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"Forecasting Business surveys indicators: neural networks vs. time series models"

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Abstract

The objective of this paper is to compare different forecasting methods for the short run forecasting of Business Survey Indicators. We compare the forecasting accuracy of Artificial Neural Networks (ANN) vs. three different time series models: autoregressions (AR), autoregressive integrated moving average (ARIMA) and self-exciting threshold autoregressions (SETAR). We consider all the indicators of the question related to a country's general situation regarding overall economy, capital expenditures and private consumption (present judgement, compared to same time last year, expected situation by the end of the next six months) of the World Economic Survey (WES) carried out by the Ifo Institute for Economic Research in co-operation with the International Chamber of Commerce. The forecast competition is undertaken for fourteen countries of the European Union. The main results of the forecast competition are offered for raw data for the period ranging from 1989 to 2008, using the last eight quarters for comparing the forecasting accuracy of the different techniques. ANN and ARIMA models outperform SETAR and AR models. Enlarging the observed time series of Business Survey Indicators is of upmost importance in order of assessing the implications of the current situation and its use as input in quantitative forecast models.

Keywords: Business surveys; Forecasting; Time series models; Nonlinear models; Neural networks

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1. Introduction

Business surveys provide detailed information about agents' perceptions and expectations. The fact that survey results are based on the knowledge of the respondents operating in the market and are rapidly available makes them very valuable for forecasting purposes and decision-making. Survey results are presented as weighted percentages of respondents expecting a variable to go up, to go down or to remain unchanged. The qualitative nature of survey results has often lead to quantify them making use of business survey indicators, such as the balance statistic.

The objective of the present paper is to compare different times series methods to Artificial Neural Networks for the short-run forecasting of business survey indicators. As far as we know, there are only a few studies that conduct forecast competitions for the case of business survey indicators (Clar *et al.*, 2007; Ghonghadze and Lux, 2009). Such an exercise helps to analyse which forecasting technique presents the best behaviour (Hendry and Clements, 2003; Stock and Watson, 2003). The usefulness of this comparison is twofold. First, it will allow having the best qualitative forecast to predict business cycle turning points (Diebold and Rudebusch, 1989). Second, it will allow that the best forecast is used as an explanatory variable in quantitative forecasts models (Biart and Praet, 1987; Parigi and Schlitzer, 1995) or when quantifying Business Survey data (Claveria *et al.*, 2006).

In order to compare different times series methods to Artificial Neural Networks for the forecasting of Business Survey Indicators we used the data of the World Economic Survey (WES) carried out by the Ifo Institute for Economic Research in co-operation with the International Chamber of Commerce (ICC). We used the raw data from all the indicators of the question related to a country's general situation regarding overall economy, capital expenditures and private consumption (present judgement, compared to same time last year, from now on - expected situation by the end of the next six months) for fourteen countries of the European Union. The data set included 18 quarterly indicators and 18 quarterly composite indicators (balance and weighted balance statistics) for each country for the period ranging from 1989 to 2008, giving a total of 80 observations per variable.

The structure of the paper is as follows. Section 2 briefly describes the business surveys indicators used in the paper. Section 3 presents our methodological approach,

including both time series models and Artificial Neural Networks models. The data set and the results of the forecasting competition are described in Sections 4 and 5. Last, conclusions are given in Section 6.

2. Business Surveys Indicators

Business surveys have become an essential tool for gathering information about a wide range of economic variables, as they provide very detailed information about agents' perceptions and expectations. The fact that survey results are based on the knowledge of the respondents operating in the market and are rapidly available makes them very valuable for forecasting purposes and decision-making. Survey results are presented as weighted percentages of respondents expecting a variable to go up, to go down or to remain unchanged. As a result, tendency surveys contain two pieces of independent information at time t, R_t and F_t , denoting the percentage of respondents at time t-1expecting an economic variable to rise or fall at time t. The information therefore refers to the direction of change but not to its magnitude.

The qualitative nature of survey results has often lead to quantify them making use of business survey indicators. The most commonly used indicator to present survey results is the balance statistic ($B_t = R_t - F_t$). Assuming that the expected percentage change in a variable remains constant over time for agents reporting an increase and for those reporting a decrease, Anderson (1951) defined the balance statistic as a measure of the average changes expected in the variable. As the balance statistic (B_t) does not take into account the percentage of respondents expecting a variable to remain constant (C_t), Claveria (2010) proposed a non-linear variation of the balance statistic (WB_t , weighted balance) that accounts for this percentage of respondents:

$$WB_{t} = \frac{R_{t} - F_{t}}{R_{t} + F_{t}} = \frac{B_{t}}{1 - C_{t}}$$
(1)

Weighting the balance statistic by the proportion of respondents expecting a variable to rise or fall allows discriminating between two equal values of the balance statistic depending on the percentage of respondents expecting a variable to remain constant.

Since the objective of the paper is to assess alternative methods and models for forecasting business survey indicators, we have considered raw data for the percentage of respondents expecting an economic variable to rise (R_t) , the percentage of respondents expecting an economic variable to fall (F_t) , the balance statistic (B_t) and the weighted balance statistic (WB_t) .

3. Methodology-Forecasting Models

In order to assess alternative methods and models for forecasting Business Surveys Indicators described in Section 2, we used both time series models and artificial neural networks (NN).

3.1 Time series models

Time series models explain a variable with regard to its own past and a random disturbance term. We chose three different time series models to obtain forecasts for Business Surveys Indicators: autoregressions (AR), integrated moving-average models (ARIMA) and self-exciting threshold autoregressions models (SETAR). In order to determine the number of lags that should be included in the model, we have selected the model with the lowest value of the Akaike Information Criteria (AIC) considering models with a minimum number of 1 lag up to a maximum of 8 quarters (including all the intermediate lags)

We first considered autoregressions. AR models explain the behaviour of the endogenous variable as a linear combination of its own past values:

$$x_{t} = \phi_{1} x_{t-1} + \phi_{2} x_{t-2} + \dots + \phi_{p} x_{t-p} + \varepsilon_{t}$$
(2)

ARIMA models were first proposed by Box and Jenkins (1970). The general expression of an ARIMA model is the following:

$$\chi_t^{\lambda} = \frac{\Theta_s(L^s)\theta(L)}{\Phi_s(L^s)\phi(L)\Delta_s^D\Delta^d} \varepsilon_t$$
(3)

where $\Theta_s(L^s) = (1 - \Theta_s L^s - \Theta_{2s} L^{2s} - ... - \Theta_{Qs} L^{Qs})$ is a seasonal moving average polynomial, $\Phi_s(L^s) = (1 - \Phi_s L^s - \Phi_{2s} L^{2s} - ... - \Phi_{Ps} L^{Ps})$ is a seasonal autoregressive polynomial, $\theta(L) = (1 - \theta_1 L^1 - \theta_2 L^2 - ... - \theta_q L^q)$ is a regular moving average polynomial, and $\phi(L) = (1 - \phi_1 L^1 - \phi_2 L^2 - ... - \phi_p L^p)$ is a regular autoregressive polynomial, λ is the

value of the Box-Cox (1964) transformation, Δ_s^D is the seasonal difference operator, Δ^d is the regular difference operator, *S* is the periodicity of the considered time series (*S*=4 for quarterly data), and ε_t is the innovation which is assumed to behave as a white noise.

As Clements and Smith (1999) and Hansen (1997) stated, there seems to be a cyclical asymmetry in the behaviour of most economic variables. A Self-Excited Threshold Autoregressive model (SETAR) for the time series x_t can be summarised as follows:

$$B(L):x_t + u_t \text{ if } x_{t-k} \le x \tag{4}$$

$$\zeta(L) \cdot s_t + v_t \text{ if } x_{t-k} > x \tag{5}$$

where u_t and v_t are white noises, B(L) and $\zeta(L)$ are autoregressive polynomials, the value k is known as delay and the value x is known as threshold. This two-regime self-exciting threshold autoregressive process is estimated for each indicator and the Monte Carlo procedure is used to generate multi-step forecasts. The values of the threshold are given by the variation of the analysed variable.

3.2 Artificial Neural Networks models (ANN)

In recent years, the study of artificial neural networks (ANN) has aroused great interest as they are universal function approximators capable of mapping any linear or nonlinear function (Kock and Teräsvirta, 2011; Cybenko, 1989; Funahashi, 1989; Hornik, Stinchcombe and White 1989; Wasserman, 1989). ANN's flexibility in function approximation make them very useful in tasks involving pattern classification, estimating continuous variables and forecasting (Nakamura, 2005; Qi, 2001; Adya and Collopy, 1998; Swanson and White, 1997; Kaastra and Boyd, 1996; Hill, Marquez, O'Connor and Remus, 1994). ANN have been applied in many fields (Song and Li, 2008), but never before for the short-run forecasting of Business Survey Indicators.

