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Assessing innovation efficiency: the case of post-communist EU member states

Ocena innowacyjnej efektywności post-komunistycznych krajów członkowskich UE

Abstract

Innovation plays a key role in driving progress and responding to the constantly changing economic, social, and technological requirements that modern economies face. This article assesses the innovative efficiency of the 11 post-communist EU member states in order to identify those that have achieved the weakest results in transforming pro-innovation inputs into innovative results. The Data Envelopment Analysis (DEA) method was used to estimate efficiency scores. The study analysed two models: Model A – covering 28 EU member states; and Model B – covering 16 EU countries and 12 countries from Europe, Asia and South America that are more similar in terms of economic development as measured by GDP per capita. The data on the input and output measures come from the 2015-2020 Global Innovation Index (GII) reports. The main findings indicate that among post-communist EU member states, Poland and Lithuania have achieved the lowest DEA-efficiency scores in transforming innovation inputs into innovations.

Keywords: innovation, DEA efficiency, post-communist EU member states.

JEL: C67, 031, 032

Streszczenie

Innowacje odgrywają kluczową rolę w napędzaniu postępu i kreowaniu odpowiedzi na zmieniające się potrzeby i wyzwania, przed którymi stają współczesne gospodarki w wymiarze ekonomicznym, społecznym czy technologicznym. Celem niniejszego artykułu jest ocena innowacyjnej efektywności 11 postkomunistycznych krajów członkowskich UE w celu zidentyfikowania tych, które osiągają najsłabsze wyniki w przekształcaniu proinnowacyjnych nakładów w innowacyjne rezultaty. Jako narzędzie do oszacowania efektywności została zastosowana metoda DEA. W badaniu dokonano analizy dwóch modeli: Modelu A – obejmującego 28 krajów członkowskich UE oraz Modelu B – obejmującego 16 krajów UE i 12 krajów z Europy, Azji i Ameryki Południowej, które są bardziej podobne pod względem rozwoju ekonomicznego mierzonego PKB na mieszkańca. Wykorzystane w badaniu dane dotyczące mierników nakładu i rezultatu pochodzą z raportów Global Innovation Index z lat 2015-2020. Główne ustalenia wskazują, że wśród postkomunistycznych krajów członkowskich UE, Polska i Litwa osiągają najniższe wyniki DEA-efektywności w przekształcaniu proinnowacyjnych nakładów w innowacje.

Słowa kluczowe: Innowacje, efektywność DEA, postkomunistyczne kraje UE.

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1. Introduction

J. A. Schumpeter (1934) defined innovation as the critical dimension of economic change and pursued the idea that innovation-initiated market power can bring better results than Smith´s 'invisible hand' and free-market price competition (Pol & Carroll, 2006). Innovation involves capitalising on new ideas to: create marketable new products, processes, or services; or exploit them in a manner that culminates in new products, services, or systems that add value, improve quality, or both. Innovation also implies using new technology to good advantage and employing 'out-of-the-box' thinking to generate new values and induce significant societal changes. Singh & Aggarwal (2022) applied a grounded theory approach to unify a definition of innovation. Their research revealed seven themes common to the various definitions of innovation: (i) creative potential; (ii) motivation; (iii) action; (iv) psychological processes; (v) ecological processes; (vi) newness; (vii) outcomes in the form of value creation, competitive advantage, harnessing technology and/ or invention, and economic growth. After synthesising 208 definitions, they define innovation as the operationalisation of creative potential with a commercial and/ r social motive by implementing new adaptive solutions that create value, harness new technology or inventions, and which contribute to competitive advantage and economic growth.

Innovation performance can be then understood as an innovation's improvement of the significance, usefulness, or performance of products or services and the competitive advantage it creates for innovation ecosystems (Robertson et al., 2023). It is broadly accepted that innovativeness is a crucial factor for a country's development (Hasan & Tucci, 2010; Gilbert, 2022; Posen et al., 2023). Filippopoulos & Fotopoulos (2022), building on the work of Gössling & Rutten (2007), point to the correlation between economic welfare and innovation: economic welfare is a precondition for innovation and innovation creates wealth, i.e. economic welfare. Fritsch & Slavtchev (2011) discovered that regions dominated by large establishments tend to be less efficient than regions whose establishments are smaller on average. Regional innovation systems differ in terms of quality and/or efficiency. This leads to different levels of innovative output even if the inputs are quantitatively and qualitatively identical. Moreover, Yin et al. (2022) stress the importance of rural innovation, which is interesting given that most post-communist EU member states are predominantly rural. There are many studies on innovation performance in the business sector and quite a few on public sector innovation performance in the developed countries of Western Europe, but comparatively few on the innovation performance of post-communist countries. These facts were a primary motivation for conducting the present research, which compares countries in terms of innovativeness and on the basis of data from the GII.

The GII is one of the most popular innovation-focused investigations. It is recognised worldwide for its annual country ranking based on the capacity for, and success in, innovation. The annual GII report aims to capture the multi-dimensional facets of innovation and provide tools to help devise policies to encourage long-term output growth, enhanced productivity, and job development. The GII is computed by calculating the simple arithmetic mean of the scores in two sub-indices: (i) the Innovation Input Index (III), which has 5 pillars; and (ii) the Innovation Output Index (IOI), which has 2 pillars. Each pillar is further divided into sub-pillars consisting of individual indicators (82 in total) (Kozuń-Cieślak, 2017). The GII dataset provides a country-level innovation efficiency score that captures innovation performance based on the output and input sub-index scores.

