clark and West (2007) forecast evaluation test for nested models in order to shed light on whether the confidence indicators contribute to more accurate GDP forecasts. In doing so, we contribute to the related literature tracing back to Smith (1997 [1766]) and Keynes (1936) which assesses to what extent confidence constitutes a direct cause of economic fluctuations (Barsky and Sims, 2012; Chauvet and Guo, 2003). Similarly, our paper also falls into the stream of literature focusing on GDP forecasting (Homaifar et al., 2013; Koeda, 2012). The modern theoretical underpinnings for examining the relation between confidence and growth are put forward by Beaudry and Poitier (2004), who show how expectations of the future economic environment can create business cycles. Several empirical applications have followed the Beaudry and Poitier (2004) model using various vector autoregression models (Barsky and Sims, 2012; Beaudry and Poitier, 2006).

In addition, we examine whether German confidence indicators are able to predict future Czech GDP. The Czech Republic is a highly open economy and about two-thirds of its exports go to Germany. As a consequence, German confidence indicators may in principle be relevant for forecasting Czech economic activity. To our knowledge, the forecasting ability of foreign confidence indicators for domestic economic activity has not been examined so far. Clearly, this follows from the fact that, unlike the Czech Republic, most countries have no clear major trade partner.

Our results suggest that even though confidence indicators are contemporaneously well correlated with GDP, they do not help improve the GDP forecasts vis-à-vis the baseline macroeconomic model (or vis-à-vis the forecasts generated by the AR(1) model for GDP growth). This result holds for all three confidence indicators examined: the Czech business sector confidence indicator, the Czech consumer confidence indicator, and the German Ifo Business Climate indicator (the expectations part), as well as for all underlying components of the Czech confidence indicators (industry, construction, trade, and consumers).

This paper is organized as follows. Section 2 presents the related literature. The construction of the confidence indicators is discussed in section 3. Section 4 presents the data and VAR model. Section 5 provides the results. The conclusions are given in section 6.

2. Related Literature

This section briefly discusses the previous empirical literature focusing on the interactions of confidence indicators and economic activity. There are several streams of this literature. First, some studies perform Granger-causality testing of the confidence-GDP growth nexus. Second, several studies examine to what degree confidence can be influenced by policy measures, in order to assess whether

 $^{^2}$ This is a commonly used specification for small open economies (see, for example, Mojon and Peersman, 2001) and has been extensively used in the Czech context, too (Borys et al., 2009; Havranek et al., 2012).

economic policy can contribute to moderating an economic crisis.³ Third, there is a literature examining the forecasting properties of confidence indicators along with other leading indicators for predicting future economic activity. In a similar vein, the role of confidence indicators for assessing the current economic stance is evaluated, too. The literature on the determinants of confidence indicators is not discussed here and the reader is referred to two recent empirical studies (Duch and Kellstedt, 2011, and Ramalho et al., 2011) and references therein.

Matsusaka and Sbordone (1995) estimate a VAR model of the U.S. economy and find that confidence indicators systematically influence the degree of economic activity. Based on variance decompositions, they find that confidence accounts for about 20% of the innovation variance of GNP. Similarly, Howrey (2001) examines the predictive ability of the University of Michigan Survey Research Center's Index of Consumer Sentiment and finds that the confidence indicator improves the GDP forecasts especially at the two to four quarter horizon, as compared to the GDP forecast based on the autoregressive process. The forecasts for one quarter ahead resulted in a negligible improvement in forecasting accuracy.

Mourougane and Roma (2003) examine whether confidence indicators in several European countries help forecast future GDP growth. Confidence indicators are found to improve the forecasts in most countries except Spain. Nevertheless, we differ from this study, and in fact from Howrey (2001), too. While they evaluate the forecasting performance of confidence indicators vis-à-vis the univariate process for GDP, we evaluate it also vis-à-vis the macroeconomic VAR model, which is likely to be more informative for policy makers given that it contains several commonly followed variables.

Chauvet and Guo (2003) investigate whether confidence affects the fluctuations in real activity in the U.S. More specifically, based on VAR models, they divide the confidence indicators into fundamental and non-fundamental parts and assess to what degree the non-fundamental part—assessing waves of optimism/pessimism influences economic activity. They find that waves of pessimism indeed contributed to deepening economic recessions.

