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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 potentially 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 (EU) members, as well as on the aggregate EU level. The obtained results are robust across specifications, although the out-of-sample results are to some extent less firm than the in-sample ones.

Keywords Business and Consumer Surveys · Economic sentiment indicator · Nonlinear optimization with constraints · Leading Indicator

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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, BCS celebrated their 50th 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 of otherwise "intangible" factors such as expectations or perceptions (see, e.g., Antonides 2008). On the other hand, BCS are also utilized to construct composite leading indicators.

The role of leading indicators is especially accentuated in times of economic downfall (such as the recent global crisis). Namely, it is well established in the literature that standard macroeconomic forecasting models are of limited value due to the fact that they do not account for psychological factors such as the economic sentiment. The researchers are united in the conclusion that the intensity and longevity of this crisis was stirred up by the drastic downfall of economic sentiment (Kindleberger and Aliber 2011).[1]

An efficient leading indicator would be a variable capable of predicting the targeted macroeconomic series several months/quarters in advance. Even a slightly lagging indicator might be very useful for the economic policy holders because of the publication lags in the data release calendar. This can be easily verified on the example of the European economic sentiment indicator (ESI). Namely, ESI is regularly published in the last week of each month, whereas quarterly GDP figures are published with a considerable time lag. For example, the September 2014 ESI was published on September 29, while the corresponding 2014 Q3 GDP figures were published by Eurostat as late as December 5, 2014.

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. The European Commission (EC) indeed does have firm arguments in favour of methodological harmonization: it enables long time spans of data at the national level (which would be impossible in case of frequent methodological changes and structural breaks), as well as it ensures data comparability among the Member States.

In calculating ESI, the EC employs data gathered from five distinct BCS sectors: the industrial sector, retail trade, the services, consumer sector, and construction. 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 (e.g., due to 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). This obviously calls upon a reappraisal of ESI's methodological foundations, which is precisely the issue that this paper aims to tackle.

Therefore, this paper analyzes standard ESI components for 26 individual EU Member States (Luxembourg and Ireland are not considered because of data unavailability), as well as for the aggregate EU and Euro area (EA). 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

[1] The same argument has also been proven valid for other unanticipated and abrupt downfall episodes, such as the one of the US economy during the Persian Gulf War (Garner 1991).

by OLS method using ESI as the predictor variable for various lead lengths (up to 12 months).[2] 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 lead lengths. Both employed estimation methods significantly enhance ESI's forecasting accuracy, in some cases by as much as 35 %.

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 Sect. 4 presents the obtained results. The concluding section offers clear policy implications and recommendations for future work on the topic.

2 Literature review

Existing empirical studies on economic sentiment mostly focus on ESI's predictive characteristics with regard to targeted macroeconomic variables. As an example, consider one of the most influential studies of that sort. Gayer (2005) estimates several bivariate 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, the 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 (3 monthly lags vs. six lags in the US case).

It is worthwhile mentioning two papers that specifically compare BCS leading indicators' quality in Old (OMS) and New EU member states (NMS). The first is Silgoner (2007), who examines the predictive content of ESI, its industrial subcomponent (industrial confidence indicator), and the BCS question focusing on industrial production expectations with regard to EU industrial production. It is found that all three measures Granger-cause 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

[2] It should be noted here that actual macroeconomic tendencies might also heavily influence economic agents' sentiment. This leads to potential bi-directioanl causality between ESI and GDP, encouraging the researcher to model this kind of feedback relationship by vector autoregressive (VAR) models (Gayer 2005; Sorić et al. 2013). However, this paper is concerned exclusively with the forecasting performance of ESI.

for 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 et al. (2013). The authors utilize five bivariate panel VAR models for 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 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 for both OMS and NMS. Although the authors utilize these results to state that the European BCS can be called a success story at their 50th 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 an analysis of 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. Still, it is worth noting that the forecasting accuracy of the two novel estimators improves as the forecast horizon increases.

Summarising the conclusions drawn from the cited references, several points need to be emphasized. First, 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.

Second, the existing European ESI studies either aggregate the data in a panel framework (Silgoner 2007; or Sorić et al. 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, and for the EU and EA aggregates. Thus, a more in-depth and wide-ranging study is offered.

Third, this paper offers a detailed sensitivity analysis of the "optimal" ESI weights with respect to changing forecast horizons (up to 12 months). Accordingly, it is clearly 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. Further, potential differences will be examined between the OMS and NMS.[3]

[3] The OMS group comprises Belgium, France, Germany, Italy, Luxembourg, Netherlands, Denmark, Ireland, United Kingdom, Greece, Portugal, Spain, Austria, Finland, and Sweden (15 countries in total). The NMS group includes Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, Slovenia, Bulgaria, Romania, and Croatia (13 countries in total).

Last, 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. To propose a new ESI weighting scheme for 26 individual EU Members, 15 ESI subcomponents are analyzed. The goal of this study is to find weights that will maximize the forecasting quality of ESI with respect to year-on-year GDP growth rates.

The officially published ESI at the EU level is depicted (with respect to quarterly GDP year-on-year growth rates) on Fig. 1.

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 Sect. 3.1.

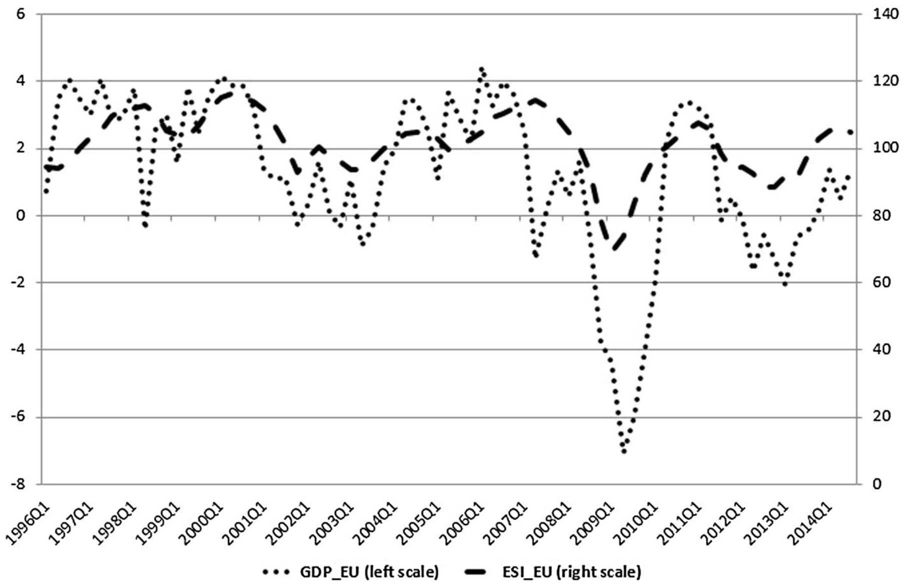

Fig. 1 ESI and GDP growth at the EU level

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), and 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 covariance matrix Σ. Equation (1) is valid for $3n$ months (n quarters). Applying the generalized least squares regression (GLS), an estimate of β is found:

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

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 Σ. Namely, it is assumed that the monthly residuals from Eq. (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 Σ has the form:

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

The algorithm for obtaining $\widehat{\mathbf{y_h}}$ is stepwise (Sax and Steiner 2013). First, a preliminary quarterly series is calculated as $\mathbf{y_p} = \hat{\beta}X$. 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:

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

Here, the regressors used for estimating monthly GDP are retail trade volume and industrial production.

