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Social capital and smart growth of the EU countries

Iwona SKRODZKA

University of Bialystok, Poland

Abstract: Social capital according to OECD definition is networks together with shared norms, values and understandings that facilitate co-operation within or among groups. Currently, social capital is identified as a one of the key factors of economic development. Most of the existing literature focuses on the role of social capital for economic growth, meanwhile the purpose of this study is to examine the role which social capital plays in the processes of smart growth in the EU countries. Smart growth is based on knowledge and innovation. The notion of smart growth, its factors and measuring methods are new categories which emerge from the concept of EU's strategic development objectives. The study uses a soft modelling method which allows for measuring and analysis of the relationships among unobserved variables (latent variables).

Keywords: social capital, smart growth, European Union, soft modelling

JEL codes: *C59, O11, Z13*

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1. Introduction

The concept of social capital was developed as a response to the difficulties in explaining cross-country disparities in economic growth. The production factors discussed: physical capital, labour and human capital did not sufficiently explain the differences between the rate of economic growth or levels of development in individual countries. Therefore, researchers began investigating social, cultural, political, and psychological factors.

The notion that social relations, networks, norms, and values matter in the functioning and development of society has long been present in the economics, sociology, anthropology,

Correspondence Address: Iwona Skrodzka, Department of Econometrics and Statistics, Faculty of Economics and Management, University of Bialystok, Warszawska 63 15-062 Białystok, Poland. Tel.: +48857457723 E-mail: i.skrodzka@uwb.edu.pl

and political science literature. Only in the past 20 years or so, however, has the idea of social capital been put forth as a unifying concept embodying these multidisciplinary views (Grootaert and van Bastelaer, 2001: 4). The concept has been developed by researchers, such as James Coleman (1988, 1990), Robert Putnam (1993) and, to a lesser extent, Pierre Bourdieu (1986).

Despite the on-going dispute, no universal definition of social capital or an accurate measurement method have been developed as yet. This is not because of any methodological deficiencies or underdevelopment of the concept itself, but due to the fact that social capital is a complex and multi-faceted phenomenon (Bartkowski 2007: 69).

The concept of social capital can be viewed along three dimensions: its scope (or unit of observation), its forms, and the channels through which it affects development (Grootaert and van Bastelaer, 2001: 4-5).

Putnam (1993) is usually cited as the author of a classical analysis of social capital at the micro level. He defines social capital as those features of a social organization, such as networks of individuals or households, and the associated norms and values, which create externalities for the community as a whole. By expanding the unit of observation and introducing a vertical component to social capital, Coleman (1990) opened the door to a broader social capital. His definition of social capital as a variety of different entities which all consist of some aspect of a social structure, and which facilitate certain actions of actors – individual or corporate ones – within the structure, implicitly considers relations among groups, rather than individuals. The third view of social capital involves the social and political environment that shapes social structures and enables norms to develop. In addition to the largely informal, and often local, horizontal and hierarchical relationships of the first two concepts, this view also accounts for the macro-level, most formalized institutional relationships and structures, such as the political regime, the rule of law, the court system, and civil and political liberties. This focus on institutions draws on the work of North (1990) and Olson (1982), who have argued that such institutions have a critical effect on the rate and pattern of economic development.

Researchers distinguish two main forms of social capital: structural and cognitive (Uphoff, 2000: 218). The structural category is associated with various forms of social organization, particularly roles, rules, precedents and procedures as well as a wide variety of networks that contribute to cooperation, and specifically to mutually beneficial collective action, which is the stream of benefits that results from social capital. As such, it is a relatively objective and externally observable construct. The cognitive category derives from mental processes and resulting ideas, reinforced by culture and ideology, specifically norms, values, attitudes and beliefs that contribute to cooperative behaviour and mutually beneficial collective action. It is, therefore, a more subjective and intangible concept.

Measuring capital is far from easy. It is associated, e.g. with the following problems (Łopaciuk-Gonczaryk, 2012: 2-3):

- lack of a universal definition of social capital,
- uncertainty whether all the effects of social capital are positive or whether it should be perceived neutrally, as capable of influencing different variables in different ways,
- unobservability of social capital,
- multidimensionality of social capital and insufficient knowledge about the relationships between its particular dimensions,
- different levels of analysis (micro, mezo, and macro) and lack of certainty as to aggregation methods.

The significance of social capital for the processes of socio-economic development is appreciated by many international institutions conducting research in this field. The most important projects include:

- ‘Social Capital Initiative’, World Bank, where the following definition of social capital was proposed: ‘social capital of a society includes the institutions, the relationships, the attitudes and values that govern interactions among people and contribute to economic and social development’ (World Bank, 1998:1),
- ‘The Well-being of Nations: The Role of Human and Social Capital’, OECD, which defines social capital as ‘networks together with shared norms, values and understandings that facilitate co-operation within or among groups’ (OECD, 2001: 41),
- ‘The Contribution of Social Capital in the Social Economy to Local Economic Development in Western Europe’, European Commission, where the proposed definition holds that ‘social capital consists of resources within communities that are created through the presence of high levels of trust, reciprocity and mutuality, shared norms of behaviour, shared commitment and belonging, both formal and informal social networks, and effective information channels which may be used productively by individuals and groups to facilitate actions to benefit individuals, groups and community more generally’

(European Commission, 2003: 42).

