Do Confidence Indicators Help Predict Economic Activity? The Case of the Czech Republic

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Abstract

We examine whether confidence indicators – and its underlying components – improve the forecasts of future economic activity. Using the quarterly data from the Czech Republic in 1999-2011, we estimate the vector autoregression model of Czech economy (consisting of several commonly-used macroeconomic variables) and compare its forecasting performance vis-à-vis the models, which additionally contain the domestic and foreign confidence indicators and credit growth. Our results suggest that although confidence indicators are contemporaneously well correlated with the GDP, they fail to improve the GDP forecasts vis-à-vis the model based on macroeconomic variables only. On the other hand, we find that adding the credit growth into the macroeconomic VAR model makes the GDP forecasts more accurate. This supports the view that financial shocks are important for understanding macroeconomic fluctuations.

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1 Introduction

The recent financial and economic crisis has reminded us of the role confidence plays for economic activity. Consumer and business sector confidence has fallen dramatically during the crisis deepening further the economic slowdown. Statistical offices and other authorities measure the confidence using various surveys and regularly report its estimates. An interesting question for market participants as well as for policy makers is whether these confidence indicators contain some useful information about future economic activity and more importantly, whether confidence indicators are able to deliver more precise (out-of-sample) forecasts of confidence indicators vis-à-vis some other commonly followed indicators. Comparing the precision of out-of-sample forecasts differentiates us from previous literature that largely focused 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 the data on confidence indicators in the Czech Republic and examine its forecasting performance. To do so, we first estimate canonical vector autoregression model (VAR) of Czech economy consisting of the following variables: real GDP growth, consumer prices, interest rate and exchange rate.[2] We label this as macroeconomic model for convenience. We use the forecasts from this commonly used model as a benchmark to which we compare the forecasting accuracy of confidence indicators. More specifically, we include the business sector and consumer confidence indicators one after the other in the macroeconomic model and use 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 addition, we also examine whether German confidence indicators are able to predict the future Czech GDP. The Czech Republic is a highly open economy and about two thirds of its exports are directed to Germany. As a consequence, German confidence indicators may in principle be relevant for forecasting the Czech economic activity. Finally, we include credit growth into the macroeconomic model and examine its forecasting performance, too. Doing so, we follow the burgeoning literature highlighting the importance of examining the

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

[2] This is 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, or Havranek et al., 2012).

macro-finance interactions (see Goodhart et al., 2009; Stock and Watson, 2003, among others). In this context, Havranek et al. (2012) have shown that financial variables have a systematic effect on economic fluctuations in the Czech Republic.

Our results suggest that even though the confidence indicators are contemporaneously well correlated with the GDP, they do not help improve the GDP forecasts vis-à-vis the baseline macroeconomic model. This result holds for all three confidence indicators examined: the Czech business sector confidence indicator, the Czech consumer confidence indicator and German Ifo Business Climate indicator (the expectations part) as well as to all underlying components to the Czech confidence indicators (industry, construction, trade and consumers). To the contrary, we find that credit growth contributes to more precise GDP forecasts. The contribution of credit growth is both economically and statistically significant.

This paper is organized as follows. Section 2 presents the related literature. The construction of 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 more streams of this literature. First, some studies undertake Granger-causality testing of the confidence-GDP growth nexus. Second, several studies examine to what degree confidence can be influenced by policy measures with the motivation to assess whether economic policy may contribute to moderate the economic crisis.[3] Third, there is literature examining the forecasting properties of confidence indicators along with some other leading indicators for predicting the 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.

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

Matsusaka and Sbordone (1999) estimate the 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% in the innovation variance of GNP. Similarly, Howrey (2001) examines the predictive ability of University of Michigan Survey Research Center's Index of Consumer Sentiment and finds that the confidence indicator improves the GDP forecasts especially in two to four quarter horizon, as compared to the forecast of GDP based on the autoregressive process. The forecasts for one quarter ahead resulted in negligible improvement of forecasting accuracy.[4] 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 non-fundamental part assessing the waves of optimism/pessimism influence the economic activity. They find that the waves of pessimism indeed contributed to deepening of economic recessions.