Barsky and Sims (2012) propose an identification strategy to disentangle the fluctuations in confidence indicators into two factors: (i) the causal effect of animal spirits on economic activity, and (ii) new fundamental information about future economic activity. They suggest that the latter factor is the main cause of innovations in confidence indicators. Bachmann and Sims (2012) investigate whether confidence matters for the effectiveness of fiscal policy shocks. Their results indicate that the importance of confidence strongly varies with the business cycle and that the role of confidence is critical during recessions. Similarly, Konstantinou and Tagkalakis (2011) investigate whether consumer and business confidence helps moderate economic recessions and suggest that sound fiscal policy is essential for the effect of confidence on economic activity.

Finally, there is a large literature focusing on examining the role of leading indicators in short-term GDP forecasting or GDP nowcasting (see, for example, Runstler et al., 2009; Angelini et al., 2011, or Feldkircher, 2012, for recent con-

³ Note that there is an intense discussion of what confidence indicators represent and, specifically, of whether or not they are a measure of animal spirits (Akerlof and Shiller, 2009).

tributions). These contributions put forward that incorporating large datasets and employing various factor models typically give a more accurate picture about current and near-term GDP (this is also the case for the Czech data–see Arnostova et al., 2011). The set of leading indicators often includes some measure of confidence, but the contribution of these confidence indicators to GDP forecasting is typically not assessed explicitly.

3. Construction of Confidence Indicators

This section discusses the construction of confidence indicators (especially in the Czech Republic and Germany, and in the U.S., where they originated).⁴ A confidence indicator is a measure of the optimism/pessimism about current and future economic conditions. The underlying data for the construction of confidence indicators come from survey questions. These surveys are typically carried out by statistics offices or policy research institutions at monthly frequency.

The most common confidence indicators in the U.S. are the University of Michigan's Consumer Sentiment Index and the Conference Board's Consumer Confidence Index.⁵ The Ifo Business Climate is a widely followed German confidence indicator (available since the early 1990s). Czech confidence indicators are produced by the Czech Statistical Office. A business indicator was launched in 1993, followed by a consumer confidence indicator in 1998.

The polls are typically carried out among consumers and firms in various sectors, such as industry, trade, construction, and services. Sector weights are specified according to the sizes of the sectors in order to produce a representative aggregate confidence index.

The surveys typically have both a present situation and an expectations component. The respondents are asked questions relating to both their current financial situation and their expected financial situation in the 12 months to come (or 6 months in some surveys). Nevertheless, some consumer surveys have a very strong forwardlooking element. For example, Czech consumers are asked only about their expected financial situation, the expected overall economic situation, expected total unemployment (with an inverted sign), and their expected savings in the 12 months to come.

The respondents in these surveys typically choose from three answers: increase, no change, decrease (or good, satisfactory, bad, depending on how the question is formulated). These answers serve to create a so-called balance value, which is typically defined as the difference between the percentages of the positive vs. negative responses. The balance values are aggregated into a confidence index. Finally, the confidence indicators are often seasonally adjusted.

The number of respondents to confidence surveys varies from some 500 for the University of Michigan Consumer Sentiment Index to 7,000 for the Ifo Business Climate. Clearly, larger sample size reduces the sampling error. In this respect,

⁴ These indicators were developed by the Hungarian-born American economic psychologist George Katona at the University of Michigan in the 1940s.

⁵ The Michigan index is available as an annual survey from the late 1940s, as a quarterly survey from 1952, and as a monthly survey from 1978 onwards. The Conference Board introduced its index on a bimonthly frequency in 1967 and expanded it to a monthly series in 1977.





Curtin (2002) shows that increasing the sample size by an additional 1,000 respondents in the Michigan survey would reduce the sampling error from ± 3.3 index points to ± 1.9 index points. The sample size for the Czech confidence indicators is approximately 3,000 respondents.