Most of the existing literature focuses on the role of social capital for economic growth. The effects of social capital on economic growth can be theoretically modelled both at an individual and aggregate level. Regarding microeconomic channels, trust and cooperation within a company, industry or market may lower transactions costs, help enforce contracts, and improve credit access. In a macroeconomic perspective, for instance, social capital can increase the effectiveness of economic policies. Related empirical literature searches for evidence of a positive correlation between social capital and economic growth, without distinguishing microeconomic from macroeconomic channels. In fact, most of the studies connecting social capital and economic growth use a definition of social capital at the aggregate level, using, as a proxy for social capital, a measure of trust provided by the World Bank (Thompson, 2018: 4).

The purpose of this study is to examine the role which social capital plays in the processes of smart growth in the EU countries. Smart growth is based on knowledge and innovation. The notion of smart growth, its factors and measuring methods are new categories which emerge from the concept of EU's strategic development objectives (European Commission, 2010). Although the concept of smart growth is relatively new, it has already been discussed by other authors, e.g. Bal-Domańska (2013), Markowska and Strahl (2012; 2016), Skrodzka (2018). But studies concerning the issue so far have not been very numerous. The majority of authors unanimously emphasise that more in-depth research, both of theoretical and empirical nature, is required.

2. Research method

This research uses the method of soft modelling developed by H. Wold (1980, 1982). It allows users to examine links between variables which are not directly observable (latent variables). The values of these variables cannot be directly gauged because of the lack of a widely accepted definition or method of their measurement. The soft model consists of two sub-models: an internal one (structural model) and an external one (measurement model).

The internal sub-model describes dependencies between latent variables implied by the assumed theoretical model. Formally, according to Rogowski (1990: 34), the internal sub-model can be expressed as:

$$\mathbf{\Xi_{end}} = \mathbf{\Xi_{end}}\,\mathbf{B} + \mathbf{\Xi_{egz}}\mathbf{C} + \mathbf{V}, \tag{1}$$

where

$\mathbf{B} = [b_{ij}]$ – n-square matrix with a diagonal of zeroes,

$\mathbf{C} = [c_{ij}]$ – $((k\text{-}n)\times n)$ – dimensional matrix of structural parameters associated with endogenous and predetermined variables, respectively,

$\mathbf{V} = [v_j]$ – n-dimensional vector of random components with expected values equal to zero and finite variances,

$\mathbf{\Xi_{end}} = [\xi_1, \ldots, \xi_n]$ – n-dimensional row vector of unlagged endogenous variables,

$\mathbf{\Xi_{egz}} = [\xi_{n+1}, \ldots, \xi_k]$ – $(k\text{-}n)$-dimensional row vector of predetermined theoretical variables.

Additionally, it is assumed that the random component of the j-th equation v_j is not correlated with this equation's independent variables ($j = 1, \ldots, n$).

In the external model, latent variables are defined by means of observable variables (indicators). The indicators allow for indirect observation of the latent variables and are selected on the basis of a theory or the researcher's intuition. A latent variable can be defined inductively: the approach is based on the assumption that indicators form latent variables (formative indicators), or deductively, based on the premise that indicators reflect their theoretical notions (reflective indicators). In the deductive approach, a latent variable – as a theoretical notion – is a starting point in the search for empirical data (the variable precedes a given indicator). In the inductive approach, it is indicators that precede the latent variable which they form. Under both approaches, latent variables are estimated as weighted sums of their indicators. However, depending on the definition, indicators should have different statistical properties – a lack of correlation in the case of the inductive definition and high correlation in the case of the deductive definition (Wold, 1982; Rogowski, 1990: 35-37).

The formal notation of external relations is as follows (Rogowski, 1990: 36-37):

$$\underset{j=1,\ldots,k}{\forall}\ \underset{t=1,\ldots,T}{\forall}\ \xi_{tj} = \sum_i w_{ij} x_{tij}\ . \tag{2}$$

Therefore, it is assumed that each latent variable is a weighted sum of its indicators. Moreover, for each reflective indicator, the relation measuring the strength of reflection is given:

$$\underset{j=1,\ldots,k}{\forall}\ \underset{t=1,\ldots,T}{\forall}\ x_{tij} = \pi_{ij0} + \pi_{ij}\xi_{tj} + \mu_{tij}\,, \tag{3}$$

where

ξ_{tj} – t-th values of variables, respectively, ξ_j and i-th indicator of this variable,

w_{ij} – weight associated with x_{ij}, when defining ξ_j,

π_{ij} – factor loading measuring the strength of reflection of the latent variable ξ_j by its *i*-th indicator,

μ_{tij} – random component with expected values equal to zero.

Moreover, it is assumed that random components are not correlated in time (no autocorrelation) or between equations, or with the latent variables. Additionally, a unit-variance ξ_j is also assumed in order to ensure uniqueness.

The estimation of soft model parameters is performed by means of the partial least squares method – PLS (Lomhmöller, 1989; Esposito Vinzi et al., 2010). The quality of the model is assessed using coefficients of determination (R^2), calculated for each equation. The significance of the parameters is analysed by means of standard deviations, calculated with the help of the Tukey's test. Besides, in the case of the external model, estimators of factor loadings can be treated as the degree of fit between each indicator and the latent variable which they define. The prognostic quality of the model is assessed by means of the Stone-Geisser test (S-G), which measures the accuracy of a prognosis performed on the basis of the model in juxtaposition to a trivial prognosis. The tests statistics take values from the range of $(-\infty,1>$. For an ideal model, the value of the test equals 1 (prognoses are accurate in comparison with trivial prognoses). If the value is equal to zero, the quality of the model's prognosis is, on average, identical to the quality of a trivial prognosis. Negative values indicate low quality of the model (worse predictive value of the model in comparison with a trivial prognosis).

