International Technology Transfer and Smart Growth of EU countries in 2010-2015

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Abstract

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. Technology transfer, meanwhile, is a multidimensional process, whose effects include both the implementation and diffusion of technologies in new economic environments. It is regarded as one of the key factors behind diminishing technology gaps and a driver of innovation-based growth. International transfer of technology involves those technologies which have been devised in a country different from that where they are implemented. The purpose of the present paper is to examine the role that international technology transfer plays in the development of EU countries. Owing to the fact that neither of the two categories is measurable, the study uses a soft-modelling method which allows for measuring and analysis of the relationships among the latent variables.

Keywords: *international technology transfer, smart growth, European Union, soft modelling*

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1 Introduction

Modern economies operate in the conditions of globalization, considerable developmental disparities, and technology gaps. Transfer of technology (TT), as a multidimensional process consisting in implementation and diffusion of technologies in new economic environments is considered to be a key factor which helps narrow development gaps and which determines development based on innovation (Ciborowski, 2015).

Technology can be defined as the ability to apply knowledge for solving practical problems and achieving utilitarian goals, or as a collection of methods and procedures allowing its users to obtain certain resources and transform them into useful products (Kubielas, 2009). A new technology can be an outcome of own R&D efforts, production experience, knowledge derived from relevant literature published elsewhere in the world, purchase of patents, recruitment of human capital, collaboration among enterprises and higher education institutions, takeovers of companies, joint ventures, purchase of licences, know-how, or research contracts (Freeman, 1992). The significance of technology for economic

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growth and development is emphasised in both theoretical and empirical models. Historical analyses also indicate that TT, combined with accumulation of domestic technologies, lies at the core of accelerated economic growth (Hoekman et al., 2005; Saggi, 2002).

TT is not a new phenomenon. Authors stress, however, that it is still difficult to agree on a definition of the term, among other things, because of the complex nature of the process and the variety of components that must be taken into account (Ciborowski, 2016). TT can be defined in two ways: narrowly and broadly. As an example of a narrow approach can serve the UNCTAD definition, according to which the process of technology transfer is a mechanism as a result of which, through agreements concluded between parties (a supplier and a recipient), diffusion of technology takes place (UNCTAD, 2005). This interpretation is practically limited to indicating the participants of the process and the necessity of co-operation between them. Meanwhile, the broad approach to defining technology transfer makes it possible to consider the process of creating technology and knowledge, its conveyance to the place where it is implemented, as well as the eventual acceptance and implementation of the technology by the final user (Ciborowski, 2016).

Not only defining of TT, but also its measurement is far from easy. This is caused, among other things by the difficulty in making a clear-cut distinction between its particular stages and effects. Transfer of technology is a phenomenon that has many aspects and dimensions. Its constituent elements frequently overlap, and their consequences are ambiguous. In the majority of studies, authors focus on analysing individual, selected components of technology transfer or, alternatively, on a part of the process which can be distinguished and measured quantitatively. The lack of a universal and comprehensive measure makes macroeconomic analysis and international comparisons rather difficult (Ciborowski, 2016).

International technology transfer (ITT) refers to technologies devised in a country other than that in which they are implemented. There are numerous channels through which technology may be transferred across international boundaries. One major channel is trade in goods, especially capital goods and technological inputs. A second is foreign direct investment (FDI), which may be expected generally to transfer technological information that is newer or more productive than that of local firms. A third is technology licensing, which may be done either within firms or between unrelated firms at arm's-length. Licenses typically involve the purchase of production or distribution rights (protected by some intellectual property right) and the technical information and know-how required to make effective the exercise of those rights. In this regard patents, trade secrets, copyrights, and trademarks serve as direct means of information transfer (Maskus, 2004).

The purpose of this study is to examine the role which ITT 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 (EU Commission, 2010). Although the concept of smart growth is relatively new, it has already been discussed by other authors, but studies concerning the issue are so far not very numerous. Authors unanimously emphasize that more in-depth research, both of theoretical and empirical nature, is required.

In this paper it was assumed that the level of smart growth can be defined by two aspects:

- by knowledge that is created and developed within the R&D sector,
- by the level of innovation in the economy, which is reflected by the innovative activity of individuals and enterprises.