Barsky and Sims (2012) propose an identification strategy to disentangle the fluctuations in confidence indicators into two factors: The causal effect of animal spirits on economic activity and the new fundamental information about future economic activity. They suggest that the latter factor is the main cause for the 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 business cycle and the role of confidence is critical during recessions. Similarly, Konstantinou and Tagkalakis (2011) investigate whether consumer and business confidence help moderate the economic recessions and suggest the 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 for short-term GDP forecasting or GDP nowcasting (see, for example, Runstler et al., 2009, Angelini et al., 2011, or Feldkircher, 2012, for recent contributions). These contributions put forward that incorporating large datasets and employing various factor models typically give 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 include some measure of

[4] Note that we do not compare the forecasting ability of consumer indicators vis-à-vis the AR process for the GDP, as we find the macroeconomic VAR model more informative for policy makers given that it contains several commonly followed variables.

confidence, but the contribution of these confidence indicators for GDP forecasting is typically not assessed explicitly.

3 The Construction of Confidence Indicators

This section discusses the construction of confidence indicators (especially in the Czech Republic, Germany and in the U.S., where they originated).[5] The confidence indicator is a measure of 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 statistical offices or various policy research institutions at the 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.[6] Ifo Business Climate is the German widely followed confidence indicator (available from the early 1990s). The Czech confidence indicators are produced by the Czech Statistical Office. The business indicator was launched in 1993, followed by the consumer confidence indicator in 1998.

The polls are typically carried out among consumers and firms in various sectors such as in industry, trade, construction or services.[7] The weights for sectors are specified according to the size of these sectors in order to produce representative aggregate confidence index.

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

[6] 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.

[7] However, the EU also carries out the survey specifically focused on financial sector (http://ec.europa.eu/economy_finance/db_indicators/surveys/time_series/index_en.htm). The survey is available at the quarterly frequency as well as monthly frequency from 2007 onwards. For the indicator at the quarterly frequency, the respondents are asked 18 questions related to their (current and expected) competitive position and financial health. The balance values are reported for three categories: Financial intermediation, except insurance and pension funding, Insurance and pension funding, except compulsory social security, and Activities auxiliary to financial intermediation. For the indicator reported at the monthly frequency, the respondents are primarily asked three questions related to their current business situation, the current evolution of the demand and the expectation about the demand for their products. In a similar vein, starting from 2009, Kellogg School of Management at Northwestern University and the University of Chicago Booth School of Business publish the financial trust index and conduct the survey on to what degree the consumers have trust in the private institutions (such as banks, stock markets, mutual funds and large corporations) in which they can invest their money (see http://www.financialtrustindex.org/).

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

The respondents in these surveys typically choose from three answers: increase, do not change, decrease (or "good, satisfactory, bad" depending on how the question is formulated). These answers serve to create the 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 the confidence index. Finally, the confidence indicators are often seasonally adjusted.

The number of respondents to the survey on confidence varies from some 500 respondents for the University of Michigan Consumer Sentiment Index to 7000 respondents for the Ifo Business Climate. Clearly, larger sample size reduces the sampling error. In this respect, Curtin (2002) shows that increasing the sample size by additional 1000 respondents in the Michigan survey would reduce the sampling error from $\pm$ 3.3 index points to $\pm$ 1.9 index points. The sample size for the Czech confidence indicators is approximately 3000 respondents.

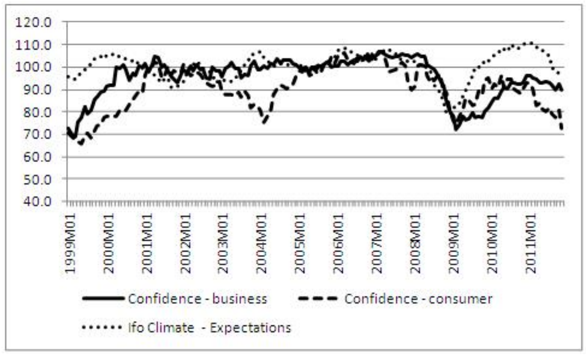
4 Data and VAR Model

4.1 Data

To predict the Czech GDP growth, we use the quarterly data in 1999Q1-2011Q3.[8] The sample is restricted to 1999Q1 onwards given that the CZK/EUR data are not available for 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 received from the Ifo Institute. The confidence indicators are available at the monthly frequency. Since the GDP data are available only at

[8]We use ex-post GDP data. While for analyzing the monetary policy rules of monetary transmission mechanism, real-time data may be important to identify the policy shocks (see Croushore, 2011), it is less clear in the situation, when we want to evaluate whether the confidence indicators are helpful for understanding *actual* economic activity. On the top of that, real-time data for the Czech GDP are not easily available.