By applying the PLS method, an estimation of values of the latent variables is made. They can be treated as values of synthetic measures and can be used to produce a linear ordering of the studied objects. These values depend not only on external relationships, but also on the relationships among the latent values assumed in the internal model. This means that the cognitive process is not only dependent on the definition of a given notion, but also on its theoretical description.

3. Specification of soft model

The model which was used for realisation of the research objective contained the following equation:

$$SG_t = \alpha_1 SC_t + \alpha_0 + v, \quad (4)$$

where SC_t – social capital in year t, SG_t – the level of smart growth in year t, α_0, α_1 – structural parameters of the model, v – random component.

The latent variables *SC* and *SG* are defined by means of observable variables on the basis of the deductive approach, i.e. the latent variable, as a theoretical concept, serves as a starting point to identify empirical data. The statistical data come from the Eurostat and European Innovation Scoreboard (EIS) databases. The indicators for the model were selected based on criteria of substantive and statistical nature. Using the available domestic and international literature, primary sets of indicators of the variables *SC* and *SG* were developed. The methodologies used comprised, among others, 'Knowledge Assessment Methodology' (Chen and Dahlman, 2005), 'European Innovation Scoreboard Methodology' (European Commission, 2017) and 'Social participation and integration statistics' (Eurostat, 2017) – ad-hoc module of EU statistics on income and living conditions (EU-SILC). The selection of research period (2015) was determined by the availability of statistical data. The developed database was checked in terms of missing data. Data shortages were overcome by using naive prognosis, consisting in replacing a lacking value with the value for the previous year. The choice of such a forecasting method was related to the fact that for indicators: *SC*8, *INN1*, *INN*2, *INN*3 only short time series were available. Forecasts by naive methods are unfortunately not accurate and can only be verified after the implementation of forecasts

From the statistical point of view, the following considerations were taken into account: variability of indicator values (coefficient of variation above 10%) and an analysis of the quality of the estimated model (an *ex post* analysis). The indicators which passed substantive and statistical verification are presented in Tables 1 and 2.

The *SC* latent variable is defined by nine indicators. One indicator – 'Frequency of getting together with relatives and friends – never' (*SC*5) is a destimulant, i.e. the higher the value of this indicator, the lower the level of the *SC* latent variable. The rest of indicators are stimulants, i.e. the higher the value of the indicator, the higher the level of the *SC* latent variable. The indicators *SC*1, *SC*2, *SC*3 relate to the involvement of the individuals in matters relating to society. The *SC*4 and *SC*5 indicators reflect the strength of informal social ties. The *SC*7 indicator relates to professional cooperation between individuals, while indicators *SC*6, *SC*8 and *SC*9 concern cooperation between selected organizations (enterprises, universities, research units).

The *SG* latent variable is defined by thirteen indicators. All of them are stimulants. Six indicators: *KNOW*1, *KNOW*2, *KNOW*3, *KNOW*4, *KNOW*5, *KNOW*6 relate to the level of knowledge of society, meanwhile seven indicators: *INN*1, *INN*2, *INN*3, *INN*4, *INN*5, *INN*6, *INN*7 reflect the level of innovation of country.

Table 1. Indicators of social capital

Symbol of indicator	Indicator	Year[1]	Source
*SC*1	Participation in voluntary activities – formal (% of people aged 16 and over)	2015	EU-SILC
*SC*2	Participation in voluntary activities – informal (% of people aged 16 and over)	2015	EU-SILC
*SC*3	Active citizens[2] (% of people aged 16 and over)	2015	EU-SILC
*SC*4	Frequency of getting together with relatives and friends – every week (% people aged 16 and over)	2015	EU-SILC
*SC*5	Frequency of getting together with relatives and friends – never (% people aged 16 and over)	2015	EU-SILC
*SC*6	Public-private co-publications (per million population)	2015	EIS
*SC*7	International scientific co-publications (per million population)	2015	EIS
*SC*8	Innovative SMEs collaborating with others (% of SMEs)	2014	EIS
*SC*9	Private co-funding of public R&D expenditures (% of GDP)	2015	EIS

Source: author's own elaboration

Table 2. Indicators of smart growth

Symbol of indicator	Indicator	Year[1]	Source
*KNOW*1	Researchers (% of total employment)	2015	Eurostat
*KNOW*2	Researchers in business enterprise sector (% of total employment)	2015	Eurostat
*KNOW*3	New doctorate graduates (per 1000 population aged 25-34)	2015	EIS
*KNOW*4	Scientific publications among the top 10% most cited publications worldwide (% of total scientific publications of the country)	2014	EIS
*KNOW*5	R&D expenditure in the public sector (% of GDP)	2015	EIS
*KNOW*6	R&D expenditure in the business sector (% of GDP)	2015	EIS
*INN*1	SMEs introducing product or process innovations (% of SMEs)	2014	EIS
*INN*2	SMEs introducing marketing or organisational innovations (% of SMEs)	2014	EIS
*INN*3	SMEs innovating in-house (% of SMEs)	2014	EIS
*INN*4	PCT patent applications (per billion GDP, in PPS)	2014	EIS
*INN*5	Employment in knowledge-intensive activities (% of total	2015	EIS