4. Data and VAR Model

4.1 Data

To predict Czech GDP growth, we use quarterly data over the period 1999Q1–2011Q3.⁶ The sample is restricted to 1999Q1 onwards because CZK/EUR data are not available for the earlier period (the euro area was created in 1999). The source for all Czech data is the Czech Statistical Office. The Ifo Business Climate indicator is obtained from the Ifo Institute. The confidence indicators are available at monthly frequency. Since the GDP data are available only at quarterly frequency, the value of the confidence indicators in the last month of the quarter is employed. For GDP and consumer prices, we use annualized quarter-on-quarter values to avoid the complicated structure that typically arises in the regression residuals when year-on-year growth rates are used. Interest rate and exchange rate data remain in levels.

Our confidence indicators are plotted in *Figure 1*. The values of the confidence indicators seem to correspond to economic activity. The values of the Czech confidence indicators are particularly low at the end of the 1990s and from 2009 onwards, which are periods characterized by weak economic activity. While in the former period, the weak economic activity was directly related to financial instability (banks with large amounts of bad loans borrowing very prudently), the recent financial crisis hit the Czech Republic mainly through a fall in external demand, and the financial sector remains in very good condition (Financial Stability Report, 2011). By contrast, the values are highest in the mid-2000s, when the Czech

⁶ We use ex-post GDP data. When analyzing the monetary policy rules of the monetary transmission mechanism, real-time data may be important for identifying policy shocks (see Croushore, 2011), but the picture is less clear when we want to evaluate whether confidence indicators are helpful for understanding actual economic activity. On the top of that, real-time data are not readily available for Czech GDP.

Republic experienced solid growth. The consumer confidence index is rather more volatile than the business sector confidence index (the coefficient of variation is about 20% higher for the consumer confidence index). The business sector and consumer confidence indicators typically co-move, the exception being the period before EU entry. While business sector confidence remains largely unchanged, consumer confidence drops to very low levels. This decrease is probably associated with expectations of rising prices (partly due to EU tax harmonization) and with expectations of foreigners driving up the price of Czech land once they were allowed to buy it.

4.2 VAR Model

The VAR system—developed by Sims (1980)—is employed to model the Czech economy and generate GDP forecasts. We begin with a general specification assuming that the economy is described by a structural form equation which is of linear, stochastic dynamic form (omitting constant and other deterministic terms):

$$\mathbf{A}(\mathbf{L})\mathbf{y}_{\mathbf{t}} = \mathbf{e}_{\mathbf{t}} \tag{1}$$

where A(L) is an *mxm* matrix polynomial in the lag operator (with non-negative powers), y_t is an *mx*1 vector of observations, and e_t is an *mx*1 vector of structural disturbances or shocks. e_t is serially uncorrelated and $var(e_t) = \Lambda$, and Λ is a diagonal matrix where the diagonal elements are the variances of the structural disturbances.

The vector of variables for the baseline VAR model consists of a measure of economic activity—annualized quarter-on-quarter real GDP growth (x_t) , a measure of aggregate inflation—the annualized quarter-on-quarter consumer inflation rate (p_t) , the short-term interest rate—3M PRIBOR (i_t) , and the CZK/EUR exchange rate (s_t) . Therefore, the baseline model is based on macroeconomic variables only. The number of lags in the VAR model is set according to the Schwarz information criterion.

We choose a simple VAR model for forecasting, since the previous literature employing more advanced VAR-type models to the Czech data did not deliver more promising results. Borys et al. (2009) apply several VAR models, including the factoraugmented VAR, simple VAR, structural VAR, and Bayesian sign-restriction VAR model to study the monetary transmission mechanism in the Czech Republic. They find that the factor-augmented VAR resulted in very large confidence intervals, often with a sign on the impulse response which was not consistent with the theory. All the other VAR models that Borys et al. (2009) employed gave very similar impulse response results.

The ordering of the variables and shock identification are not relevant for our forecasting exercise (Lutkepohl, 2006). We estimate the baseline (macroeconomic) VAR model using data up to 2010Q4 and produce the corresponding (pseudo) outof-sample forecasts for the following three quarters. The forecast evaluation for three quarters ahead should be sufficient given that the confidence indicators are meant to provide an assessment of the economic conditions in the near future (see also Bram and Ludvigson, 1998, or Howrey, 2001). The choice of 2010Q4 is to maximize our sample. However, we alternatively use 2010Q3 and 2010Q2 as the starting dates for the forecasts as a robustness check.

