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EXPLORING EFFICIENCY GROWTH OF ADVANCED TECHNOLOGY-GENERATING SECTORS IN THE EUROPEAN UNION: A STOCHASTIC FRONTIER ANALYSIS

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Abstract. This study investigates the efficiency growth of advanced technology-generating sectors within the European Union (EU). Using a stochastic frontier analysis of annual sector-level panel data from 2000 to 2019, we examine sectoral (NACE two-digit level) and territorial implications. Our findings indicate that technological change was more intense in advanced technology-generating sectors than in other economic sectors, primarily driven by fixed capital investments. However, the impact of in-house research and development varied. Economic sectors such as pharmaceuticals and motor vehicles struggled to improve their production efficiency due to high competition and market specificity. A comparative analysis of EU economies showed a lower level of production efficiency in catching-up economies. Nevertheless, these economies contributed to the shift of the production possibility frontier in certain sectors on the EU level. Therefore, this study contributes to the ongoing scientific discussion on technological innovations in diverse territories, suggesting that less-developed economies could generate technological advancements in specific areas. We also discuss the implications for innovation and industrial policy actions.

Keywords: production efficiency, economic sectors, advanced technologies, technological progress, technical efficiency, stochastic frontier analysis, R&D, smart specialization.

JEL Classification: L60, O14, O30, O33.

Introduction

Recent problems with European economic growth cannot simply be explained by structural problems of the monetary union or financial markets (European Commission [EC], 2009a; Overbeek, 2012). Rather, there is a need for changes in economic structures for all European countries and regions, regardless of their level of economic development and technologies used (Krammer, 2017). Diversification into more sophisticated products leads to higher levels of per capita income, but because of global competition, this remains a major challenge both for economically advanced economies and stagnating territories in the European Union

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(EU) (Hartmann et al., 2021). With a gap of 10–20%, the efficiency of the euro area lies far below the world's production frontier, suggesting the need for structural changes and efforts to enhance the use of resources (Sanchez, 2021).

With the recent technological progress, the role of advanced technologies (key enabling technologies (KETs) and key digital technologies) in structural change and economic development is inevitable (COM/2009/0512 final) (EC, 2009b). Therefore, the European Commission initiated strategic directions to support industrial change, such as a Digital Single Market strategy for Europe (COM(2015) 192 final) (EC, 2015), a common strategy for KETs in the EU (COM/2009/0512) final, and smart specialization strategies (Foray, 2018; Dzemydaitė, 2021). These new approaches to industrial and innovation policies require tracking the level of advanced technology generation, production, and uptake and their impacts across sectors and countries.

Regardless of the role of the EU framework condition and support instruments for strengthening research base and broadening industrial capacities for the development of AT, the necessary R&D and its specific applications are primarily the responsibility of businesses (COM/2009/0512 final). An important question in the academic literature and public debates is the amount of productivity growth that is gained from technological advancements in diverse territories (Andrews et al., 2015; EC, 2021).

This research follows this line of thinking and aims to evaluate the production efficiency of economic sectors in the EU. The focus is on economic sectors that develop advanced technologies. These sectors were chosen because of policy aims in the EU, particularly concerning smart specialization strategies, where efforts to enhance innovation are usually concentrated on the smart growth of selected economic sectors. All sectors involved in the analysis were smart specialization areas in parts of the EU regions (EC, 2023). In selecting advanced technology-generating sectors we followed methodological report of "Advanced technologies for industry" project (ATI) initiated by European Commission. Project aimed to capture the processes of technology generation, uptake or both across countries and industries (EC, 2021).

This study is built on panel data of overall 36 economic sectors in 22 countries from 2000 to 2019, which formed a database for panel stochastic frontier estimation (SFA) with time-varying effects. SFA captures growth dynamics in the production efficiency of economic sectors, revealing catching-up and innovation processes (shifts in the available frontier technology) (Sickles & Zelenyuk, 2019). Our research question was: to what extent is the change in production efficiency of advanced technology-generating sectors in the EU due to technology generation processes?

This study aims to build upon previous scientific research from several points of view. Unlike previous studies that have broadly focused on the adoption of advanced technologies (Ghobakhloo & Ching, 2019; Toufaily et al., 2021; Stornelli et al., 2021), analysed the efficiency of a specific country, or industry (Li et al., 2019; Novotná et al., 2021; Yang & Wang, 2022) or conversely, a more aggregated sectoral level (Kumbhakar et al., 2012; Liik et al., 2014), this study provides insights into individual advanced technology-generating sectors. Furthermore, it expands upon recent research on catching-up processes in the EU by examining these transformative changes from a sectoral perspective, an aspect that has not been sufficiently explored in the literature on production efficiency (Burger et al., 2022; Teirlinck

& Khoshnevis, 2022). Thus, this study fills important gaps in the literature by providing a more nuanced understanding of efficiency in advanced technology-generating sectors and the role of catching-up processes at the sectoral level.