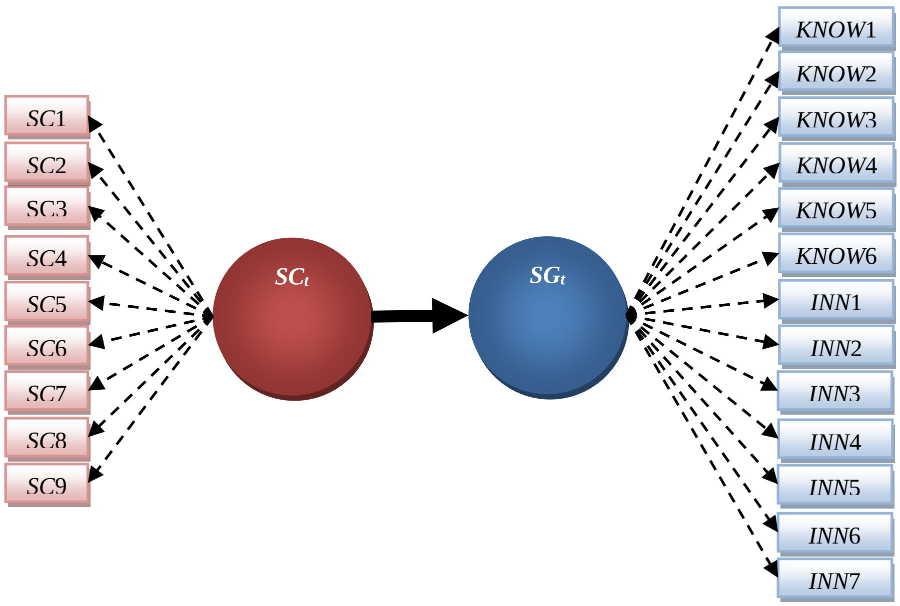
[1] Most recent year for which data are available.
[2] Active citizenship in the 2015 ad-hoc module is understood as participation in activities related to political groups, associations or parties, including attending any of their meetings or signing a petition.

	employment)		
*INN*6	Exports of medium and high technology products (as a share of total product exports)	2015	EIS
*INN*7	Knowledge-intensive services exports (% of total services exports)	2015	EIS

Source: author's own elaboration

A schematic diagram of the soft model, taking into consideration both the internal and external relationships is presented in Figure 1[3].

Figure 1. Diagram of internal and external relationships in the soft model



Source: author's own elaboration

The model was estimated using the PLS method, which enables simultaneous estimation of the external model parameters (weights and factor loadings) and the internal model parameters (structural parameters). The estimation was conducted with the help of PLS software.[4]

4. Results of estimation

The results of the estimation of the external model are presented in Table 3. Each weight represents the relative share of a given indicator's value in the estimated value of a latent variable.

[3] The solid line represents an internal model relationship, while the broken line – external model relationships.
[4] The software was developed by Prof. J. Rogowski from the Faculty of Economics and Management, University of Bialystok and is free of charge.

Factor loadings are coefficients of correlation between indicators and latent variables, thus indicating the degree and direction in which the variability of an indicator reflects the variability of a latent variable. The ordering of indicators according to weight is performed when a latent variable is defined inductively. In the deductive approach, which was applied in this research, it is the factor loadings that are interpreted. The following interpretation of the π_{ij} factor loading was assumed (Nowak, 1990: 92-93): $|\pi_{ij}| < 0.2$ – no correlation, $0.2 \leq |\pi_{ij}| < 0.4$ – weak correlation, $0.4 \leq |\pi_{ij}| < 0.7$ – moderate correlation, $0.7 \leq |\pi_{ij}| < 0.9$ – strong correlation, $|\pi_{ij}| \geq 0.9$ – very strong correlation.

In terms of the signs of the estimated parameters, the results are consistent with the expectations. Stimulants have positive estimations of weights and factor loadings, whereas a destimulant has negative ones. Moreover, all the parameters are statistically significant, in accordance with the '2s' principle (see Table 3, column "Standard deviation").

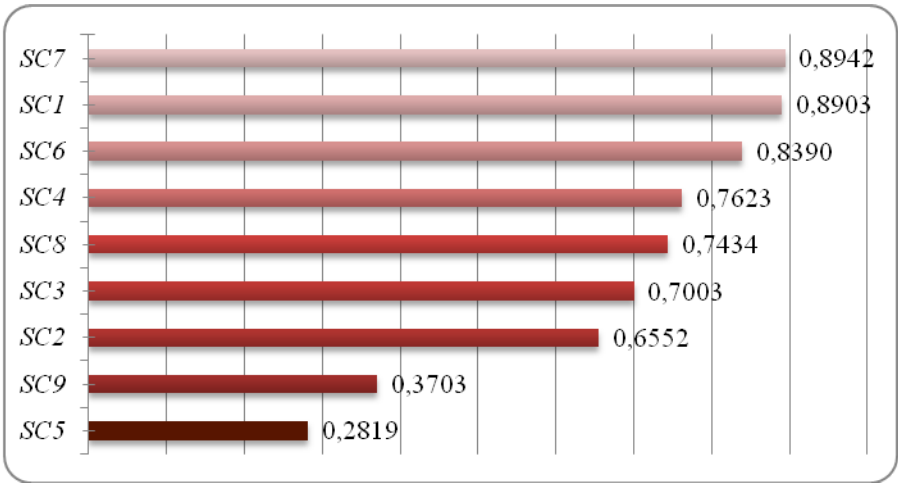
Table 3. Estimations of external relationships parameters in the soft model

