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European economic sentiment indicator: An empirical reappraisal

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Abstract

In the last five decades the European Economic Sentiment Indicator (ESI) has positioned itself as a high-quality leading indicator of overall economic activity. Relying on data from five distinct business and consumer survey sectors (industry, retail trade, services, construction and the consumer sector), ESI is conceptualized as a weighted average of the chosen 15 response balances. However, the official methodology of calculating ESI is quite flawed because of the arbitrarily chosen balance response weights. This paper proposes two alternative methods for obtaining novel weights aimed at enhancing ESI's forecasting power. Specifically, the weights are determined by minimizing the root mean square error in simple GDP forecasting regression equations; and by maximizing the correlation coefficient between ESI and GDP growth for various lead lengths (up to 12 months). Both employed methods seem to considerably increase ESI's forecasting accuracy in 26 individual European Union countries. The obtained results are quite robust across specifications.

Key words
Business and Consumer Surveys, Economic Sentiment Indicator, Nonlinear Optimization with Constraints, Leading Indicator

JEL classification
C53, C61, E32, E37

Abstract

In the last five decades the European Economic Sentiment Indicator (ESI) has positioned itself as a high-quality leading indicator of overall economic activity. Relying on data from five distinct business and consumer survey sectors (industry, retail trade, services, construction and the consumer sector), ESI is conceptualized as a weighted average of the chosen 15 response balances. However, the official methodology of calculating ESI is quite flawed because of the arbitrarily chosen balance response weights. This paper proposes two alternative methods for obtaining novel weights aimed at enhancing ESI's forecasting power. Specifically, the weights are determined by minimizing the root mean square error in simple GDP forecasting regression equations; and by maximizing the correlation coefficient between ESI and GDP growth for various lead lengths (up to 12 months). Both employed methods seem to considerably increase ESI's forecasting accuracy in 26 individual European Union countries. The obtained results are quite robust across specifications.

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1 Introduction

Business and Consumer Surveys (BCS) are a unique way of extracting empirical data on managers' and consumers' views on relevant variables from their economic environment. In 2011 the BCS have celebrated their 50$^{\text{th}}$ jubilee in the EU (European Commission, 2014). Accordingly, over the last decades they have become an integral part of macroeconomic modelling. They are widely employed in empirical studies of two main sorts. Their first role is to serve as a data source for quantifying the prevailing business climate in particular branches of the national economy (Gayer, 2005) or to get estimates for non-measurable factors such as expectations or perceptions (see e.g. Antonides, 2008). On the other hand, BCS are also utilized to construct composite leading indicators. An efficient leading indicator would be a variable capable of predicting the targeted macroeconomic series several months/quarters in advance. This is precisely the segment of BCS research that this paper aims to tackle.

Namely, since the sole beginning of conducting the Joint Harmonised EU Programme of Business and Consumer Surveys in 1961, the methodology of constructing official European composite indicators has not altered much. This paper concentrates specifically on the European Sentiment Indicator (ESI). In calculating ESI, the European Commission (EC) employs data gathered from five distinct BCS sectors: the industrial sector, retail trade, services, consumer sector and the construction sector. In order to obtain

ESI, the EC weights individual sector data according to their relative share in the national economy. However, the chosen weights are not continuously altered to reflect the underlying changes in the economic system (due to e.g. the recent crisis, some other extreme event or simply due to long-term structural economic shifts). Consequentially, the predictive accuracy of ESI has been brought into question recently (Gelper and Croux, 2010).

Therefore this paper analyzes the standard ESI components for 26 individual EU Member States (Luxembourg and Ireland are not considered because of data unavailability). Using nonlinear optimization with constraints a new weighting scheme is proposed for each of the observed countries. The novel weights are proposed using two separate methods. Firstly, GDP forecasting equations are estimated by OLS method using ESI as the predictor variable for various lead lengths (up to 12 months). The weights are then chosen by minimizing the root mean squared error from the estimated equations. For the purpose of a robustness check, the same empirical exercise is then repeated by maximizing the correlation coefficient between ESI and GDP growth rates for up to 12 months of lead lengths. Both employed estimation methods significantly enhance ESI's forecasting accuracy, in some cases by as much as 50%.

The paper is organized as follows. Section 2 offers a brief review of the most prominent ESI empirical studies. Section 3 explains the employed methodological framework, while section 4 presents the obtained results. The concluding section offers clear policy implications and recommendations for future work on the topic.

2 Literature review

The existing empirical studies of the economic sentiment mostly focus on ESI's predictive characteristics with regards to targeted macroeconomic variables. For example, one of the most influential studies of that sort is made by Gayer (2005). The author estimates several bivariate vector autoregression (VAR) models on aggregate euro area data. Each of the models comprises GDP growth and one of the BCS sectoral leading indicators (in retail trade, industry, consumer sector, construction and services) or the EC's composite indicators (ESI and the Business Climate Indicator). Standard Granger causality tests point to accentuated predictive characteristics of BCS indicators. However, VAR-based out-of-sample GDP forecasts reveal a much more informative view of the issue. The obtained results firmly suggest that BCS indicators can be used as merely short-term predictors of GDP (one or two quarters in advance). Out of the observed indicators, ESI provides the largest added value in comparison to a benchmark AR(1) GDP model.