ANN models have two learning methods: supervised and unsupervised. The neuronal network model most widely used in time series forecasting is the multi-layer perceptron (MLP) method. The MLP is a supervised neural network based on the original simple perceptron model, but with additional hidden layers of neurons between the input and output layers that increases the learning power of the MLP. The number of hidden

neurons determines the MLP network's capacity to learn (Palmer, Montaño and Sesé, 2006). Selecting the network which performs best with the least possible number of hidden neurons is most recommended (Masters, 1993).

Due to their flexibility, ANN lack a systematic procedure for model building. Therefore, obtaining a reliable neural model involves selecting a large number of parameters experimentally through trial and error. Kock and Teräsvirta (2011) and Zhang, Patuwo and Hu (1998) review the main ANN modelling issues: the network architecture (determining the number of input nodes, hidden layers, hidden nodes and output nodes), the activation function, the training algorithm, the training sample and the test sample, and the performance measures.

In this work we used the MLP specification suggested by Kuan and White (1994):

$$x_{t} = f\left(\beta_{0} + \sum_{j=1}^{q} \beta_{j} g\left(x_{t-1} \varphi_{ij} + \varphi_{0j}\right)\right)$$

$$\left\{\varphi_{ij}, i = 1, \cdots, p, j = 1, \cdots, q\right\}$$

$$\left\{\beta_{j}, j = 1, \cdots, q\right\}$$
(6)

where *f* is the output function; *g* is the activation function; *p* is the number of inputs; *q* is the number of neurons in the hidden layer; x_t is the output; x_{t-1} is the input; β_j are the weights connecting the output with the hidden layer and φ_{ij} are the weights connecting the input with the hidden layer. We chose an MLP(1;3) architecture that allowed us to represent the possible non-linear relationship between x_t and x_{t-1} . The model is illustrated in Fig. 1.

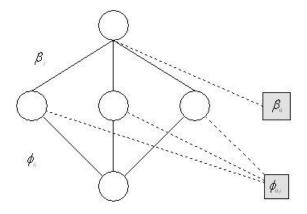


Figure 1. Multilayer feed-forward MLP(1;3)

Following Bishop (1995) and Ripley (1996), we divided the collected data into three sets: training, validation and test sets. This division seeks to improve the performance of the network with new cases. To achieve a more reliable and accurate result, a four year period served as the training set. Based on these considerations, the period from 1989.I to 2001.IV was selected as the training set (66%), 2002.I to 2006.IV as the validation set (25%) and 2007.I to 2008.IV as the testing set (10%) (see Fig. 2):

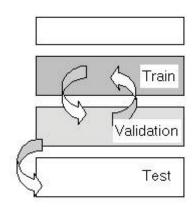


Figure 2. Train, Validation and Test sets

These models were implemented using Matlab[™] and its Neural Networks module. Inputs were normalised in order to facilitate the learning process. We used Levenberg-Marquardt backpropagation in order to calculate the weights in each of the iterations based on the minimization of the mean squared error.

4. Data

For our analysis, we used information from the World Economic Survey (WES) carried out quarterly by the Ifo Institute for Economic Research in co-operation with the International Chamber of Commerce. The WES assesses worldwide economic trends by polling organisations worldwide on current economic developments in their respective countries, allowing for a rapid assessment of the economic situation prevailing around the world. In April 2011, 1107 economic experts in 120 countries were polled.

The survey questionnaire focuses on qualitative information: assessments of a country's general situation and expectations regarding important economic indicators.

The survey results are published as aggregated data. The aggregation procedure is based on country classifications. Within each country group or region, the country results are weighted according to the share of the specific country's exports and imports in total world trade (CESifo World Economic Survey, 2011). For a detailed analysis of WES data see Stangl (2008).

The design of the forecast competition was based on all the information available for the first three questions of the WES: the country's general situation regarding overall economy, capital expenditures and private consumption. For each question we in turn used three different kind of expectations stated by the agents: their present judgement, their judgement compared to same time last year and their expectation by the end of the next six months. The dataset analysed includes therefore 36 indicators for each country: four indicators (R_t , F_t , B_t and WB_t) for each of the three different expectations (present judgement, compared to same time last year, expected situation by the end of the next six months) of each question. The forecast competition is undertaken for fourteen countries of the European Union: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands (NL), Portugal, Sweden and the United Kingdom (UK).

Before showing the results of the forecast competition, in Tables 1a, 1b, 2a, 2b, 3a and 3b we present the main descriptive statistics for the data set. The statistical properties of Business Survey Indicators differ substantially from those of the main macroeconomic variables. Survey results are presented as weighted percentages of respondents expecting a variable to go up, to go down or to remain unchanged.

As a result, business survey indicators can only take values between 0 and 100. As it could be expected, in all countries aggregate business survey indicators (the balance statistic, B_t , and the weighted balance, WB_t) show higher dispersion than R_t and F_t , denoting the percentage of respondents at time t-1 expecting an economic variable to rise or fall at time t. Therefore, aggregate business survey indicators tend to show lower levels of kurtosis than R_t and F_t in most countries. Regarding the coefficient of skewness, aggregate business survey indicators also tend to show negative values more often than R_t and F_t for all three questions in most countries.

		This	country	's genera	al situat	tion reg	arding o	verall ec	conomy			
		Present	judgmen	ıt	Cor	*	to same year	time		tion by	on: expe the end months	
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Austria	-											-
Mean	33.0	11.3	21.7	31.9	38.2	27.3	10.9	16.8	28.6	19.8	8.8	20.8
Std. Dev.	33.5	18.3	45.7	77.7	30.1	29.3	55.4	76.6	23.0	21.9	40.9	75.7
Skewness	0.8	1.6	0.1	-0.6	0.4	0.9	-0.2	-0.3	0.6	1.0	-0.2	-0.4
Kurtosis	2.3	4.1	2.1	1.8	1.9	2.7	2.0	1.5	2.5	2.8	2.2	1.7
Belgium												
Mean	23.1	19.9	3.2	-1.0	30.4	30.3	0.1	-0.2	30.9	16.8	14.0	25.1
Std. Dev.	27.2	23.8	45.8	90.2	29.3	28.3	54.7	84.6	26.1	20.3	42.2	73.0
Skewness	1.0	1.1	0.1	0.0	0.6	0.5	0.0	0.0	0.7	1.3	-0.1	-0.5
Kurtosis	2.8	3.3	2.1	1.2	2.2	1.9	1.7	1.2	2.6	3.9	2.4	1.8
Denmark												
Mean	46.0	9.8	36.1	55.3	42.1	14.4	27.7	41.4	30.2	12.6	17.6	28.8
Std. Dev.	31.9	20.9	47.0	73.0	30.2	20.2	45.7	73.4	28.2	17.8	40.2	79.0
Skewness	0.2	3.0	-0.8	-1.4	0.1	1.4	-0.5	-0.9	0.6	1.3	-0.1	-0.6
Kurtosis	2.0	11.9	3.6	3.3	1.9	4.1	2.3	2.2	2.5	3.6	2.4	1.8
Finland												
Mean	40.1	19.7	20.4	37.5	41.8	27.7	14.1	22.1	39.0	16.7	22.3	37.3
Std. Dev.	38.0	35.9	65.2	81.3	32.8	33.3	62.0	79.8	28.0	22.3	46.5	71.7
Skewness	0.4	1.5	-0.6	-0.8	0.3	1.0	-0.4	-0.4	0.4	1.4	-0.4	-0.8
Kurtosis	1.6	3.5	2.2	2.0	1.9	2.8	2.0	1.5	2.5	3.7	2.5	2.3
France												
Mean	17.1	30.7	-13.6	-30.6	30.8	31.7	-0.9	4.3	35.6	15.2	20.4	39.0
Std. Dev.	25.3	28.5	48.8	82.8	28.7	31.7	56.7	78.5	22.3	18.2	37.5	65.4
Skewness	1.4	0.6	0.4	0.7	0.9	0.7	0.0	-0.1	0.4	1.4	-0.5	-0.8
Kurtosis	3.4	2.2	2.2	1.7	2.8	2.2	2.0	1.4	2.5	4.8	2.7	2.3
Germany												
Mean	24.7	29.9	-5.2	-10.2	41.8	29.3	12.5	18.2	42.5	15.5	27.0	43.4
Std. Dev.	32.8	32.8	59.6	88.2	32.9	32.4	62.8	80.5	26.3	19.6	42.5	62.4
Skewness	1.1	0.7	0.2	0.2	0.2	0.8	-0.3	-0.3	0.2	1.4	-0.4	-0.9
Kurtosis	2.6	1.9	1.8	1.2	1.6	2.2	1.7	1.4	1.8	3.9	2.3	2.3
Greece												
Mean	14.1	37.8	-23.7	-23.8	31.7	19.8	11.8	10.4	41.0	8.6	32.3	48.3
Std. Dev.	25.3	40.9	57.6	80.7	34.6	25.6	53.7	82.9	33.4	15.3	43.5	68.6
Skewness	2.2	0.7	0.1	0.4	0.8	1.1	0.1	-0.2	0.4	2.5	-0.2	-1.0
Kurtosis	6.8	2.2	2.4	1.6	2.3	2.9	2.0	1.4	1.9	10.0	2.4	2.6

 Table 1a. Descriptive statistics I:1989 to IV:2008. Raw data

Note: Std. Dev. - Standard deviation.