Symbol of indicator	Weight	Standard deviation	Factor loading	Standard deviation
***SC* latent variable**				
*SC*1	0.2000	0.0041	0.8903	0.0013
*SC*2	0.1169	0.0065	0.6552	0.0040
*SC*3	0.1592	0.0053	0.7003	0.0034
*SC*4	0.1753	0.0056	0.7623	0.0010
*SC*5	-0.0297	0.0036	-0.2819	0.0037
*SC*6	0.1930	0.0053	0.8390	0.0022
*SC*7	0.2041	0.0021	0.8942	0.0012
*SC*8	0.1645	0.0041	0.7434	0.0028
*SC*9	0.0678	0.0038	0.3703	0.0031
***SG* latent variable**				
*KNOW*1	0.1103	0.0084	0.8575	0.0243
*KNOW*2	0.1216	0.0074	0.9191	0.0178
*KNOW*3	0.0877	0.0062	0.6918	0.0219
*KNOW*4	0.1118	0.0025	0.8650	0.0073
*KNOW*5	0.0954	0.0102	0.6683	0.0866
*KNOW*6	0.1106	0.0074	0.8469	0.0255
*INN*1	0.1031	0.0076	0.8569	0.0397
*INN*2	0.0919	0.0092	0.8002	0.0287
*INN*3	0.0983	0.0117	0.8200	0.0654
*INN*4	0.1200	0.0021	0.8764	0.0044
*INN*5	0.0891	0.0159	0.7052	0.0637
*INN*6	0.0246	0.0045	0.2692	0.0643
*INN*7	0.0893	0.0096	0.6909	0.0252

Source: author's own elaboration

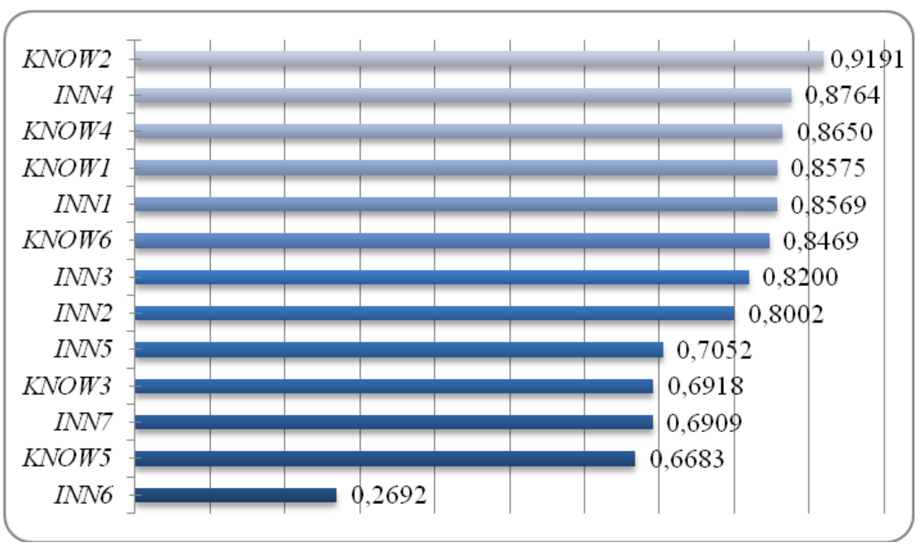
The indicators reflect *SC* latent variable with varying strength (see Figure 2). The variable is moderately correlated with one indicator: 'Participation in voluntary activities – informal' (*SC*2) and weakly correlated with two indicators: 'Private co-funding of public R&D expenditures' (*SC*9) and 'Frequency of getting together with relatives and friends – never' (*SC*5). Six other indicators (*SC*7, *SC*1, *SC*6, *SC*4, *SC*8, *SC*3) strongly reflect *SC* variable.

Figure 2. Estimations of factor loadings of *SC* latent variable (absolute values)[5]



Source: author's own elaboration

Figure 3. Estimations of factor loadings of *SG* latent variable



Source: author's own elaboration

[5] Darker colour relates to the destimulant.

The indicator ‘Researchers in business enterprise sector’ (*KNOW*2) reflect the *SG* variable most strongly (see Figure 3). Moreover the variable is strongly reflected by seven indicators: *INN*4, *KNOW*4, *KNOW*1, *INN*1, *KNOW*6, *INN*3, *INN*2. Four following indicators: ‘Employment in knowledge-intensive activities’ (*INN*5), ‘New doctorate graduates’ (*KNOW*3), ‘Knowledge-intensive services exports (% of total services exports)’ (INN7), ‘R&D expenditure in the public sector’ (KNOW5) are moderately correlated with the variable, but the values of their factor loadings are relatively high (higher than 0.65). One indicator – ‘Exports of medium and high technology products ’ (*INN*6) is weakly linked with the variable.

The outcomes of the internal model estimation are illustrated by the following equation.

$$SG_{2015} = \underset{(0.0146)}{0.9357} \cdot SC_{2015} + \underset{(0.1050)}{0.5647} \qquad R^2 = 0.88 \tag{2}$$

The brackets contain standard deviations calculated by means of the Tukey's test. The structural parameters are statistically significant (‘2s’ rule). The value of the coefficient of determination R^2 justifies the conclusion that, to a very high extent, the independent variable *SC* determines the variability of the dependent variable *SG*. The values of the Stone-Geisser test, which verifies the soft model in terms of its predictive usefulness (see Table 4) are positive, which proves the model's high prognostic quality. The indicator ‘Exports of medium and high technology products’ (*INN*6) has the weakest predictive power, while ‘Researchers in business enterprise sector’ (*KNOW*2) is the strongest one.