Figure 1: Confidence Indicators, 1999-2011



the quarterly frequency, the value of confidence indicators in the last month of particular quarter is employed. For the GDP and consumer prices, we use the annualized quarter-on-quarter values to avoid the complicated structure in the regression residuals typically arising 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 confidence indicators seem to correspond to the economic activity. The values of Czech confidence indicators are particularly low at the end of 1990s and from 2009 onwards, which are the periods characterized by weak economic activity. To the contrary, the values are highest in the mid-2000s, when the Czech Republic experienced a solid growth. The consumer confidence index is a bit more volatile than the one for business sector (the coefficient of variation is about 20% higher for the consumer confidence index).

4.2 VAR Model

The VAR system – developed by Sims (1980) - is employed to model the Czech economy and to generate the 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):

$$A(L)y_t = \varepsilon_t \tag{1}$$

where $A(L)$ is an $m \times m$ matrix polynomial in the lag operator (with non-negative powers), y_t is an $m \times 1$ vector of observations, and ε_t is an $m \times 1$ vector of structural disturbances or shocks. ε_t is serially uncorrelated and $var(\varepsilon_t) = \Lambda$, 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 – the annualized quarter-on-quarter real GDP growth (x_t), a measure of the 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 ($e_t^{CZK/EUR}$). Therefore, the baseline model is based on the macroeconomic variables only. The number of lags in the VAR model is set according to the Schwartz information criterion.

We choose a simple VAR model for forecasting, since the previous literature employing the 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 factor-augmented VAR, simple VAR, structural VAR, and Bayesian sign-restriction VAR model to study the monetary transmission mechanism in the Czech Republic. They find that factor-augmented VAR resulted in very large confidence intervals often with a sign of impulse response not consistent with theory. All other VAR models that Borys et al. (2009) employed gave very similar results in terms of impulse responses.

Since we are concerned only with the forecasting exercise in this paper, ordering of variables and shock identification is not relevant in this regard (Lutkepohl, 2006). We estimate the baseline (macroeconomic) VAR model using data up to 2010Q4 and produce the corresponding (pseudo) out-of-sample forecasts for the following 3 quarters. The forecast evaluation for 3 quarters ahead should be sufficient given that confidence indicators are meant to provide an assessment of economic conditions in near future. The choice of 2010Q4 is to maximize our sample. However, we alternatively use 2010Q3 and 2010Q2 as the starting dates for forecasts for a robustness check.

Next, we include the confidence indicators and the Czech credit growth one after the other into 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 into the baseline model due to the 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 five models:

1) Macroeconomic model:

$y_t' = \left(x_t, p_t, i_t, e_t^{CZK/EUR}\right)$

2) Consumer confidence model:

$y_t' = \left(x_t, p_t, i_t, e_t^{CZK/EUR}, conf_t^{consumer}\right)$

3) Business confidence model:

$y_t' = \left(x_t, p_t, i_t, e_t^{CZK/EUR}, conf_t^{business}\right)$

4) German Ifo confidence model:

$y_t' = \left(x_t, p_t, i_t, e_t^{CZK/EUR}, conf_t^{Ifo}\right)$

5) Credit growth model:

