Are uncertainty measures powerful predictors of real economic activity in the Euro Area?

Sławomir Śmiech[1], Aleksandra Mucha[2]

Abstract

In the paper we propose and collect measures that are related to different aspects of economic uncertainty and examine their predictive power for real economic activity in the Euro Area. The set of uncertainty measures investigated includes: the European News Index, Economic Policy Uncertainty index, uncertainty indices related to the global financial and commodity markets, and the Euro Area industry uncertainty measures calculated using business surveys provided by the European Commission. Macroeconomic activity indicators used in the study describe production, investment and unemployment. The analysis covers quarterly data from 2000 to 2014. The study is based on the rolling scheme and different specifications of VAR models. Two main conclusions can be drawn. First, uncertainty measures are, to a great extent, independent of one another. Second, some uncertainty indices perform well in forecasting economic activity indicators. It seems, however, that the best strategy is to apply forecast averaging techniques and to combine information provided by all uncertainty indices.

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1 Introduction

Economic uncertainty is an important economic category in both theoretical analyses (Ellsberg, 1961; Dequech, 1999) and empirical studies (Bloom, 2009; Baker et al., 2016; Kang et al., 2016). It seems obvious that high uncertainty affects the decisions made by consumers, who restrict their purchases, and entrepreneurs, who limit hiring and investing, which leads to a decrease in production and employment.

The consensus about the definition of economic uncertainty has not been reached so far: in the Knightian tradition it is "non-quantitative" (Knight, 1921), while in more recent literature attempts are made at measuring uncertainty, and the most popular approaches include: economic and political uncertainty (measured with the EPU index) (Baker et al., 2016); financial uncertainty (measured with the VIX index and the Financial Stress Index STRESS), uncertainty related to credit risk or uncertainty related to expectations of entrepreneurs

[1]Corresponding author: Cracow University of Economics, Department of Statistics, Rakowicka 27, 31-510 Kraków, Poland, e-mail: smiechs@uek.krakow.pl.
[2]Cracow University of Economics, Rakowicka 27, 31-510 Kraków, Poland, email: aleksandra.mucha94@gmail.com

(Bachmann et al., 2013). Although all these measures are expected to quantify the same economic phenomenon, it is not clear to what extent they are independent of one another and how accurate they are in explaining actual economic activity.

The paper has two objectives: first, to collect and compare uncertainty measures which are related to European economy, and, second, to analyse their predictive power with reference to economic activity in Europe. The set of uncertainty measures includes seven indices, which reflect different aspects of uncertainty: (1) economic policy uncertainty measured with the European News Index (ENI) and the Policy Uncertainty Index (EPI); (2) industrial sector uncertainty measured with the Euro Area Industrial uncertainty indices (INDU, INDU_f); (3) uncertainty in financial markets measured with the common volatility of stock exchange indices in the Euro Area (FIN_EA) and the index of common volatility of stock exchange indices (FIN); (4) uncertainty in the global commodity markets measured with the index of common volatility of prices on these markets (COMU). Economic activity in Europe is measured with: industrial production (PROD), employment (EMPL) and gross fixed capital formation (INVEST). All macroeconomic variables are seasonally adjusted.

The study covers quarterly data spanning the period from January 2000 to January 2014[3], which yields 65 observations. The data are obtained from the Eurostat database, European Commission website, Economic Policy Uncertainty website, Word Bank, and Thompson Reuters DataStream.

The empirical strategy consists of two steps. In the first one, the uncertainty indices are collected and analysed. Two measures (EPI, ENI) are taken from the Economic Policy Uncertainty website, and the reaming uncertainty indices are estimated. As the measures describe different aspects of uncertainty, their mutual relations are investigated by analysing correlations and Granger causality between the measures. In the second step, the predictive power of the uncertainty indicators regarding the US are compared to predicted economic activity in Europe. The comparison is performed by estimating two-dimensional VAR models with a number of lags from 1 to 4 and different settings of a deterministic trend. The models include one variable relating to economic activity (PROD, INVEST, UNEMP) and one of the uncertainty measures (EPU, ENI, INDU, INDU_f, FIN_EA, FIN, COMU). Each of the models (21 models in total) is used to determine the forecasts for one period ahead in the rolling forecasting scheme. The rolling windows include observations of 31 consecutive quarters. The first forecasts are obtained for Q4 2007, which means that the largest recent