Ξ

		This	country	's gener	al situa	tion reg	garding o	verall e	conomy			
		Present	judgmen	t	Co	*	to same t year	time		tion by	on: expe the end months	
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Ireland	-	-				-					-	
Mean	60.2	5.2	55.0	65.8	42.9	22.5	20.5	36.0	30.9	14.7	16.2	42.9
Std. Dev.	39.3	12.8	47.6	69.9	29.5	30.6	55.5	77.2	20.3	22.3	37.7	72.0
Skewnes	-0.3	3.3	-0.7	-1.8	0.2	1.2	-0.6	-0.7	0.4	1.7	-0.8	-0.8
Kurtosis	1.5	14.8	2.4	4.5	1.9	3.1	2.2	1.9	2.6	5.5	3.4	2.1
Italy												
Mean	13.0	38.1	-25.2	-33.5	30.4	34.5	-4.1	-6.5	35.0	14.2	20.8	35.5
Std. Dev.	17.6	31.1	45.3	78.2	28.7	29.6	54.6	73.8	21.7	14.0	32.8	62.7
Skewnes	1.4	0.4	0.1	0.7	0.7	0.7	0.0	0.2	0.4	1.1	-0.2	-0.8
Kurtosis	4.0	2.0	2.0	1.8	2.2	2.2	1.9	1.5	2.7	4.2	2.5	2.5
NL												
Mean	38.5	16.9	21.6	31.8	36.8	26.1	10.6	21.0	30.8	18.0	12.8	26.8
Std. Dev.	34.5	25.8	55.4	87.1	29.9	30.9	57.1	82.2	28.1	23.7	46.0	79.4
Skewnes	0.3	1.2	-0.3	-0.6	0.5	0.9	-0.3	-0.4	0.9	1.3	-0.1	-0.5
Kurtosis	1.5	2.8	1.8	1.6	2.3	2.4	1.9	1.4	2.5	3.6	2.2	1.6
Portugal												
Mean	11.2	30.5	-19.3	-28.4	21.9	33.3	-11.4	-9.5	26.9	12.4	14.6	25.3
Std. Dev.	18.6	30.5	44.1	89.3	22.8	32.7	50.8	81.4	27.5	18.1	38.7	73.7
Skewnes	1.4	0.4	0.2	0.6	0.8	0.7	-0.1	0.2	0.9	1.4	0.1	-0.5
Kurtosis	3.7	1.6	1.8	1.5	2.4	2.2	1.9	1.4	3.3	4.1	2.7	1.9
Spain												
Mean	25.5	22.0	3.5	12.4	30.4	33.5	-3.1	-1.1	21.9	22.1	-0.2	-0.3
Std. Dev.	25.6	32.5	52.0	86.4	31.2	32.3	59.2	77.7	21.0	20.9	37.5	68.7
Skewnes	0.6	1.6	-0.6	-0.3	1.1	0.7	0.1	-0.1	1.4	1.2	0.2	0.2
Kurtosis	2.0	4.1	2.5	1.3	3.5	2.0	2.0	1.4	4.5	3.8	3.0	1.7
Sweden												
Mean	30.6	29.5	1.2	0.6	41.8	31.6	10.1	12.1	33.2	19.9	13.3	19.2
Std. Dev.	36.6	37.1	66.5	88.7	37.7	35.2	68.5	83.2	28.2	23.6	46.6	77.7
Skewnes	0.8	1.0	-0.1	0.0	0.3	0.8	-0.2	-0.3	0.5	1.4	-0.3	-0.5
Kurtosis	2.1	2.4	1.8	1.3	1.7	2.3	1.7	1.4	2.3	4.5	2.5	1.7
UK												
Mean	26.3	22.2	4.1	21.8	32.2	35.8	-3.6	-1.7	27.6	26.3	1.3	2.4
Std. Dev.	25.2	33.5	52.6	81.7	28.7	31.3	57.5	77.3	22.9	24.0	42.8	69.8
Skewnes	0.7	1.5	-0.7	-0.5	0.8	0.4	0.2	0.1	0.8	0.8	0.0	0.1
Kurtosis	2.4	3.6	2.5	1.6	2.5	1.8	1.7	1.3	2.6	2.6	2.2	1.6

Table 1b. Descriptive statistics I:1989 to IV:2008. Raw data

Note: Std. Dev. - Standard deviation.

		This co	untry's g	general s	ituation	regardi	ng cap i	ital expe	enditur	es		
	I	Present j	udgmen	t	Com	pared to last y		time		m now o tion by t next 6	he end	of the
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Austria												
Mean	24.5	14.6	10.0	21.5	30.1	23.4	6.7	14.6	21.9	17.4	4.5	19.6
Std. Dev.	26.3	21.2	41.4	81.0	25.0	25.2	46.4	79.3	16.5	20.1	32.2	76.8
Skewness	1.1	1.4	0.0	-0.3	0.8	0.9	-0.1	-0.3	0.3	1.3	-0.7	-0.5
Kurtosis	3.3	3.9	2.4	1.5	3.1	2.8	2.2	1.5	2.1	3.5	2.7	1.7
Belgium												
Mean	21.9	24.2	-2.3	-4.4	26.8	28.0	-1.2	4.5	25.3	18.3	7.0	19.′
Std. Dev.	24.5	24.5	44.5	82.7	24.3	27.7	48.2	79.1	21.7	22.2	39.3	78.4
Skewness	1.0	0.7	0.1	0.1	0.6	0.8	-0.2	-0.1	0.8	1.1	-0.2	-0.4
Kurtosis	2.8	2.2	2.0	1.4	2.1	2.3	1.9	1.4	2.8	3.1	2.3	1.:
Denmark												
Mean	25.9	23.4	2.5	5.3	22.9	16.2	6.7	19.9	26.2	13.6	12.6	25.4
Std. Dev.	28.5	26.1	49.1	84.8	20.0	20.2	34.7	79.3	25.5	18.1	37.3	80.:
Skewness	1.1	0.9	0.1	-0.1	0.6	1.0	-0.2	-0.3	1.3	1.3	0.3	-0.:
Kurtosis	3.3	2.5	2.3	1.4	2.7	3.1	2.4	1.6	5.5	4.0	3.3	1.
Finland												
Mean	23.2	30.1	-6.9	-0.1	34.5	30.6	3.9	11.0	32.1	19.3	12.8	25.0
Std. Dev.	24.1	35.2	54.2	85.5	28.1	32.1	57.2	79.9	24.8	22.7	44.1	77.
Skewness	0.8	1.0	-0.4	0.0	0.4	0.8	-0.3	-0.2	0.6	1.1	-0.3	-0.0
Kurtosis	2.6	2.6	2.1	1.3	2.2	2.5	1.9	1.4	3.0	3.3	2.3	1.3
France												
Mean	15.1	37.3	-22.2	-37.5	22.2	28.7	-6.4	-2.8	30.1	12.5	17.5	35.
Std. Dev.	22.9	30.4	48.9	78.9	22.9	28.6	47.7	80.4	20.6	13.9	31.6	67.0
Skewness	1.5	0.4	0.4	0.9	1.1	0.8	0.0	0.1	0.6	1.4	-0.2	-0.
Kurtosis	4.0	2.0	2.3	2.1	3.3	2.2	2.0	1.4	2.8	4.7	2.6	2.
Germany												
Mean	25.7	35.9	-10.2	-15.3	37.8	29.0	8.8	15.5	39.0	16.4	22.6	37.2
Std. Dev.	32.1	33.3	60.8	85.3	30.1	31.3	58.8	78.4	22.9	18.3	39.1	63.9
Skewness	1.0	0.4	0.3	0.3	0.3	0.9	-0.3	-0.4	0.0	1.2	-0.5	-0.3
Kurtosis	2.6	1.6	1.7	1.3	1.7	2.4	1.8	1.4	1.8	3.6	2.2	2.2
Greece												
Mean	13.0	34.8	-21.8	-25.9	19.9	17.9	2.0	2.4	30.8	7.8	23.0	48.0
Std. Dev.	17.8	33.3	46.3	81.7	22.0	22.1	37.0	77.7	24.3	13.0	32.0	65.0
Skewness	1.1	0.6	-0.1	0.5	0.8	1.1	0.0	0.0	0.9	1.9	0.1	-1.
Kurtosis	2.9	2.0	1.8	1.6	2.4	3.1	2.2	1.5	3.7	6.3	3.2	2.