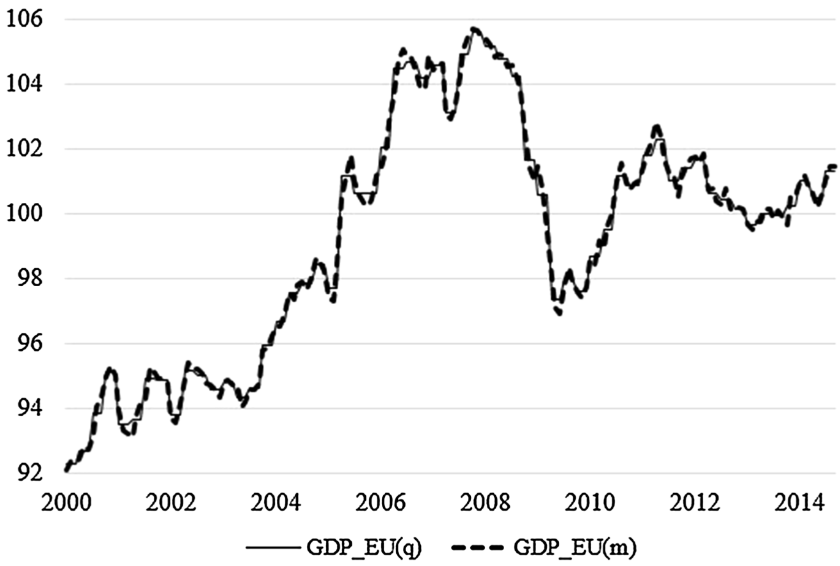

Fig. 2 Quarterly and monthly GDP (2010 = 100) indices at the EU level

The obtained monthly GDP at the EU level (together with its quarterly counterpart) is depicted on Fig. 2.[4]

3.2 ESI aggregation and data issues

ESI is the most comprehensive BCS composite indicator. It includes 15 individual response balances (x_j) 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).

The first step of calculating ESI at the national level is data standardization:

$$y_{j,t} = \frac{x_{j,t} - \bar{x}_j}{s_j}, \quad \forall j = 1, 2, \ldots, 15; \; t = 1, 2, \ldots, n, \tag{7}$$

$$\bar{x}_j = \frac{1}{T'} \sum_{t=1}^{T'} x_{j,t}; \quad s_j = \sqrt{\frac{1}{T' - 1} \sum_{t=1}^{T'} (x_{j,t} - \bar{x}_j)^2}. \tag{8}$$

The standardization procedure is applied over a frozen period (T') to avoid continuous monthly revisions of ESI. The frozen period is set by the EC for each country separately, spanning from the starting date of conducting BCS to the first month of the current year. To ensure the inclusion of the most recent data, the frozen period is updated each January. A preliminary version of ESI (z_t) is calculated as a weighted average of the standardized 15 subcomponents $(y_j, j = 1, \ldots, 15)$:

[4] The other 27 obtained monthly GDP series are not graphically presented here for brevity purposes, but can be easily obtained from the authors.

$$z_t = \frac{\sum_{j=1}^{15} w_j \cdot y_{j,t}}{\left(\sum_{j=1}^{15} w_j\right)}, \quad t = 1, 2, \ldots, n. \tag{9}$$

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 weights w_j 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. The weights are fixed (not time-varying) and exactly equal for each EU Member State, as follows: industry 0.4; services 0.3; consumers 0.2; construction 0.05, and retail trade 0.05 (European Commission 2014).

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:

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

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.

The final aim of BCS is to provide short-term indicators at the EU and EA level. Therefore the EU and EA aggregate ESI indices are obtained as a weighted average of the national ESI indicators. The weights are alternated on a yearly basis, depending on the share of each national economy in the total EU/EA industrial sector, services, consumer, retail and construction sector (respectively).[5] This study focuses on improving the forecasting quality of ESI for individual EU countries, as well as for the aggregate EU and EA level. The only two Member States excluded from the analysis are Ireland and Luxembourg (because of data unavailability).

The authors argue that (despite the advantages of BCS harmonization), there are negative side effects of the official ESI weights being fixed and exactly equal across Member States. This approach can potentially lead to sub-optimal forecasting quality of ESI because the shares of the respective BCS sectors in GDP are diverse and volatile. This can be best proven by Figs. 3 and 4. The authors use the share of industrial production in GDP of EU countries, and the shares of services in EU GDP through time, as illustrative examples of how much the sector shares in GDP are both significantly different among the EU countries, as well as they are extremely time-variable.

The respective shares of each particular sector in each country's GDP is shown in Tables 1, 2 and 3 (for 2005 and 2011). That way a wider perspective can be obtained on how much each of the analyzed sectors is volatile through time and different among the analyzed countries. The shares of services in GDP is obtained from the World Development Indicators database, while all the remaining sector shares are obtained from Eurostat. The estimation period used for each individual country depends on data availability. Explicit time spans for all analyzed countries are given in Table 6 in Appendix 1.

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 source of the entire dataset is seasonally adjusted using Dainties, as suggested by the European Commission.

[5] The utilized weights are published on the European Commission web pages.

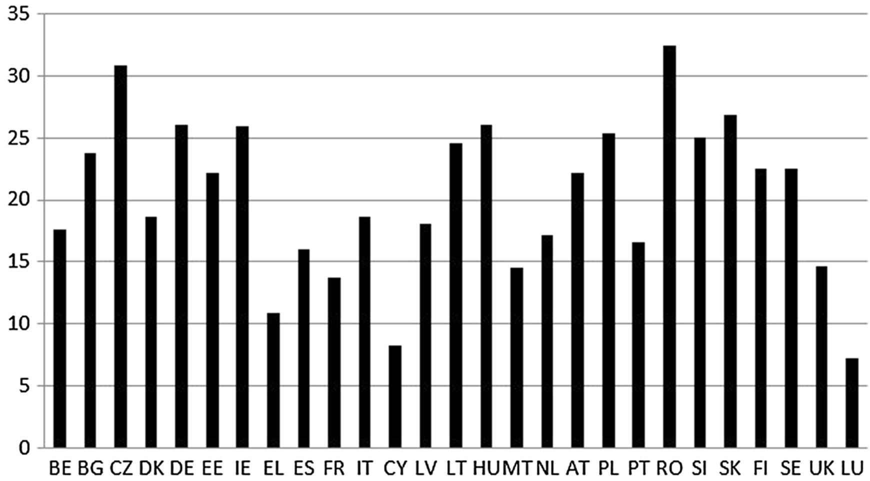

Fig. 3 The share of industrial production in GDP of EU Member States in 2011. *Note* Country abbreviations used hereinafter are as follows: AT = Austria, BE = Belgium, BG = Bulgaria, CY = Cyprus, CZ = Czech Republic, DE = Germany, DK = Denmark, EE = Estonia, EL = Greece, ES = Spain, FI = Finland, FR = France, HU = Hungary, IE=Ireland, IT = Italy, LT = Lithuania, LU=Luxembourg, LV = Latvia, MT = Malta,NL = Netherlands, PL = Poland, PT = Portugal, RH = Croatia, RO = Romania, SE = Sweden, SI = Slovenia, SK = Slovakia, UK = United Kingdom

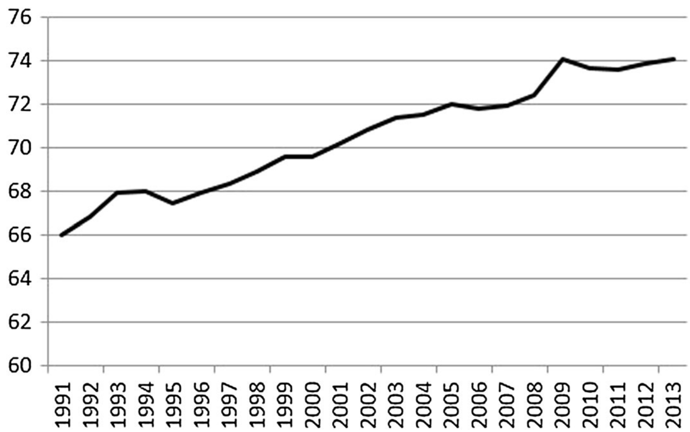

Fig. 4 The share of services in EU GDP

3.3 Quadratic 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, the 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

Table 1 Optimization results—optimal sector weights (part 1)