This paper consists of three main parts. Section 1 discusses related works on production theory, production efficiency, and the role of advanced technologies in the production process. Section 2 presents the data and the methodology applied. Section 3 discusses the empirical results regarding factors of production efficiency of economic sectors in diverse territories in the EU, technology generation and uptake processes, and inefficiencies in economic structures.

1. Related works

While describing a production process, the key elements for consideration are the number and the nature of inputs and outputs and the ability of a decision-making unit to utilize all inputs in the most efficient way, given market prices. Both concepts of "productivity" and "efficiency" explain performance, but from different perspectives (Sickles & Zelenyuk, 2019). Production inefficiency is defined as the gap between actual and potential performance. Measurements of efficiency incorporate two output levels: actual and potential. Productivity measurements assess a situation as it is, without comparison to the technologically attainable production level (production possibility frontier). In this study, we chose to analyse production efficiency, more specifically technical efficiency, due to a need to analyse both the actual level of productivity and the efficient frontier that could be influenced by emerging advanced technologies.

Production efficiency studies reveal the capacity to produce maximum output with given inputs (Sickles & Zelenyuk, 2019). Behind the optimization dilemma, there is the technology that is used in the production process. Through changes in technology, firms may be able to move closer to the efficient frontier or shift it to new levels of overall productivity. Firms benefit from technological progress through two pathways: technology generation (innovation), which involves being an active part in the creation of new technologies or technology uptake by adoption of already-developed technologies in the market (König et al., 2016). Technological progress can be influenced by context conditions, such as culture, institutions, climate conditions or initial endowments (Piesse & Thirtle, 2000; Severgnini, 2009).

Gains from technological transformation at the sectoral level may come from several sources (Capello & Lenzi, 2021). Firstly, firms can serve as providers of new technologies to the market. Secondly, firms can benefit from technology generation by taking advantage of in-house technological innovation for new production styles within the company. Therefore, economic sectors can benefit from technology manufacturing, adopting new technologies, or both. European Commission (EC, 2020a) has indicated that the main technological trends shaping industries are product innovations, process innovations, and new business models that can create value-added gains within companies or be diffused to the market.

In the age of the fourth industrial revolution, the development of new ATs is an inevitable form of technological progress that will shape the production process. ATs are characterized as already-developed or future technologies that are expected to substantially amend business and social environments (Schwab, 2017). Advanced technologies consist of KETs (advanced materials, advanced manufacturing technologies, micro- and nanoelectronics, nanotechnologies, industrial biotechnology, photonics, robotics) and digital technologies (the internet of things, artificial intelligence, security, connectivity, cloud technology, blockchain, big data, augmented/virtual reality, and IT for mobility) with increasing number over time (EC, 2021). ATs are multidisciplinary; they can be applied in various fields of activity and some of them can be generic in nature (Bresnahan & Trajtenverg, 1995; Culot et al., 2020).

The question behind this is how different firms and territories will benefit from technological advancements. A study by Bender et al. (2018) revealed that firms usually encounter difficulties in using ATs at a transformative scale due to the number and extent of technological solutions required to sufficiently transform a firm's processes to capture the value of new ATs. ATs can be more relevant to specific industries depending on their propensities to integrate digital technologies or KETs in business processes or products (EC, 2021; Dzemydienė et al., 2022). Therefore, the impact of the generation or uptake of ATs on production efficiency may vary considerably between firms, economic sectors and territories. While there is a variety of research on productive efficiency and technological change in high technology sectors (Li et al., 2019; Haschka & Herwartz, 2020; Yang & Wang, 2022), previous research has not extensively addressed the specific dynamics of advanced technology-generating sectors, which encompass a wider range of sectors than those previously studied.

Finally, despite extensive research on productive efficiency across countries, high technology industries and firms, the literature lacks sufficient exploration of the transformative changes and catching-up processes within the EU from a sectoral perspective, particularly in the context of production efficiency. On the one hand, studies assessing the efficiency of high technology industries do not adequately highlight the role of emerging economies in technological change and hence, their potential to shift the production possibility frontier (Kumbhakar et al., 2012; Liik et al., 2014; Haschka & Herwartz, 2020). On the other hand, research exploring cross-country gaps in patenting or efficiency typically does not provide a detailed sectoral perspective (Fu & Yang, 2009; Sanchez, 2021). Our study seeks to bridge these gaps by employing stochastic frontier analysis in the specific context of advanced technology-generating sectors in the EU, and by exploring the production efficiency and catching-up processes of these sectors in detail.