Next, we include the confidence indicators one after the other in the baseline VAR model and examine whether these additional variables improve the GDP

forecasts. Following Havranek et al. (2012), we do not include all the variables jointly in the baseline model due to degrees of freedom considerations (in other words, too many parameters would have to be estimated given the sample size). As a consequence, we compare the forecasting performance of the following four models:

1. Macroeconomic model:

 $y_t' = (x_t, p_t, i_t, s_t)$

2. Consumer confidence model:

 $y_t = (x_t, p_t, i_t, s_t, conf_t^{consumer})$

3. Business confidence model:

 $y_t' = (x_b \ p_b \ i_b \ s_b \ conf_t^{business})$

4. German Ifo confidence model:

 $y_t = (x_t, p_t, i_t, s_t, conf_t^{Ifo})$

More specifically, we compare the forecasting performance of models (2)-(4)with that of model (1). In addition, we use a univariate model for GDP growth to produce forecasts. More specifically, we generate forecasts assuming AR(1) for growth (the lags are set according to Hannan-Rissanen model selection). First, we generate the squared forecast errors and mean square errors. Second, we use the Clark and West (2007) forecast evaluation test to assess whether models (2)-(4) improve the forecasts of model (1) in a statistical significant way.⁷ The choice of the Clark and West (2007) test is motivated by the fact that model (1) is nested within models (2)-(4). In such a setting, Clark and West (2007) show that larger models introduce noise into the forecasts. Therefore, the comparison of the resulting mean square errors must be adjusted for the noise (this is labeled as the adjustment term). The Clark and West (2007) test statistic equals the MSE of model (1) minus the MSE of the selected model (for example, (2)) plus an adjustment term, which is defined as the squared difference between the forecasts generated by model (1) and model (2). The null hypothesis of the test is that the forecasting accuracy of models (1) and (2) is identical, while the alternative is that model (2) yields more precise forecasts. The test statistic is constructed in such a way that an increase in its values results in a higher probability of rejecting the null hypothesis.

As a further robustness check, we conduct the forecasting exercise on different forecast dates. In addition to the five models mentioned above, we examine the forecasting performance of the underlying components of the confidence indicators. Specifically, we evaluate the forecasting performance of the quarter-onquarter change in the balance values of industry, construction, trade, and consumer confidence.⁸

5. Results

This section contains the results. First, we present simple cross-correlations to assess to what degree the confidence indicators are correlated with GDP growth and whether the lagged or lead values of the confidence indicators are more correlated

⁶ See Clark and McCracken (2011) for a recent survey of forecast evaluation.

⁷ Note that the balance value of services is not used, since these data are available only from 2002 onwards.



Figure 2 Confidence Indicators and GDP Growth, Cross-Correlations

with GDP growth. Second, we carry out a formal forecasting exercise to evaluate the predictive performance of the confidence indicators.

5.1 Initial Analysis

The cross-correlations between the confidence indicators and GDP growth are given in *Figure 2*. The cross-correlation is defined as *corr(confidence_t, y_{t+i})*. As a result, an informal assessment of whether the confidence indicators lead GDP growth is to see whether the correlations of the confidence indicators and GDP growth are stronger with y_{t+i} when i > 0 (i.e., the right part of *Figure 2*). On the other hand, if the correlations are stronger for i < 0, it suggests that the confidence indicators follow GDP growth changes with a lag.

The results show that the contemporaneous correlation between the business sector confidence indicator and GDP growth is about 0.6. A similar value is obtained for the correlation of the Ifo Business Climate (expectations) indicator. The contemporaneous correlation of the consumer confidence indicator and GDP growth is rather lower, taking a value of 0.38. The correlations seem to be stronger for the current confidence indicators with lagged GDP growth rather than vice versa. As a consequence, the cross-correlations give little support to the hypothesis that the confidence indicators lead Czech GDP growth. We assess this finding more formally below.