In this context, what makes innovation efficiency so important is that it is a way of quantifying a country's innovation capability; one that captures the potential transformation from realizing desired innovation outputs with a limited set of resources (innovation inputs) (Nigg-Stock et al., 2023). The present study contributes to the literature on evaluating innovative efficiency at the country level by applying the DEA method to determine which post-communist countries have performed worst in transforming their pro-innovative inputs into innovative outputs and to pinpoint their inefficiencies. This paper aims to analyse the innovative performances of 11 post-communist European Union (EU) member states in order to find the low achievers when it comes to transforming innovation inputs into innovation outputs. With this objective in view, the following research questions (RQ) were posed:

RQ1: Which post-communist EU member states are the least efficient of the EU member states in transforming innovation inputs into innovation outputs?

RQ2: Which post-communist EU member states are the least efficient, when included in a group of similar countries (selected on the basis of GDP proximity), in transforming innovation inputs into innovation outputs?

The answers to these questions should enhance our understanding of how to assess the innovativeness of selected countries and serve as a beneficial resource for policy-makers in formulating plans for the economic development of the EU and its member states.

The paper is structured in the conventional way. After the Introduction and Literature Review, the Methodology and Data are presented. DEA is applied to estimate the technical efficiency of two samples: (i) Model A, which comprises the 28 EU member states; and (ii) Model B, which comprises 16 EU member states and 12 other countries from Europe, Asia and South America, which are more similar in terms of economic development as expressed by GDP per capita. Then come the Results and discussion, on the main findings regarding previous studies. The final section summarises the conclusions.

2. Literature review

The recent literature abounds in studies examining various aspects and perspectives of innovativeness at the country level. Many studies consider the relationship between various economic and socio-cultural factors and a country's innovative potential or innovation drivers. These relationships are important as they elucidate the reasons for, and the method(s) by which, certain indicators are selected for composite indices, i.e. finding the correlations between various factors can determine the impact that these factors have on innovativeness. If significant, they qualify for inclusion in the GII. For example, Filippetti & Guy (2016) analysed the impact of internationalisation (as expressed by FDI) on innovation performance (expressed by patent applications) in 40 countries. The factor of internalisation was used by Genc et al. (2019), Elia et al. (2020), Leung & Sharma (2021) and Xiao & Sun (2022). Other authors combined internalisation with research and development (R&D), e.g. Laurens et al. (2022) and Puertas et al. (2022). Savrul & Incekara (2015) focused on the effect of R&D intensity on innovation performance. They found that positive environmental factors significantly impact a country in transforming its innovation investments to innovation performance. Sipa et al. (2016) focused on the relationship between R&D expenditure, R&D employment, public access to the Internet, and the number of patent applications submitted to the EPO in the Visegrád Group Countries. Bednář & Halásková (2018) analysed convergence and divergence related to innovation performance and R&D expenditures among Western European NUTS 2 regions, and illustrated the local variation of convergence and divergence, as well as general spatial regime divergence, in innovation performance and R&D expenditures within those regions. At the regional level, several NUTS 2 regions demonstrated convergence dynamics. However, the general spatial divergence regime should lead to more activities regarding R&D policies under the 2014-2020 EU programming period. Hervás-Oliver et al. (2021) also pointed out that innovation policies based on R&D may not be the most adequate to harness innovation in Europe and that collaboration and networks are more powerful drivers for regional innovation.

Kukharuk et al. (2017) aimed to identify the relationships between a country's economic development level and its innovation activity. They found, for example, that in Scandinavian and Asian countries, the relationships between the level of economic infrastructure, the degree of economic freedom, and innovation activity are direct and tight. By contrast, the impact of economic freedom on innovation activity is reasonably low, and the influence of the economic infrastructure is significant, in Western Europe. Raghupathi & Raghupathi (2017) examined OECD countries. They found that countries with low GDP rely on foreign collaboration for innovation, that education stimulates innovation, and that government and higher education have higher R&D expenditures than the private and non-profit sectors. In addition, Erdin & Çağlar (2023) analysed the national innovation efficiency of OECD countries and found that innovation efficiency was generally high. However, they concluded that these countries would be well advised to focus on how to create more innovation outputs.

Bariş (2019) analysed the OECD member countries to determine whether institutional quality influences innovative potential, and found that innovation is positively related to accountability, political stability and the rule of law. Shkolnykova et al. (2022) focused on the institutional dimensions and innovation systems of CEE countries. Stable institutions, e.g. freedom of the press and freedom of expression, positively affect innovativeness.

Murswieck et al. (2020) analysed the relationship between cultural dimensions and innovation performance within the 28 EU countries to determine whether cultural dimensions influence innovation performance. Using open data from the

Summary Innovation Index–European Innovation Scoreboard and Hofstede cultural dimensions, they identified innovation performance influencing factors in the form of enablers and blockers. Cultural-conditioned blockers within the innovation phases may explain why innovation is implemented more successfully in some countries than others and why some countries are more inclined to implement it than others.

Vītola (2015) identified the characteristics of the relationships between the different levels of government that had implemented innovation policies. Demircioglu & Audretsch (2017) examined innovative activity in the public sector, and found that important conditions specific to a public organisation influence the likelihood of innovative activity. In particular, experimentation, responding to low-performers, feedback loops, and motivation to make improvements enhanced the likelihood of innovative activity. In contrast, budget constraints did not have a statistically significant effect on a single innovation. Finally, they concluded that intrinsic factors such as experimentation and motivation to improve performance are crucial for achieving innovation in the public sector. Kozuń-Cieślak (2016) evaluated the innovativeness of 35 regions of the Visegrád countries (V4) by applying two quantitative approaches (based on R&D employment, R&D expenditure, and patent applications). These two approaches to evaluating innovation resulted in two different images of the V4 region, both surprising and disappointing. Odei et al. (2021) also examined the innovativeness of the Visegrád countries. Using probit regression analysis, they found that the main drivers of innovations in the V4 are competing in foreign markets, engaging in innovation activities such as R&D, and in-house training.