Table 2a. Descriptive statistics I:1989 to IV:2008. Raw data

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Note: Std. Dev. - Standard deviation.

		This c	country's	general	situati	on rega	rding caj	pital exp	enditur	es		
	-	Present	judgmer	nt	Coi	*	to same year	time		tion by	on: expe the end months	
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Ireland												
Mean	42.0	13.8	28.2	41.7	36.8	19.5	17.3	35.3	28.0	13.3	14.8	42.2
Std. Dev.	30.5	18.8	43.7	74.2	26.8	26.3	47.8	73.6	20.3	19.8	34.7	73.1
Skewnes	0.0	1.4	-0.5	-0.9	0.3	1.4	-0.6	-0.7	0.6	1.7	-0.7	-0.8
Kurtosis	1.7	4.5	2.4	2.4	2.0	3.9	2.6	2.1	3.0	5.6	3.5	2.3
Italy												
Mean	8.2	40.2	-32.0	-48.4	24.4	31.2	-6.7	-7.2	28.9	14.2	14.6	29.7
Std. Dev.	12.1	28.7	38.0	69.9	22.4	26.9	46.0	72.1	18.8	14.4	30.3	65.1
Skewnes	1.8	0.3	0.2	1.2	0.8	0.7	-0.1	0.0	0.4	1.2	-0.2	-0.6
Kurtosis	5.5	2.0	2.1	2.9	2.8	2.3	2.1	1.5	2.7	4.2	2.6	2.1
NL												
Mean	30.2	23.3	6.9	19.1	30.4	28.3	2.1	6.8	29.4	20.5	8.9	19.4
Std. Dev.	28.3	29.4	53.8	90.2	28.7	28.8	53.6	81.1	24.6	22.6	43.0	76.9
Skewnes	0.5	0.8	-0.3	-0.4	0.8	0.7	-0.1	-0.2	0.8	1.0	-0.1	-0.4
Kurtosis	1.8	2.0	1.7	1.3	2.5	2.3	1.9	1.3	2.8	2.8	2.2	1.6
Portugal												
Mean	12.0	34.3	-22.3	-32.8	18.5	31.1	-12.6	-10.7	25.9	9.6	16.3	32.4
Std. Dev.	21.6	31.9	47.6	85.9	17.2	27.5	40.8	75.5	24.8	14.1	32.4	73.0
Skewnes	1.9	0.2	0.4	0.7	0.7	0.6	-0.2	0.2	1.0	1.3	0.4	-0.6
Kurtosis	5.6	1.5	2.1	1.7	2.7	2.2	2.1	1.6	4.1	3.6	3.1	2.1
Spain												
Mean	20.5	29.4	-8.8	-3.3	24.1	32.0	-7.9	-5.0	18.8	20.2	-1.5	-2.8
Std. Dev.	22.5	32.5	49.8	79.4	23.9	30.2	50.4	76.9	18.1	19.2	33.1	70.2
Skewnes	1.3	1.1	-0.4	0.0	1.0	0.7	-0.1	0.1	1.4	1.5	-0.1	0.0
Kurtosis	4.2	2.9	2.3	1.4	3.0	2.3	2.0	1.5	4.8	5.5	3.4	1.7
Sweden												
Mean	26.0	31.8	-5.9	0.5	28.1	34.5	-6.4	-6.0	26.0	24.7	1.3	5.0
Std. Dev.	25.8	34.9	57.0	85.6	27.6	31.6	54.9	78.8	23.0	25.6	43.2	75.5
Skewnes	0.6	0.9	-0.3	0.0	0.8	0.7	-0.1	0.1	0.9	1.0	-0.2	-0.1
Kurtosis	1.9	2.4	1.8	1.3	2.8	2.2	2.0	1.4	3.5	3.1	2.5	1.5
UK												
Mean	12.4	38.1	-25.7	-29.0	23.0	32.5	-9.5	-8.1	24.8	25.2	-0.4	2.3
Std. Dev.	13.3	31.6	41.6	70.0	21.7	28.7	47.4	75.6	22.3	22.7	40.7	70.8
Skewnes	1.3	0.7	-0.4	0.6	0.9	0.7	-0.1	0.1	1.2	0.8	0.1	0.0
Kurtosis	4.7	2.3	2.2	2.0	3.1	2.5	2.0	1.4	3.8	2.5	2.4	1.5

Table 2b. Descriptive statistics I:1989 to IV:2008. Raw data

Note: Std. Dev. - Standard deviation.

		This co	ountry's	general	situatio	n regar	ding pri	vate con	sumptio	on		
	Ι	Present	judgmer	nt	Con		to same year	time		ion by t	on: expe the end months	
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Austria												
Mean	27.8	13.2	14.6	20.2	33.5	21.5	12.1	16.0	26.5	16.6	9.9	24.5
Std. Dev.	29.7	17.2	41.6	78.1	28.6	22.4	47.1	77.8	19.3	17.2	32.7	74.4
Skewness	1.0	1.3	0.3	-0.3	0.7	0.8	0.1	-0.2	0.4	0.7	-0.2	-0.5
Kurtosis	2.6	3.6	2.2	1.5	2.5	2.6	2.0	1.5	2.7	2.1	2.1	1.9
Belgium												
Mean	24.8	26.4	-1.6	-2.2	26.0	25.6	0.3	1.5	27.3	14.8	12.5	29.1
Std. Dev.	26.0	27.7	48.9	83.2	23.6	24.5	44.9	77.4	20.7	18.2	34.3	72.1
Skewness	0.9	0.9	0.0	0.0	0.8	0.8	0.0	0.1	0.7	1.6	-0.3	-0.5
Kurtosis	2.6	2.7	2.1	1.3	2.8	2.8	2.1	1.4	2.5	5.6	2.6	1.8
Denmark												
Mean	31.8	21.0	10.8	6.2	37.6	17.0	20.6	35.1	28.4	17.6	10.7	22.7
Std. Dev.	35.6	25.2	55.3	86.9	28.5	23.3	46.3	75.4	24.9	22.5	41.6	79.1
Skewness	0.8	1.1	0.1	-0.2	0.4	1.4	-0.4	-0.7	0.7	1.4	-0.3	-0.5
Kurtosis	2.2	3.3	2.0	1.3	2.2	4.0	2.4	1.9	2.7	4.7	2.8	1.7
Finland												
Mean	47.9	21.5	26.4	38.7	39.3	24.0	15.3	30.0	30.6	20.4	10.2	25.8
Std. Dev.	37.1	36.1	68.2	89.5	30.8	33.3	59.1	77.2	26.8	27.3	48.9	79.9
Skewness	-0.2	1.3	-0.8	-0.9	0.4	1.4	-0.6	-0.7	0.8	1.2	-0.3	-0.5
Kurtosis	1.4	3.1	2.1	1.8	2.1	3.5	2.5	1.9	2.7	3.3	2.3	1.7
France												
Mean	24.5	32.8	-8.3	-10.8	27.3	31.0	-3.7	-1.3	30.9	14.3	16.6	36.2
Std. Dev.	26.0	30.3	53.1	82.5	22.9	26.1	46.3	71.5	18.9	16.0	31.4	61.1
Skewness	0.7	0.6	0.0	0.2	0.9	0.6	0.0	0.0	0.4	1.4	-0.5	-0.7
Kurtosis	2.3	2.1	1.8	1.4	3.2	2.2	2.1	1.5	2.2	4.4	2.8	2.3
Germany												
Mean	14.0	46.7	-32.8	-45.1	27.5	27.8	-0.4	0.1	39.4	15.0	24.3	44.9
Std. Dev.	24.0	32.6	52.1	72.6	23.9	25.2	45.7	68.4	20.0	17.8	35.5	59.8
Skewness	2.3	-0.1	0.9	1.1	0.9	1.0	-0.1	0.0	-0.2	1.5	-0.9	-1.0
Kurtosis	7.4	1.5	2.9	2.6	2.9	3.0	2.3	1.7	1.9	4.3	2.9	2.7
Greece												
Mean	11.3	39.2	-27.9	-32.6	10.0	30.5	-20.5	-42.1	14.1	16.0	-1.9	-7.9
Std. Dev.	14.3	35.2	45.6	74.3	16.6	26.4	35.5	62.5	19.9	17.5	30.2	70.1
Skewness	0.9	0.7	-0.3	0.6	2.7	1.3	-0.1	0.8	2.3	1.1	0.7	0.2
Kurtosis Note: Std. Dev	2.7	2.7	2.1	1.9	12.9	6.6	5.3	2.7	9.9	4.3	5.2	1.9

 Table 3a. Descriptive statistics I:1989 to IV:2008. Raw data

Note: Std. Dev. - Standard deviation.