This paper proposes the following research hypothesis: ITT has a positive impact on the level of smart growth of EU countries. Because of the multi-dimensional and intangible character of both phenomena, a soft-modelling method was applied. The obtained results have allowed the author to verify a research hypothesis, identify the channels of technology transfer that are the most significant for ITT processes in EU states, identify the most crucial aspects of smart growth, and order the countries according to the size of ITT and level of smart growth. The study encompasses the years 2010-2015, the selection of which was determined by the availability of statistical data. Two soft models are estimated: one for the beginning of the studied period (2010), the other for its end (2015).

2 Soft modelling method

The soft modelling method (in the literature also referred to as PLS Path Modeling) was developed by H. Wold (1980). The method makes it possible to investigate relations between variables which are not directly observable (latent variables). The values of such variables cannot be measured in a straightforward manner because of the lack of a widely accepted definition or a uniform 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 depicts the relationships between the latent variables on the basis of the assumed theoretical description. The external sub-model defines latent variables by means of observable variables (indicators). Indicators allow for direct observation of latent variables and are selected according to the assumed theory or the intuition of the researcher. A latent variable can either be defined (with the use of indicators) inductively: the approach is based on the assumption that the indicators make up latent variables (formative indicators), or deductively: when it is assumed that indicators reflect the respective theoretical notions (reflective indicators). Under the deductive approach, the latent variable, as a theoretical notion, is a point of departure for a search of empirical data (the variable is primary to a given indicator). In the inductive approach, it is the indicators that are primary to the latent variable which they comprise. Both the approaches use latent variables that are estimated as the weighted sums of their indicators. However, depending on the definition, indicators should be characterized by different statistical properties – no correlation in the case of inductive definition and high correlation in the deductive one (Rogowski, 1990).

The estimation of the parameters of the soft model is performed by means of the partial least squares method (PLS method). The description of the method can be found in: Boardman et al. (1981), Lohmoller (1988), Westland (2005). The quality of the model is assessed with the use of determination coefficients (R^2), established for each equation. The significance of the parameters is checked by means of the standard deviations calculated with the Tukey's cut method ('2s' rule: a parameter significantly differs from zero if double standard deviation does not exceed the value of the estimator of this parameter). Besides, in the case of the external submodel, the estimators of factor loadings can be treated as the degree in which the indicators match the latent variable that they define. The prognostic property of model can be evaluated by means of the Stone-Geisser test [3], which measures the accuracy of the forecast obtained as a result of the model's application as compared with a trivial forecast. The test statistics take values from the range $<-\infty,1>$. In the ideal model, the value of the test equals 1 (the forecasts are perfectly accurate in comparison with trivial forecasts). When the value of the test equals zero, the quality of the model's forecast and the trivial forecast tend to be virtually identical. Negative values indicate a low quality of the model (its weak predictive usefulness compared with a trivial forecast).

Using the partial least squares method, it is possible to obtain the estimated values of latent variables, which can be regarded as the values of synthetic measures. They can be employed for linear ordering of the examined objects. These values depend not only on the external relationships, but also on the relationships between the latent variables which are assumed for the internal model. This means that the cognitive process hinges not merely on the definition of a given notion, but also on its theoretical description (Rogowski, 1990).

3 Model specification

The model used in the present paper to reach its aim of determining the influence of ITTon the level of smart growth contains the following equation

$$SG_t = \alpha_1 ITT_t + \alpha_0 + \xi \quad (1)$$

where *SG* – the level of smart growth,*ITT* – international technology transfer,α_0, α_1 – structural parameters of the model, ξ – random parameter,*t* – year 2010 or 2015.

The latent variables *ITT* 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 World Bank 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 *ITT* and *SG* were developed. The methodologies used comprised, among others, 'Knowledge Assessment Methodology' (Chen and Dahlman, 2005) and 'European Innovation Scoreboard Methodology' (EU Commission, 2017). 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 an adjacent one. Two countries, Greece and United Kingdom, were excluded from the estimation (due to significant data shortages).

From the statistical point of view, the following considerations were taken into account: variability of indicator values (coefficient of variation above 10%) and analysis of the quality of the estimated model (ex post analysis).

The set of indicators reflecting *ITT*:

*ITT*01 – Foreign direct investment, net inflows as % of GDP (%).

*ITT*02 – High-tech import as % of total (%).

*ITT*03 – Product and/or process innovative enterprises, engaged in any type of innovation co-operation with a partner in EU countries, EFTA or EU candidates countries (% of total).

*ITT*04 – Product and/or process innovative enterprises, engaged in any type of innovation co-operation with a partner in United States (% of total).