There are also several interesting studies which investigate innovation efficiency. Hudec (2015), having applied DEA, found that the Visegrád countries are not among the EU's most innovative or competitive. The findings show a substantial difference when innovation performance, as commonly evaluated, is replaced by efficiency scores. Another analysis of innovativeness, as a determinant of competitiveness of selected European countries, was carried out by Despotovic et al. (2016), who used cluster analysis to visualise the components of the pillar Innovation for 10 European countries classified as innovation leaders and innovation learners in 2013. The results revealed that they differed widely. Time series graphs for 2006–2015 were then applied for each of the clusters in the groups of countries under analysis. As most macroeconomic time series exhibit time dependence, the dynamic relations between them were analysed using the VAR (vector autoregression) model. Using simple linear regression, the authors concluded that innovativeness had a positive impact on the level of GDP per capita in countries classified as 'innovation learners'.

Research conducted by Hollanders & Esser (2007) divided the indicators of the European Innovation Scoreboard (EIS) into 3 innovation input dimensions covering 15 indicators and 2 innovation output dimensions covering 10 indicators. Employing a constant-returns-to-scale output-oriented DEA, they identified innovation leaders (Sweden, Denmark, Finland, Germany, Israel, Japan, Switzerland, the UK), innovation followers (Austria, Belgium, Canada, France, Iceland, Ireland, Luxembourg, and the Netherlands), moderate innovators (Cyprus, Czech Republic, Estonia, Italy, Norway, Slovenia, Spain), and the catching-up countries (Bulgaria, Croatia, Greece, Hungary, Latvia, Lithuania, Poland, Portugal, Romania and Slovakia). As can be seen, most of the catching-up countries, i.e. low-performers in the terms of innovation efficiency, are from the post-communist bloc. Anderson & Stejskal (2019) similarly took the EIS rankings, and by using DEA, found contrasting diffusion efficiency scores of member states. Their research revealed that innovation efficiency, to a certain extent, did not depend on the innovation excellence or deficiency of member states. This is evidenced by Sweden, which was the most innovative but least efficient EU member state.

Zhukovski & Gedranovich (2016) considered the efficiency evaluation of innovation activity in 69 developed and developing economies using input indicators such as the number of scientists per one million population, the number of engineers and technical personnel per one million population, and R&D costs at purchasing power parity. The number of patents granted by national patent offices to residents and the number of scientific articles published were used as the output indicators. Fang and Chiu (2017) examined innovation efficiency and the technology gap in China's economic development. Their research showed that university-industry collaboration in research is an efficient way to increase innovation performance.

In the European Union, innovation is seen as the basis for sustainable economic development based on knowledge in order to ensure social well-being. With this in mind, Brodny et al. (2023) conducted research to evaluate the level of innovation in the EU member states on the basis of 12 selected indicators characterizing them in terms of their scientific and research activities, their level of human and social capital, and the innovativeness of their enterprises from 2013 to 2020. The Evaluation Based on Distance from Average Solution (EDAS) method and correlation were used in the analysis. The results confirmed significant differences in the level of innovativeness between the EU-27 countries. The highest level was found among the 'old EU' countries, with Luxembourg and Sweden in the lead, and the lowest in the 'new EU' countries. Kalapouti et al. (2017) derived the innovation efficiency of 192 European regions over a 12-year period (1995–2006) using DEA, and found that high-innovation regions, as measured by patents, have higher innovation efficiency. Additionally, those regions with high levels of employment exploit their sources of innovation efficiently.

Kozuń-Cieślak & Murray Svidroňová (2017) analysed the innovation performance of the then 28 EU member states (the UK left in 2020) and showed possible ways of increasing efficiency with public sector innovations. The case of Slovakia proved that NGOs are engines of innovation in the public sector. Similarly, Kurkela et al. (2019) stressed the role of the third sector in innovation processed by eight Finnish municipalities.

Previous research has used cluster analysis, time series analysis, linear regression, or case studies to assess innovativeness and innovation efficiency. However, most of these studies used DEA as the appropriate quantitative method to evaluate efficiency. The advantages and disadvantages of the DEA method will be discussed in Section 3.

To recapitulate: there are many studies on innovation performance in the developed countries of western Europe, but few on the innovation performance of the post-communist countries of CEE Europe. Their predominantly rural character makes them stand out in the diverse array of countries that make up the EU. The measures taken to develop innovativeness necessarily vary from country to country. The present study focuses on the innovative performance of the 11 post-communist EU member states in order to identify the low-performers in transforming innovation inputs into innovation outputs and the most significant areas (sources) of their inefficiency.

3. Methodology and Data

Data Envelopment Analysis (DEA) was the primary method employed. DEA has been extensively explored in scholarly literature due to its many advantages and relatively few limitations (Emrouznejad & Yang, 2018).

The key advantages of the DEA method, which make it the most frequently used approach in research on the assessment of innovative efficiency, are as follows (Kozuń-Cieślak, 2011):

- The empirical orientation of DEA assumes no random component, eliminates the need for a priori assumptions about the functional relationship between the analysed variables, and makes the testing of goodness-of-fit measures redundant. This makes DEA a convenient tool for estimating efficiency when defining a precise functional dependence between inputs and outputs is difficult or even impossible.
- DEA allows us to use a set of heterogeneous data (inputs and outputs can be expressed in different units of measurement).
- A unique feature of DEA, based on mathematical linear programming, is that an empirical quantity of inputs and outputs is reduced to a single 'synthetic input' and a single 'synthetic output'. These can then be used to calculate the efficiency ratio of the object, i.e. the Decision-Making Unit (DMU). This ratio is an objective function that should be maximized for each DMU. The variables for the inputs and outputs are the empirical data, and their weights are optimized variables. DEA therefore does not require prior knowledge of weights, as it determines those weights that maximize the efficiency of each object.
- DEA is aimed at identifying frontier trends. Unlike parametric methods that attempt to fit the regression plane through the "average" data, DEA constructs a frontier (polyhedron) based on extreme data, which appears to be particularly suitable for exploring the best production achievements, which remain 'invisible' when using other techniques.
- DEA enables the creation of models that incorporate multiple inputs and multiple outputs, with efficiency determined by comparing the productivity of a given DMU to that of the most efficient (frontier) DMUs. By identifying a group of leading units which can serve as benchmarks, DEA provides best practice recommendations to each inefficient DMU. This helps the inefficient units improve their performance by adopting the technologies and production solutions used by the more efficient leaders.