[3]There are two reasons to limit the dataset until 2014: first, the EPU index avulability, and second, the Euro Zone countries seem to be recovering since the end of 2013.

slowdown of economic activity in Europe, related to the global financial crisis, is taken into account. The last forecasts are obtained for the first quarter of 2014. The forecasts obtained from the VAR models are compared with the forecasts obtained with benchmark models, which include AR(1), AR(4) and naive forecasts. Accuracy of forecasts is assessed using RMSE and MAPE. Forecasts of trend changes are also analysed by comparing forecast errors with differences of original variables.

The contributionof the paper is twofold. First, new measures of uncertainty which are related to different aspects of uncertainty in Europe are proposed, and a detailed comparison of these measures is made. Second, different aspects of uncertainty in prediction of economic activity in the Euro Area are analysed. Both the mutual relations between different aspect of uncertainty and the utility of uncertainty indices in predicting the main macroeconomic indicators are of great importance for both theoretical and practical considerations.

The study consists of 4 sections. The introduction is followed by a section presenting uncertainty measures and another one reporting the empirical results, while conclusions are drown in the last section.

2 Uncertainty measures

A1. *Euro Area industrial uncertainty (INDU)*

In order to measure industrial uncertainty in the Euro Area, we follow two approaches proposed by Bachmann et al. (2013) using the survey data for the Euro Area provided by the European Commission[4]. The first approach is based on the assumption that heterogeneity of economic sentiment surveys reflects the dispersion of expectations that can be used as the proxy for macroeconomic uncertainty. The greater the heterogeneity of the survey responses, the larger uncertainty. On the other hand, high homogeneity of managers' expectations reflects high confidence and low uncertainty. As the survey results include the answer to the question "Q5: *Production expectations for the months ahead*", we calculate standard deviation of the aggregate answers (the difference between answers "increase" and "decrease") for different industrial sub-sectors:

$$INDU_t = sd\left(Q5_{t,i}\right), i = 1,..23, t = 1,..217,$$

where: $Q5_{t,i}$ indicates answers to Q5 question obtained for the i^{th}industrial subsector in the period *t*.

[4]https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en

The second approach assumes that uncertainty can by related to the forecast error of the expectations. Thus, we compare answers to two questions: Q5 (previously used) obtained in the period *t* and Q1: "*Production trend observed in recent months*" in the period *t*+3. High uncertainty appears if production expectations are not in line with production observed. In order to measure uncertainty in the period *t*, answers regarding different industrial subsectors are used in the following way:

$$INDFU_t = mean\,|(Q5_{t,i} - Q1_{t+3,i})|, i = 1,..23, t = 1,..217.$$

A2. *Policy uncertainty indices*

The European News Index (ENI) and the Economic Policy Uncertainty index measure the European policy-related economic uncertainty based on newspaper articles and are obtained from the website of Economic Policy Uncertainty. Data collected from 10 newspapers in 5 European countries: France, Germany, Italy, Spain, and the United Kingdom, are developed by Baker et al. (2016).[5]

A3. *Global commodity market uncertainty index (COMU)*

The global commodity market uncertainty index (COMU) is estimated for 24 commodities[6], which represent the following commodity market sectors: agriculture, livestock, energy, industrial metals and precious metals. Commodities which have been selected are believed to be both sufficiently significant to the world economy and are tradable through futures contracts. With the exception of several metals contracts (aluminium, copper, lead, nickel and zinc) whichtrade on the London Metals Exchange ("LME"), and the contract for Brent crude oil and gas oil, the remaining commodities are the subject of trade on different U.S. exchanges. The details regarding the underlying futures contracts and the exchanges in which they are traded are available on request. The data are obtained from Thomson Reuters DataStream.

In order to measure uncertainty related to the global commodity market, we apply methodology proposed in Kang et al. (2016). The proposition assumes that uncertainty can be estimated as a common component of volatility of returns on financial instruments. Calculating the global commodity market uncertainty requires three steps. First, commodity returns are calculated as:

[5]See http://www.policyuncertainty.com/europe_monthly.html.
[6] Details are available from the authors on request.

$$r_{c,t} = ln\frac{y_{c,t}}{y_{c,t-1}}$$

where $y_{c,t}$ denotes the average monthly price for a given commodity *c*, in period $t= 1,..,T$. Next, volatility proxy for each commodity *c* is calculated as:

$$V_{c,t} = \left(r_{c,t} - \bar{r}_{c,t}\right)^2,$$

where $\bar{r}_{c,t}$ is the sample mean of $r_{c,t}$.