		This cou	ntry's g	eneral s	ituatio	n regard	ling pri	vate con	sumptio	on		
	Р	resent jı	ıdgmen	t	Con		to same year	time	situat		on: expe the end months	
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Ireland												
Mean	49.7	8.1	41.7	59.0	45.8	17.9	27.9	43.0	33.7	13.3	20.4	49.6
Std. Dev.	36.8	18.7	49.5	72.7	30.7	26.3	52.8	73.3	19.4	19.2	34.3	64.0
Skewness	0.0	2.6	-0.6	-1.4	0.2	1.6	-0.6	-0.9	0.5	1.7	-0.9	-1.0
Kurtosis	1.6	9.3	2.6	3.4	1.9	4.6	2.5	2.2	3.6	5.4	3.9	2.7
Italy												
Mean	9.6	41.4	-31.8	-58.5	23.5	33.7	-10.2	-10.9	30.2	14.4	15.8	30.2
Std. Dev.	19.2	29.0	42.6	62.0	20.9	26.7	44.0	68.7	19.5	14.4	31.2	63.9
Skewness	2.8	0.4	0.7	1.5	0.9	0.7	-0.1	0.2	0.3	1.2	-0.3	-0.7
Kurtosis	10.2	2.2	3.7	4.3	2.9	2.6	2.1	1.6	2.6	3.5	2.4	2.4
NL												
Mean	32.4	16.6	15.8	21.8	30.8	23.6	7.2	16.5	25.4	17.1	8.2	17.4
Std. Dev.	33.4	24.9	51.8	85.5	27.7	27.5	50.8	82.2	23.0	20.1	38.5	78.2
Skewness	0.6	1.5	-0.2	-0.4	0.7	1.0	-0.2	-0.3	0.9	1.1	0.0	-0.3
Kurtosis	1.9	4.1	2.1	1.5	2.4	2.9	2.0	1.4	2.9	3.2	2.1	1.:
Portugal												
Mean	15.3	35.5	-20.2	-23.7	15.4	34.2	-18.8	-20.2	17.7	19.2	-1.5	0.8
Std. Dev.	22.5	31.8	47.9	83.1	16.8	30.3	42.7	77.0	21.6	22.2	36.4	76.1
Skewness	1.9	0.4	0.3	0.5	1.3	0.6	-0.1	0.4	1.9	1.0	0.2	0.0
Kurtosis	6.3	2.1	2.3	1.5	4.8	2.2	2.2	1.7	8.2	2.8	3.6	1.6
Spain												
Mean	29.6	26.9	2.7	10.6	26.2	31.7	-5.5	-7.5	21.8	28.0	-6.1	-12.0
Std. Dev.	29.2	33.1	57.5	83.7	26.9	29.8	52.6	75.3	21.3	23.0	41.4	71.9
Skewness	0.7	1.0	-0.3	-0.3	0.9	0.8	0.0	0.1	1.0	0.6	0.3	0.4
Kurtosis	2.4	2.4	1.9	1.4	2.6	2.4	2.0	1.5	2.9	2.5	2.2	1.7
Sweden												
Mean	28.6	29.5	-0.9	6.8	36.5	25.6	10.9	16.0	27.9	19.0	8.8	20.5
Std. Dev.	32.2	35.8	62.5	90.7	31.5	30.5	57.6	82.0	22.5	21.4	39.2	71.8
Skewness	0.8	0.7	-0.1	-0.2	0.5	1.1	-0.3	-0.3	0.7	1.1	-0.3	-0.4
Kurtosis	2.4	1.9	1.7	1.2	1.9	3.1	2.0	1.4	2.9	3.7	2.7	1.9
UK												
Mean	30.3	22.0	8.2	16.0	31.4	30.5	0.9	6.0	25.6	29.1	-3.5	-5.2
Std. Dev.	27.3	28.2	50.5	84.1	24.0	26.1	47.0	68.6	22.0	23.0	41.7	68.
Skewness	0.4	1.5	-0.5	-0.4	0.9	0.5	0.1	0.1	1.1	0.4	0.4	0.4
Kurtosis	1.9	4.1	2.3	1.4	2.7	2.0	2.0	1.5	3.3	2.0	2.2	1.

Table 3b. Descriptive statistics I:1989 to IV:2008. Raw data

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Note: Std. Dev. - Standard deviation.

4. Empirical Results

The design of the forecast competition was based on all the information available for the first three questions of the WES: the country's general situation regarding overall economy, capital expenditures and private consumption. For each question we in turn used three different kind of expectations stated by the agents: their present judgement, their judgement compared to same time last year and their expectation by the end of the next six months. The dataset analysed includes therefore 36 indicators for each country: four indicators (R_t , F_t , B_t and WB_t) for each of the three different expectations (present judgement, compared to same time last year, expected situation by the end of the next six months) of each question. The forecast competition is undertaken for fourteen countries of the European Union: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands (NL), Portugal, Sweden and the United Kingdom (UK).

In order to evaluate the relative forecasting accuracy of the models, each model was estimated for all the indicators included up to 2007.IV and forecasts for 1 quarter ahead were computed. The model specifications are based on information up to 2007.IV and, thereafter, the models were re-estimated each quarter and the forecasts were computed with these estimation results. Given the availability of actual values p to 2008.IV, we were able to compute the forecast error for each indicator and method in a recursive way. In order to summarise this information, the Root Mean Square Error (RMSE) was computed. These values provide useful information for analysing the forecast accuracy of each method, and enabled us to rank the methods according to their values.

In Tables 4a, 4b, 5a, 5b, 6a and 6b we present the main results of the forecast competition for raw data, using the last eight quarters for comparing the forecasting accuracy of the different techniques (AR, ARIMA, SETAR and ANN models). Tables 1a and 1b show the results for the question about the country's general situation regarding overall the economy, Tables 2a and 2b show the results for the question about the country's general situation about the country's general situation regarding capital expenditures and Tables 3a and 3b show the results for the question about the country's general situation regarding private consumption.

With regard to the question about the country's general situation regarding overall the economy, ARIMA and ANN models outperformed the rest of the models in most cases. Nevertheless, the lowest RMSE for the present judgement was obtained with the SETAR model for Denmark (F_t). For the judgement compared to the same time last year and for the expectation by the end of the next six month the ARIMA model showed the lowest RMSE for Spain (R_t). AR models only outperformed the rest of the models in two cases out of 42.

As for the results of the forecast comparison regarding the question about the country's general situation with respect to capital expenditures, again ARIMA and ANN models outperformed the rest of the models in most cases. The lowest RMSE was also obtained with the SETAR model for Portugal (R_t) and Germany (F_t) for the present judgement and the judgement compared to the same time last year respectively. For the expectation by the end of the next six month the ARIMA model showed the lowest RMSE for Denmark (R_t) .

Finally, with regard to the question about the country's general situation regarding private consumption, ANN and ARIMA models outperformed the rest of the models in most cases. Again the lowest RMSE for the present judgement was obtained with the SETAR model for Finland (F_t) , with the ANN model for the judgement compared to the same time last year for Austria (F_t) an with the ARIMA model for the expectation by the end of the next six month for Spain (R_t) .

In spite of the fact that it is usually possible to find a situation in which one indicator proves to have better predicting power compared with another, we found that ARIMA and ANN models clearly outperformed SETAR and AR models in the 504 scenarios compared. These results differ from those obtained by Clar *et al.* (2007), who found that the univariate autoregressions were not outperformed by other methods for the Euro Area. Nevertheless, the lowest RMSE for the present judgement was obtained with the SETAR for all three questions (overall economy, capital expenditures and private consumption). The expectations regarding the present judgement also showed lower RMSE that the judgement compared to the same time last year and the expectation by the end of the next six months.

We also found that Business Surveys Indicators $(R_t, \text{ and } F_t)$ displayed better forecasts that the Balance (B_t) and the Weighted balance (WB_t) , which are calculated from Business Surveys Indicators. This result also differs from the evidence found for the Euro Area in Clar *et al.* (2007), who found that indirect methods performed best for the Euro Area.