A similar study is done by Van Aarle and Kappler (2012). They also focus on the interrelationship between ESI and overall macroeconomic performance,

but they expand the euro area analysis by also modeling US data. Conventional tools within the VAR methodology (impulse response functions and variance decompositions) suggest that ESI shocks indeed positively feed into euro area retail trade and industrial production, while its relationship with unemployment is negative. A comparable case is also shown for the US data. The only exception is that the European ESI is much more short-term than the US indicator (three monthly lags vs. six lags in the US case).
It is worthwhile mentioning two papers which specifically compare BCS leading indicators' quality in Old (OMS) and New EU member states (NMS). The first one is done by Silgoner (2007). She firstly examines the predictive content of ESI, its industrial subcomponent (industrial confidence indicator) and the BCS question focusing on industrial production expectations with regards to EU industrial production. It is found that all three measures Granger-cause the industrial production. However, other obtained results seem quite contradictory: ESI is found to be a lagging (not a leading) indicator, while its forecasting performance is easily beaten by a simple autoregressive model. Out of the three competing measures, the production expectations balance of responses seems to be the best industrial production predictor. Silgoner (2007) then moves to the estimation of two separate panel regressions for the OMS and NMS. It is found that all three measures of economic sentiment have considerably lower forecasting qualities in NMS then in OMS.
One of the most comprehensive existing studies of European BCS is written by Sorić, Škrabić and Čižmešija (2013). The authors utilize five bivariate panel VAR models for the OMS and NMS separately, each of them comprising the BCS confidence indicator and its sector-related macroeconomic variable. The examined variables are retail trade volume, construction volume, personal consumption, industrial production (paired with their respective BCS confidence indicators) and GDP (paired with ESI). On the basis of standard Granger causality tests and innovation analysis it is confirmed that the predictive characteristics of NMS' BCS indicators (including ESI) are of comparable quality to the same indicators in OMS. To be more specific, all BCS variables Granger-cause their respective macroeconomic tendencies with a lagging time of 4 quarters. The same conclusion is corroborated both for the OMS and NMS. Although the authors utilize these results to state that the European BCS can be called a success story at their 50$^{\text{th}}$ jubilee, this does not mean that the predictive accuracy of BCS indicators cannot be improved.

This paper builds upon the study of Gelper and Croux (2010), who (to the best of the authors' knowledge), are the only ones to provide an alternative weighting scheme for the European ESI. Namely, Gelper and Croux (2010) apply the partial least squares method and dynamic factor modelling to construct a novel ESI indicator. They conduct the analysis on BCS data from 15 EU OMS. Using correlation analysis with respect to the industrial production series, the authors prove that the partial least squares estimator outperforms both the official European ESI and the dynamic factor estimator. However, in terms of out-of-sample forecasting accuracy, the results are not that robust. It is found that (in the vast majority of the observed countries), the two proposed estimators do not offer any significant added value in comparison to the official ESI. It is nevertheless worthwhile noticing that the forecasting accuracy of the two novel estimators enhances as the forecast horizon increases.

Summarising the conclusions drawn from the cited references, several points need to be emphasized. Firstly, it is obvious that the issue of alternating the ESI weighting scheme deserves more attention since the existing literature is mostly silent on the topic. This paper aims to provide new insights by applying nonlinear mathematical programming with constraints, a methodology insofar neglected in related studies.
Secondly, the existing European ESI studies either aggregate the data in a panel framework (Silgoner, 2007; or Sorić, Škrabić and Čižmešija, 2013), or restrict the analysis to OMS (Gelper and Croux, 2010). This study improves ESI's predictive characteristics for as much as 26 individual EU Member States. That way a more in-depth and wide-ranging study is offered.
Thirdly, this paper offers a detailed sensitivity analysis of the "optimal" ESI weights with respect to changing forecast horizons (up to 12 months). That way it is shown which of the BCS sectors contribute significantly to efficient GDP predictions for shorter, and which for longer forecast horizons. Conclusions can also be drawn about the quality of BCS in each of the 5 sectors examined in constructing the European ESI. Also important, potential differences will also be examined between the OMS and NMS.
Lastly, all previous ESI studies analyze quarterly data (which does not provide adequate data frequency to timely and accurately assess tipping points in the national economy) or employ industrial production as a proxy variable for total economic activity. Silgoner (2007, p.203) even admits that the industrial production accounts for only 25 percent of the EU GDP, but still uses it as a GDP proxy because of its monthly frequency. This paper circumvents the proxy/frequency issue by estimating monthly GDP values for each EU Member State using the widely known Chow and Lin (1971) temporal decomposition technique.

3 Methodological issues

The empirical approach followed in this paper consists of several steps. In order to propose a new ESI weighting scheme for 26 individual EU Member State, the 15 ESI subcomponents are analyzed. The goal of this study is to find weights which will maximize the forecasting quality of ESI with respect to year-on-year GDP growth rates.

Since the GDP figures are published only at the quarterly level, the Chow and Lin (1971) procedure is utilized to estimate monthly GDP series for each of the EU economies. The technical details of the Chow and Lin (1971) temporal decomposition procedure are given in section 3.1.

3.1 Estimating monthly GDP

The issue of estimating high-frequency GDP data is quite present in the literature for some time now. For example, Proietti (2006, p.357) states that a vast number of developed western countries continuously employ temporal disaggregation for obtaining flash estimates of their monthly national economic accounts. In that context the Chow and Lin (1971) procedure is found to be the most efficient and most widely used. Some of its recent empirical applications include Abeysinghe and Lee (1998), Abeysinghe and Rajaguru (2004) or Doran and Fingleton (2013).
Some basic properties of the Chow and Lin (1971) procedure are given as follows.
The method is used to decompose a low frequency time series (y_l) to a high frequency one (y_h). It is assumed that the variable of interest (y_h) is modelled using a linear regression with p independent variables.