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights (2011)
AT	INDU	0.324	0.083	0.415	0.466	0.124	0	23.3	22.2
	SERV	0.516	0.674	0.393	0.272	0.126	0	68.2	69.8
	CONS	0.096	0.113	0.159	0.233	0.377	0.458	52.3	51.8
	RETA	0	0	0	0.03	0.373	0.542	12.6	13.1
	BUILD	0.064	0.13	0.032	0	0	0	7.0	6.4
BE	INDU	0	0	0	0	0	0	20.3	17.6
	SERV	0.465	0.481	0.481	0.458	0.073	0	73.9	75.9
	CONS	0.535	0.519	0.519	0.542	0.723	1	49.3	50.3
	RETA	0	0	0	0	0.204	0	13.4	12.7
	BUILD	0	0	0	0	0	0	4.9	5.7
BG	INDU	0.274	0.218	0.256	0.242	0	0	22.7	23.8
	SERV	0.081	0.101	0.076	0.088	0	0	62.5	64.6
	CONS	0.258	0.296	0.37	0.354	0.435	0.804	68.7	61.8
	RETA	0.283	0.315	0.258	0.316	0.565	0.196	12.2	11.9
	BUILD	0.104	0.069	0.04	0	0	0	6.1	6.2
CY	INDU	0	0	0.22	0.052	0	0	10.1	8.3
	SERV	0.509	0.594	0.473	0.585	0.315	0	77.7	78.3*
	CONS	0.079	0	0.001	0	0.123	0.144	60.6	65.0
	RETA	0.092	0	0	0.005	0.333	0.433	14.7	14.1
	BUILD	0.32	0.406	0.307	0.358	0.229	0.422	10.0	6.7
CZ	INDU	0.349	0.394	0.434	0.489	0.455	0	31.0	30.9
	SERV	0.338	0.334	0.351	0.34	0.172	0.353	59.5	60.6
	CONS	0.018	0.075	0.124	0.171	0.372	0.647	60.6	48.6
	RETA	0.165	0.13	0.079	0	0	0	11.3	10.3
	BUILD	0.129	0.067	0.013	0	0	0	6.7	6.2
DE	INDU	0.035	0.035	0.021	0	0	0.121	25.4	26.0
	SERV	0.965	0.965	0.979	1	1	0	70.0	68.7
	CONS	0	0	0	0	0	0.104	56.3	54.3
	RETA	0	0	0	0	0	0	10.5	10.1
	BUILD	0	0	0	0	0	0.774	3.9	4.4
DK	INDU	0.083	0.114	0.246	0	0	0	20.8	18.7
	SERV	0.795	0.708	0.693	0.854	0.577	0	72.4	75.1
	CONS	0	0	0	0	0.423	0.349	46.3	46.6
	RETA	0	0	0	0	0	0.651	11.9	12.4
	BUILD	0.122	0.178	0.061	0.146	0	0	5.4	4.7
EE	INDU	0	0	0.044	0.095	0.211	0	21.2	22.2
	SERV	0.032	0.159	0.268	0.36	0.706	1	66.7	66.7
	CONS	0	0	0.029	0.057	0.083	0	53.7	49.1
	RETA	0.447	0.43	0.331	0.245	0	0	14.4	12.1
	BUILD	0.521	0.41	0.328	0.243	0	0	8.6	7.0

Table 1 continued

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights (2011)
EL	INDU	0.675	0.746	0.787	0.823	0.723	0.807	13.2	10.9
	SERV	0.325	0.254	0.213	0.177	0	0	75.9	82.2
	CONS	0	0	0	0	0	0.193	66.1	67.7
	RETA	0	0	0	0	0.277	0	13.1	12.2
	BUILD	0.001	0	0	0	0	0	6.1	3.4
ES	INDU	0.638	0.696	0.748	0.779	0.587	0.03	16.9	16.0
	SERV	0.018	0.034	0.016	0	0	0	66.5	72.6
	CONS	0	0	0	0	0.196	0.072	56.8	56.9
	RETA	0	0	0	0	0.085	0.611	10.3	10.9
	BUILD	0.344	0.27	0.236	0.221	0.132	0.287	10.4	6.9
FI	INDU	0.045	0.14	0.182	0.193	0.202	0	27.1	22.5
	SERV	0.312	0.256	0.183	0.138	0	0	63.8	68.4
	CONS	0	0.048	0.164	0.264	0.633	1	47.5	51.0
	RETA	0	0	0	0	0	0	9.8	9.8
	BUILD	0.643	0.556	0.471	0.405	0.165	0	6.4	6.4
FR	INDU	0.264	0.36	0.401	0.516	0.576	0	16.0	13.7
	SERV	0.736	0.64	0.599	0.484	0.141	0	76.6	78.3
	CONS	0	0	0	0	0.284	0	53.4	53.8
	RETA	0	0	0	0	0	0	11.0	10.4
	BUILD	0	0	0	0	0	1	5.5	6.1
HU	INDU	0	0.115	0.162	0.217	0.328	0	25.9	26.1
	SERV	0.592	0.484	0.497	0.462	0.185	0	64.3	65.3
	CONS	0	0.053	0.095	0.129	0.368	1	53.0	51.0
	RETA	0	0	0	0	0	0	10.3	10.3
	BUILD	0.408	0.349	0.246	0.193	0.119	0	5.5	4.0

* Stands for a data point observed at 2010

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).[6] 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. ESI's leading indicator qualities can be best quantified through the number of months/quarters it precedes to GDP movements. Due to lags between ESI publications and GDP data releases, ESI offers added value to GDP

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

Table 2 Optimization results—optimal sector weights (part 2)

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights (2011)
IT	INDU	0.602	0.647	0.673	0.712	0.617	0	20.0	18.6
	SERV	0.206	0.191	0.179	0.17	0	0	71.9	73.7
	CONS	0	0	0	0.019	0.319	1	58.9	61.0
	RETA	0	0	0.013	0	0.064	0	11.9	11.3
	BUILD	0.192	0.163	0.135	0.099	0	0	5.9	5.6
LT	INDU	0	0	0.131	0.273	0.31	0.934	24.9	24.6
	SERV	0.407	0.527	0.557	0.575	0.539	0	62.5	68.7**
	CONS	0	0	0.002	0.081	0.151	0.066	64.5	62.3
	RETA	0	0	0	0	0	0	17.3	17.7
	BUILD	0.593	0.473	0.31	0.071	0	0	7.8	6.4
LV	INDU	0	0.014	0.146	0.246	0.478	0.673	16.4	18.1
	SERV	0.477	0.525	0.418	0.411	0	0	74.5	74.1**
	CONS	0.006	0	0	0	0.036	0	60.6	61.4
	RETA	0	0	0.061	0.09	0.451	0.327	16.4	14.7
	BUILD	0.517	0.461	0.374	0.253	0.036	0	6.4	5.4
MT	INDU	0	0.442	0.608	0.438	0.045	0.228	16.2	14.5
	SERV	0	0.507	0.161	0.019	0.021	0.336	58.7	65.4
	CONS	0	0.051	0.23	0.153	0.88	0.437	61.3	56.9
	RETA	1	0	0	0.276	0.053	0	12.7	11.3
	BUILD	0	0	0	0.114	0	0	7.3	4.7
NL	INDU	0.315	0.364	0.412	0.505	0.352	0	18.2	17.2
	SERV	0.215	0.261	0.286	0.234	0.436	0.616	74.4	75.9
	CONS	0	0	0	0.012	0.211	0.384	47.8	44.1
	RETA	0	0	0	0	0	0	13.1	13.4
	BUILD	0.47	0.375	0.302	0.249	0	0	5.4	5.2
PL	INDU	0.602	0.668	0.761	0.771	0.835	0.66	25.2	25.4
	SERV	0.229	0.25	0.239	0.229	0.165	0	64.6	63.0
	CONS	0	0	0	0	0	0.34	62.2	60.5
	RETA	0.169	0.083	0	0	0	0	19.1	18.5
	BUILD	0	0	0	0	0	0	6.9	8.3
PT	INDU	0.382	0.259	0.4	0.323	0.106	0	17.7	16.6
	SERV	0.616	0.406	0.352	0.203	0	0	72.7	75.8
	CONS	0	0	0.092	0.112	0.469	1	62.7	63.9
	RETA	0.002	0.304	0.156	0.362	0.426	0	13.5	13.9
	BUILD	0	0.031	0	0	0	0	6.9	5.5
RH	INDU	0.127	0	0.158	0.51	0	0	NA	NA
	SERV	0.47	0.811	0.728	0.467	0	0	66.0	68.3
	CONS	0.052	0.095	0.005	0	0	0.12	59.1	58.7
	RETA	0.202	0.094	0.109	0.023	0	0	11.0	9.5
	BUILD	0.148	0	0	0	1	0.88	6.4	5.2