	This country's general situation regarding overall economy											
]	Present	judgme	nt	Cor	*	to same year	time		m now tion by next 6		of the
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Austria												
AR	25.8	11.4	26.9	59.9	21.4	20.4	38.0	62.6	27.7	35.5	60.3	99.6
ARIMA	24.1	7.8	23.7	48.0	17.8	21.4	23.4	49.7	22.4	22.2	43.1	82.6
SETAR	41.5	9.6	33.5	49.8	45.4	19.3	43.7	78.0	25.0	39.5	79.0	115.6
ANN	19.8	6.3	23.1	42.5	17.6	20.4	26.5	45.0	12.0	22.7	32.1	63.9
Belgium												
AR	26.0	25.3	37.1	71.0	21.2	36.1	55.8	70.6	29.6	42.2	71.4	108.2
ARIMA	18.9	21.0	31.1	64.9	16.0	21.4	35.0	64.0	7.6	26.4	36.4	46.6
SETAR	58.6	43.3	48.5	186.6	44.2	18.8	63.5	111.0	15.0	24.3	30.7	83.7
ANN	19.5	21.0	28.7	41.0	15.8	20.7	32.4	58.9	7.8	34.7	33.4	46.7
Denmark												
AR	29.7	2.7	28.9	32.1	28.4	32.0	61.4	95.5	17.5	26.8	41.8	123.6
ARIMA	25.0	2.0	23.9	41.0	17.5	16.4	29.0	58.1	8.0	16.1	23.5	54.8
SETAR	42.2	0.7*	46.2	37.6	56.4	38.9	41.7	105.5	29.5	17.1	45.5	135.0
ANN	26.2	2.0	28.4	33.8	15.1	21.8	28.5	39.3	21.2	15.5	32.9	50.4
Finland												
AR	13.7	12.4	13.9	23.8	27.4	21.3	46.5	72.2	28.7	33.1	59.7	105.3
ARIMA	16.9	1.2	13.7	3.3	25.8	14.4	30.3	43.9	8.3	17.5	19.4	43.8
SETAR	25.8	1.1	24.3	6.1	36.3	15.5	49.5	75.8	32.8	17.8	33.1	80.5
ANN	19.7	3.6	16.4	14.2	19.8	13.3	28.0	35.7	15.0	20.1	28.9	46.0
France												
AR	23.9	17.2	36.7	115.0	30.2	32.1	46.7	70.0	30.3	26.8	55.9	112.2
ARIMA	17.7	20.4	35.2	101.6	29.3	21.8	44.4	69.5	20.5	19.5	30.6	60.5
SETAR	21.2	19.8	31.8	162.0	43.9	10.7	56.7	74.8	33.8	23.7	61.2	119.8
ANN	9.2	17.4	27.5	90.2	16.0	21.3	41.3	49.1	20.2	15.6	39.9	68.3
Germany												
AR	38.1	27.6	53.2	89.4	22.2	19.5	35.6	69.2	37.5	31.2	62.2	91.3
ARIMA	15.2	7.9	16.4	33.0	11.8	10.7	15.3	26.7	16.7	18.1	27.0	47.8
SETAR	33.4	10.3	36.6	44.0	36.3	11.9	44.2	48.1	26.4	23.3	49.8	94.4
ANN	19.7	5.9	20.7	35.1	13.8	11.3	22.4	33.2	14.3	18.0	25.8	54.8
Greece												
AR	11.5	6.9	16.2	43.2	26.4	32.4	53.2	89.1	25.2	31.5	50.0	93.2
ARIMA	10.8	7.7	13.7	44.2	13.1	17.4	25.0	48.7	16.9	23.2	26.2	91.2
SETAR	17.4	14.7	22.7	138.9	28.0	39.3	53.1	106.9	22.5	32.5	32.6	138.6
ANN	24.8	7.8	13.1	72.2	23.6	18.5	31.1	56.3	20.9	40.1	36.1	156.3

Table 4a. RMSE – Recursive forecasts from I:2007 to IV:2008. Raw data

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Italics: best model for each country

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* Best model - Matrix singular or not positive definite

	This country's general situation regarding overall economy												
]	Present	judgmei	nt	Cor	npared t last	to same year	time		tion by	on: expe the end months		
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	
Ireland													
AR	47.3	27.2	68.1	79.0	35.1	44.4	72.3	107.2	30.7	49.3	74.8	122.7	
ARIMA	29.8	18.5	42.5	64.6	23.8	20.4	30.6	58.4	10.5	22.4	27.7	78.3	
SETAR	50.7	15.1	59.4	88.2	41.5	20.5	46.3	140.7	23.2	50.0	25.6	125.4	
ANN	24.9	22.5	47.5	74.8	27.1	31.8	22.7	55.6	27.2	47.5	32.3	125.9	
Italy													
AR	9.5	32.0	32.2	43.1	15.2	29.0	42.8	67.1	23.3	23.3	45.6	96.3	
ARIMA	5.8	15.8	19.2	50.4	12.5	18.3	26.8	32.7	13.4	15.7	26.6	69.4	
SETAR	16.5	32.9	36.1	62.3	40.2	35.2	59.0	79.0	41.6	25.2	45.6	78.2	
ANN	8.0	18.8	24.0	45.0	13.9	18.2	32.4	40.8	12.5	16.0	26.1	54.1	
NL													
AR	18.5	8.1	22.1	27.4	18.2	25.8	43.8	55.6	33.3	42.4	66.9	98.4	
ARIMA	17.9	5.1	20.0	35.0	14.7	20.1	26.4	38.6	19.1	18.8	27.7	47.5	
SETAR	63.2	6.0	43.5	44.2	45.1	17.5	75.8	76.7	48.6	24.8	79.1	89.4	
ANN	19.8	4.4	20.8	39.9	15.6	18.4	29.5	30.3	7.7	32.9	22.9	33.3	
Portugal													
AR	3.4	21.0	23.6	28.4	27.6	20.4	44.9	76.2	25.0	20.6	39.9	65.5	
ARIMA	5.7	20.3	23.1	22.0	13.0	16.7	29.1	45.4	17.0	21.8	33.6	67.6	
SETAR	12.2	32.4	32.7	31.7	33.9	16.1	58.0	145.5	50.5	27.4	57.9	84.1	
ANN	9.8	17.8	23.5	12.7	30.1	16.7	33.5	43.8	23.5	21.5	29.1	100.0	
Spain													
AR	32.0	32.9	73.1	99.7	22.3	53.4	78.9	101.8	15.9	43.3	57.9	70.4	
ARIMA	14.1	17.5	23.2	48.8	4.2*	22.1	28.1	43.1	3.0*	25.4	22.6	35.0	
SETAR	32.9	38.7	47.0	89.7	23.1	35.5	70.1	74.6	13.2	44.5	28.3	28.4	
ANN	11.5	21.5	26.7	46.7	6.8	27.8	29.7	44.4	11.1	33.4	41.7	44.7	
Sweden													
AR	19.1	9.4	37.8	29.1	30.4	33.5	61.4	72.0	31.7	32.0	62.0	117.3	
ARIMA	16.0	7.7	23.4	32.2	15.9	20.1	29.2	48.2	9.6	22.2	27.3	65.9	
SETAR	79.9	11.6	41.7	111.9	55.5	17.6	72.9	87.1	24.1	26.8	55.0	109.4	
ANN	14.7	9.6	18.8	30.6	20.1	13.4	27.6	48.2	13.0	19.5	29.0	86.7	
UK													
AR	23.2	28.1	49.7	96.8	26.4	35.1	49.4	55.7	20.4	35.9	56.5	84.9	
ARIMA	19.7	23.2	31.8	92.8	11.0	19.5	23.3	30.8	6.1	18.2	21.9	48.5	
SETAR	35.3	31.2	43.1	107.6	30.7	19.8	44.1	82.8	16.8	24.7	32.7	70.5	
ANN	19.4	24.0	33.7	85.6	10.4	20.9	26.7	39.1	10.4	15.1	36.4	38.1	

Table 4b. RMSE – Recursive forecasts from I:2007 to IV:2008. Raw data

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 Italics: best model for each country