Table 4. Values of the Stone-Geisser test

Symbol of indicator	**Value of S-G test**
*KNOW*1	0.5535
*KNOW*2	0.6605
*KNOW*3	0.3354
*KNOW*4	0.5889
*KNOW*5	0.3795
*KNOW*6	0.5347
*INN*1	0.5058
*INN*2	0.4020
*INN*3	0.4165
*INN*4	0.6336
*INN*5	0.3301
*INN*6	0.0313
*INN*7	0.3755
General value	0.3621

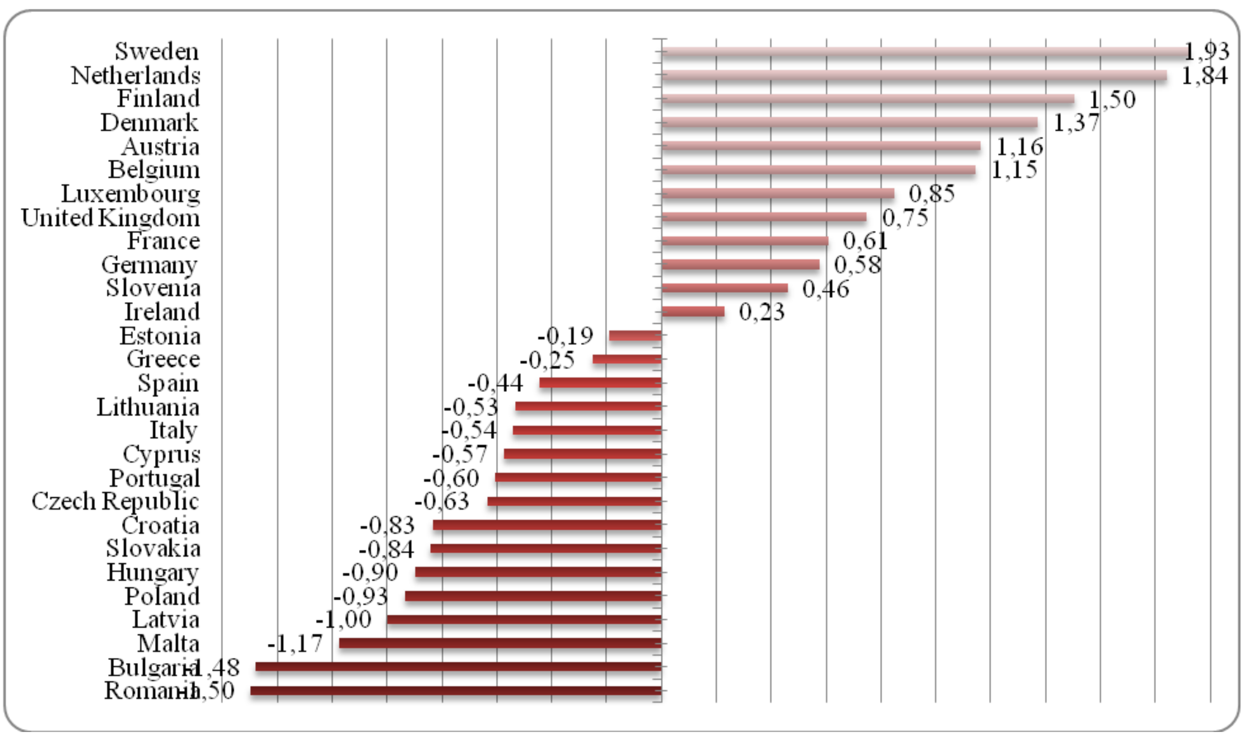
Source: author’s own elaboration

The estimation of the internal model parameters indicates a strong, positive and significant correlation between social capital and smart growth in the studied group of 28 European Union countries in 2015. This means that those countries which reported higher level of social capital had also a higher level of smart growth in that year. Furthermore, the impact of social capital on smart growth was very strong.

Apart from examining the relationship between latent variables, soft modelling also helps estimate the values of these variables (weighted sums of indicators). Therefore, for each of the latent variable in the model, a synthetic measurement is calculated, which can be used to obtain a linear ordering of the analysed objects. The results of estimations are shown in Figures 4 and 5.