$$\mathbf{y_h} = \mathbf{X}\beta + \mathbf{u}, \tag{1}$$

where $\mathbf{y_h}$ is a $3n \times 1$ vector, $\mathbf{X}$ is a $3n \times p$ matrix of regressors and $\mathbf{u}$ is a random vector with mean 0 and a covariance matrix $\mathbf{\Sigma}$. Equation (1) is valid for $3n$ months (n quarters). Applying the Generalized Least Squares Regression (GLS), an estimate of β is found:

$$\hat{\beta} = [\mathbf{X^T C^T}(\mathbf{C \Sigma C^T}]^{-\mathbf{1}}\mathbf{X^T C^T}(\mathbf{C \Sigma C^T})^{-\mathbf{1}}\mathbf{y_l}, \tag{2}$$

where $\mathbf{C}$ is a $n \times 3n$ matrix used to convert n quarterly observations of y_l into $3n$ monthly observations of y_h:

$$\mathbf{C} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & & \cdots & 0 \\ 0 & 0 & 0 & 1 & 0 & & \cdots & 0 \\ & & & & \cdots & & & \\ & \cdots & & & & 1 & 0 & 0 \end{bmatrix}. \tag{3}$$

A crucial puzzle in the Chow and Lin (1971) procedure is the estimation of the covariance matrix $\mathbf{\Sigma}$. Namely, it is assumed that the monthly residuals from equation (1) follow an AR(1) process $u_t = \rho u_{t-1} + \epsilon_t$, where ϵ_t is $WN(0, \sigma_\epsilon)$ and $|\rho| < 1$.
It follows that $\mathbf{\Sigma}$ has the form:

$$\mathbf{\Sigma} = \frac{\sigma_\epsilon^{\mathbf{2}}}{\mathbf{1} - \rho^{\mathbf{2}}} \begin{bmatrix} 1 & \rho & \cdots & \rho^{n-1} \\ \rho & 1 & \cdots & \rho^{n-2} \\ \vdots & \vdots & \ddots & \vdots \\ \rho^{n-1} & \rho^{n-2} & \cdots & 1 \end{bmatrix}. \tag{4}$$

The algorithm for obtaining $\widehat{\mathbf{y_h}}$ is stepwise (Sax and Steiner, 2013). Firstly a preliminary quarterly series is calculated as $\mathbf{y_p} = \hat{\beta}\mathbf{X}$. The final estimate of $\widehat{\mathbf{y_h}}$ is obtained as the sum of the preliminary quarterly series and the distributed quarterly residuals:

$$\widehat{\mathbf{y_h}} = \mathbf{y_p} + \mathbf{D}\mathbf{u_l}, \tag{5}$$

where $\mathbf{u_l}$ is a $n \times 1$ vector of differences between the estimated quarterly values of y_p and the actual values of y_l. Likewise, $\mathbf{D}$ is a distribution matrix:

$$\mathbf{D} = \mathbf{\Sigma C^T (C \Sigma C^T)^{-1}}. \tag{6}$$

The regressors used for estimating monthly GDP here are retail trade volume and industrial production. [1]

3.2 ESI aggregation and data issues

ESI is the most comprehensive BCS composite indicator. It includes 15 individual response balances from five BCS sectors: industry, retail trade, construction, services and the consumer sector (see European Commission (2014) for a detailed presentation of the 15 chosen questions).
A preliminary version of ESI (z_t) is calculated as a weighted average of the standardized 15 subcomponents ($y_j, j = 1, ..., 15$):

$$z_t = \frac{\sum_{j=1}^{15} w_j \cdot y_{j,t}}{(\sum_{j=1}^{15} w_j)}, t = 1, 2, ..., n. \tag{7}$$

In doing so, the questions related to stock volume (Q4 in the industrial survey and Q2 in the retail trade survey), as well as the unemployment level question (Q7 in the consumer survey) are included in ESI calculation with an inverted sign.
The standardisation procedure is applied over a frozen period to avoid continuous monthly revisions of ESI. The frozen period is set by the EC, spanning from the starting date of conducting BCS in a particular country to the most recent month.
The weights applied in ESI calculation are set arbitrarily by the European Commission. They are conceptualized to represent the shares of each sector in the national economy. For EU countries the weights are given as follows: industry 0.4; services 0.3; consumers 0.2; construction 0.05 and retail trade 0.05 (European Commission, 2014).

[1] The obtained monthly GDP series are not graphically presented here for brevity purposes, but can easily be obtained from the authors.

The final estimate of ESI index is obtained by scaling z_t to have a long-term mean of 100 and a standard deviation of 10:

$$ESI_t = \frac{z_t - \bar{z}}{s_z} \cdot 10 + 100, t = 1, 2, ..., n, \tag{8}$$

where s_z is the standard deviation of z_t. The aim of this step is to facilitate the interpretation of the published ESI figures.

This study focuses on improving the forecasting quality of ESI for 26 individual EU countries. The only two Member States excluded from the analysis are Ireland and Luxembourg (because of data unavailability).

The estimation period used for each individual country depends on data availability. The end of the estimation period is 2014 M09 for each of the analyzed countries. The starting date is, however, quite diverse. The majority of countries (Austria, Belgium, Bulgaria, Czech Republic, Estonia, Greece, Hungary, Italy, Netherlands, Portugal, Romania, Slovakia Spain, and the UK) is analyzed from 2001 M01. Germany and France have the data from 1996 M01, while the Swedish time span starts in 1996 M08. The Latvian dataset starts from 2001 M05; Slovenia and Cyprus have the data from 2002 M05; while the estimation period for Finland, Poland, Lithuania, Croatia, Denmark and Malta (respectively) starts from May 1997, January 2003, January 2006, May 2008, May 2010 and May 2011.