Given the data matrix (24xT dimension) with $V_{c,t}$ for 24 commodities in the final step, the principal component for the correlation matrix is estimated. The first principal component is used as the global commodity market uncertainty proxy.

A4. *Financial market uncertainty index (FIN, FIN_EA)*

The global financial market uncertainty index (FIN) is estimated for the main indices of 10 largest stock exchanges in the world in terms of market capitalization. The data are obtained from Thomson Reuters Datastream.

The global financial market uncertainty index is calculated in the same way as the global commodity market uncertainty index, which means that common volatility of returns is calculated using the principal component analysis.

The Euro Area financial market uncertainty index (FIN_EA) is based on the same idea, but uses equity indices of 10 largest stock exchanges in the Euro Zone countries.

3 Empirical results

The first step of the study is dedicated to the analysis of mutual relations between the uncertainty measures. Fig. 1 presents standardized series of uncertainty measures[7]. The results presented reveal a rather moderate similarity between the indices. Most shocks identified, similar to Jurado et al. (2015)[8], are *specific* to the particular aspect of uncertainty. In general, there is no overlap between shocks. The only exception is the outbreak of the global financial crisis in which different uncertainty shocks occur simultaneously. Correlations between the uncertainty indices are positive, yet moderate for most pairs (see Fig. 1 the right panel). Correlations larger than 0.5 are obtained only for (NEWS, EPU), (FIN, FIN_EA) and (FIN, INDU_f) pairs. Granger causality for each pair of uncertainty indices is examined as well. *p*-values of the tests are presented in Table 1. There is no Granger causality between most pairs,

[7]The range of the series is limited to 2014 as EPI index is available up to this date.

[8]An uncertainty shock is an event in which a given uncertainty index deviates from its mean level by more than 1.65 standard deviation.

which means that past values of one uncertainty index cannot reduce forecast variance of another uncertainty index. There are, however, some exceptions. FIN Granger causes both industrial uncertainty measures. INDU_f is influenced (in the Granger sense) by almost all other uncertainty aspects.

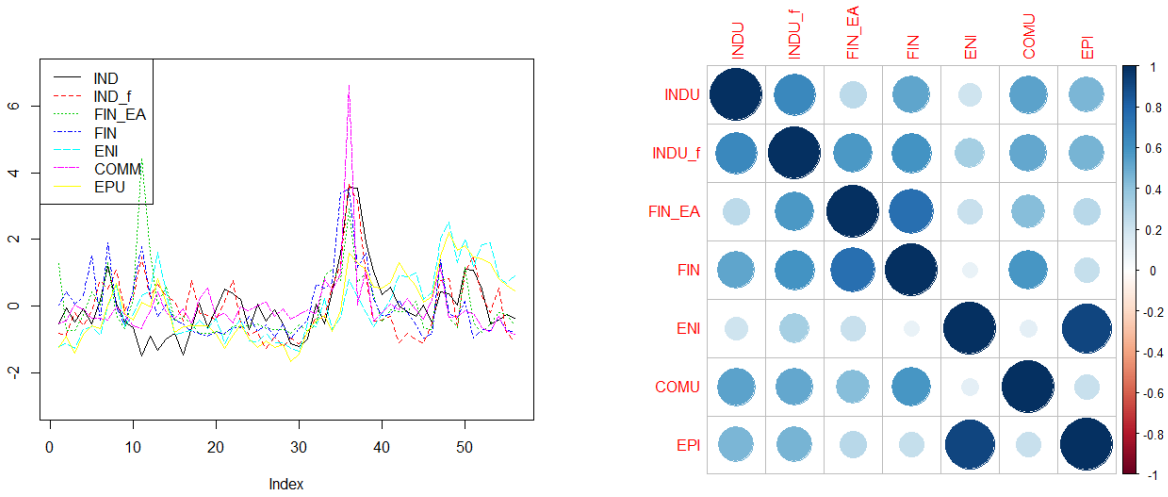

Fig. 1. Standardized uncertainty indices (left) and the correlation between them (right).