2. Research methodology

2.1. Research approach for evaluating production efficiency of economic sectors

For the explanation of the research approach on efficiency modelling in this paper, we follow methodological specifications by Sickles and Zelenyuk (2019), Schaffer et al. (2011) and Battese and Coelli (1992), among others. In production theory, any production process is a process whereby some technology transforms a set of inputs (x) into a set of outputs (y). This multidimensionality of x and y implies that x and y are vectors in the nonnegative, real (Euclidian) space of some finite dimensions (N, $x=\left(x_1,\ldots,x_N\right)'\in R_{+}^{N}$) and ($M$, $y=\left(y_1,\ldots,y_M\right)'\in R_{+}^{M}$). The technology of a particular firm can be characterized by the technology set ψ, which is a set of all possible combinations of x and y in the production process:

$$\psi = \left\{ (x, y) \in R_{+}^{N+M} \middle| y \text{ is producible from } x \right\}. \tag{1}$$

The boundaries of ψ reflect maximum outputs with the given inputs. The efficiency frontier is generally defined as:

$$Y^{\delta} = \left\{ \left(x, y^{\delta}(x)\right) \mid y^{\delta}(x) \in Y(x) : \lambda y^{\delta}(x) \notin Y(x), \forall \lambda > 1 \right\}. \tag{2}$$

$Y(x)$ means the set of technology feasible outputs and $y^{\delta}(x)$ is the maximum achievable output of the unit with input level x. Efficiency score $\lambda(x,y)$ of a unit is defined as:

$$\lambda(x, y) = \sup\left\{ \lambda \mid (x, \lambda y) \in \psi \right\} = \sup\left\{ \lambda \mid \lambda y \in Y(x) \right\}, \tag{3}$$

where $\lambda(x,y)$ is the proportionate increase of output to the efficient level estimated by the model (Schaffer et al., 2011). Efficiency score (technical efficiency, TE) close to 1 reveal that the unit analysed is close to the efficient frontier. To generate more output, more inputs are needed, or, if technically inefficient, outputs increase with current inputs. To determine the unknown ψ and $\lambda(x,y)$, various estimation approaches can be applied, such as non-parametric techniques (usually, Data Envelopment Analysis (DEA), Order-α, Order-m analysis, and the Full Disposal Hull method), parametric analysis (usually, SFA) with a panel or cross-sectional data or machine learning techniques (Esteve et al., 2020).

The main difference between parametric and nonparametric analysis is that parametric analysis gives insight into the elasticities of different inputs' contributions to production efficiency. Additionally, external conditions can affect the efficiency measurement, which is the main benefit of parametric techniques (Mandl et al., 2008). However, not all parametric models are the same and applicable to innovation studies. Cross-sectional models are generally unable to capture growth dynamics and separate catch-up and shift in available frontier technology (Sickles & Zelenyuk, 2019). Researchers have recognized this shortcoming and developed alternatives with panel treatments. Using our sufficient data sample, we were therefore able to employ a panel data model of SFA. SFA is a sensitive method, so the robustness of stochastic frontier analysis is recommended (Stead et al., 2023). Therefore, for the robustness check, we aimed to show that the key results of the paper hold true even if we estimate efficiency with non-parametric method of DEA (an explanation in Appendix 4).

2.2. Selection of economic sectors

Identification of AT-generating sectors is not straightforward, as little research has analysed this issue in depth. A more systematic piece of work on sectoral roles can be attributed to Capello and Lenzi (2021), who aimed to identify sectors based on their roles in technology supply, adoption or both, according to servitisation, digitalisation and industry 4.0 indicators. Additionally, a comparatively broader study to capture the processes of technology generation, uptake or both across industries and countries could be attributed to European Commission that initiated the "Advanced technologies for industry" project (ATI) producing a methodological report based on literature review and the recommendations of the High-Level Expert Group (EC, 2021).