The 15 ESI subcomponents are obtained from the European Commission, while the GDP data (as well as the retail trade and industrial production series) are gathered from Eurostat. The entire dataset is seasonally adjusted using Dainties, as suggested by the European Commission.

3.3 Nonlinear optimization with constraints

The ESI indicator is, in its essence, a simple weighted mean of standardized survey answers. The weights are arbitrarily chosen by the European Commission and have not experienced any major revision since its introduction. However, European Commission (2014) states that the weights are chosen according to the "representativeness" of the sector in question and its tracking performance vis-à-vis the reference variable. Since ESI reflects attitudes and expectations about the economy as a whole, the usual reference variable is GDP growth rate. This paper aims to explore possible areas of improvement in ESI's tracking performance.

3.3.1 Optimization problem

Tracking performance can be viewed from various aspects depending on its definition. The usual starting model is a simple regression equation with ESI as an independent variable and reference variable as the dependent variable (estimated for various ESI lead lengths).[2] Since ESI is a monthly indicator, its main purpose is to predict the behavior of the national economy prior to the publication of official data. Namely, GDP is published on quarterly basis and has revisions. ESI's leading indicator qualities can be best quantified through the number of months/quarters it precedes to GDP movements. Therefore various prognostic horizons h are considered here ($h \in \{0, 1, \ldots, 12\}$).

The optimization problem comes down to finding the optimal weights $\mathbf{w}' = (w_1, w_2, \cdots, w_{15})$ which minimize the root mean square error ($RMSE$) for the simple regression model $GDP_{t+h} = \alpha + \beta ESI_t + \varepsilon_t$. The problem can mathematically be formulated as follows:

$$\begin{aligned} &\min_{\mathbf{w},\alpha,\beta} \quad \sqrt{\tfrac{1}{T-h-2} \sum_{t=1}^{T-h} \left(GDP_{t+h} - \alpha - \beta ESI_t\left(\mathbf{w}\right)\right)^2} \\ &\text{subject to} \quad 0 \le w_1, w_2, \cdots, w_{15} \le 1 \\ &\qquad\qquad\quad \sum_{i=1}^{15} w_i = 1, \end{aligned} \tag{9}$$

where α and β are regression parameters and T is sample size.

As defined by the European Commission (2014), the weights are bounded by 0 and 1, and in sum give unity. The problem in equation (9) can be simplified by omitting the square root function and omitting multiplication with a scalar $\frac{1}{T-h-2}$. Also, transformations from $w_1 y_{1,t} + \cdots + w_{15} y_{15,t}$ to ESI do not influence the optimization procedure and ultimately yield the same solution. With that in mind, the problem in equation (9) is equivalent to the problem:

$$\begin{aligned} &\min_{\mathbf{w},\alpha,\beta} \quad \sum_{t=1}^{T-h} \left(GDP_{t+h} - \alpha - \beta\left(w_1 y_{1,t} - \cdots - w_{15} y_{15,t}\right)\right)^2 \\ &\text{subject to} \quad 0 \le w_1, w_2, \cdots, w_{15} \le 1 \\ &\qquad\qquad\quad \sum_{i=1}^{15} w_i = 1, \end{aligned} \tag{10}$$

where $y_{1,t}, y_{2,t}, \ldots, y_{15,t}$ are standardized survey answers as defined in Section 3.2. The optimization problem in equation (10) is simpler (has less functions) and is therefore expected to converge to the globally optimal

[2]This framework is the basis for Granger causality testing and VAR analysis, which are cornerstones of all milestone studies mentioned in the literature review.

solution. The problem consists of one equality constraint ($\sum_{i=1}^{15} w_i = 1$) and 15 bound constrains ($0 \leq w_1, w_2, \cdots, w_{15} \leq 1$). Parameters α and β are not bounded and the problem is nonlinear in parameters. Therefore a nonlinear optimization method should be used. Nevertheless, relation (10) can be viewed as a quadratic programming problem by substituting $b_i = \beta w_i$ and changing constraints on weights to $b_i \geq 0 \ \forall i = 1, \ldots, 15$ or $b_i \leq 0 \ \forall i = 1, \ldots, 15$ (parameters $b_1, \ldots, b_{15}$ have the same sign). Finally, the optimization problem becomes:

$$\begin{aligned} \min_{\mathbf{w},\alpha,\beta} \quad & \sum_{t=1}^{T-h} \left(GDP_{t+h} - \alpha - b_1 y_{1,t} - \cdots - b_{15} y_{15,t}\right)^2 \\ \text{subject to} \quad & \operatorname{sgn}(b_1) = \operatorname{sgn}(b_2) = \cdots = \operatorname{sgn}(b_{15}). \end{aligned} \tag{11}$$

The problem in (11) is a special case of a quadratic programming problem of the form $\min \mathbf{d'b} + \frac{1}{2}\mathbf{b'Db}$ with the constraints $\mathbf{A'b} \geq \mathbf{b_0}$. When matrix $\mathbf{D}$ is positive definite, the dual method of Goldfarb and Idnani (1982, 1983) can be employed to find the optimal parameters. The R package `quadprog` implements the algorithm and is used in estimating the unknown parameters.