DEA has been increasing in popularity over the past four decades. The literature shows that performance measurement in economics and business has remained its main area of application (Fotova et al., 2022). DEA, as a non-parametric deterministic method, is the most common way to conduct relative efficiency evaluations. This method was first used by Charnes, Cooper & Rhodes (1978). The objective of DEA is to compare several similar operating units, generally referred to as Decision-Making Units (DMUs), that use inputs to produce outputs. The DEA method assesses units only against the best ones that form the frontier of efficiency (productivity frontier). DMU is recognised as 100% efficient (DEA score = 1) when comparisons with other units in a sample do not provide evidence of inefficiency in using any input or output. If any object is not at the frontier, it indicates inefficiency, i.e. its distance from the frontier defines the inefficiency level and a DEA score < 1.

DEA can be used in both input-oriented and output-oriented approaches. In input-oriented DEA, the focus is on minimising the inputs required to produce a given set of outputs, meaning that the efficiency of a DMU is measured by how well it uses its inputs to generate a given level of outputs. In output-oriented DEA, by contrast, the focus is on maximising the outputs that can be generated from a given set of inputs, meaning that the efficiency of a DMU is measured by how well it can generate a given level of outputs using its inputs. Because innovation is a catalyst for economic growth, and economic growth can stimulate innovation by creating a favourable environment for innovative activities, it cannot be assumed that the 'production of innovations' is independent of the scale of production. Moreover, looking for solutions that increase the amount of innovation in the country while maintaining the existing level of pro-innovation inputs is a more fruitful approach for the economy as a whole. For these reasons, the output-oriented variant of DEA was used. To be precise, the output-oriented BCC model, with the assumption of variable returns to scale (DEA BCC-O-V), was applied to the rank the analysed countries on the basis of their innovative efficiency. The DEA model, in this case, attempts to identify the most efficient DMUs by comparing their output levels to those of other DMUs. This model was also chosen because it delivers projections of the input-output indicators required to achieve better DEA scores. The mathematical formulations of the DEA BCC-O-V model are expressed as follows (Cheng, 2014; Tone, 2002):

$$\delta^{DEA\ BCC-O-V} = \min \sum_{i=1}^{m} v_i x_{ik} + v_0 \tag{1}$$

subject to:

$$\sum_{r=1}^{q} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - v_0 \leq 0$$

$$\sum_{r=1}^{s} \mu_r y_{rk} = 1$$

$$v \geq 0; \mu \geq 0; v_0 \textit{ free}$$

$i = 1, 2, \ldots, m;\ r = 1, 2, \ldots, q;\ j = 1, 2, \ldots, n$

where:

the $\delta^{DEA\ BCC\text{-}O\text{-}V}$ – efficiency score of $DMU_{O,}$
x_i – is the value of *i-th* input of the DMU_j,
y_r – is the value of *r-th* output of the DMU_j,
v_i – is the weight of input x_i,
μ_r – is the weight of output y_r.

It should be noted that DEA gives the relative efficiency of a given DMU relevant to the examined group, and that it is not possible to switch to an absolute measure of efficiency. In addition, even minor changes in selecting entities from the examined group (e.g. a change in their number) may significantly impact the final result.

Research responsibility requires that the disadvantages of the DEA method be enumerated. Like any quantitative method, DEA has specific limitations. These include (Bezat, 2009):

- As DEA is a deterministic approach to efficiency measurement it does not allow for estimation or measurement error. The full distance of the unit (DMU) to the efficiency frontier is interpreted as inefficiency. As DEA is a nonparametric technique, statistical hypothesis tests are difficult.
- Efficiency measurements can differ depending on the model (input- vs. output-oriented models) and the variable specification (e.g. the degree of aggregation and the units used to measure inputs and outputs).
- The efficiency scores are only relative to the best DMU in the sample. The addition of an extra DMU can reduce efficiency scores but it cannot increase the DEA scores of the existing DMUs. The DEA scores of any single decision-making unit (DMU) estimated using DEA will tend to decrease as the number of DMUs in the sample increases.
- As DEA estimates 'relative' efficiency, the measurements it gives are only valid for the sample it tests. Units which have not been included in the sample can shift the efficiency frontier. The method's results say nothing about the efficiency of one sample relative to another; they merely reflect the dispersion of efficiencies within a given sample. Therefore, the efficiency scores of two studies cannot be compared.
- The addition of an extra input or output cannot result in a reduction in efficiency scores in the DEA model. When there are few observations (DMUs) and many inputs and/or outputs, then many of DMUs will appear on the DEA frontier. DEA scores can be increased by reducing the sample size and/or increasing the number of inputs and/or outputs. It is recommended that the number of DMUs in the sample be at least three times the sum of input and output indicators.

The above limitations do not prevent the use of the DEA method to assess a country's innovation efficiency (which is supported by the literature), but they do require caution and attentiveness in interpreting research results and drawing conclusions.

Because there is no single universally accepted and exhaustive set of indicators used to express pro-innovation inputs and innovative outputs, selecting the appropriate indicators is crucial for the final assessment of a country´s innovative performance.