Before we present the impulse response results, variance decompositions, and forecasting evaluations, we discuss the stability of the estimated VAR models. This is important, since non-crisis and crisis years are mixed together. We carry out the Chow forecast test with bootstrapped *p*-values and the CUSUM test. We choose the Chow forecast test with bootstrapped *p*-values as Candelon and Lutkepohl (2001) show that the standard version of the test rejects the null hypothesis too often and bootstrapping the *p*-value is strongly advisable in small samples. Our results suggest that the VAR models are stable on the whole. Nevertheless, some Chow forecast tests with bootstrapped *p*-value is very close to 0.1 around the beginning of the crisis. For this reason, we also introduce a dummy variable assessing the effect of the crisis. The dummy takes a value of one from 2007Q3 onwards, and zero otherwise. The Czech Republic was hit by the global financial





14 16

 10 12 14 16 18 20

Bivariate model, Response: GDP

10 12 14 16 18 20

 crisis mostly through a fall in external demand (i.e., a negative GDP shock) and its financial systems remained largely stable. The Chow forecast test with bootstrapped *p*-values and the CUSUM test for the model suggest that the estimated VAR models are stable. The results are available upon request.

5.2 Impulse Responses and Variance Decompositions

We present the impulse responses and variance decompositions in this subsection to examine the in-sample relations between confidence and growth. We follow Knotek and Khan (2011) and we first present the results for the bivariate VARs (GDP and confidence indicator) and then show the results for the multivariate VARs as defined in the previous section. The results are available in *Figure 3*. For the bivariate model, we find that the business sector confidence indicator and the Ifo Business Climate indicator have a positive and statistically significant effect on GDP growth in the first one or two quarters. On the other hand, the consumer confidence indicator does not have a significant effect. When we estimate the multivariate VAR models, the significant effect of confidence disappears even for the two remaining indicators. Broadly speaking, this result is consistent with Knotek and Khan (2011), who examine the effect of uncertainty on consumer spending. They find a statistically significant effect only in the bivariate VARs. This effect dissipates in the multivariate VARs.

Next, we present the variance decompositions in *Table 1*. The results suggest that confidence indicators explain a very small part of the GDP fluctuations. In general, these proportions are smaller than in the case of the U.S. evidence by Matsusaka and Sbordone (1995). Matsusaka and Sbordone (1995) find that confidence indicators account for approximately 20% of GDP forecast errors. Nevertheless, our results are in line with our forecasting evaluation in the following sub-section.

5.3 Forecast Evaluation

We present the relative mean square errors in *Table 2*. Models (2), (3), and (4), which capture the effect of confidence indicators, do not make the GDP forecasts more accurate. This result broadly accords with Al-Eyd (2009), who finds the information content of confidence indicators for future consumption in the U.S. to be rather small. We test this formally using the Clark and West (2007) test. The results are available in *Table 3*. We do not reject the null hypothesis of identical forecasting performance. In other words, the models containing the confidence indicators do not improve the GDP forecasts. Similarly, the confidence indicators do not improve the forecasts generated by the AR(1) process for GDP growth. In consequence, this result is not in line with Howrey (2001), who finds the opposite for the U.S. data.

In order to assess the robustness of the baseline results, we carry out an identical forecasting exercise, but now the forecasts start in 2010Q3 and 2010Q2, i.e., one and two quarters earlier. The results for the former exercise are available in *Tables 4* and 5; the results for the latter are available upon request. The robustness checks support our baseline findings. The confidence indicators are not found to produce more accurate forecasts.

Proportions of Forecast Error Accounted by:				
forecast horizon	business sector confidence	consumer confidence	lfo business climate	
1	0	0	0	
2	0.05	0.01	0.07	
3	0.07	0.03	0.12	

Table 1 Variance Decompositions of GDP Growth

Table 2	Mean Square	Errors Relativ	e to the N	<i>lacroeconomic</i>	Model	(1)
---------	-------------	----------------	------------	----------------------	-------	-----

	Model no.			
	(2)	(3)	(4)	AR(1)
2011Q1	1.94	0.93	117.43	0.10
2011Q2	1.30	1.10	11.86	0.79
2011Q3	1.26	1.13	5.96	0.89

Notes: Model (1) consists of macroeconomic variables only, model (2) in addition to macroeconomic variables includes the Czech business sector confidence indicator, model (3) includes the consumer confidence indicator, and model (4) includes the German Ifo Business Climate indicator (expectations part). Values below one indicate that models (2)–(4) exhibit smaller mean square errors than model (1).