Table 1. Granger causality test for uncertainty measures (p-values).

Cause\Effect	EPU	FIN_EA	ENI	INFU	INFU_f	FIN	COMU
EPU		0.485	0.305	0.237	**0.003**	**0.055**	0.965
FIN_EA	0.608		0.501	0.056	**0.014**	**0.038**	**0.000**
ENI	0.250	0.825		0.187		0.262	0.872
INDU	0.732	0.171	0.896		**0.013**	0.163	0.378
INDU_f	0.201	0.931	0.059	0.139		0.565	0.791
FIN	0.367	0.509	0.446	0.469	**0.044**		0.769
COMU	0.617	0.217	0.446	0.509	**0.002**	**0.017**	

Note: bold numbers indicate statistically significant relations.

In the next step, the predictive power of uncertainty measures for forecasting economic activity in the Euro Area is examined. Forecasts for the next quarter are generated using VAR(1) and VAR(4) models with or without trend component within the rolling forecasting scheme. The first forecasts are obtained for the fourth quarter of 2007, the last for the fourth quarter of 2013. The smallest errors are obtained for the most parsimonious specification i.e.

VAR(1) without trend[9]. Owing to the limited space, only the results obtained with this specification are discussed here. The results obtained for the VAR models are compared with the set of benchmark models, which includes: AR (1), AR (4) and the naive model. Fig.2 shows a series of forecast errors for each macroeconomic variable (the panel on the left), and the comparison of forecast errors with changes in the direction (difference) of the predicted variable. Two remarks should be made here. First, a high variety of forecast errors is observed. For almost all analysed periods there are models that produce both negative and positive forecast errors. The largest forecast errors are obtained for the periods between 2008 and 2009, which results from the global financial crises (a structural change is observed for uncertainty as well as macroeconomic variables). Second, there is no correlation between forecast errors and the change of activity in the Euro Area when all the models are considered. Both above observations suggest thata forecast combination could serve as a potentially effective tool for predicting macroeconomic variables.