The data for the present study were based on measures introduced by the GII. The GII reports provide information on the innovativeness of most countries in the world (the 2020 report includes 131 economies) in the form of an innovation index. This index is the average of the Innovation Input Sub-Index (IIS) and the Innovation Output Sub-Index (IOS), which are constructed from seven component measures (called *pillars* in the GII). Furthermore, each pillar is divided into three sub-pillars that cover appropriately selected source data (altogether, the GII uses more than 80 source data items, see www.globalinnovationindex.org).

The present study uses these GII component measures as input-output indicators that reflect the transition of pro-innovation outlays into innovation outcomes (Table 1), i.e. the choice of input-output indicators for DEA was dictated by the GII methodology.

The Data Envelopment Analysis Software PIM version 3.2. was used to estimate innovative efficiency.

Table 1.

DEA input-output indicators (based on the GII pillars)

Input indicators (average 2015–2020)	Output indicators (average 2015–2020)
Institutions (INST)	Knowledge and technology outputs (KT)
Human capital and research (HCR)	Creative outputs (CO)
Infrastructure (INFR)	
Market sophistication (MS)	
Business sophistication (BS)	

Source: the authors' elaboration.

The period from which the statistical data were taken is also significant. It has to be borne in mind that assessing efficiency essentially involves determining the relationship(s) between the input and output variables. When analysing innovation, the time lags introducing the inputs and obtaining the outputs are significant but difficult to determine. It is difficult and often even impossible to precisely determine the causal relationship between inputs and outputs, especially when the analysis concerns innovation at the country level. The present study expresses input and output variables as arithmetic means from 2015–2020 in order to account for these time lags. Obviously, this approach to statistical data is merely an arbitrarily applied simplification. It does not solve the problem.

The present study adopted two approaches to evaluating innovation efficiency using DEA as the quantitative tool. These two approaches (models) differ in the way they define the sample of DMUs.

The first approach, model (A), evaluated the innovation efficiency of 11 post--communist countries among the then 28 EU member states (the UK only left in January 2020). This model assumed that the sample was homogeneous on the basis of a comparable level of civilisational development in terms of material and non--material culture, formal and informal social institutions, and degree of environmental control. Moreover, EU membership guaranteed similar legal and institutional frameworks. Unfortunately, the member states showed significant differences in terms of economic development as expressed by average PPP GDP per capita for 2015–2021 (the coefficient of variation of GDP per capita was CV = 0.43).

The second approach, Model (B), constructed a more representative sample by selecting countries with less disparate levels of economic development. Twelve of the EU member states (Austria, Belgium, Cyprus, Denmark, Finland, Germany, Ireland, Luxembourg, Malta, the Netherlands, Sweden and the United Kingdom) were replaced by Argentina, Russia, Chile, Turkey, Kazakhstan, Malaysia, South Korea, Israel, Panama, Uruguay, New Zealand, and Japan. This almost halved the coefficient of variation of PPP GDP per capita (CV = 0.22). The countries included in model B were selected solely on the criterion of similarity of GDP per capita.

The output-oriented DEA method was used to identify those post-communist EU member states that exhibit the least innovative efficiency and to determine the key sources of this inefficiency. Both of the models used were focused on projecting an increase in the output indicators at the current level of inputs.

Hence, the primary focus is on the DEA output indicators, i.e. the KT indicator (knowledge and technology outputs) and the CO indicator (creative outputs). The GII methodology distinguishes three KT sub-indicators (areas) and three CO sub--indicators (built together on 27 primary indicators).

1) The KT sub-indicators define the benefits of knowledge generation:
   - knowledge creation – shows the benefits of creating knowledge products;
   - the impact of knowledge – describes how knowledge affects economic results;
   - the diffusion of knowledge – reflects how knowledge is implemented in business practice.

Measurable results are expected when certain inputs (outlays) for improving a country's innovativeness are introduced. However, it has to be emphasised that defining appropriate measures of knowledge outcomes is challenging because the concept of knowledge (especially useful knowledge) is very broad. Each of these areas is essential for making knowledge capable of marketing goods.

2) The CO sub-pillars define the results of creative activity:
   - intangible assets;
   - multimedia services and products, prints, pictures, etc.;
   - online creativity.

The fact that an economy is developing dynamically, and people are living well is reflected in creative work that, while not necessarily contributing to economic results, satisfies higher-order needs. Moreover, some of these creative outputs are measurable in money and result innovativeness in the field of culture.

It should be noted that, according to the findings of Altintaş (2020), a country's most important innovation component is its creative output.

4. Results and Discussion

Table A1 (appendix) shows the DEA efficiency scores of the countries in the two samples (Model A and B). These scores measure their success in transforming given outlays into tangible results, as expressed by the input-output indicators listed in the previous section.

The DEA scores for Model A reveal that eight countries qualified as relatively inefficient (0.6% to 13.7%). These DEA-inefficient countries were (in descending order): Austria, Belgium, France, Denmark, Finland, Lithuania, Poland, and Italy.

The DEA scores for Model B reveal that 11 countries qualified as relatively inefficient (1.5% to 19.8%). The DEA-inefficient countries were (in descending order) Chile, Lithuania, Poland, Greece, Croatia, Malaysia, New Zealand, Japan, France, Portugal and Italy.

The study shows that most post-communist EU member states are DEA-efficient both in comparison to other EU member states (Model A) and to those countries with the most similar level of economic development, as expressed by GDP *per capita* (Model PPP GDP per capita).

It should be noted that a country's innovative efficiency is not the same as its innovativeness.

It is crucial to emphasize that when the DEA method is used to estimate a country's innovative efficiency, it estimates its *technical* innovative efficiency. This assesses how successfully specific pro-innovation inputs have been transformed into innovations (expressed by specific output measures). Therefore, a country that is assessed as DEA-efficient (DEA technical efficiency = 100%) is not necessarily the most innovative country, i.e. it is not the most capable of continuously creating and implementing new ideas, technologies, products, services or processes that bring social and economic benefits (although it might be). Conversely, the country with the lowest technical innovative efficiency is not necessarily the one with the lowest innovation potential. This result simply means that this country is not making the best use of specific inputs, i.e. other countries could put them to better use and achieve better results, as expressed by a predetermined set of output measures. For this reason, not only countries commonly recognised as leaders and promoters of innovation qualify as DEA-efficient, but also countries that are far from being either. The same applies to countries with DEA scores of less than 1.