Table 2 continued

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights (2011)
RO	INDU	0	0.129	0.245	0.322	0.538	0.679	28.2	32.5
	SERV	0.155	0.169	0.154	0.138	0.172	0.208	51.1	51.5
	CONS	0.291	0.305	0.27	0.23	0	0	67.9	61.5
	RETA	0.344	0.339	0.331	0.31	0.29	0.113	10.8	5.1
	BUILD	0.21	0.057	0	0	0	0	7.8	9.1
SE	INDU	0.65	0.671	0.658	0.448	0.028	0	24.2	22.5
	SERV	0.294	0.305	0.223	0.264	0.12	0	69.2	70.1
	CONS	0	0	0	0	0	0	44.4	44.9
	RETA	0	0.024	0.12	0.288	0.851	0	10.5	10.9
	BUILD	0.057	0	0	0	0	1	5.5	5.8
SI	INDU	0.119	0.23	0.328	0.503	0.634	0.194	27.6	25.0
	SERV	0.362	0.347	0.298	0.321	0.021	0	63.3	66.8
	CONS	0	0	0	0	0.122	0.397	52.8	55.1
	RETA	0.397	0.342	0.257	0.05	0	0	11.9	12.1
	BUILD	0.122	0.081	0.117	0.126	0.223	0.409	6.5	5.9
SK	INDU	0.157	0.064	0.252	0.333	0.407	0.078	29.3	26.8
	SERV	0.193	0.274	0.191	0.194	0.32	0.735	60.3	60.9
	CONS	0.132	0.223	0.171	0.158	0.273	0.187	55.7	56.4
	RETA	0.265	0.278	0.203	0.134	0	0	15.2	14.6
	BUILD	0.253	0.161	0.183	0.18	0	0	6.8	8.8
UK	INDU	0.393	0.4	0.395	0.382	0.129	0	16.3	14.6
	SERV	0	0	0	0	0	0	76.3	78.4
	CONS	0	0	0	0	0.664	0.641	61.2	60.9
	RETA	0	0	0	0.044	0.207	0.359	11.6	11.1
	BUILD	0.607	0.6	0.605	0.574	0	0	6.8	6.3

NA not available

** Stands for a data point observed at 2010

nowcasting/forecasting even as a coincident or slightly lagging indicator. Therefore, various prognostic horizons h are considered here ($h \in \{-2, -1, 0, 1, \ldots, 12\}$ months).

The optimization problem comes down to finding the optimal weights $\mathbf{w}' = (w_1, w_2, \ldots, w_5)$, 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:

$$\min_{\mathbf{w},\alpha,\beta} \sqrt{\frac{1}{T-h-2}\sum_{t=1}^{T-h}\left(GDP_{t+h} - \alpha - \beta ESI_t(\mathbf{w})\right)^2}$$

$$\text{subject to} \quad 0 \le w_1, w_2, \ldots, w_5 \le 1 \tag{11}$$

$$\sum_{i=1}^{5} w_i = 1,$$

Table 3 Optimization results—optimal sector weights (part 3)

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights (2011)
EU	INDU	0.519	0.495	0.489	0.471	0.347	0	NA	NA
	SERV	0.146	0.271	0.341	0.426	0	0	71.7	73.6
	CONS	0	0	0	0	0.554	1	NA	NA
	RETA	0	0	0	0	0.099	0	NA	NA
	BUILD	0.336	0.235	0.17	0.103	0	0	NA	NA
EA	INDU	0	0.013	0.053	0.063	0	0	NA	NA
	SERV	0.026	0.036	0	0	0	0	71.7	73.3
	CONS	0.184	0.229	0.27	0.311	0.508	0.362	NA	NA
	RETA	0	0	0	0	0	0	NA	NA
	BUILD	0.789	0.723	0.676	0.626	0.492	0.638	NA	NA

NA Non available

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 Eq. (11) can be simplified by omitting the square root function and omitting multiplication with a scalar $\frac{1}{T-h-2}$. Further, transformations from $w_1 y_{1,t} + \ldots + w_5 y_{5,t}$ to ESI do not influence the optimization procedure and ultimately yield the same solution. With that in mind, the problem in Eq. (11) is equivalent to the following problem:

$$\min_{\mathbf{w},\alpha,\beta} \sum_{t=1}^{T-h} \left(GDP_{t+h} - \alpha - \beta\left(w_1 y_{1,t} - \ldots - w_5 y_{5,t}\right)\right)^2$$

$$\text{subject to} \quad 0 \le w_1, w_2, \ldots, w_5 \le 1 \tag{12}$$

$$\sum_{i=1}^{5} w_i = 1,$$

where $y_{1,t}, y_{2,t}, \ldots, y_{5,t}$ are average of standardized survey answers as defined in Sect. 3.2. The optimization problem in Eq. (12) is simpler (has less functions) and is therefore expected to converge to the globally optimal solution. The problem consists of one equality constraint ($\sum_{i=1}^{5} w_i = 1$) and 5 bound constrains ($0 \le w_1, w_2, \ldots, w_5 \le 1$). Parameters α and β are not bounded and the problem is nonlinear in parameters. Therefore, a nonlinear optimization method should be used. Nevertheless, relation (12) can be viewed as a quadratic programming problem by substituting $b_i = \beta w_i$ and changing constraints on weights to $b_i \ge 0 \; \forall i = 1, \ldots, 5$ or $b_i \le 0 \; \forall i = 1, \ldots, 5$ (parameters $b_1, \ldots, b_5$ have the same sign). Finally, the optimization problem becomes:

$$\min_{\mathbf{w},\alpha,\beta} \sum_{t=1}^{T-h} \left(GDP_{t+h} - \alpha - b_1 y_{1,t} - \cdots - b_5 y_{5,t}\right)^2 \tag{13}$$
$$\text{subject to} \; \operatorname{sgn}(\mathrm{b}_1) = \operatorname{sgn}(\mathrm{b}_2) = \ldots = \operatorname{sgn}(\mathrm{b}_5).$$

The problem in (13) is a special case of a quadratic programming problem of form $\min \mathbf{d}'\mathbf{b} + \frac{1}{2}\mathbf{b}'\mathbf{D}\mathbf{b}$ with constraint $\mathbf{A}'\mathbf{b} \ge \mathbf{b_0}$. 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 a 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 (11). The problem can mathematically be formulated as follows:

$$\max_{\mathbf{w}} \frac{\sum_{t=1}^{T-h}\left(GDP_{t+h}-\overline{GDP}\right)\left(ESI_t-\overline{ESI}\right)}{\sqrt{\sum_{t=1}^{T-h}\left(GDP_{t+h}-\overline{GDP}\right)^2}\sqrt{\sum_{t=1}^{T-h}\left(ESI_t-\overline{ESI}\right)^2}} \\ \text{subject to } 0 \le w_1, w_2, \ldots, w_5 \le 1 \text{ and } \sum_{i=1}^{5} w_i = 1. \tag{14}$$

After obtaining novel ESI weights through quadratic optimization with constraints, the new aggregate EU and EA ESI indicators are also proposed, using the officially utilized EC weights for each of the analyzed countries. Namely, treating these national weights as unknowns in the quadratic optimization problem would lead to obvious over-parametrization of the problem. In some cases the number of parameters to estimate would be even larger than the number of data observations.

3.3.2 Assessing the quality of the 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). 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:

$$||\mathbf{w}-\mathbf{w}^{EC}||_2 = \sqrt{\sum_{i=1}^{5}(w_i - w_i^{EC})^2} \tag{15}$$

$$||\mathbf{w}-\mathbf{w}^{EC}||_\infty = \max_{i=1,\ldots,5}|w_i - w_i^{EC}|, \tag{16}$$

where $w^{EC'} = (0.4, 0.3, 0.2, 0.05, 0.05)$.

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 empirical strategy followed in this paper allows different weights for each of the 5 analyzed BCS sectors. The "optimal" weights obtained by minimizing *RMSE* in GDP forecasting equations (for chosen forecasting horizons $h \in \{-2, -1, 0, 1, 6, 12\}$) are summarized in Tables 1, 2 and 3.[7]

[7] The remaining forecast horizons are not mentioned here to save space.