ESI's tracking performance can also be assessed by Pearson's correlation coefficient between ESI and GDP growth rate for various lead lengths. For the purpose of robustness check of the results obtained from minimizing $RMSE$s, the problem of maximizing the correlation coefficient is also considered. The same constraints apply here as in problem (9). The problem can mathematically be formulated as follows:

$$\begin{aligned} \max_{\mathbf{w}} \quad & \frac{\sum_{t=1}^{T-h}\left(GDP_{t+h} - \overline{GDP}\right)\left(ESI_t - \overline{ESI}\right)}{\sqrt{\sum_{t=1}^{T-h}\left(GDP_{t+h} - \overline{GDP}\right)^2}\sqrt{\sum_{t=1}^{T-h}\left(ESI_t - \overline{ESI}\right)^2}} \\ \text{subject to} \quad & 0 \leq w_1, w_2, \cdots, w_{15} \leq 1 \text{ and } \sum_{i=1}^{15} w_i = 1. \end{aligned} \tag{12}$$

3.3.2 Assessing the quality of ESI indicator

One of the tasks of this study is to quantify the extent to which the official European ESI can be improved (in terms of forecasting accuracy) in individual EU Member States. In order to provide evidence on the topic, the distance between the optimal weights obtained here and the EC weights is calculated by two norms: the Euclidean and the maximum norm. The precise formulae are:

$$\left\|\mathbf{w} - \mathbf{w}^{EC}\right\|_2 = \sqrt{\sum_{i=1}^{15}\left(w_i - w_i^{EC}\right)^2} \tag{13}$$

$$\left\|\mathbf{w}-\mathbf{w}^{EC}\right\|_{\infty}=\max_{i=1,\cdots,15}\left|w_i-w_i^{EC}\right| \tag{14}$$

where $w^{EC\prime}=\left(\frac{0.4}{3},\frac{0.4}{3},\frac{0.4}{3},\frac{0.3}{3},\frac{0.3}{3},\frac{0.3}{3},\frac{0.2}{4},\frac{0.2}{4},\frac{0.2}{4},\frac{0.2}{4},\frac{0.05}{3},\frac{0.05}{3},\frac{0.05}{3},\frac{0.05}{2},\frac{0.05}{2}\right)$.

If the optimal weights differ only slightly in comparison to the official EC weights, the norm will be close to zero. On the other hand, the maximum value of both norms is close to unity ($\frac{2.95}{3}$).

4 Estimation results

The "optimal" weights obtained by minimizing $RMSE$ in GDP forecasting equations (for chosen forecasting horizons $h \in \{0,1,2,3,6,9,12\}$) are presented in Tables 1, 2 and 3.[3]

The empirical strategy followed in this paper allows different weights for each of the 15 analyzed BCS questions. Therefore the obtained results consist of a large-dimension dataset, summarized in Tables 1, 2 and 3 by summing up the calculated 15 weights in a sectoral fashion (e.g. the obtained weights for Q2, Q4 and Q5 from the industrial survey (see Appendix for details) are summed up to form an aggregate industrial sector weight, etc.).[4]

After carefully examining Tables 1, 2 and 3, several conclusions can be drawn. First, the highest weights are (on average) indeed attached to the industrial sector. Namely, the average calculated weights (for all examined countries and forecast horizons) are as follows: 0.310, 0.169, 0.296, 0.133 and 0.132 for the industrial sector, services, consumers, retail trade and construction (respectively). It instantly becomes evident that these results significantly deviate from the official ESI weighting scheme.

As far as the industrial sector is concerned, its hereby proposed weights should be put in reference to the Silgoner (2007, p.203) argument that the share of industrial production in the EU GDP is only 25%. Therefore one can conclude that the optimization procedure applied here produces less biased industrial sector weight and moves it closer to its "true" value. It is no surprise that the net results is an enhancement of ESI's forecasting accuracy with respect to GDP growth.

The official European ESI is calculated with a weight of as much as 0.30 attached to the services sector. Nevertheless, this analysis has shown that the importance and the predictive characteristics of the services sector is

[3]The remaining forecast horizons are left out here for brevity purposes.

[4]Country abbreviations used hereinafter are as follows: AT=Austria, BE=Belgium, BG=Bulgaria, CY=Cyprus, CZ=Czech Republic, DE=Germany, DK=Denmark, EE=Estonia, EL=Greece, ES=Spain, FI=Finland, FR=France, HU=Hungary, IT=Italy, LT=Lithuania, LV=Latvia, MT=Malta,NL=Netherlands, PL=Poland, PT=Portugal, RH=Croatia, RO=Romania, SE=Sweden, SI=Slovenia, SK=Slovakia, UK=United Kingdom.

Table 1: Optimization results - sum of sector weights (Part 1)