A country's success in transforming pro-innovative inputs into innovations is influenced by a combination of many economic, social, political, and cultural factors. These factors interact in complex ways and help create an environment that is conducive to innovation. The selection of indicators to use in the analysis is also crucial.

The work of Murswieck et al. (2020) is noteworthy here. The authors consider the cultural-conditioned blockers within the various phases of the innovation process.

These determine whether, and if so, to what extent, innovation will be successful and explain why certain countries are more successful in creating and implementing innovative ideas than others. In turn, Sohn et al. (2015) argue that the GII does not consider the potential structural relationships between the factors that influence a country's innovation performance. A similar conclusion was reached by Erdin & Çağlar (2023), whose research shows that the totality of innovation indices of the GII cannot be the only indicator of the performance of national innovation systems.

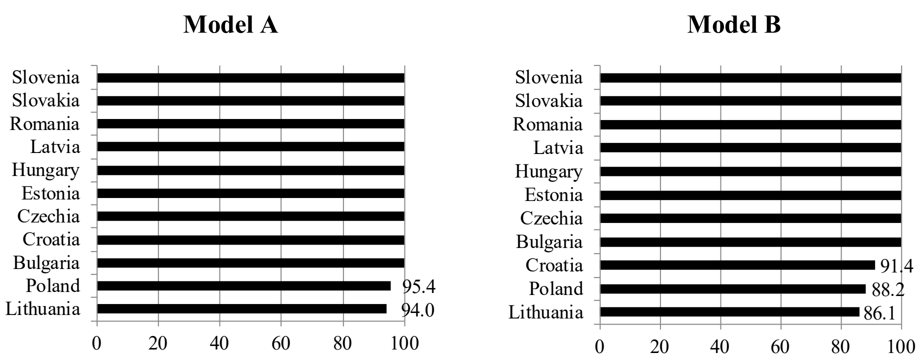
The above observations confirm how challenging and complex it is to assess a country's innovativeness by making international comparisons. Difficulties arise in both the conceptual aspects and the constraints associated with the application of specific quantitative methods.

Therefore, all the research findings on the innovative efficiency of the countries examined in this study require caution and careful interpretation, as well as an acknowledgement of the myriad limitations inevitably encountered when applying quantitative techniques for appraising complex phenomena subject to the influence of economic, social, cultural, environmental, political, and other factors.

The efficiency indicators for post-communist EU countries are the most important for the purposes of the present study. Figure 1 compares the DEA scores of the eleven post-communist EU members obtained by the two models.

Figure 1.

DEA innovation efficiency scores of post-communist EU member countries (%)



Note: The order of countries rated as DEA = 100% is not relevant (it is random).
Source: own work based on Table A1 (Appendix).

Comparing the DEA efficiency scores in the two models reveals that Poland and Lithuania were the only two post-communist EU members to exhibit inefficiencies in transforming pro-innovation inputs into tangible innovative outputs. Poland had an efficiency gap of around 4.6% in Model A and 11.8% in Model B. The corresponding figures for Lithuania, are 6% and 13.9%. Additionally, Model B identifies Croatia as having a relative DEA inefficiency of approximately 8.6%. All the remaining post-communist states, including Bulgaria, Czech Republic, Estonia, Latvia, Romania, Slovakia, Slovenia, and Hungary, were found to be DEA-efficient in both models (indicated by a DEA score of 1).

Furthermore, it's worth noting that the efficiency gaps were notably larger in Model B than in Model A. This suggests that the set of countries covered by Model B found it more challenging to convert pro-innovative inputs into tangible innovations. These innovations encompass not only the products of knowledge, new technology, impact, and diffusion, but also creative endeavours that result in the development of intangible assets, multimedia products, and internet-based creativity.

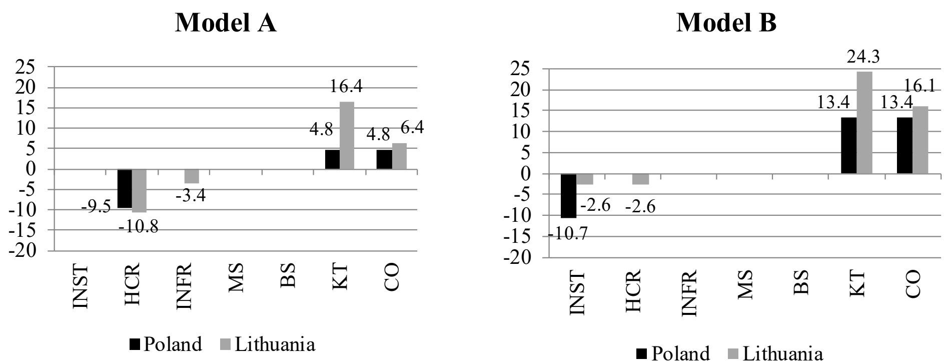
While the efficiency gaps identified in both models are relatively modest, it is worth exploring the origins of this inefficiency. Since the DEA method employs mathematical programming techniques, it enables us to project how adjustments in the magnitudes of input and output variables can position inefficient countries onto the efficiency curve.

When output-oriented DEA models are used, the projection of the change in output indicators shows how much output indicators have to increase to move the analysed entity (DMU) to the empirically determined efficiency frontier (i.e. achieve a DEA score = 1). Conversely, the projection of changes in input indicators shows how much the input measures can be reduced without reducing the efficiency levels of the analysed entities.