We followed EC framework and data provided for identification of AT-generating sectors. Overall, 13 economic sectors that had AT generation activities were identified (Appendix 2). Out of them, 5 economic sectors had both AT patenting activities and AT firms (chemicals, pharma industries and medical devices, electronics, machinery, and automotives) and 7 economic sectors had AT firms but no clear attribution of AT patenting activities due to specifics of economic sectors (financial services, professional services, telecommunications, textiles, tourism, retail and wholesale and agro-food) (EC, 2020c). In our research, we chose to evaluate production efficiency of overall 13 economic sectors that had associated AT firms. Additionally, we chose to conduct an in-depth analysis of 5 economic sectors that have both AT firms and clearly attributed patenting activities of AT.

2.3. Model specification and data

We analysed industry-level data from the International Standard Industrial Classification of Economic Activities (Rev. 4) from the period of 2000 to 2019. An entire sample consisted of 22 countries[1] and 36 industries (sectors). Industry-level input and output data were from OECD STAND and ANBERD databases. For external condition variables, we used data from the World Bank and Eurostat (see a detailed list of databases in Appendix 1). Data was collected with R packages: "eurostat", "OECD", and "WDIR". The equation was estimated with the package "frontier".

The production function corresponds to a Cobb-Douglas function in log terms. The dependent variable was labour productivity (*Y/L*), while capital inputs were fixed capital per employee[2] and R&D stock per employee. Per capita values permitted both elimination of country-size effects and standardization of the data. We also involved the number of employees within an economic sector as a control variable to account for scale elasticity and increasing returns, so that underlying production technology would not be restricted to linear homogeneous inputs (Kumbhakar et al., 2012). The SFA model for industry-level panel data is as follows:

$$\ln Y_{it} = b_0 + b_1 \ln\left(K\right)_{it} + b_2 \ln\left(R\,\&\,D\right)_{it} + b_1 \ln\left(E\right)_{it} + \delta_i \ln\left(z\right)_{it} + t + v_{it} - u_{it}\,, \qquad (4)$$

where Y_{it} – value added per employee in i industry at time period t, where $i = 1\ldots N$ and $t = 1\ldots T_i$; K – fixed capital per employee; *R&D* – R&D capital stock per employee; E – number of employees; z_{it} – external factors; t – time trend for Hicks-neutral technical change; $\nu_{it} \sim N\left(0,\sigma_\nu^2\right)$ is a random noise; $u_{it} \sim N\left(\mu,\sigma^2\right)$ is a time-varying inefficiency. The panel data is unbalanced and each industry may have a different number of time periods (T_i). The R&D capital stock was evaluated by the widely applied perpetual inventory method (Hall et al., 2010), presented in Appendix 3. The equation was estimated using random effects with the time-varying efficiency model of Battese and Coelli (1992) explained in Section 3.1.

[1] The data set consists of EU countries that were part of OECD: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Great Britain, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Netherlands, Poland, Portugal, Slovak Republic, Slovenia, Sweden and Spain, except Luxembourg due to missing values. This data set characterizes a significant portion of the EU countries. Even though these countries differ in economic structures, from a global perspective, this choice of countries contributes to more accurate insights by comparing units that have more in common in terms of economic development and economic integration practices.

[2] Gross fixed capital formation consisted of both tangible and intangible fixed assets that were accounted for in National Accounts (OECD, 2022; European Communities, 2009).

While constructing a SFA model and its variables we followed a production function modelling approach coming from a seminal work of Griliches (1979) followed by research that measured efficiency at a sectoral level (Kumbhakar et al., 2012; Liik et al., 2014). The SFA revealed how the production efficiencies of economic sectors were influenced by capital inputs (physical capital and R&D capital per employee), while external factors revealed technological level of the society (mobile users, ICT imports, and exports) or quality of the human capital (e.g., working-age population with tertiary education). SFA also allowed comparison of countries in terms of how far they are from a production possibility frontier through the analysis of efficiency scores.

3. Empirical results and discussion

3.1. Estimation results within economic sectors

Table 1 shows the results of eight different estimates from Eq. (4): for the whole sample (36 economic sectors), for AT-generating sectors (13 economic sectors), for AT-generating sectors that generally patent new technologies (5 economic sectors), and for separate sectors. Several findings could be summarized from the results. (1) Most of the economic sectors had a significant trend of technological change. The trend of technological change in AT-generating sectors was higher than for the whole sample of economic sectors. The technological change was 3.2% and 1.1%, respectively. These results are in agreement with the expectation that AT-generating sectors should have higher rates of technical progress than other economic sectors. (2) Fixed capital accumulation was a driving force of production efficiency of economic sectors in the EU in almost all the sectors analysed. (3) The relationship between R&D capital and production efficiency varied across economic sectors.