Table 3 Clark and West (2007) Forecast Evaluation Test for Nested Models: Do Confidence Indicators Improve the Forecasts of GDP?

Model no.	<i>t</i> -stat
(2)—Confidence, business	-1.78
(3)—Confidence, customer	-1.45
(4)—Ifo Business Climate	-2.46
AR(1) process for GDP growth	0.56

Notes: With a test statistic larger than +1.282 and +1.645, the null hypothesis is rejected at a significance level of 10% and 5%, respectively.

Table 4 Mean Square Errors Relative to the Macroeconomic Model (1),Forecasts as of 2010Q3

	Model no.			
	(2)	(3)	(4)	AR(1)
2010Q4	2.50	0.93	314.68	2.22
2011Q1	2.14	1.38	74.84	0.29
2011Q2	1.42	1.23	8.87	0.62

Note: See Table 2.

Table 5 Clark and West (2007) Forecast Evaluation Test for Nested Models: Do Confidence Indicators Improve the Forecasts of GDP?

Model no.	<i>t</i> -stat	
(2)—Confidence, business	-1.30	
(3)—Confidence, customer	-1.18	
(4)—Ifo Business Climate	-1.84	
AR(1) process for GDP growth	0.68	

Notes: Forecasts as of 2010Q3. With a test statistic larger than +1.282 and +1.645, the null hypothesis is rejected at a significance level of 10% and 5%, respectively.

Table 6 Mean Square Errors Relative to the Macroeconomic Model (1), Underlying Components of Aggregate Confidence Indicator

	Model no.			
	(2)	(3)	(4)	(5)
2011Q1	48.39	0.98	0.93	8.22
2011Q2	4.01	0.98	0.98	1.10
2011Q3	1.94	0.99	0.99	1.01

Notes: Forecasts as of 2010Q4. Model (1) consists of macroeconomic variables only, model (2) in addition to macroeconomic variables includes the q-o-q change in the balance value of the industrial component of the Czech business sector confidence indicator, model (3) includes the q-o-q change in the balance value of the construction component of the Czech business sector confidence indicator, model (4) includes the q-o-q change in the balance value of the component of the Czech business sector confidence indicator, model (5) includes the q-o-q change in the balance value of the Czech business sector confidence indicator, and model (5) includes the q-o-q change in the balance value of the component of the Czech business sector confidence indicator. Values below one indicate that models (2)–(5) exhibit smaller mean square errors than model (1).

Table 7 Clark and West (2007) Forecast Evaluation Test for Nested Models: Do Specific Confidence Indicators Improve the Forecasts of GDP?

Model no.	<i>t</i> -stat	
(2)—Confidence, industry	-2.08	
(3)—Confidence, construction	0.95	
(4)—Confidence, trade	1.18	
(5)—Confidence, consumer	0.30	

Notes: Forecasts as of 2010Q4. With a test statistic larger than +1.282 and +1.645, the null hypothesis is rejected at a significance level of 10% and 5%, respectively.

Finally, we also evaluate the forecasting performance of the components underlying the aggregate confidence indicators. The results are available in *Tables 6* and 7. We find that the construction and trade components of the aggregate confidence indicator perform as well as, or marginally better than, the baseline macroeconomic model (see columns 2 and 3 in *Table 6*). Nevertheless, as the results presented in *Table 6* suggest, they do not improve the forecasts in a statistically significant way. The two remaining components (industry and consumers) produce less accurate forecasts than the baseline macroeconomic model.