 * Best model

 - Matrix singular or not positive definite

	This country's general situation regarding capital expenditures											
	Ι	Present j	udgmer	nt	Cor	npared t last	to same year	time		tion by	on: expe the end months	
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Austria												
AR	24.9	8.5	27.2	67.3	23.7	13.2	30.7	67.1	19.0	35.6	52.7	97.0
ARIMA	20.6	5.6	22.3	58.0	14.9	13.0	20.7	41.0	13.5	26.7	33.0	89.2
SETAR	44.4	8.3	33.4	78.8	70.3	18.4	34.3	120.1	20.0	23.5	40.8	126.2
ANN	21.9	6.0	23.9	64.1	17.7	13.1	25.6	44.1	15.2	26.4	38.0	120.1
Belgium												
AR	19.2	17.8	33.3	60.9	20.6	32.4	50.5	84.1	22.5	40.6	63.1	100.4
ARIMA	25.4	15.6	31.1	51.2	21.9	21.2	36.7	61.6	14.3	28.9	32.8	65.8
SETAR	38.6	21.3	54.9	88.2	36.8	15.3	57.5	105.1	24.4	45.6	53.0	102.7
ANN	24.8	17.6	32.7	43.6	17.7	18.2	33.0	58.4	14.5	26.7	33.9	59.5
Denmark												
AR	50.8	7.2	42.3	62.6	9.7	31.5	31.6	57.5	18.7	29.8	43.6	127.7
ARIMA	31.0	6.7	34.5	72.2	12.1	28.7	23.9	35.5	6.4*	20.1	25.2	74.5
SETAR	63.0	5.3	54.1	77.8	33.6	32.0	27.5	120.1	21.2	22.2	39.4	129.4
ANN	33.3	5.6	20.9	68.2	11.3	26.6	27.8	70.6	16.2	21.0	21.8	68.0
Finland												
AR	28.3	20.7	26.1	56.9	16.1	17.0	34.0	51.5	18.9	34.0	49.3	87.0
ARIMA	20.6	3.3	21.6	14.0	19.6	16.2	31.9	56.8	9.3	25.1	31.6	52.4
SETAR	32.4	9.3	28.7	16.9	30.5	15.3	51.7	102.1	29.0	21.5	52.0	57.2
ANN	21.3	4.6	23.4	29.9	16.9	14.3	27.6	48.1	13.2	23.0	30.7	48.0
France												
AR	9.1	19.5	25.0	71.6	19.9	24.8	39.2	65.2	23.7	23.0	44.5	102.8
ARIMA	9.5	23.5	33.7	67.4	21.9	24.4	42.8	98.1	14.4	16.7	21.4	63.2
SETAR	9.7	20.1	34.1	66.7	36.2	27.8	44.6	93.4	30.0	19.3	45.0	117.2
ANN	8.4	21.1	27.4	48.5	21.7	24.0	40.9	57.8	14.3	14.8	23.6	63.0
Germany												
AR	23.5	25.4	42.7	81.2	21.2	17.3	35.5	52.3	34.3	30.8	63.4	102.7
ARIMA	9.7	10.3	17.5	41.5	10.7	9.7	18.5	37.8	9.5	19.2	26.2	42.8
SETAR	51.4	11.5	34.8	72.4	29.4	6.9	46.4	67.5	24.0	20.9	42.5	84.8
ANN	14.6	8.4	57.6	42.1	14.0	11.8	19.6	32.2	12.4	24.4	49.9	50.8
Greece												
AR	12.9	11.9	23.0	100.3	12.4	26.2	31.1	66.7	16.6	36.3	33.2	99.8
ARIMA	13.1	9.9	20.3	85.3	10.3	11.2	21.1	47.1	13.2	15.3	23.9	68.5
SETAR	20.8	32.0	40.5	156.7	34.3	13.2	44.9	63.2	42.8	16.0	50.7	98.2
ANN	11.1	7.6	13.5	66.6	11.0	16.0	24.6	66.6	19.7	24.7	23.8	115.4

Table 5a. RMSE – Recursive forecasts from I:2007 to IV:2008. Raw data

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Italics: best model for each country * Best model - Matrix singular or not positive definite

	This country's general situation regarding capital expenditures											
]	Present	judgmei	nt	Cor	1	to same year	time		m now o tion by next 6		of the
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Ireland												
AR	39.0	24.4	54.8	82.0	24.3	37.4	56.4	91.0	28.0	41.8	63.6	126.7
ARIMA	30.6	22.1	39.4	68.6	9.0	25.3	31.5	72.6	9.2	27.4	34.9	86.5
SETAR	47.3	30.2	51.6	101.4	57.9	33.9	45.5	135.0	18.2	38.1	49.7	115.1
ANN	37.8	22.6	51.1	61.8	25.2	34.4	56.5	93.9	19.8	34.1	46.2	108.7
Italy												
AR	5.3	22.7	28.8	32.8	17.2	31.0	47.8	68.9	19.7	22.3	43.3	96.9
ARIMA	4.8	14.6	18.6	34.1	12.1	14.5	20.4	36.0	10.1	15.6	26.9	51.7
SETAR	15.2	15.7	19.8	38.0	26.9	17.8	37.0	86.4	25.8	25.7	40.5	81.0
ANN	8.4	14.0	19.3	49.6	17.4	14.1	21.0	51.6	11.7	15.8	23.2	98.3
NL												
AR	19.3	3.6	16.2	39.2	21.8	22.5	38.9	53.8	26.4	40.4	64.4	98.9
ARIMA	15.8	8.5	18.3	21.3	14.7	19.2	23.7	45.3	12.4	19.2	27.4	42.9
SETAR	27.4	9.0	32.2	67.6	27.6	39.9	56.0	71.1	28.5	37.7	38.6	66.9
ANN	15.8	3.7	17.2	57.6	13.1	19.0	24.2	40.4	10.0	17.3	26.8	32.1
Portugal												
AR	3.7	17.4	15.2	19.3	16.5	15.1	28.9	60.0	17.3	13.0	24.7	43.8
ARIMA	3.4	22.3	20.5	9.7	12.7	17.6	20.8	38.2	14.9	13.0	24.1	42.5
SETAR	3.2*	39.9	32.5	210.6	22.4	22.9	55.4	84.0	45.7	15.1	50.1	48.1
ANN	3.4	17.3	15.9	11.4	9.9	14.4	20.2	69.6	10.9	12.3	15.6	53.9
Spain												
AR	22.5	25.0	52.1	62.3	20.6	43.1	63.1	93.8	17.2	35.5	52.1	95.9
ARIMA	11.0	14.0	17.5	48.9	8.6	16.9	25.1	53.0	7.1	16.6	11.0	25.8
SETAR	25.9	25.7	47.2	115.4	32.8	21.1	46.3	150.9	16.7	12.2	21.0	54.3
ANN	8.5	15.8	21.3	44.9	9.4	19.1	26.9	53.4	10.0	26.5	24.2	41.0
Sweden												
AR	11.6	10.5	20.7	55.6	17.1	28.9	43.7	69.0	25.0	33.0	55.7	104.0
ARIMA	16.5	14.5	27.2	46.1	15.1	15.4	23.3	52.8	13.7	21.6	30.6	82.2
SETAR	35.8	13.3	34.3	70.1	36.5	20.1	50.9	78.6	20.4	22.5	25.3	126.3
ANN	16.8	10.9	26.2	44.7	13.9	17.4	25.1	46.4	12.0	21.6	32.6	62.3
UK												
AR	15.3	25.8	34.5	90.8	20.8	36.2	51.6	55.1	18.6	35.5	53.8	95.8
ARIMA	15.1	22.3	26.7	78.7	16.0	18.8	23.9	56.2	7.5	20.2	23.5	63.4
SETAR	24.6	37.0	52.0	148.9	25.6	23.3	35.3	78.1	32.5	13.2	25.1	131.3
ANN	16.5	20.3	28.4	59.3	11.5	17.8	24.8	54.6	9.1	15.7	30.6	76.4

Table 5b. RMSE – Recursive forecasts from I:2007 to IV:2008. Raw da	Table 5b. RMSE	– Recursive	forecasts from	I:2007 to	IV:2008.	Raw data
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Italics: best model for each country * Best model - Matrix singular or not positive definite