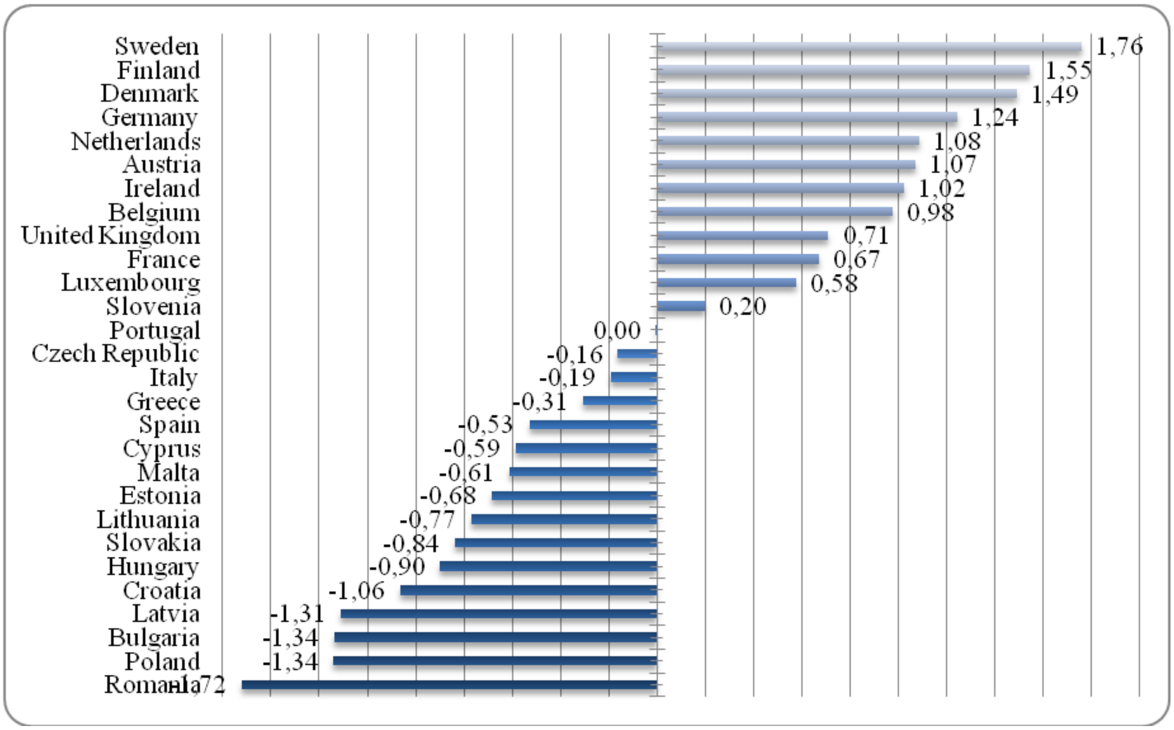
Basing on the synthetic measurements of the variables *SC* and *SG*, two rankings of the studied countries were compiled: a ranking of social capital and a ranking of the level of smart growth. The results are shown in Table 5.

Figure 4. Estimations of *SC* latent variable values



Source: author's own elaboration

Figure 5. Estimations of *SG* latent variable values



Source: author's own elaboration

The countries also were divided into typological groups according to similar social capital stock and similar smart growth level. The results of the grouping are presented in Figures 6 and 7. The boundaries between the groups were established on the basis of the arithmetic mean and standard deviation of the synthetic measure z_i (equal to 0 and 1, respectively, for each of the latent variables). The groups are as follows: Group I. (a very high level of the latent variable): $z_i \geq 1$; Group II. (a high level of the latent variable): $0 < z_i \leq 1$; Group III. (a medium and low level of the latent variable): $-1 < z_i \leq 0$; Group IV. (a very low level of the latent variable) $z_i \leq -1$.

In 2015, the following countries boasted very high stocks of social capital (see Figure 6): Sweden, the Netherlands, Finland, Denmark, Austria and Belgium. Six countries were classified in the group with a high stock of social capital: Luxembourg, the United Kingdom, France, Germany, Slovenia and Ireland. The group with medium and low stocks of social capital comprised thirteen countries: Estonia, Greece, Spain, Lithuania, Italy, Cyprus, Portugal, the Czech Republic, Croatia, Slovakia, Hungary, Poland and Latvia. Very low stocks of social capital were recorded only in three countries: Malta, Bulgaria and Romania.

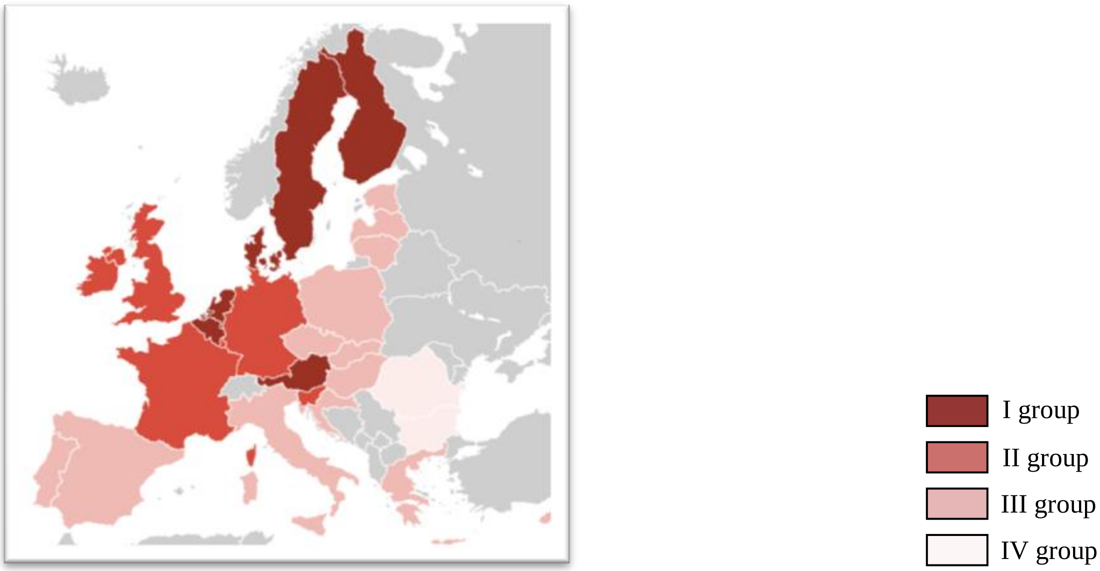
Seven countries made up the group with a very high level of smart growth in 2015 (see Figure 7), namely: Sweden, Finland, Denmark, Germany, the Netherlands, Austria and Ireland. The group of countries with a high level of smart growth included: Belgium, the United Kingdom, France, Luxembourg and Slovenia. The third group of medium- and low-social capital economies was comprised of: Portugal, the Czech Republic, Italy, Greece, Spain, Cyprus, Malta, Estonia, Lithuania, Slovakia and Hungary. Very low stocks of social capital were recorded in: Croatia, Latvia, Bulgaria, Poland and Romania.