*ITT*05 – Product and/or process innovative enterprises, engaged in any type of innovation co-operation with a partner in China or India (% of total).

The set of indicators reflecting *SG*:

*KNOW*01 – Researchers as percentage of total employment (%).

KNOW02 – Researchers in business enterprise sector as percentage of total employment (%).

*KNOW*03 – Graduates in tertiary education, in science, mathematics, computing, engineering, manufacturing, construction per 1000 of population aged 20-29 (person).
*KNOW*04 – Graduates at doctoral level, in science, mathematics, computing, engineering, manufacturing, construction per 1000 of population aged 25-34 (person).
*KNOW*05 – Scientific and technical journal articles per 1 million inhabitants (number).
*INNO*01 – Patent applications to the EPO per 1 million inhabitants (number).
*INNO*02 – Exports of high technology products as a share of total exports (%).
*INNO*03 – Product and/or process innovative enterprises as percentage of total (%).
*INNO*04 – Organization and/or marketing innovative enterprises as percentage of total (%).
*INNO*05 – Total turnover of innovative enterprises as percentage of GDP (%).
*INNO*06 – Charges for the use of intellectual property (receipts) as percentage of GDP (%).

The data on three of the indicators *ITT*01, *KNOW*05, *INNO*06 were obtained from the World Bank database, while all the others from the Eurostat.All the indicators qualified for the model were stimulants of latent variables.

4 Results

Table 1 presents the estimations of factor loadings (parameters of the external model). Because of the adopted deductive approach, estimations of weights are not given.

As was expected, the estimations of the factor loadings for all the indicators were positive. However, not all the indicators proved to be statistically significant. In 2010, six indicators, *ITT*01, *ITT*02, *KNOW*03, *INNO*02, *INNO*04, and *INNO*06 had no statistical significance, while in 2015, only one of them – *KNOW*03.

Both in 2010 and 2015, indicators *ITT*04 and *ITT*05 were strongly or very strongly correlated with the ITT variable[2]. As for the *SG* variable, the correlated indicators included: *KNOW*01, *KNOW*02, *KNOW*05, and *INNO*01. The *ITT* variable was insignificantly (2010) or moderately significantly (2015) reflected by indicators *ITT*01 and *ITT*02. The *SG* variable was insignificantly or weakly (depending on the year) associated with the following indicators: *KNOW*03, *INNO*02, *INNO*04, *INNO*05, and *INNO*06.

[2]The following interpretation of factor loading ρ were adopted: $|\rho| < 0.2$ – no correlation; $0.2 \le |\rho| < 0.4$ – weak correlation; $0,4 \le |\rho| < 0,7$ – moderate correlation; $0.7 \le |\rho| < 0.9$ – strong correlation; $|\rho| \ge 0.9$ very strong correlation.

Table 1. Estimations of factor loadings in soft model 2010 and soft model 2015.

Symbol of indicator	Soft model 2010 Factor loading	Soft model 2010 Standard dev.	Soft model 2015 Factor loading	Soft model 2015 Standard dev.
*ITT*01	0.251	0.277	0.402	0.062
*ITT*02	0.205	0.286	0.588	0.048
*ITT*03	0.723	0.252	0.602	0.042
*ITT*04	0.964	0.270	0.929	0.018
*ITT*05	0.957	0.280	0.872	0.033
*KNOW*01	0.834	0.341	0.856	0.043
*KNOW*02	0.956	0.233	0.939	0.048
*KNOW*03	0.066	0.298	0.234	0.144
*KNOW*04	0.609	0.389	0.710	0.028
*KNOW*05	0.866	0.291	0.878	0.025
*INNO*01	0.893	0.290	0.859	0.057
*INNO*02	0.282	0.279	0.393	0.056
*INNO*03	0.628	0.210	0.548	0.114
*INNO*04	0.018	0.210	0.338	0.130
*INNO*05	0.336	0.169	0.494	0.078
*INNO*06	0.072	0.320	0.563	0.069

$$\underset{}{\hat{S}G_{2010}} = \underset{(0.101)}{0.641} \cdot ITT_{2010} + \underset{(0.855)}{0.587}, \quad \mathrm{R}^2 = 0.41, \tag{2}$$

$$\hat{S}G_{2015} = \underset{(0.017)}{0.667} \cdot ITT_{2015} + \underset{(0.181)}{1.129}, \quad \mathrm{R}^2 = 0.44. \tag{3}$$

Positive values of the estimated parameters of the ITT_t variables are consistent with expectations.Also, both parameters are significantly different from zero (in accordance with the '2s' rule). The values of the coefficient of determination R^2 are not high, suggesting that the independent variables ITT_t determine the variability of the dependent variables SG_tonly to a limited extent. The overall values of the S-G test are positive and stand at 0.087 for the 2010 model and 0.123 for the 2015 model. This proves that the prognostic capacity of the model estimated on the basis of 2015 data is better.