$y_t' = \left(x_t, p_t, i_t, e_t^{CZK/EUR}, credit_t\right)$

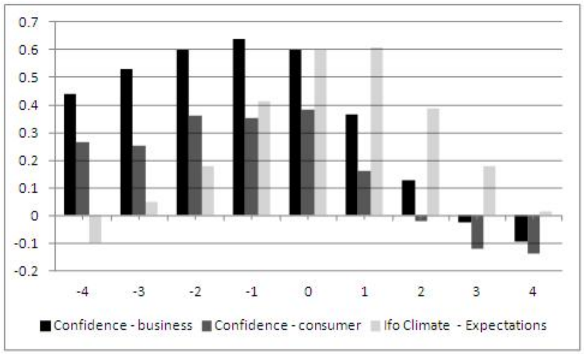
More specifically, we compare the forecasting performance of models (2) – (5) to the model (1). First, we generate the squared forecast errors and mean square errors. Second, we use the Clark and West (2007) forecast evaluation test to assess whether models (2) – (5) improve the forecasts of the model (1) in a statistical significant way.[9] The choice of Clark and West (2007) test is motivated by the fact that the model (1) is nested within the models (2) – (5). In such a setting, Clark and West (2007) show that that larger models introduce noise into its forecasts. Therefore, the comparison of resulting mean square errors must be adjusted for the noise (this is labelled as the adjustment term). The Clark and West (2007) test statistic equals to the MSE of model (1) minus the MSE of selected model (for example, (2)) plus the adjustment term, which is defined as the squared difference between the forecasts generated by the 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 the way that increase in its values results in a higher probability of rejecting the null hypothesis.

As a further robustness check, we conduct the forecasting exercise at a different forecast dates. In addition to the five abovementioned models, we also examine the forecasting performance of underlying confidence indicators components. Namely, we evaluate the forecasting performance of the quarter-on-quarter change in the balance value of industry, construction, trade and consumer confidence.[10]

[9] See Clark and McCracken (2011) for a recent survey on forecast evaluation.

[10] 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



5 Results

This section contains the results. First, we present the simple cross-correlations to assess to what degree the confidence indicators are correlated with GDP growth and whether the lagged or lead values of confidence indicators are more correlated with GDP growth. Second, we carry out a formal forecasting exercise to evaluate the predictive performance of confidence indicators.

The cross-correlations between confidence indicators and GDP growth are given in Figure 2. The cross-correlation is defined as the

$corr\,(confidence_t, GDPgrowth_{t+i})$. As a result, an informal assessment that the confidence indicators are leading the GDP growth is to see that the correlations of confidence indicators and GDP growth are stronger with $GDPgrowth_{t+i}$, when $i > 0$ (i.e. the right part of Figure 2). On the other hand, if the correlations are stronger for $i < 0$, it rather suggests that the confidence indicators follow the developments of GDP growth with a lag.

The results show that the contemporaneous correlation between business sector confidence indicator and GDP growth is about 0.6. The similar value is received for the correlation of Ifo Business Climate (expectations) indicator. The contemporaneous correlation of consumer confidence indicator and GDP growth is a bit lower and reaches the 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 suggest little support that confidence indicators lead the Czech GDP growth. We assess this finding more formally below.

Table 1: Mean Square Errors Relative to the Macroeconomic Model (1)

	Model no.			
	(2)	(3)	(4)	(5)
2011Q1	1.94	0.93	117.43	0.01
2011Q2	1.30	1.10	11.86	0.71
2011Q3	1.26	1.13	5.96	0.86

Note: The model (1) consists of macroeconomic variables only, the model (2) in addition to macroeconomic variables includes the Czech business sector confidence indicator, the model (3) includes the consumer confidence indicator, the model (4) includes the German Ifo Business Climate indicator (expectations part), and the model (5) additionally includes the credit growth. The values below one indicate that models (2)-(5) exhibit smaller mean square errors than model (1).

We present the relative mean square errors in Table 1. The models (2), (3) and (4), which capture the effect of confidence indicators, do not help make the GDP forecasts more accurate. This result broadly accords with Al-Eyd (2009), who find the information content of confidence indicators for future consumption in the U.S. to be rather small. The results suggest that model (5) is the only model delivering more precise forecast, as the relative mean square error is below 1. Therefore, the results indicate that credit growth rather than confidence indicators is useful for predicting future GDP growth.