For the purposes of the present study, when output-oriented DEA models are used, the projection of changes in the output indicators shows the extent to which they have to increase to move an inefficient decision-making unit (here, Poland and Lithuania) to the empirically established efficiency frontier (i.e. achieve a DEA score of 1). Conversely, the projection of changes in the input indicators shows how much these measures can be reduced without compromising the efficiency level of the analysed DMUs. Figure 2 displays the anticipated changes in input and output indicators for Poland and Lithuania.

Figure 2.

Input-output adjustments to achieve DEA efficiency for Poland and Lithuania (%)



Source: own work based on Table A2 (Appendix).

The projection of optimal levels of input-output indicators for Poland and Lithuania shows the origins of the inefficiencies in the two countries.

Model A shows that there is a need to improve both output indicators in the two countries (i.e. KT and CO). In Poland, the two output measures should increase by approximately 5%. Lithuania should strive to increase the KT indicator by approximately 16% and the CO index by approximately 6%.

Model B also identifies the source of Poland's and Lithuania's inefficiency as the low achievement reflected in both output indicators, but to a much greater extent than Model A. From the Model B results, it is recommended that Poland strive to increase the KT and CO indicators by approximately 13% and that Lithuania improve the KT indicator by approx. 24% and the CO indicator by 16%.

As both output indicators are synthetic measures, each of which expresses the arithmetic mean of three sub-indicators, which were constructed from 27 primary data items, they are now examined in detail.

Table 2 shows the fourteen primary data items that were used to build the three sub-pillars that illustrate a country's innovation by means of 'knowledge and technology outputs'.

Table 2.

Components of the GII knowledge and technology (KT) indicator

GII output measure		
pillar	sub-pillar	primary data
KT – knowledge and technology outputs	Knowledge creation	• Number of resident patent applications filed at a given national or regional patent office (per billion USD PPP GDP) • Number of Patent Cooperation Treaty applications (per billion USD PPP GDP) • Number of resident utility model applications filed at the national patent office (per billion USD PPP GDP) • Number of published scientific and technical journal articles (per billion USD PPP GDP) • The H-index is the economy's number of published articles (H) that have received at least H citations
	Knowledge impact	• Growth rate of GDP per person employed (%, 3-year average) • New business density (new registrations per thousand population 15–64 years old) • Total computer software spending (% of GDP) • ISO 9001 Quality management systems – Requirements: Number of certificates issued (per billion USD PPP GDP) • High-tech and medium-high-tech manufacturing (% of total manufacturing output)
	Knowledge diffusion	• Charges for use of intellectual property, i.e., receipts (% of total trade, 3-year average) • High-tech net exports (% of total trade) • Telecommunications, computers, and information services exports (% of total trade) • Foreign direct investment (FDI), net outflows (% of GDP, 3-year average)

Source: own work based on the 2020 GII: Appendix III Sources and Definitions.

Table 3 displays the thirteen indicators that were employed in the formation of three sub-pillars, that illustrate a country's innovation performance by means of 'creative outputs'.

Table 3.
Components of GII creative outputs (CO) measure

GII output measure		
pillar	sub-pillar	primary data
CO – creative outputs	Intangible assets	• Number of classes in resident trademark applications issued at a given national or regional office (per billion PPP USD GDP) • Global brand value of the top 5,000 brands (% of GDP) • Number of designs contained in resident industrial design applications filed at a given national or regional office (per billion USD PPP GDP) • Average answer to the question: In your country, to what extent do ICTs enable new organizational models (e.g. virtual teams, remote working, telecommuting) within companies?
	Creative goods and services	• Cultural and creative services exports (% of total trade) • Number of national feature films produced (per million population 15–69 years old) • Global entertainment and media market (per thousand population 15–69 years old) • Printing publications and other media (% of manufactures total output) • Creative goods exports (% of total trade)
	Online creativity	• Generic top-level domains (gTLDs) (per thousand population 15–69 years old) • Country-code top-level domains (ccTLDs) (per thousand population 15–69 years old) • Wikipedia yearly edits by country (per million population 15–69 years old) • Global downloads of mobile apps (scaled by per billion PPP $ GDP)

Source: own work based on the 2020 GII: Appendix III Sources and Definitions.

The primary data presented in Tables 2 and 3 encompass a diverse array of actions that Poland and Lithuania should consider to enhance their pro-innovation activities.

Regrettably, the present study does give any indication of the extent to which the synthetic measures (the sub-pillars) should be increased. This applies *a fortiori* to the primary indicators.

Hollanders & Esser (2007) similarly find that Poland and Lithuania have low innovative efficiencies. According to the European Commission (2018), most member states (14) are moderate innovators. Of these moderate innovators, 7 (Czech Republic, Greece, Hungary, Latvia, Malta, Poland, Slovakia and Spain), were found to be relatively efficient. By contrast, Croatia, Cyprus, Italy, Estonia, Lithuania and Portugal were found to be inefficient. The present study corroborates the finding that Lithuania and Poland are innovatively inefficient.

In contrast to the present study, Anderson & Stejskal (2019) found that Lithuania is quite efficient (score of 0.87) and Poland very efficient (score of 1) in turning pro-innovation input into innovation output. These contrary findings may be due to the use of different innovation measurement variables. Anderson & Stejskal (2019) used the European Innovation Scoreboard published by European Commission (2018) and employed a different DEA model (CCR).

Kalapouti et al. (2020) found that regions engaged in a lot of innovative activity, as evidenced by patent filings, are characterised by a high level of innovative efficiency. The present study similarly shows that countries with low innovation efficiency should strive to increase knowledge and technology inputs, including patents (see Table 2).

The level of innovativeness not only has a major economic impact; it profoundly affects the EU's environment, energy, and social life (Brodny et al., 2023). Although innovation is not a linear process where inputs are automatically transformed into outputs, it is nevertheless worth examining differences in efficiency by assuming that efficiency can be defined as the ratio of outputs over inputs.