All in all, we find little evidence that the confidence indicators in the Czech Republic help generate more precise GDP forecasts than the commonly used VAR model based solely on macroeconomic variables. Interestingly, this issue has been raised several times recently by Czech National Bank representatives. They argue that the confidence indicators are too low given the state of Czech economy. For example, consider the minutes of the Bank Board monetary policy meeting on 27 September 2012 (the minutes are available on the Czech National Bank website), which state that: *"The Board discussed in detail whether household consumption was in line with the condition of the domestic economy or whether it was lower as a result of households' falling consumer confidence. [...] It was also said that households were showing low consumer sentiment, hence their consumption was below the level consistent with economic fundamentals." Maybe the forecasting power of confidence indicators decreases during crisis periods.*

However, although we raise some skepticism about the forecasting performance of confidence indicators, this does not necessarily mean that they are useless for policy. The confidence indicators are available on a monthly basis and seem to be well correlated with contemporaneous GDP, which is available only at quarterly frequency and with a lag of one quarter. Therefore, they may well nowcast the current state of economy.

6. Conclusions

In this paper, we assess whether confidence indicators contain useful forwardlooking information about future economic activity. To assess this issue formally, we set up a simple canonical VAR model of the Czech economy consisting of several macroeconomic variables and generate forecasts of GDP. Next, we include business sector and consumer confidence indicators in this model and evaluate their contribution to the accuracy of the GDP forecasts. Additionally, we examine the German confidence indicator and the specific components underlying the aggregate confidence indicator in this way.

Our results suggest that domestic confidence indicators are contemporaneously well correlated with GDP growth, but they help little in terms of more accurate forecasting of future economic activity as compared to the baseline macroeconomic VAR model and the AR(1) process for GDP growth. Clearly, this does not mean that confidence indicators are irrelevant for future GDP growth, but it does suggest that following changes in confidence indicators is unlikely to improve the forecasts and it can therefore be said that they contain a certain degree of noise. These pessimistic results also hold for the specific components underlying the aggregate confidence indicators (e.g. industry, construction, trade, and consumers). Interestingly, the German confidence indicators deliver very imprecise GDP forecasts and are therefore unlikely to be a useful indicator of the future evolution of the Czech economy. However, the results cannot be interpreted as a sign that firms and households are not forward-looking. Our results suggest that the Czech confidence indicators do not provide any insight on future economic activity in addition to the information already contained in some standard macroeconomic variables. On top of that, it has to be kept in mind that we examine the forecasting power of confidence indicators during a crisis, and not during "normal" times.

In terms of future research, we believe that useful extensions would be to carry out the forecasting exercise in real time as well as to examine whether the confidence indicators help nowcast the current economic situation. In addition, it may be worthwhile to examine the confidence indicators in relation to uncertainty, such as in Bloom (2009).

REFERENCES

Akerlof GA, Shiller RJ (2009): Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism. Princeton University Press.

Al-Eyd A, Barrell R, Davis EP (2009): Consumer confidence indices and short-term forecasting of consumption. *Manchester School*, 77:96–111.

Angelini E, Camba-Mendez G, Giannone D, Reichlin L, Rünstler G (2011): Short-term forecasts of euro area GDP growth. *Econometrics Journal*, 14:C25–C44.

Arnoštová K, Havrlant D, Růžička L, Tóth P (2011): Short-Term Forecasting of Czech Quarterly GDP Using Monthly Indicators. *Finance a úvěr - Czech Journal of Economics and Finance*, 61(6):566–583.

Bachmann R, Sims E (2012): Confidence and the Transmission of Government Spending Shocks. *Journal of Monetary Economics*, 59:235–249.

Barsky RB, Sims E (2012): Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence. *American Economic Review*, 102:1343–1377.

Beaudry P, Portier F (2004): An Exploration into Pigou's Theory of Cycles. *Journal of Monetary Economics*, 51:1183–1216.

Beaudry P, Portier F (2006): News, Stock Prices, and Economic Fluctuations. *American Economic Review*, 96:1293–1307.

Bloom N (2009): The Impact of Uncertainty Shocks. Econometrica, 77:623-85.

Borys Morgese M, Franta M, Horváth R (2009): The Effects of Monetary Policy in the Czech Republic: An Empirical Study. *Empirica*, 36:419–443.

Bram J, Ludvigson S (1998): Does Consumer Confidence Forecast Household Expenditure? A Sentiment Index Horse Race. Federal Reserve Bank of New York Economic Policy Review, June 1998:59–78.

Candelon B, Lutkepohl H (2001): On the Reliability of Chow-Type Tests for Parameter Constancy in Multivariate Dynamic Models. *Economics Letters*, 73(2):155–160.