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: 0.282, 0.229, 0.240, 0.124 and 0.125 for the industrial, services, consumers, retail trade, and construction sectors (respectively). It is immediately 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 %. To obtain fresh insight, Tables 1, 2 and 3 summarize the shares of each sector in GDP for individual countries, the EU, and EA. They reveal that the average share of industrial production in GDP for the analyzed EU countries is 23.6 % in 2011. 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.

Also, the proposed industry weight is lower than the official EC one in the vast majority of countries (and forecast horizons). This is completely in line with the global long-term trend of deindustrialization (Brady 2006). In the dilemma between BCS harmonization (fixed weights) and optimal forecasting quality, the EC has opted for the former option.

The only countries that (on average) have higher industrial weight than the EC one are Greece, Spain, Italy, Poland, Romania and Slovenia. It instantly becomes evident these countries have either a long history of socialist industrialization, or a form of state capitalism dominated by large industrial corporations.

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 predictive characteristics of the services sector is not that pronounced. To be more specific, its average proposed weight is considerably smaller 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 et al. (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. To corroborate that, the average share of services in GDP is calculated for the analyzed countries (on the basis of Tables 1, 2 and 3), and it is equal to exactly 70 % in the 2011.

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 $h = 1, 6$. Such pronounced dominance of the services sector in Germany is also corroborated by the official statistics. Namely, Franke and Kalmbach (2005) acknowledge the business services as the fastest growing sector of the German economy.

The consumer and retail trade sectors are intrinsically interdependent, so it is obvious that they exhibit similar properties. Both are attached considerably larger weights then in the official ESI calculation scheme. This is not surprising since, on average, the final consumption of households accounts for as much as 60.9 % of GDP in the analyzed EU countries in 2011 (see Tables 1, 2 and 3). Moreover, the strong relationship between personal consumption and GDP is well-established in the literature (Crossley et al. 2013; Tapsin and Hepsag 2014).

One particularly interesting feature of the consumer and retail trade sectors is observed here. Namely, both sectors on average 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. This explains why macroeconomic forecasts can often be improved if consumer sentiment is taken into account (see Batchelor and Dua (1998) and all the paper cited there). Short-term GDP predictions are, on the other hand, to the greatest extent influenced by the industrial sector.

The construction sector weights are mostly rather small throughout the analyzed model specifications. Some of the exceptions include France, Germany, Finland, and Spain (among EA members),[8] as well as e.g. Croatia and Sweden (among non-EA countries) for some of the analyzed lead lengths. All the mentioned countries (except Croatia) are highly developed. Namely, the literature offers clear evidence of strong correlation between income and dwelling investments in such countries. As an example, Arestis and Gonzalez-Martinez (2015) characterize the construction sector as strategically important due to its strong forward and backward linkages in OECD economies. Leamer (2007) also identifies housing investments as a remarkably accurate recession predictor for the US economy. Croatia, on the other hand, is a quite atypical European economy, highly dependent on its construction sector. It is well-documented that the entire Croatian economic expansion from 2000 to 2008 was founded on a real estate bubble (Tkalec and Vizek 2014).

Apart from interpreting the obtained results from the aspect of actual sector shares in GDP, one might also raise a question of the BCS respondents' capacity to form accurate macroeconomic forecasts. This notion relates to the famous rational expectations hypothesis (see e.g. Sabrowski 2008), which states that economic agents are fully rational (their expectations are correct on average) and take into account the whole available information set. In that context, the "optimal" weights obtained here prove that the industrial sector managers (on average) poses the deepest knowledge of the underlying economic mechanisms, which enable them to form the most accurate predictions.

In order to extract homogeneous groups of countries with respect to the obtained sectoral weights, cluster analysis is applied on the five sector weights (cases for the 5 variables are obtained as average weights over the 15 analyzed lead lengths; $h \in \{-2, -1, 0, 1, \ldots, 12\}$). The optimal number of five distinctive clusters is obtained on the basis of Charrad (2014) procedure in R software. Using the K-means clustering method, the analyzed countries are grouped in the following way. The first cluster comprises Germany, Denmark, and Estonia. The second cluster consists of the Czech Republic, France, Hungary, Lithuania, Netherlands, and Slovakia. They are followed by Cyprus, Latvia, Croatia and Sweden in cluster three. The fourth groups comprises Greece, Spain, Italy, Poland, Romania, and Slovenia. The final group is made of Austria, Belgium, Bulgaria, Finland, Malta, Portugal, and the UK.

The plot of cluster means is depicted on Fig. 5.

It is evident that the clusters are extracted based on the dominant sector in their member countries. For example, the first cluster is dominated by the services sector since all three countries exhibit extremely large services weights.

[8] It should be evident from Table 3 that these results have also triggered the share of construction in EA ESI to be rather high.

Likewise, the third cluster is consisted of construction-driven economies. Members of the fourth cluster are dominated by large industrial corporations, while the economies in the fifth cluster can best be described by consumer sentiment. Finally, the second cluster represents a “moderate” group of countries, mostly characterized by typical (average observed) weights for all five BCS sectors.

The newly obtained ESI indicator at the EU and EA level (at forecast horizon $h = 0$) is depicted on Figs. 6 and 7, along with the corresponding monthly GDP series. It is evident that the “new” ESI follows GDP more closely, without any time lagging. Therefore the hereby proposed calculation scheme has brought about an improvement in ESI’s now-casting quality. Similar evidence is also obtained for other forecast horizons. However, it is important to inspect whether the results obtained up to this point are solely an in-sample characteristic, or are the drawn conclusions valid even for the out-of sample forecasting.

For each of the analyzed countries, the cut-off point has been set separately to the last 24 and 36 monthly observations. Using the dataset up to that point in time, a pseudo out-of-sample forecasting exercise is performed. The results are presented in Table 4.

The results presented in Table 4 range from very bad (in case of Spain and Germany) to considerable improvements (Czech Republic, Belgium, Finland, Hungary, etc.). Just as in Gelper and Croux (2010), an improvement is also noticed on the aggregate EU level for the 36 months cut-off point. However, the same cannot be said about the 24 months cut-off point. In general, at least an incremental rise of ESI’s forecasting quality is observed for the vast part of analyzed countries.

The optimization problem in (14) 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 available in Tables 7, 8, 9, 10 and 11 in Appendix 2. Again, ESI’s in-sample forecasting quality is considerably enhanced, while the out-of-sample results are not so convincing.

To quantify the extent to which the weights obtained through *RMSE* minimization differ from the official ESI figures, the obtained Euclidean and maximum norms are presented in Table 5. Further, an index of the obtained *RMSE*s is presented in the final column. An index value larger than 100 corresponds to an improvement in the newly proposed weighting scheme in comparison to the official EC weights.

All three applied distance measures reveal similar tendencies. The last two rows of Table 5 are particularly interesting, showing that (on average) the proposed weighting scheme offers somewhat more added value in OMS than in the NMS. What strikes as the most peculiar result is that Germany, 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.[9]

Additionally, a parallel can be drawn between the results from Tables 1, 2 and 3 and the ones in Table 5. Namely, the majority of countries with exceptionally high construction sector weights (Germany, Finland, Spain, Croatia, etc.) are among the best-placed Member States according to the ESI improvement obtained by this study. This proves that attaching higher weight to the construction sector adds to the accuracy of ESI-based predictions, and