For countries with low innovative efficiencies, it may be more effective to focus on policies aimed at improving their efficiency in transforming inputs into outputs. In-depth research is therefore indispensable to providing precise recommendations on tailored programs designed to improve specific indicators that encapsulate progress in innovation.

5. Conclusion

Research in measuring innovation efficiency has shown that the EU's 11 post-communist member states are its least efficient in transforming innovation inputs into innovation outputs (answer to RQ1). This study shows that Poland and Lithuania are the least efficient of these 11 countries in transforming pro-innovative inputs into innovative outputs, as measured by two innovation indicators that cover the following areas:

- the benefits of knowledge generation, manifested by creating knowledge products;
- the impact of knowledge describes how implemented knowledge affects economic results;
- the diffusion of knowledge reflects how knowledge is implemented in business practice;
- intangible assets generated by creators;
- multimedia services and products, prints, pictures, etc.;
- online creativity.

The DEA method used to estimate the technical efficiency scores showed that Poland and Lithuania achieved lower results than the other post-communist EU member states when analysed in two different samples. Compared to other EU member countries (Model A), Poland's DEA efficiency score was estimated at approximately 95%, which should be understood to mean that, at the same level of pro-innovative inputs available, Poland should make efforts to achieve innovative results that are approx. 5% higher. In the case of Lithuania, the efficiency gap was assessed at 6%. Compared to countries where the level of economic development is more similar in terms of GDP per capita (Model B, answer to RQ2), the innovative efficiency of Poland and Lithuania was even weaker, with efficiency gaps of 12% and 14%.

For countries with low innovative efficiencies, as measured by one or both output indicators, it may be more effective to focus on policies aimed at improving their efficiency in transforming inputs into outputs. The DEA projection of optimal levels of output indicators for Poland and Lithuania shows the origins of existing inefficiencies in the two countries. According to Model A, both countries need to improve the two result indicators. In Poland, the two output indicators should increase by approximately 5%. Lithuania should strive to increase the KT indicator by approximately 16% and the CO indicator by 6%. Model B also identified the source of Poland's and Lithuania's inefficiency as the low achievement reflected in both output indicators, but to a much greater extent. According to the Model B DEA results, Poland should strive to increase the KT and CO indicators by approximately 13% while Lithuania needs to increase the KT indicator by approximately 24% and the CO indicator by 16%. These findings are relevant to all stakeholders, but especially policymakers, dealing with the EU economy and its innovativeness.

The added value of the present study lies in its deepening our knowledge on evaluating the innovation efficiency of selected EU member states. It should be a valuable source of information to policymakers in devising development strategies for the EU and its individual member states. Given that the output indicators employed in this study are composed of sub-indicators that represent the innovation domains enumerated above, further research using data at a more granular level of aggregation is recommended.

Pinpointing particular measures that require a targeted increase and determine the extent of this increase requires more detailed research. This could be done by using e.g. DEA models that used output indicators at a lower level of aggregation (sub-pillars or simply primary data). DEA only reveals the efficiency of a member state compared with another. This relative efficiency is therefore affected by the sample size. Moreover, it should be noted that any modifications to DEA models must take into account the fact that, like any quantitative method, it has its limitations (see Section 3).

The years used for the input and output variables, despite being sourced from the latest GII, may constitute another limitation of the present study. From the review of the literature on innovativeness and innovation efficiency, which was by no means exhaustive, it can be said that there is a very extensive body of literature on the subject. By contrast, there are very few studies on evaluating the innovation efficiency of EU member states, and in particular, those from the post-communist bloc. Therefore, future research should also focus on these countries and assess the innovativeness and innovation efficiency in a complex and multidimensional way by employing more methods and indicators (compare results of DEA using GII or EIS rankings).

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Appendix

Table A1.
DEA scores referring to innovative efficiency – Model A vs. Model B

Model A		Model B	
DMU	DEA scores (%)	DMU	DEA scores (%)
Austria	86.3	Argentina	100
Belgium	86.4	Bulgaria	100
Bulgaria	100	Chile	80.2
Croatia	100	Croatia	91.4
Cyprus	100	Czech Rep.	100
Czech Rep.	100	Estonia	100
Denmark	91.9	France	96.9
Estonia	100	Greece	90.7
Finland	92.7	Hungary	100
France	90.8	Israel	100
Germany	100	Italy	98.5
Greece	100	Japan	95.8
Hungary	100	Kazakhstan	100
Ireland	100	Korea, Rep.	100
Italy	99.4	Latvia	100
Latvia	100	Lithuania	86.1
Lithuania	94	Malaysia	92.5
Luxembourg	100	New Zealand	93.3
Malta	100	Panama	100
Netherlands	100	Poland	88.2
Poland	95.4	Portugal	97.3
Portugal	100	Romania	100
Romania	100	Russian Fed.	100
Slovakia	100	Slovakia	100
Slovenia	100	Slovenia	100
Spain	100	Spain	100
Sweden	100	Turkey	100
United Kingdom	100	Uruguay	100

Source: own computations using the Data Envelopment Analysis Software PIM version 3.2.

Table A2.
Input-output adjustments to achieve DEA efficiency for Poland and Lithuania (%)

DMU	Inputs projection (%)										Outputs projection (%)			
	INST		HCR		INFR		MS		BS		KT		CO	
	Model													
	A	B	A	B	A	B	A	B	A	B	A	B	A	B
Poland	0	-10.7	-9.5	0	0	0	-2.9	0	0	0	4.8	13.4	4.8	13.4
Lithuania	0	-2.6	-10.8	-2.6	-3.4	0	-3.7	0	0	0	16.4	24.3	6.4	16.1

Source: own computations using the Data Envelopment Analysis Software PIM version 3.2.