		This co	ountry's	general	situati	on regard	ding pr i	ivate con	sumpti	on		
]	Present	judgme	nt	Co	mpared t last	o same year	time		tion by	on: expe the end months	
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t
Austria												
AR	19.8	22.7	44.7	95.3	18.4	13.5	25.8	45.7	17.9	16.2	27.7	73.7
ARIMA	16.6	11.5	23.5	46.5	16.5	8.3	22.8	42.2	17.2	10.5	28.8	58.0
SETAR	34.6	8.4	39.0	93.0	48.5	7.6	52.4	70.6	29.1	27.6	39.7	88.8
ANN	19.9	12.4	25.7	58.4	17.8	5.9*	25.4	37.5	16.4	10.0	21.4	58.2
Belgium												
AR	25.0	13.9	31.8	67.5	19.7	33.4	52.6	82.9	19.9	41.1	60.0	96.9
ARIMA	23.1	9.9	32.8	52.2	16.8	15.2	34.1	64.2	9.2	26.0	28.8	37.4
SETAR	56.4	10.0	51.4	119.3	50.8	27.3	57.8	110.4	21.7	22.7	39.7	91.4
ANN	20.9	11.1	24.2	39.5	14.4	26.1	37.8	48.0	11.8	26.3	45.0	51.4
Denmark												
AR	36.7	6.7	53.6	61.8	26.0	41.8	62.8	113.1	19.6	31.2	44.0	100.3
ARIMA	24.8	11.1	30.4	56.6	16.6	22.2	34.8	67.5	11.7	23.1	28.8	51.4
SETAR	51.7	10.0	45.1	76.0	38.9	28.1	54.9	113.4	20.2	28.8	39.4	105.3
ANN	21.1	6.9	23.0	41.2	16.5	23.6	41.9	50.5	14.2	21.5	32.2	83.1
Finland												
AR	21.9	11.4	20.3	8.3	20.3	18.7	37.2	74.7	14.4	30.6	44.0	82.4
ARIMA	16.7	2.1	18.3	3.5	12.6	14.0	20.9	53.0	10.1	15.6	24.6	51.5
SETAR	27.0	0.9*	27.6	5.2	34.8	20.3	51.7	89.2	19.5	19.2	53.9	104.0
ANN	19.3	3.4	16.6	7.8	17.5	13.9	32.9	55.1	10.8	12.6	23.9	48.7
France												
AR	24.2	21.3	48.2	74.6	23.4	31.9	46.5	66.6	25.2	29.4	51.9	102.3
ARIMA	18.5	16.3	32.7	38.5	13.7	20.0	26.4	49.5	19.4	19.1	31.2	71.6
SETAR	36.3	15.1	40.2	78.8	29.3	19.3	44.6	77.8	47.2	16.4	43.9	107.5
ANN	17.3	9.9	22.3	43.1	12.8	18.6	26.8	48.5	21.6	17.6	43.5	71.9
Germany												
AR	3.4	22.8	29.9	40.0	10.7	9.2	18.9	27.4	18.0	33.3	47.1	78.8
ARIMA	6.6	8.5	9.4	26.2	13.9	8.1	16.4	22.3	14.9	16.8	30.3	46.6
SETAR	11.8	14.7	26.7	78.9	39.4	11.2	40.9	47.5	29.6	78.6	77.7	130.7
ANN	6.5	13.1	9.4	30.8	11.0	10.1	19.7	23.2	15.7	15.7	29.5	46.7
Greece												
AR	11.6	11.8	24.0	62.4	6.0	24.1	25.9	48.7	11.9	31.9	45.7	103.1
ARIMA	12.0	12.6	21.0	61.6	6.2	19.6	18.3	45.3	7.6	21.0	23.7	57.1
SETAR	12.4	17.0	37.2	98.9	-	120.3	56.8	111.3	37.9	30.7	48.7	132.6
ANN	14.8	10.8	23.5	53.4	6.1	15.3	16.9	35.8	7.5	25.5	30.3	67.1

Table 6a. RMSE – Recursive forecasts from I:2007 to IV:2008. Raw data

 Italics: best model for each country

 * Best model

 - Matrix singular or not positive definite

	This country's general situation regarding private consumption												
	Present judgment				Compared to same time last year				From now on: expected situation by the end of the next 6 months				
	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	R_t	F_t	B_t	WB_t	
Ireland													
AR	40.9	32.5	72.4	87.3	29.7	48.5	69.4	98.6	27.4	44.5	71.1	136.5	
ARIMA	32.7	24.2	45.8	69.8	18.0	23.2	35.9	62.5	11.7	22.6	31.5	46.2	
SETAR	57.8	19.8	62.6	92.4	48.4	34.9	79.1	100.1	32.0	18.1	70.3	80.6	
ANN	26.3	17.4	42.2	52.8	22.6	38.2	51.5	69.6	12.8	38.5	45.7	67.8	
Italy													
AR	9.2	22.7	24.9	36.7	12.8	28.2	36.7	47.9	21.3	23.6	43.1	92.7	
ARIMA	8.7	14.5	17.5	34.6	11.5	17.2	22.7	18.2	12.6	17.7	25.8	61.9	
SETAR	13.4	26.6	34.0	41.8	25.2	20.5	39.1	56.4	25.0	39.1	48.3	96.9	
ANN	6.6	18.8	22.1	25.6	13.6	18.6	30.0	40.4	11.9	16.0	25.3	59.1	
NL													
AR	35.3	8.0	73.3	71.9	19.2	24.7	37.1	57.5	27.3	35.5	60.7	86.0	
ARIMA	19.9	8.8	23.2	38.7	29.3	19.6	31.5	53.2	14.1	16.8	32.2	50.5	
SETAR	31.7	85.6	33.3	115.2	81.5	47.8	67.0	118.2	43.9	19.4	43.6	92.1	
ANN	16.8	10.7	20.5	53.1	26.4	18.2	28.6	37.7	8.0	18.5	22.9	43.5	
Portugal													
AR	5.1	28.6	29.5	43.6	7.1	25.8	32.9	50.9	13.3	20.1	28.5	69.7	
ARIMA	4.9	14.2	15.0	12.6	7.4	20.4	29.8	40.7	14.1	21.1	24.3	68.8	
SETAR	7.3	21.9	21.2	32.5	24.7	24.8	35.2	96.3	47.6	29.7	34.1	144.8	
ANN	6.0	16.3	13.6	13.6	7.3	21.8	29.6	39.3	9.4	21.9	22.8	45.6	
Spain													
AR	32.7	35.7	68.6	95.2	21.9	48.9	70.3	88.0	12.7	41.1	50.4	53.2	
ARIMA	11.0	18.3	25.1	53.2	7.7	14.9	18.4	21.6	4.7*	15.1	17.6	28.6	
SETAR	27.3	25.5	51.6	111.9	21.3	37.6	22.1	21.2	10.4	14.8	18.9	45.7	
ANN	10.0	18.1	24.2	46.7	15.6	18.1	23.0	38.2	8.8	30.0	43.6	95.6	
Sweden													
AR	21.7	6.1	44.8	26.7	33.0	37.9	69.0	92.0	21.3	34.6	55.3	95.5	
ARIMA	16.8	8.3	23.1	25.7	22.3	21.7	31.5	60.3	16.7	23.7	32.7	64.1	
SETAR	35.9	19.3	43.7	75.1	39.5	20.0	53.1	155.0	32.0	30.0	45.6	99.6	
ANN	21.2	8.3	19.5	25.5	20.1	17.2	32.6	58.1	15.3	24.6	30.1	51.7	
UK													
AR	20.9	21.4	40.1	83.2	18.0	38.1	51.8	64.5	14.4	35.2	50.9	68.0	
ARIMA	16.5	23.3	33.4	99.6	7.4	26.5	27.5	56.8	8.4	15.9	19.6	35.4	
SETAR	30.2	22.7	53.5	107.9	14.9	28.9	63.3	84.6	24.7	22.7	34.7	42.7	
ANN	15.1	20.7	29.5	86.3	7.3	27.7	25.2	57.1	8.7	16.2	24.4	41.0	

Table 6b. RMSE – Recursive forecasts from I:2007 to IV:2008. Raw data

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Italics: best model for each country

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* Best model - Matrix singular or not positive definite

6. Conclusions and discussion

The objective of this paper was to compare different forecasting methods for the short run forecasting of Business Survey Indicators. We compared the forecasting accuracy of Artificial Neural Networks (ANN) vs. three different time series models: autoregressions (AR), autoregressive integrated moving average (ARIMA) and selfexciting threshold autoregressions (SETAR). We considered all the indicators of the question related to a country's general situation regarding overall economy, capital expenditures and private consumption (present judgement, compared to same time last year, from now on - expected situation by the end of the next six months) of the World Economic Survey (WES) carried out by the Ifo Institute for Economic Research. The forecast competition was undertaken for fourteen countries of the European Union for the period ranging from 1989 to 2008, using the last eight quarters for comparing the forecasting accuracy of the different techniques.

We found that both ANN and ARIMA models outperformed SETAR and AR models. These results suggest that more complex methods like neural networks can attain a higher forecasting accuracy than time series models as they are far better able to handle non-linear behaviour. Interestingly, for all the questions analysed, our results showed that the expectations regarding the present judgement showed lower RMSE that the judgement compared to the same time last year and the expectation by the end of the next six months. Business Surveys Indicators displayed better forecasts that aggregated indicators calculated form Business Surveys Indicators. Finally, enlarging the observed time series of Business Survey Indicators and extending the analysis to the rest of the questions of the World Economic Survey would be of up most importance in order to assess the implications of the current situation and its use as input in quantitative forecast models.

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