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

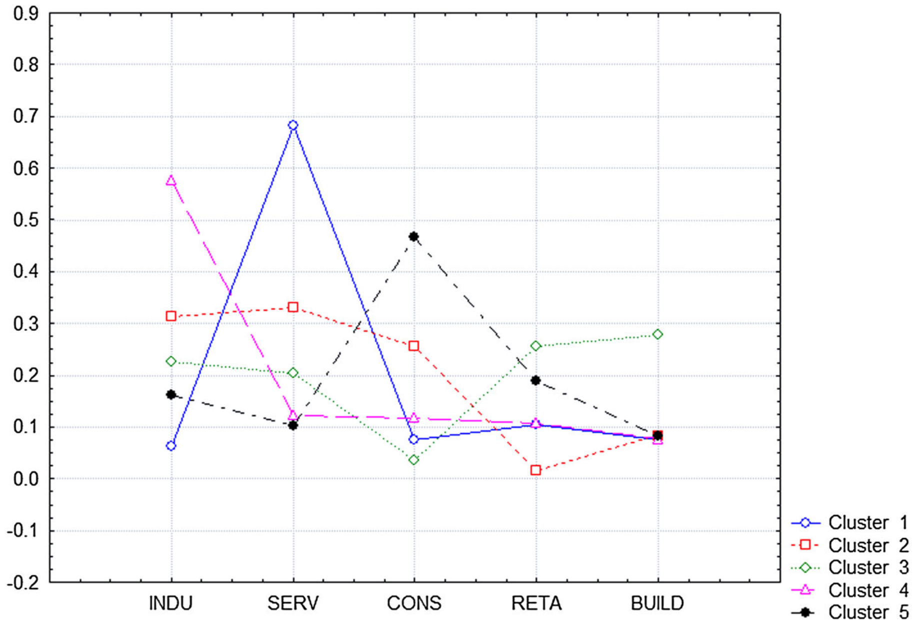

Fig. 5 Means plot for the obtained 5 country clusters

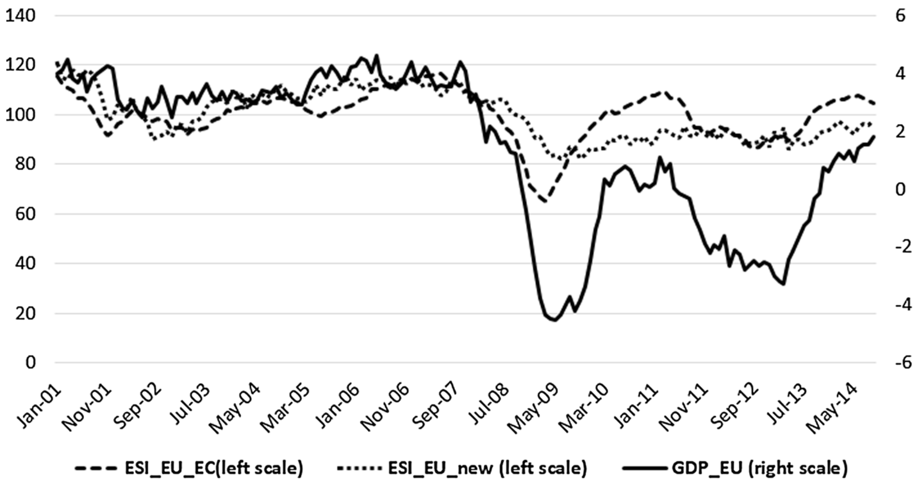

Fig. 6 The official and new ESI with respect to GDP growth at the EU level

corroborates the relevance of the construction sector in determining the business cycles of developed European countries.

The results presented in Table 5 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 5 merely reveals how much room for improvement does each particular Member State have in terms of ESI's predictive

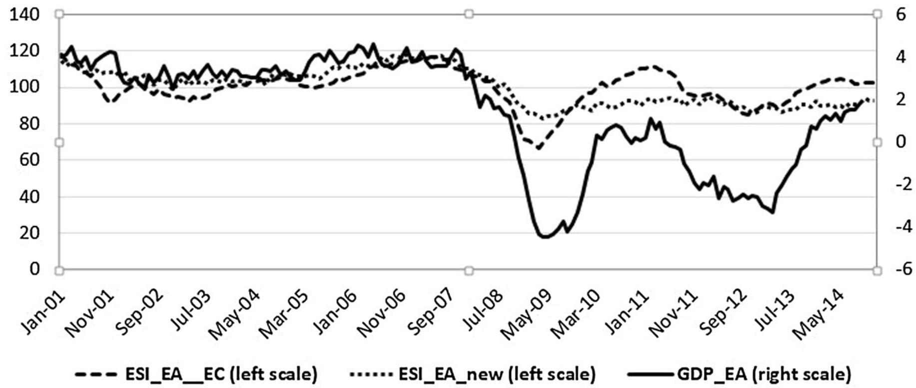

Fig. 7 The official and new ESI with respect to GDP growth at the EA level

accuracy. In fact, one can 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 the 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 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 a 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 EU and EA. The weights are found by minimizing the *RMSE*s obtained from simple GDP forecasting equations including ESI as the predictor variable.

The obtained in-sample results have showed that ESI's forecasting accuracy can be significantly improved by attaching larger weights to the retail trade and consumer sectors. On the other hand, the importance of the industrial sector is heavily overestimated by the official EC weights. The empirical analysis of this study has shown that lowering the industrial weights significantly improves ESI's leading properties.

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 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 NMS economies.

Table 4 Comparison of ESI indicator quality—out of sample

Country	Avg $\frac{RMSE_{EC}}{RMSE} \cdot 100$ (2012:12)	Avg $\frac{RMSE_{EC}}{RMSE} \cdot 100$ (2011:12)
AT	102.0	101.8
BE	103.8	97.2
BG	100.8	103.9
CY	99.3	96.9
CZ	109.1	101.1
DE	78.9	94.3
DK	101.7	NA
EE	97.6	101.6
EL	100.7	101.4
ES	80.3	84.9
FI	104.4	94.9
FR	100.0	100.3
HU	107.7	102.4
IT	102.7	104.3
LT	100.8	99.8
LV	99.9	100.6
MT	99.8	NA
NL	99.8	103.1
PL	98.4	100.1
PT	99.1	97.4
RH	99.0	100.3
RO	100.9	100.0
SE	99.7	115.7
SI	98.9	106.0
SK	101.0	100.9
UK	101.0	99.8
EU	100.0	102.4
EA	81.4	75.6

NA not available

The cut-off point is given in brackets

The obtained results are proven to be robust by also finding weights that maximize the correlation coefficient between GDP and ESI for various lead lengths.

This study provides valuable information about the functioning mechanisms of EU Member States economies. The countries are clearly grouped into five clusters, each of them dominated by a particular sector.

The out-of-sample forecasting exercise offers mixed evidence on the quality of novel ESI calculation. The results are not uniform, but the proposed weighting scheme results in at least a marginal improvement for the majority of the observed countries, as well as for the EU in case of 3 years data cut-off point. Whether the obtained improvements are good enough to officially change the ESI weighting scheme, it is for the European Commission to decide.

If one wished to 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 by changing the frozen period employed in its calculation. This means that past ESI

Table 5 Comparison of ESI indicator quality

Country	Avg $\frac{RMSE_{EC}}{RMSE} \cdot 100$	Country	Avg 2-norm	Country	Avg max-norm
EA	135.845	DE	0.832	DE	0.700
RH	125.552	SE	0.801	SE	0.690
DE	124.283	RH	0.797	RH	0.675
FI	116.551	EA	0.742	BE	0.564
ES	112.304	BE	0.728	EA	0.503
EL	112.156	BG	0.659	PT	0.484
DK	112.039	UK	0.640	FI	0.472
BG	111.398	PT	0.637	EE	0.462
LV	111.185	FI	0.609	BG	0.457
BE	110.692	DK	0.579	UK	0.441
UK	110.530	EE	0.576	DK	0.439
SE	110.279	CY	0.564	MT	0.413
EE	108.819	EU	0.535	IT	0.406
MT	108.061	MT	0.527	EU	0.405
IT	107.668	EL	0.521	EL	0.384
HU	107.212	IT	0.517	CY	0.372
SI	106.840	ES	0.512	ES	0.370
CY	106.578	LV	0.494	FR	0.357
PT	106.505	AT	0.460	PL	0.347
AT	106.278	FR	0.451	LV	0.343
RO	104.374	HU	0.428	HU	0.336
CZ	103.823	PL	0.424	AT	0.305
PL	103.814	SI	0.373	SI	0.264
LT	103.328	RO	0.339	LT	0.253
EU	103.308	NL	0.325	RO	0.246
NL	102.917	LT	0.319	NL	0.240
SK	102.848	CZ	0.273	CZ	0.206
FR	102.621	SK	0.209	SK	0.152
OMS	110.371	OMS	0.585	OMS	0.450
NMS	107.987	NMS	0.460	NMS	0.348

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 to some extent raise the forecasting accuracy (both in-sample and out-of-sample) of ESI in individual Member States and at the aggregate EU level.

This paper suggests merely two of the possible methodological paths to improving ESI's forecasting accuracy. Future research should certainly test whether the potentially low quality in an 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, for example, exact response rates (but merely targeted response rates) or sampling errors for all countries and sectors.