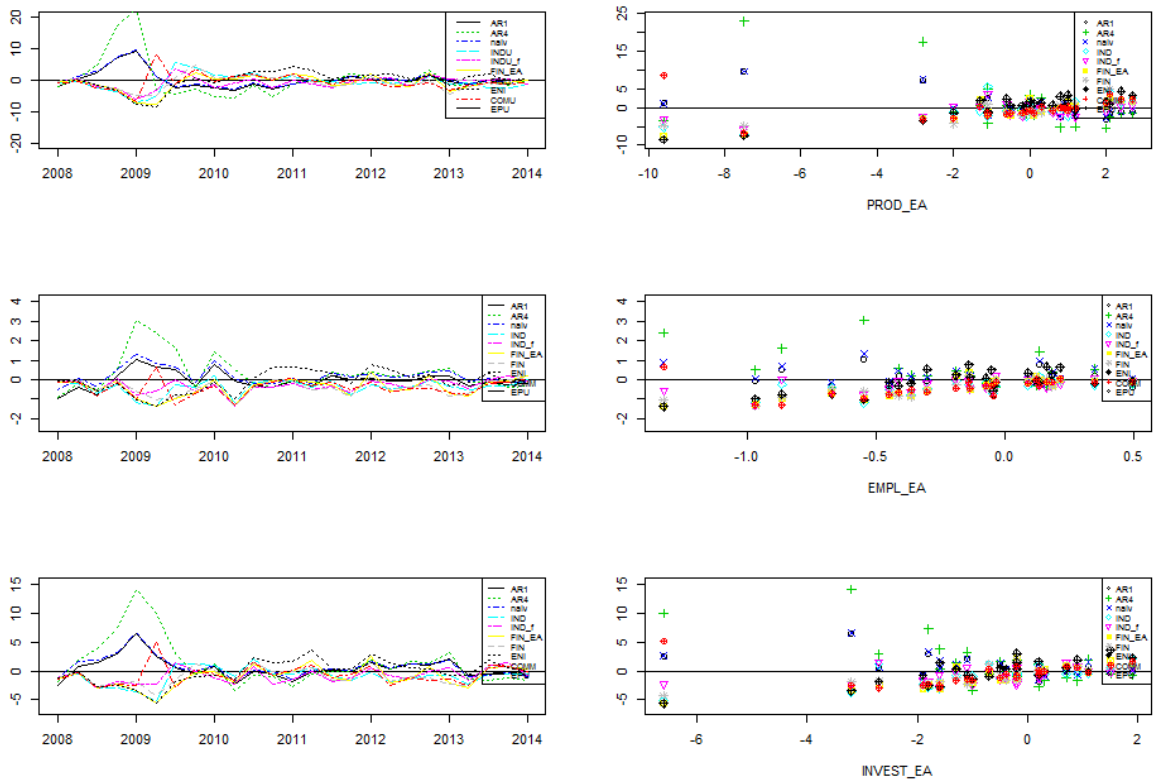

Fig.2 Forecast errors and the relations between the difference of macroeconomic variables and forecast errors.

[9]The results of the remaining specifications are available from the authors on request.

Forecast error measures for all models are presented in Table 2.The last two columns show the average rank of the models regarding RMSE and MAPE. The last row presents the results obtained for the combination of forecasts obtained from seven VAR models. Three observations can be made here. First, different uncertainty measures provide different forecasting accuracy. The smallest forecast errors are obtained for VAR models that include INDU_f and EPU indices. At the opposite end there are models that use ENI index. Second, the benefits of using uncertainty measures to forecast economic activity in the Euro Area are not obvious. AR(1) model turns out to be the best (in comparison to VAR models) in predicting employment. This model performs well when MAPE is taken as the criterion for the two reaming variables. Third, forecast combinations (the last row in Table 2) obtained as the average of forecasts from VAR models generate forecasts with the smallest errors (for all variables when MAPE is taken into account).

Table 2. Forecast error measures obtained for benchmark models and models incorporating uncertainty measures.

	PROD		**EMPL**		**INVEST**			
	RMSE	**MAPE**	**RMSE**	**MAPE**	**RMSE**	**MAPE**	**Rank 1**	**Rank 2**
AR1	2.78	1.7	**0.44**	**0.24**	1.83	1.19	4.7	3.00
AR4	6.35	3.55	0.96	0.46	4.14	2.53	11.00	11.00
naiv	2.77	1.63	0.46	0.24	1.87	1.25	6.33	3.00
INDU	2.68	1.99	0.54	0.29	1.84	1.38	6.00	7.00
INDU_f	***1.97***	*1.42*	0.46	*0.25*	1.47	1.22	2.33	3.00
FIN_EA	2.66	1.88	0.6	0.33	2.05	1.58	7.67	8.67
FIN	2.22	1.69	0.56	0.31	1.69	1.35	4.67	5.67
ENI	2.91	2.05	0.56	0.32	2.05	1.53	8.67	8.67
COMU	2.67	1.82	0.59	0.33	1.86	1.43	7.00	7.67
EPU	2.81	2.2	**0.44**	*0.25*	1.67	1.31	4.33	6.33
FC	2.02	**1.39**	0.45	**0.23**	**1.43**	**1.09**	**2.00**	**1.00**

Notes: bold numbers indicate the models that yield the most accurate forecasts; numbers in italics indicate the best model among models using the uncertainty measures; Rank 1 (Rank 2) show an average rank obtained for models regarding RMSE (MAPE) for three macroeconomic indicators.

Conclusion

The study proposes measures of uncertainty, next examines their mutual relations, and finally assesses their predictive power in forecasting real activity in the Euro Area between 2000 and 2014. The results obtained reveal that individual uncertainty measures are - to a great extent - independent and seem to be related to different aspects of economic uncertainty. The predictive power of uncertainty measures is varied as well. Uncertainty in the industrial sector turns out to be the best predictor of real production and investment in the Euro Area. The economic policy uncertainty index is the best predictor of employment. Nevertheless, the information provided by single measures of uncertainty does not seem to be enough to beat all benchmark models.

Considerable independence of the uncertainty measures makes the forecast combination useful. The forecasts calculated as the average of forecasts obtained from all models using uncertainty measures turn out to be the most effective in predicting the real activity in the Euro Area.

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