h		0	1	2	3	6	9	12
AT	INDU	0.312	0.406	0.422	0.441	0.335	0.024	0
	SERV	0.341	0.323	0.257	0.086	0.06	0.143	0.055
	CONS	0.265	0.17	0.159	0.212	0.314	0.527	0.749
	RETA	0	0.05	0.153	0.192	0.286	0.306	0.196
	CONSTR	0.082	0.052	0.147	0.205	0.117	0.151	0
BE	INDU	0.053	0.155	0.216	0.336	0.462	0.104	0
	SERV	0.526	0.449	0.378	0.253	0	0	0
	CONS	0.421	0.396	0.406	0.411	0.538	0.698	0.732
	RETA	0	0	0	0	0	0.198	0.268
	CONSTR	0	0	0	0	0	0	0
BG	INDU	0.138	0.076	0	0.038	0	0	0
	SERV	0.127	0.139	0.115	0.023	0.02	0.104	0.015
	CONS	0.734	0.653	0.603	0.543	0.471	0.504	0.647
	RETA	0	0.132	0.282	0.373	0.468	0.392	0.337
	CONSTR	0	0.065	0.146	0.257	0.316	0.194	0.09
CY	INDU	0.278	0.245	0.207	0.12	0.012	0	0.137
	SERV	0.184	0.25	0.335	0.349	0.412	0.284	0.007
	CONS	0.061	0.047	0.116	0.174	0.249	0.297	0.357
	RETA	0.234	0.19	0.162	0.123	0.199	0.297	0.35
	CONSTR	0.477	0.459	0.303	0.291	0.128	0.121	0.149
CZ	INDU	0.45	0.535	0.557	0.552	0.57	0.606	0.34
	SERV	0.34	0.27	0.272	0.253	0.155	0	0.066
	CONS	0.135	0.161	0.171	0.195	0.276	0.394	0.594
	RETA	0.031	0	0	0	0	0	0
	CONSTR	0.044	0.035	0	0	0	0	0
DE	INDU	0.18	0.17	0.177	0.155	0	0	0
	SERV	0.772	0.825	0.823	0.845	1	1	0
	CONS	0.048	0	0	0	0	0	0.35
	RETA	0	0.005	0	0	0	0	0
	CONSTR	0	0	0	0	0	0	0.65
DK	INDU	0.168	0.078	0.105	0.094	0.163	0.249	0.266
	SERV	0.664	0.727	0.643	0.649	0.461	0.212	0.028
	CONS	0	0	0.065	0.042	0.211	0.371	0.208
	RETA	0	0	0	0.061	0.146	0.168	0.495
	CONSTR	0.168	0.194	0.187	0.153	0.165	0.103	0.139
EE	INDU	0.216	0.234	0.275	0.23	0.044	0	0
	SERV	0.213	0.303	0.321	0.361	0.474	0.482	0.437
	CONS	0.05	0.052	0.054	0.106	0.262	0.49	0.502
	RETA	0.161	0.168	0.142	0.155	0.201	0.028	0.06
	CONSTR	0.361	0.243	0.208	0.147	0.019	0	0

Table 2: Optimization results - sum of sector weights (Part 2)

EL	INDU	0.957	0.932	0.92	0.855	0.577	0.429	0.307
	SERV	0.043	0.03	0	0	0.015	0.054	0
	CONS	0	0	0	0	0.143	0.342	0.582
	RETA	0	0.038	0.08	0.145	0.265	0.175	0.111
	CONSTR	0	0	0	0.024	0.129	0	0
ES	INDU	0.987	0.929	0.889	0.727	0.414	0.176	0.105
	SERV	0	0	0	0	0	0	0
	CONS	0	0	0.032	0.103	0.295	0.276	0.147
	RETA	0.013	0.071	0.073	0.067	0.063	0.274	0.499
	CONSTR	0	0	0.007	0.103	0.231	0.409	0.621
FI	INDU	0.293	0.236	0.255	0.233	0.193	0.171	0.124
	SERV	0.17	0.101	0.11	0.066	0.084	0.002	0.018
	CONS	0.297	0.359	0.377	0.411	0.503	0.684	0.858
	RETA	0	0.019	0.009	0.025	0	0	0
	CONSTR	0.239	0.285	0.251	0.265	0.22	0.143	0
FR	INDU	0.621	0.535	0.586	0.558	0.536	0.218	0
	SERV	0.259	0.199	0.147	0.104	0	0	0
	CONS	0.12	0.204	0.267	0.259	0.437	0.548	0.643
	RETA	0	0.062	0	0.079	0.026	0.235	0.357
	CONSTR	0	0.062	0	0	0	0	0
HU	INDU	0.325	0.271	0.301	0.189	0.254	0.312	0.341
	SERV	0.137	0.306	0.149	0.327	0.311	0.276	0.091
	CONS	0.423	0.373	0.368	0.262	0.199	0.301	0.466
	RETA	0.03	0.039	0.045	0.121	0.06	0	0
	CONSTR	0.085	0.01	0.137	0.101	0.176	0.112	0.102
IT	INDU	0.89	0.67	0.826	0.569	0.394	0.207	0.106
	SERV	0.04	0.122	0.162	0.075	0.036	0.032	0
	CONS	0.027	0	0.011	0.081	0.21	0.421	0.51
	RETA	0.043	0.14	0	0.173	0.192	0.22	0.288
	CONSTR	0.043	0.069	0.001	0.14	0.167	0.12	0.096
LT	INDU	0.187	0.19	0.202	0.301	0.318	0.435	0.622
	SERV	0.52	0.557	0.468	0.366	0.22	0	0
	CONS	0.04	0.091	0.159	0.164	0.441	0.565	0.378
	RETA	0	0	0.006	0	0.021	0	0
	CONSTR	0.253	0.163	0.164	0.169	0	0	0
LV	INDU	0.215	0.4	0.566	0.724	0.651	0.448	0.354
	SERV	0.499	0.4	0.034	0.148	0	0	0
	CONS	0	0	0	0	0.153	0.285	0.332
	RETA	0.027	0.061	0.163	0.11	0.196	0.267	0.315
	CONSTR	0.259	0.139	0.237	0.018	0	0	0
MT	INDU	0.407	0.322	0.1	0.378	0	0.474	0.346
	SERV	0.053	0	0.128	0.002	0.206	0	0.355
	CONS	0.215	0.146	0.128	0	0.241	0.455	0
	RETA	0.257	0.299	0.486	0.238	0.479	0.071	0
	CONSTR	0.068	0.233	0.158	0.381	0.073	0	0.299

Table 3: Optimization results - sum of sector weights (Part 3)