The values of relative mean square error for model (5) are well below 1 (0.01, 0.71, and 0.86) suggesting that the improvement in terms of forecasting accuracy is significant. We test this formally using the Clark and West (2007) test. The results are available in Table 2. We reject the null hypothesis of identical forecasting performance only for the model (5). In other words, the models containing the confidence indicators do not improve the GDP forecasts and it is only the model with credit growth that makes the GDP forecast more precise in a systematic way. This is broadly in line with the previous findings by Havranek et al. (2012), who examine the role of financial variables for predicting prices and economic activity in the Czech Republic.

In order to assess the robustness of 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 are available in Tables 3 and 4; the results for the latter exercise are available upon request. The robustness checks support our baseline findings. The credit growth improves the GDP forecasts, while the confidence indicators are not found to produce more accurate forecasts.

Table 2: Clark and West (2007) forecast evaluation test for nested models: Do confidence indicators improve the forecasts of GDP?

Model no.	t-stat
(2) – Confidence, business	-1.78
(3) – Confidence, customer	-1.45
(4) – Ifo Business Climate	-2.46
(5) – Credit growth	2.72**

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

Table 3: Mean Square Errors Relative to the Macroeconomic Model (1), Forecasts as of 2010Q3

	Model no.			
	(2)	(3)	(4)	(5)
2010Q4	2.50	0.93	314.68	0.19
2011Q1	2.14	1.38	74.84	0.33
2011Q2	1.42	1.23	8.87	0.89

Note: The model (1) consists of macroeconomic variables only, the model (2) in addition to macroeconomic variables includes the Czech business sector confidence indicator, the model (3) includes the consumer confidence indicator, the model (4) includes the German Ifo Business Climate indicator (expectations part), and the model (5) additionally includes the credit growth. The values below one indicate that models (2)-(5) exhibit smaller mean square errors than model (1).

Table 4: Clark and West (2007) forecast evaluation test for nested models: Do confidence indicators improve the forecasts of GDP?

Model no.	t-stat
(2) – Confidence, business	-1.30
(3) – Confidence, customer	-1.18
(4) – Ifo Business Climate	-1.84
(5) – Credit growth	3.05**

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

Table 5: 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

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

Table 6: Clark and West (2007) forecast evaluation test for nested models: Do specific confidence indicators improve the forecasts of GDP?

Model no.	t-stat
(2) – Confidence, industry	-2.08
(3) – Confidence, construction	0.95
(4) – Confidence, trade	1.18
(5) – Confidence, consumer	0.30

Note: Forecasts as of 2010Q4. With the test statistic larger than +1.282 or +1.645, the null hypothesis is rejected at the 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 5 and 6. We find that the construction and trade components of aggregate confidence indicator perform as good as or marginally better than the baseline macroeconomic model (see columns 2 and 3 in Table 5). 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 that 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 in comparison to some commonly used VAR model solely based on macroeconomic variables.

6 Conclusions

In this paper, we assess whether the confidence indicators contain useful forward-looking 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 the forecasts of GDP. Next, we include the business sector and consumer confidence indicators into this model and evaluate their contribution to the accuracy of GDP forecasts. Additionally, we examine the German confidence indicator, domestic credit growth 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 the future economic activity, as compared to the baseline macroeconomic VAR model. Clearly, this does not mean that confidence indicators are irrelevant for future GDP growth, but it suggests that following the developments of confidence indicators is unlikely to improve the forecasts. These pessimistic results also hold for the specific components underlying the aggregate confidence indicators (e.g. industry, construction, trade and consumers components). Interestingly, the German confidence indicators deliver very imprecise GDP forecasts and therefore, is unlikely to be useful indicator for understanding the future developments of Czech economy.

The forecasting performance of credit growth is more promising. Our results indicate that the inclusion of credit growth into the baseline VAR model consisting of macroeconomic variables only improves the GDP forecasts. Using the Clark and West (2007) test for the forecast evaluation of nested models, we find that credit growth improves the forecasts in a statistically significant way. Therefore, our results highlight the importance of analyzing the financial shocks for better understanding of economic fluctuations. At the very general level, the results support the view that commonly used macroeconomic models should be extended to account for financial sector developments (see e.g. Goodhart et al., 2009).

In terms of future research, we believe that the 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.

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