The obtained results indicate a positive, statistically different from zero, dependence between ITT and the level of smart growth in the studied countries in 2010 as well as in 2015. It can be concluded, therefore, that those countries where ITT was more intense were also characterised by higher levels of smart growth. ITT turns out to be a key factor of innovation growth in the entire studied group. The differences concern only its structure: transfer occurs via other channels and is embodied in different forms.

Table 2. Rankings of EU countries according to levels of international technology transfer and smart growth in 2010 and 2015.

Country	ITT_{2010}	SG_{2010}	ITT_{2015}		SG_{2015}	
Austria	10	7	11	↓	7	•
Belgium	9	8	10	↓	10	↓
Bulgaria	22	25	22	•	25	•
Croatia	19	21	19	•	22	↓
Cyprus	4	22	9	↓	21	↑
Czech Republic	14	14	13	↑	12	↑
Denmark	5	2	3	↑	4	↓
Estonia	17	12	6	↑	17	↓
Finland	1	1	5	↓	3	↓
France	8	11	14	↓	9	↑
Germany	21	4	20	↑	6	↓
Hungary	18	16	15	↑	16	•
Ireland	7	9	1	↑	5	↑
Italy	25	19	25	•	18	↑
Latvia	13	23	17	↓	23	•
Lithuania	15	20	21	↓	20	•
Luxemburg	3	5	7	↓	8	↓
Malta	11	15	16	↓	14	↑
Netherlands	16	6	8	↑	2	↑
Poland	**20**	**24**	**18**	↑	**24**	•
Portugal	24	13	26	↓	13	•
Romania	23	26	24	↓	26	•
Slovakia	12	18	4	↑	19	↓
Slovenia	6	10	12	↓	11	↓
Spain	26	17	23	↑	15	↑
Sweden	2	3	2	•	1	↑

Basing on the estimation of the value of latent variables, rankings of the analysed countries according to ITT size and smart growth level were compiled. The rankings are presented in Table 2.

When comparing the rankings, one notices considerable changes in the ordering of the countries in terms of international technology transfer (Spearman's rank correlation coefficient: 0.82) and relatively small changes in the innovation ranking (Spearman's rank correlation coefficient: 0.96). The following countries moved up spectacularly in the ITT rankings: Estonia (17th in 2010, 6th in 2015), Netherlands (16th in 2010, 8th in 2015), Slovakia (12th in 2010, 4th in 2015), Ireland (7th in 2010, 1st in 2015). Five countries recorded significant drops: Slovenia (6th in 2010, 12th in 2015), France (8th in 2010, 14th in 2015), Lithuania (15th in 2010, 21th in 2015), Cyprus (4th in 2010, 9th in 2015) and Malta (11th in 2010, 16th in 2015).

Poland took one of the last positions among European countries (24th position) in both the SG_{2010} and SG_{2015} rankings. Increasing international technology transfer, in particular a wider range of cooperation with innovative companies from USA, China and India may in the future affect the currently unfavourable situation of Poland in terms of the level of smart growth.

Conclusions

The conducted research has demonstrated that in the years 2010 and 2015, ITT was a significant determinant of smart growth in EU countries. Co-operation with partners from the USA, China and India proved to be the most important ITT channel. The significance of foreign direct investments and high-tech imports was either insignificant or limited. This can be due to the fact that the models took into consideration both highly-developed and less developed countries. The problem, therefore, requires further investigation, particularly in order to examine the impact of ITT on smart growth of highly-developed economies as compared with its influence on less developed ones.

The obtained results also make it possible to conclude that smart growth of EU countries was mainlybased on scientific and R&D activity (researchers, patents, papers in science journals) and that the influence of innovating companies is becoming increasingly important.

The formulated conclusions can be used in practice by government institutions, for example for planning the economy policy as well as innovation policy of countries.

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