Chauvet M, Guo J-T (2003): Sunspots, animal spirits, and economic fluctuations. *Macroeconomic Dynamics*, 7:140–169.

Clark TE, West KD (2007): Approximately Normal Tests for Equal Predictive Accuracy in Nested Models. *Journal of Econometrics*, 138:291–311.

Clark TE, McCracken MW (2011): Advances in Forecast Evaluation. *Federal Reserve Bank of St. Louis Working Paper Series*, no. 2011-025A.

Croushore D (2011): Frontiers of Real-Time Data Analysis. Journal of Economic Literature, 49:72–100.

Curtin R (2002): Surveys of Consumers: Theory, Methods, and Interpretation. Paper written for the *NABE 44th Annual Meeting*, September 30. Downloaded on October 28, 2012 from http://petty.sca.isr.umich.edu/fetchdoc.php?docid=26396.

Czech National Bank (2011): Financial Stability Report, 2011. Prague.

Duch RM, Kellstedt PM (2011): The heterogeneity of consumer sentiment in an increasingly homogenous global economy. *Electoral Studies*, 30:399–405.

Feldkircher M (2012): Forecast Combination and Bayesian Model Averaging: A Prior Sensitivity Analysis. *Journal of Forecasting*, 31:361–376.

Goodhart C, Osorio C, Tsomocos D (2009): An Analysis of Monetary Policy and Financial Stability: A New Paradigm. *CESifo Working Paper*, no. 2885.

Havránek T, Horváth R, Matějů J (2012): Monetary Transmission and the Financial Sector in the Czech Republic. *Economic Change and Restructuring*, 45:135–155.

Howrey EP (2001): The Predictive Power of the Index of Consumer Sentiment. *Brookings Papers on Economic Activity*, 32:175–216.

Homaifar GA, Adongo J, Zhao KM (2013): The long-run relationship between stock return dispersion and output. *Applied Economics*, 45:943–952.

Keynes JM (1936): General Theory of Employment, Interest and Money. London, Macmillan.

Koeda J (2012): How does yield curve predict GDP growth? A macro-finance approach revisited. *Applied Economics Letters*, 19:929–933.

Konstantinou P, Tagkalakis A (2011): Boosting confidence: Is there a role for fiscal policy? *Economic Modelling*, 28:1629–1641.

Knotek II ES, Khan S (2011): How Do Households Respond to Uncertainty Shocks? *Federal Reserve Bank of Kansas City Economic Review*, 2Q2011:63–92.

Ludvigson SC (2004): Consumer Confidence and Consumer Spending. Journal of Economic Perspectives, 18(2):29-50.

Lütkepohl H (2006): New Introduction to Multiple Time Series Analysis. Springer-Verlag, 1st ed.

Matsusaka JG, Sbordone AM (1995): Consumer confidence and economic fluctuations. *Economic Inquiry*, 33:296–318.

Mojon B, Peersman G (2001): A VAR Description of the Effects of Monetary Policy in Individual Countries of the Euro Area. *ECB Working Paper*, no. 92.

Mourougane A, Roma M (2003): Can confidence indicators be useful to predict short term real GDP growth? *Applied Economics Letters*, 10:519–522.

Ramalho EA, Caleiro A, Dionfsio A (2011): Explaining consumer confidence in Portugal. *Journal* of Economic Psychology, 32:25–32.

Rünstler G, Barhoumi K, Benk S, Cristadoro R, Den Reijer A, Jakaitiene A, Jelonek P, Rua A, Ruth K, Van Nieuwenhuyze C (2009): Short-term forecasting of GDP using large datasets: a pseudo real-time forecast evaluation exercise. *Journal of Forecasting*, 28:595–611.

Sims C (1980): Macroeconomics and Reality. Econometrica, 48(1):1-48.

Smith A (1997/1766): Lecture on the influence of commerce on manners. Reprinted in (Klein DB, ed.): *Reputation: Studies in the Voluntary Elicitation of Good Conduct.* University of Michigan Press.

Stock JH, Watson MW (2003): Forecasting Output and Inflation: The Role of Asset Prices. *Journal of Economic Literature*, 41(3):788–829.