Table 5. Rankings of the EU countries according to the stock of social capital and the level of smart growth in 2015

Country	SC_{2015}	SG_{2015}
Austria	5	6
Belgium	6	8
Bulgaria	27	26
Croatia	21	24
Cyprus	18	18
Czech Republic	20	14
Denmark	4	3
Estonia	13	20
Finland	3	2
France	9	10
Germany	10	4
Greece	14	16
Hungary	23	23
Ireland	12	7
Italy	17	15
Latvia	25	25
Lithuania	16	21
Luxembourg	7	11
Malta	26	19
Netherlands	2	5
Poland	24	27
Portugal	19	13
Romania	28	28
Slovakia	22	22
Slovenia	11	12
Spain	15	17
Sweden	1	1
United Kingdom	8	9

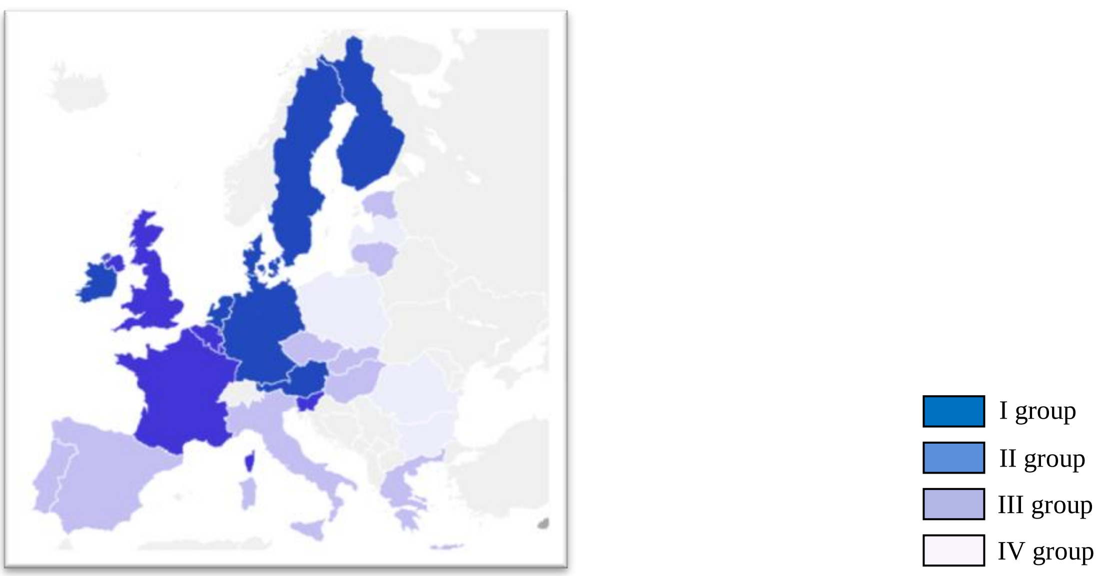
Source: author's own elaboration

Figure 6. The EU countries according to the stock of social capital in 2015



Source: author's own elaboration

Figure 7. The EU countries according to the level of smart growth in 2015



Source: author's own elaboration

4. Conclusion

The article examines the role which social capital plays in the processes of smart growth in the EU countries. The conducted research is unique, because most of the existing literature focuses on the role of social capital for economic growth and not for knowledge, innovation or smart growth. The development of the concept of smart growth and the theory of social capital is still on-going and new, significant works in this field can be expected, due to which the mechanisms will be better understood and the progress of detailed research will be improved.

The results of the study proved that there is a very strong, positive correlation between the social capital of the EU countries and the level of their smart growth. Moreover, the outcomes of the research have enabled to identify the key aspects of social capital and smart growth. In the case of social capital, it is cooperation among organizations while in the case of smart growth, the level of knowledge as well as the level of innovation turn out to be equally important. The conclusions formulated above can be used in practice by governmental institutions, for example for planning the economy policy as well as innovation policy of countries.

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Kapitał społeczny a inteligentny rozwój krajów Unii Europejskiej

Streszczenie

Kapitał społeczny zgodnie z definicją OECD to sieci wraz ze wspólnymi normami, wartościami i przekonaniami, które ułatwiają współpracę w ramach określonej grupy lub pomiędzy grupami. Obecnie kapitał społeczny jest uznawany za jeden z kluczowych czynników rozwoju gospodarczego. Większość istniejącej literatury koncentruje się na roli kapitału społecznego we wzroście gospodarczym, tymczasem przedmiotem niniejszych badań jest związek kapitału społecznego z inteligentnym rozwojem krajów UE. Inteligentny rozwój opiera się na wiedzy i innowacjach. Pojęcie inteligentnego rozwoju, jego czynniki i metody pomiaru to nowe kategorie, które wynikają z koncepcji strategicznych celów rozwoju UE. Ze względu na nieobserwowalność kapitału społecznego oraz inteligentnego rozwoju w badaniach zastosowano metodę modelowania miękkiego, która pozwala na pomiar i analizę zależności między zmiennymi nieobserwowanymi bezpośrednio (zmiennymi ukrytymi).

Słowa kluczowe: kapitał społeczny, inteligentny rozwój, Unia Europejska, modelowanie miękkie.