Regardless, the calculation of European ESI and improving its predictive accuracy deserves more attention in future research.

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Appendices

Appendix 1

See Table 6.

Table 6 Estimation periods for the analyzed countries

Country	Estimation period
DE, FR	1996 M01 to 2014 M09
FI	1997 M05 to 2014 M09
AT, BE, BG, CZ, EE, EL, HU, IT, NL, PT, RO, SK, ES, UK	2001 M01 to 2014 M09
LV	2001 M05 to 2014 M09
SI, CY	2002 M05 to 2014 M09
PL	2003 M01 to 2014 M09
LT	2006 M01 to 2014 M09
HR	2008 M05 to 2014 M09
DK	2010 M05 to 2014 M09
MT	2011 M05 to 2014 M09
EU, EA	2001 M01 to 2014 M09

Appendix 2

See Tables 7, 8, 9, 10 and 11.

Table 7 Optimization results—optimal sector weights (part 1)

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights (2011)
AT	INDU	0.356	0.144	0.422	0.455	0.119	0	23.3	22.2
	SERV	0.482	0.611	0.388	0.285	0.131	0	68.2	69.8
	CONS	0.105	0.129	0.16	0.227	0.376	0.457	52.3	51.8
	RETA	0	0	0	0.033	0.374	0.543	12.6	13.1
	BUILD	0.057	0.116	0.03	0	0	0	7.0	6.4

Table 7 continued

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights (2011)
BE	INDU	0	0	0	0	0	0	20.3	17.6
	SERV	0.465	0.48	0.481	0.458	0.075	0	73.9	75.9
	CONS	0.535	0.52	0.519	0.542	0.727	1	49.3	50.3
	RETA	0	0	0	0	0.198	0	13.4	12.7
	BUILD	0	0	0	0	0	0	4.9	5.7
BG	INDU	0.276	0.223	0.256	0.243	0	0	22.7	23.8
	SERV	0.085	0.103	0.076	0.088	0	0	62.5	64.6
	CONS	0.257	0.292	0.37	0.354	0.435	0.78	68.7	61.8
	RETA	0.281	0.318	0.258	0.315	0.565	0.22	12.2	11.9
	BUILD	0.102	0.065	0.04	0	0	0	6.1	6.2
CY	INDU	0.028	0.008	0.239	0.088	0	0	10.1	8.3
	SERV	0.485	0.577	0.463	0.547	0.31	0.005	77.7	78.3
	CONS	0.107	0.013	0.006	0	0.128	0.132	60.6	65.0
	RETA	0.079	0	0	0.041	0.341	0.407	14.7	14.1
	BUILD	0.3	0.402	0.292	0.324	0.221	0.456	10.0	6.7
CZ	INDU	0.351	0.394	0.434	0.489	0.455	0	31.0	30.9
	SERV	0.34	0.336	0.35	0.34	0.172	0.352	59.5	60.6
	CONS	0.018	0.075	0.124	0.171	0.372	0.648	60.6	48.6
	RETA	0.163	0.129	0.078	0	0	0	11.3	10.3
	BUILD	0.13	0.066	0.013	0	0	0	6.7	6.2
DE	INDU	0.035	0.041	0.021	0	0	0	25.4	26.0
	SERV	0.965	0.959	0.979	1	1	1	70.0	68.7
	CONS	0	0	0	0	0	0	56.3	54.3
	RETA	0	0	0	0	0	0	10.5	10.1
	BUILD	0	0	0	0	0	0	3.9	4.4
DK	INDU	0.083	0.114	0.246	0	0	0	20.8	18.7
	SERV	0.795	0.707	0.693	0.854	0.577	0	72.4	75.1
	CONS	0	0	0	0	0.423	0.348	46.3	46.6
	RETA	0	0	0	0	0	0.652	11.9	12.4
	BUILD	0.122	0.178	0.061	0.146	0	0	5.4	4.7
EE	INDU	0.092	0.086	0.119	0.161	0.23	0	21.2	22.2
	SERV	0.069	0.196	0.28	0.345	0.694	1	66.7	66.7
	CONS	0	0.006	0.013	0.043	0.075	0	53.7	49.1
	RETA	0.366	0.353	0.287	0.227	0	0	14.4	12.1
	BUILD	0.473	0.358	0.301	0.223	0	0	8.6	7.0
EL	INDU	0.673	0.744	0.786	0.821	0.724	0.807	13.2	10.9
	SERV	0.326	0.256	0.214	0.179	0	0	75.9	82.2
	CONS	0	0	0	0	0	0.193	66.1	67.7
	RETA	0	0	0	0	0.276	0	13.1	12.2
	BUILD	0.001	0	0	0	0	0	6.1	3.4

Table 7 continued

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights (2011)
ES	INDU	0.631	0.694	0.747	0.779	0.586	0.029	16.9	16.0
	SERV	0.032	0.039	0.02	0	0	0	66.5	72.6
	CONS	0	0	0	0	0.199	0.078	56.8	56.9
	RETA	0	0	0	0	0.084	0.607	10.3	10.9
	BUILD	0.337	0.268	0.234	0.221	0.131	0.285	10.4	6.9
FI	INDU	0.046	0.143	0.182	0.194	0.203	0	27.1	22.5
	SERV	0.31	0.256	0.183	0.14	0	0	63.8	68.4
	CONS	0	0.043	0.165	0.262	0.632	1	47.5	51.0
	RETA	0	0	0	0	0	0	9.8	9.8
	BUILD	0.644	0.558	0.47	0.404	0.165	0	6.4	6.4
FR	INDU	0.268	0.363	0.406	0.514	0.573	0	16.0	13.7
	SERV	0.732	0.637	0.594	0.486	0.143	0	76.6	78.3
	CONS	0	0	0	0	0.285	1	53.4	53.8
	RETA	0	0	0	0	0	0	11.0	10.4
	BUILD	0	0	0	0	0	0	5.5	6.1
HU	INDU	0.018	0.137	0.169	0.221	0.32	0	25.9	26.1
	SERV	0.556	0.422	0.475	0.447	0.208	0	64.3	65.3
	CONS	0	0.067	0.1	0.131	0.37	0.992	53.0	51.0
	RETA	0	0	0	0	0	0	10.3	10.3
	BUILD	0.426	0.374	0.256	0.2	0.103	0.008	5.5	4.0

* Stands for a data point observed at 2010

Table 8 Optimization results—optimal sector weights (part 2)

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights(2011)
IT	INDU	0.602	0.647	0.673	0.712	0.617	0	20.0	18.6
	SERV	0.207	0.19	0.179	0.17	0	0	71.9	73.7
	CONS	0	0	0	0.019	0.319	1	58.9	61.0
	RETA	0	0	0.013	0	0.064	0	11.9	11.3
	BUILD	0.192	0.163	0.135	0.099	0	0	5.9	5.6
LT	INDU	0	0.078	0.199	0.308	0.333	0.789	24.9	24.6
	SERV	0.416	0.499	0.527	0.555	0.524	0	62.5	68.7
	CONS	0.028	0.051	0.067	0.094	0.143	0.211	64.5	62.3
	RETA	0	0	0	0	0	0	17.3	17.7
	BUILD	0.556	0.373	0.207	0.043	0	0	7.8	6.4
LV	INDU	0	0.084	0.201	0.29	0.528	0.679	16.4	18.1
	SERV	0.45	0.472	0.406	0.418	0.032	0	74.5	74.1
	CONS	0.066	0.007	0	0	0.03	0	60.6	61.4
	RETA	0	0	0.029	0.048	0.407	0.321	16.4	14.7
	BUILD	0.484	0.437	0.363	0.243	0.004	0	6.4	5.4