NL	INDU	0.458	0.425	0.497	0.426	0.109	0	0
	SERV	0.325	0.403	0.206	0.292	0.38	0.162	0
	CONS	0.006	0.15	0.109	0.159	0.491	0.767	0.993
	RETA	0	0	0	0	0.021	0.071	0.007
	CONSTR	0.21	0.021	0.187	0.123	0	0	0
PL	INDU	0.453	0.495	0.518	0.442	0.504	0.671	0.708
	SERV	0.252	0.19	0.14	0.127	0	0	0
	CONS	0	0	0.042	0.031	0	0.211	0.292
	RETA	0.113	0.128	0.148	0.222	0.238	0.118	0
	CONSTR	0.182	0.186	0.153	0.177	0.259	0	0
PT	INDU	0.408	0.364	0.367	0.342	0.124	0	0
	SERV	0.231	0.13	0.038	0.039	0	0	0
	CONS	0.129	0.196	0.271	0.333	0.537	0.681	0.881
	RETA	0.231	0.311	0.272	0.252	0.292	0.249	0.119
	CONSTR	0	0	0.052	0.035	0.046	0.07	0
RH	INDU	0.219	0.379	0.611	0.242	0.727	0	0.242
	SERV	0.69	0.478	0.341	0.386	0	0	0
	CONS	0.021	0.044	0	0	0	0.214	0.089
	RETA	0.07	0.099	0.048	0.372	0.273	0	0.035
	CONSTR	0	0	0	0	0	0.786	0.633
RO	INDU	0.245	0.278	0.362	0.449	0.562	0.757	0.663
	SERV	0.188	0.144	0.077	0.076	0.081	0.005	0
	CONS	0.38	0.358	0.289	0.206	0.1	0.132	0.094
	RETA	0.179	0.219	0.272	0.269	0.257	0.106	0.242
	CONSTR	0.008	0	0	0	0.013	0	0
SE	INDU	0.538	0.422	0.413	0.314	0.153	0	0.257
	SERV	0.201	0.098	0.213	0.108	0	0	0
	CONS	0.023	0.036	0.066	0.05	0.337	0.558	0.31
	RETA	0.238	0.445	0.308	0.528	0.51	0.442	0
	CONSTR	0.238	0.445	0.308	0.475	0.481	0.442	0.433
SI	INDU	0.369	0.519	0.635	0.545	0.544	0.362	0.276
	SERV	0.275	0.275	0.119	0.089	0	0	0
	CONS	0.04	0.007	0.037	0.074	0.217	0.281	0.454
	RETA	0.136	0.054	0.086	0.132	0	0.054	0
	CONSTR	0.275	0.194	0.123	0.291	0.239	0.357	0.271
SK	INDU	0.302	0.335	0.186	0.239	0.368	0.436	0.315
	SERV	0.16	0.18	0.33	0.366	0.291	0.226	0.355
	CONS	0.202	0.157	0.329	0.308	0.297	0.338	0.329
	RETA	0.204	0.193	0.149	0.087	0.044	0	0
	CONSTR	0.132	0.135	0.006	0	0	0	0
UK	INDU	0.373	0.439	0.286	0.365	0.335	0.097	0
	SERV	0	0	0	0	0	0.099	0.217
	CONS	0	0.051	0.16	0.401	0.643	0.79	0.783
	RETA	0.051	0	0.199	0.083	0.022	0.014	0
	CONSTR	0.627	0.51	0.554	0.233	0.022	0.014	0

not that pronounced. To be more specific, its average proposed weight is roughly twice lower than the official one. This is one of the most striking study results. Namely, there is a consensus in the literature that the global economy has exhibited a long-term structural shift from a manufacturing economy to a service economy. For example, Dudzeviciute, Maciulis and Tvarnaviciene (2014, p. 359) provide evidence that, on the European level, the services sector share in the total value added has increased from 46.7% to as much as 70.8% since the 1970s.

Although the stated process of tertiarization is irrefutable, the results presented here clearly show that the services sector's forecasting power is rather weak. A few exceptions can also be found in that context. Table 1 reveals that the German and Danish ESI can be seriously improved by attaching exceptionally high weights to the services-related variables (the highest weight of as much as 1 is found for the German economy at $h = 6, 9$.

The consumer and retail trade sectors are intrinsically interdependent, so it is obvious that they exhibit similar properties here. Both mentioned sectors are attached considerably larger weights then in the official ESI calculation scheme. This comes as no surprise since e.g. the final consumption of households accounts for as much as 56.5% of the total EU GDP in 2011 (Gerstberger and Yaneva, 2013). Moreover, the strong relationship between personal consumption and GDP is well-established in the literature (Crossley, Low and O'Dea, 2013; Tapsin and Hepsag, 2014).

One particularly interesting feature of the consumer and retail trade sectors arises here. Namely, both sectors exhibit a growth in significance for larger forecast horizons. This is particularly emphasized for the consumer sector, making it clear that the information needed for long-term GDP forecasting lies in the hands of consumers. Short term GDP predictions are, on the other hand, to the greatest extent influenced by the industrial sector.

The construction sector weights are either negligibly small or equal to zero throughout the analyzed model specifications. One of the rare exceptions in that sense is Croatia, with a weight of as much as 0.786 for $h = 9$. Namely, Croatia is a quite atypical European economy, highly dependent on its construction sector. It is well documented in the literature that the entire Croatian economic expansion from 2000 to the global crisis in 2008 was founded on a real estate bubble. Once the bubble had burst, the Croatian economy started a free fall (see e.g. Tkalec and Vizek (2014) for a comprehensive study on the role of the real estate sector in the Croatian economy). The magnitude of this tendency is perhaps best described by the fact that negative GDP growth rates were recorded in Croatia for as much as 12 consecutive quarters, generating the worst economic trend in the history of post-World War II Europe.

The optimization problem in (12) is also considered here for the purpose of a robustness check. The analysis yields very similar results as the $RMSE$ minimization in Tables 1, 2 and 3; and is therefore left out here due to space limitations.

In order to quantify to which extent do these results differ from the official ESI figures, the obtained Euclidean and maximum norms are presented in Table 4. Also, an index of the obtained $RMSE$s is presented in the final column. An index value larger than 100 corresponds to an improvement of the newly proposed weighting scheme in comparison to the official EC weights.