Table 8 continued

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights(2011)
MT	INDU	0.442	0.362	0.608	0.438	0.095	0.228	16.2	14.5
	SERV	0.507	0.214	0.162	0.019	0.054	0.336	58.7	65.4
	CONS	0.051	0.425	0.23	0.153	0.783	0.437	61.3	56.9
	RETA	0	0	0	0.276	0.068	0	12.7	11.3
	BUILD	0	0	0	0.114	0	0	7.3	4.7
NL	INDU	0.306	0.36	0.406	0.487	0.356	0	18.2	17.2
	SERV	0.228	0.266	0.294	0.256	0.43	0.61	74.4	75.9
	CONS	0	0	0	0.021	0.214	0.39	47.8	44.1
	RETA	0	0	0	0	0	0	13.1	13.4
	BUILD	0.466	0.374	0.3	0.236	0	0	5.4	5.2
PL	INDU	0.603	0.668	0.759	0.771	0.83	0.613	25.2	25.4
	SERV	0.233	0.252	0.241	0.229	0.17	0.127	64.6	63.0
	CONS	0	0	0	0	0	0.259	62.2	60.5
	RETA	0.164	0.079	0	0	0	0	19.1	18.5
	BUILD	0	0	0	0	0	0	6.9	8.3
PT	INDU	0.379	0.276	0.409	0.327	0.127	0	17.7	16.6
	SERV	0.614	0.39	0.347	0.2	0	0	72.7	75.8
	CONS	0	0	0.099	0.115	0.486	1	62.7	63.9
	RETA	0.007	0.291	0.145	0.358	0.387	0	13.5	13.9
	BUILD	0	0.043	0	0	0	0	6.9	5.5
RH	INDU	0.226	0	0.267	0.492	1	1	NA	NA
	SERV	0.389	0.785	0.652	0.476	0	0	66.0	68.3
	CONS	0.059	0.119	0.02	0	0	0	59.1	58.7
	RETA	0.158	0.084	0.061	0.032	0	0	11.0	9.5
	BUILD	0.167	0.012	0	0	0	0	6.4	5.2
RO	INDU	0	0.139	0.268	0.332	0.541	0.681	28.2	32.5
	SERV	0.176	0.17	0.157	0.138	0.175	0.21	51.1	51.5
	CONS	0.291	0.308	0.271	0.234	0	0	67.9	61.5
	RETA	0.323	0.329	0.303	0.296	0.284	0.109	10.8	5.1
	BUILD	0.21	0.054	0	0	0	0	7.8	9.1
SE	INDU	0.644	0.662	0.647	0.445	0.106	0	24.2	22.5
	SERV	0.3	0.311	0.23	0.266	0.051	0	69.2	70.1
	CONS	0	0	0	0	0	0	44.4	44.9
	RETA	0	0.027	0.123	0.289	0.842	1	10.5	10.9
	BUILD	0.056	0	0	0	0	0	5.5	5.8
SI	INDU	0.123	0.232	0.328	0.503	0.634	0.206	27.6	25.0
	SERV	0.359	0.341	0.298	0.321	0.021	0	63.3	66.8
	CONS	0	0	0	0	0.122	0.378	52.8	55.1
	RETA	0.391	0.339	0.256	0.05	0	0	11.9	12.1
	BUILD	0.126	0.087	0.117	0.126	0.223	0.415	6.5	5.9

Table 8 continued

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights(2011)
SK	INDU	0.149	0.068	0.25	0.328	0.407	0.142	29.3	26.8
	SERV	0.201	0.271	0.193	0.198	0.32	0.698	60.3	60.9
	CONS	0.14	0.22	0.173	0.163	0.273	0.16	55.7	56.4
	RETA	0.264	0.277	0.202	0.134	0	0	15.2	14.6
	BUILD	0.246	0.164	0.181	0.177	0	0	6.8	8.8
UK	INDU	0.393	0.4	0.395	0.386	0.129	0	16.3	14.6
	SERV	0	0	0	0	0	0	76.3	78.4
	CONS	0	0	0	0.001	0.663	0.64	61.2	60.9
	RETA	0	0	0	0.039	0.209	0.36	11.6	11.1
	BUILD	0.607	0.6	0.605	0.574	0	0	6.8	6.3

NA not available

** Stands for a data point observed at 2010

Table 9 Optimization results—optimal sector weights (part 3)

h		−2	−1	0	1	6	12	Actual weights (2005)	Actual weights (2011)
EU	INDU	0.486	0.485	0.496	0.484	0.345	0	NA	NA
	SERV	0.207	0.288	0.329	0.396	0	0	71.7	73.6
	CONS	0	0	0	0	0.553	1	NA	NA
	RETA	0	0	0	0	0.103	0	NA	NA
	BUILD	0.307	0.226	0.176	0.119	0	0	NA	NA
EA	INDU	0	0.006	0.048	0.071	0	0	NA	NA
	SERV	0.038	0.047	0.018	0	0	0	71.7	73.3
	CONS	0.177	0.227	0.268	0.309	0.511	0.383	NA	NA
	RETA	0	0	0	0	0	0	NA	NA
	BUILD	0.785	0.72	0.666	0.62	0.489	0.617	NA	NA

NA Not available

Table 10 Comparison of ESI indicator quality—out of sample

Country	Avg $Corr(ESI, GDP)$ Cut off point = 2012:12	Avg $Corr(ESI_{EC}, GDP)$	Avg $Corr(ESI, GDP)$ Cut off point = 2011:12	Avg $Corr(ESI_{EC}, GDP)$
AT	0.100	0.111	0.066	0.045
BE	0.591	0.610	0.349	0.364
BG	0.095	0.193	0.011	0.233
CY	0.555	0.501	0.416	0.350
CZ	0.752	0.810	0.489	0.555
DE	0.786	0.646	0.234	0.055
DK	0.505	0.551	NA	NA

Table 10 continued

Country	Avg $Corr(ESI, GDP)$ Cut off point = 2012:12	Avg $Corr(ESI_{EC}, GDP)$	Avg $Corr(ESI, GDP)$ Cut off point = 2011:12	Avg $Corr(ESI_{EC}, GDP)$
EE	−0.029	0.055	−0.090	0.066
EL	0.113	0.107	0.494	0.512
ES	0.841	0.749	0.626	0.515
FI	0.341	0.433	−0.034	0.309
FR	0.168	0.166	0.044	0.146
HU	0.627	0.689	0.756	0.763
IT	0.560	0.594	0.462	0.565
LT	−0.031	0.015	−0.219	−0.217
LV	0.019	−0.067	−0.075	−0.081
MT	0.385	0.301	NA	NA
NL	0.634	0.620	0.465	0.465
PL	0.710	0.692	0.230	0.212
PT	0.664	0.649	0.698	0.610
RH	0.208	0.196	0.141	0.270
RO	0.131	0.077	0.175	0.126
SE	0.294	0.276	0.234	0.552
SI	0.718	0.665	0.359	0.410
SK	0.492	0.470	0.134	0.156
UK	0.524	0.528	0.635	0.633
EU	0.752	0.741	0.604	0.645
EA	0.892	0.832	0.523	0.309

Table 11 Comparison of ESI indicator quality

h	Avg $Corr(ESI, GDP)$	Avg $Corr(ESI_E C, GDP)$	Avg 2-norm	Avg max-norm
AT	0.670	0.595	0.440	0.296
BE	0.572	0.385	0.705	0.544
BG	0.688	0.586	0.619	0.428
CY	0.818	0.788	0.537	0.358
CZ	0.730	0.699	0.263	0.199
DE	0.636	0.267	0.825	0.694
DK	0.662	0.528	0.579	0.440
EA	0.791	0.587	0.753	0.523
EE	0.814	0.774	0.550	0.423
EL	0.737	0.673	0.500	0.374
ES	0.814	0.762	0.509	0.358
EU	0.611	0.555	0.494	0.373
FI	0.768	0.664	0.613	0.482
FR	0.545	0.504	0.435	0.346
HU	0.762	0.713	0.436	0.334

Table 11 continued

h	Avg $Corr(ESI, GDP)$	Avg $Corr(ESI_E C, GDP)$	Avg 2-norm	Avg max-norm
IT	0.648	0.568	0.492	0.381
LT	0.731	0.717	0.324	0.249
LV	0.851	0.802	0.475	0.330
MT	0.467	0.346	0.479	0.374
NL	0.669	0.643	0.329	0.249
PL	0.521	0.479	0.397	0.325
PT	0.642	0.553	0.592	0.451
RH	0.337	0.242	0.567	0.455
RO	0.728	0.697	0.351	0.254
SE	0.566	0.403	0.736	0.630
SI	0.711	0.663	0.382	0.271
SK	0.700	0.674	0.229	0.167
UK	0.654	0.530	0.642	0.455

NA Not available

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