Table 4: Comparison of ESI indicator quality

Country	Avg 2-norm	Country	Avg max-norm	Country	$\frac{RMSE_{EC}}{RMSE} \cdot 100$
HU	.353	HU	.209	FR	105.684
SK	.357	SK	.230	MT	107.775
RO	.390	CY	.232	RO	109.547
CY	.392	SI	.236	SK	109.691
SI	.393	DK	.266	NL	109.697
CZ	.410	LV	.275	SI	110.369
DK	.417	CZ	.279	AT	110.847
IT	.417	FI	.284	CY	111.633
LV	.427	IT	.285	PL	111.736
FI	.429	RO	.289	CZ	111.840
PT	.466	PT	.296	IT	112.770
AT	.468	MT	.316	HU	113.369
MT	.472	BE	.325	SE	115.503
ES	.484	AT	.337	EL	116.531
EL	.504	EE	.338	EE	117.166
LT	.504	LT	.357	PT	117.858
BE	.509	ES	.360	LT	119.307
EE	.510	BG	.387	LV	120.120
FR	.526	EL	.395	UK	120.867
UK	.549	UK	.406	ES	122.094
BG	.555	FR	.418	BE	123.945
PL	.582	SE	.447	FI	126.076
NL	.585	PL	.463	RH	126.423
SE	.591	NL	.494	DE	127.100
RH	.655	RH	.557	BG	128.539
DE	.770	DE	.715	DK	150.432
OMS	.516	OMS	.387	OMS	119.954
NMS	.462	NMS	.321	NMS	115.193

All three applied distance measures reveal similar tendencies. The last two rows of Table 4 are particularly interesting, showing that (on average) the hereby proposed weighting scheme offers slightly more added value in

OMS than in the NMS. What strikes as the most peculiar result is that Germany as one of the founding EU members exhibits one of the largest ESI improvement potentials (regardless of the applied distance measure). Namely, it is well founded in the literature that the German ESI performs rather badly in GDP forecasting. For example, Schröder and Hüfner (2002) compare the forecasting accuracy of German ESI to other composite indicators (IFO business expectations measure, the Purchasing Managers Index and the ZEW Indicator of Economic Sentiment). Their results reveal that, out of the analyzed indicators, ESI has the worst leading characteristics. Moreover, ESI is found to be not a leading, but a lagging indicator of total economic activity.[5]

The results presented in Table 4 can by no means be interpreted by stating that the sole methodological basis of administering the surveys (sample selection, non-response treatment, etc.) is better in NMS than in OMS. Table 4 merely reveals how much room for improvement does each particular Member State have in terms of ESI's predictive accuracy. One might even say that the BCS data from OMS have the potential to generate more accurate GDP predictions, while the same point is less valid for the NMS.

5 Conclusion

The process of euro integration and harmonization in the area of official statistics has offered several valuable advantages to both economic practitioners and researchers, as well as to economic decision-makers of any kind. BCS data are now fully harmonized in all EU Member States. This ensures the application of best international practice of conducting the BCS and enables a multi-country comparative analysis of BCS results.

However, by insisting on data comparability, the European Commission has also triggered some negative side effects of the integration process. Most importantly, the European ESI is calculated equally in all EU Member States, applying the exact same (arbitrarily chosen) sector weights. This inevitably leads to bad ESI's forecasting performance in at least some EU countries. The necessity of conceptualizing more accurate macroeconomic forecasting models has been emphasized through the recent global crisis in rather painful manner.

Therefore this paper applies nonlinear optimization techniques to propose a novel ESI weighting scheme for each of the 26 analyzed individual Member States. The weights are found by minimizing the $RMSE$s obtained from simple GDP forecasting equations including ESI as the predictor variable.

The obtained results have showed that ESI's forecasting accuracy can be significantly improved by attaching larger weights to the retail trade and

[5] See also Sabrowski (2008) for a rigorous proof that German consumers tend to produce heavily biased inflation estimates in the Joint Harmonized BCS.

consumer sector. Moreover, it is proven that the OMS are characterized by somewhat larger potential for improving ESI. Namely, several alternative distance measures have shown that the prediction improvement of the hereby proposed weighting scheme is larger for those countries then for the NMS. This can to some extent be explicated by the fact that the official ESI weights are obviously more in accordance with the structure of the NMS economies.
The obtained results are proven to be robust by also finding weights which maximize the correlation coefficient between GDP and ESI for various lead lengths.

If one should pinpoint clear policy implications from this study, they might be based on the following. Currently the ESI data are revised at the beginning of each calendar year through changing the frozen period employed in its calculation. This means that the past ESI figures are by no means comparable to the ones calculated on the basis of any of the formerly applied frozen periods. In other words, altering the weighting scheme at the same time would bring no additional cost to the European Commission. These yearly revisions of the applied weights could for example be based on the procedures applied here. This would significantly raise the forecasting accuracy of ESI in individual Member States and improve its leading indicator qualities.
This paper suggests merely two of the possible methodological paths to improving ESI's forecasting accuracy. Future research should certainly take into account the aggregation of individual country data to the EU or the euro area level; and focus on finding the weights which maximize ESI's predictive characteristics on the aggregate level. Additionally, it would be interesting to empirically test whether the diverging quality of individual country's ESI can be put in relation to the practice of conducting the surveys themselves. Namely, the European Commission does not publish data on e.g. exact response rates (but merely targeted response rates) or sampling errors for all countries and sectors.
Regardless of that, the calculation of European ESI and improving its predictive accuracy deserves more attention in future research.

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