While comparing results with previous studies on firm-level data from Europe's top R&D investors, Kumbhakar et al. (2012) found that the change of technical progress in the high-tech industries was 2.9%, while Liik et al. (2014) estimated the time trend of technical progress to be 2.6% for high-tech sectors in OECD countries. In our sample, time trend of AT-generating sectors was 3.2%. The larger number found in our study could be explained by the different samples of economic sectors and time periods. Our time range covered a period up to 2019, while Kumbhakar's et al. (2012) data went up to 2005 and Liik's et al. (2014) up to 2009. We argue that, with emerging new technologies, technological change should have become more intensive in recent years, particularly so in AT sectors.

Mixed picture of R&D impact for production efficiency could be illustrated with diverse elasticities across economic sectors. For two sectors (motor vehicles, trailers and semi-trailers and pharmaceuticals) R&D capital had negative elasticities or no significant relationship and for three sectors R&D capital had positive elasticities with comparatively high level for chemical sector. Negative elasticity revealed inefficiency in R&D spending while higher R&D does not necessarily mean higher economic output. This could be explained by high competition in these sectors in global markets, management issues of R&D activities, commercialization processes of inventories, and overinvestment without economic outputs (Sickles & Zelenyuk, 2019; Teirlinck & Khoshnevis, 2022).

Table 1. Models' parameters and efficiency estimates for different sectors (source: author's calculations)

Variable	Whole sample (36 economic sectors)	Advanced technology-generating economic sectors (13 economic sectors)	Advanced technology – generating economic sectors (patenting new technologies) (5 economic sectors)	Chemicals and chemical products	Basic pharmaceutical products and pharmaceutical preparations	Computer, electronic and optical products	Machinery and equipment	Motor vehicles, trailers and semi-trailers
Constant	3.530***	3.199***	2.856***	6.080***	–0.027	1.738**	3.4283***	–1.624**
ln(K)	0.571***	0.634***	0.502***	0.104	0.501***	0.550***	0.297***	0.493***
ln(RnD)	0.019***	0.017***	0.066***	0.334***	–0.091	0.043*	0.152*	–0.061**
ln(E)	–0.041***	0.012	0.009	0.030	0.057	0.030	–0.067	0.099*
ln(edu)	–0.370***	–0.391***	–0.220**	–0.306*	0.438***	0.145	–0.670***	0.717***
ln(ICTexport)	0.065***	0.080***	0.143***	0.111	–0.258***	0.513***	0.059	0.112
ln(ICTimport)	0.129***	0.094***	0.005	–0.126	0.261*	–0.382**	0.194*	0.220*
ln(mobileUsers)	0.038	0.009	0.036	–0.255*	0.260**	–0.057	–0.009	0.294**
ln(internetUsers)	–0.085***	–0.075***	–0.108**	–0.119	–0.056	–0.134	0.344***	–0.223**
Time	0.011***	0.016***	0.032***	0.061***	–0.035**	0.060***	0.019***	0.010
Mean efficiency	0.399	0.419	0.515	0.693	0.684	0.545	0.575	0.634
log likelihood value	49.27	693.84	68.83	34.69	58.14	25.97	79.68	54.61
Number of observations	6726	2775	1031	197	200	229	225	180

Note: *p < .05; **p < .01; ***p < .001.

Regarding the external conditions, some countries had a comparatively high general educational level of the society but at the same time lower efficiency of economic sectors. With efficiency modelling, we attempt to solve the optimization of minimizing inputs and maximizing outputs. Historically some CEE countries had comparatively high educational rates of society but lower economic outputs (Dzemydaitė et al., 2016). Educational level gained through many years does not necessarily translate to skills that are required for current technology development in particular economic sectors (Andrews et al., 2015). Due to technological change, skills become outdated more quickly than in the past and the need for new skills emerges sharply (EC, 2020b). Therefore, to balance skillset supply and demand, the strategic anticipation of skills for future work by the education system seems to be necessary for future development and empowering of new technologies in business. Additionally, more emphasis is needed on such skills as learning to learn, adaptability and fostering a change mindset.

From a sectoral perspective, the chemicals and chemical products sector stood out from the sample in two ways. Firstly, it was one of the sectors that had comparatively high technical progress during the years analysed. The rate of technological progress (elasticity for the time-varying effect 0.061) was statistically significant and more than five times higher than for the sample overall (0.011) or the other AT-generating sectors (0.032). Secondly, R&D capital revealed that this sector experienced the strongest effect on production efficiency of all the advanced-technology sectors analysed. Time-varying effects and R&D capital elasticity demonstrated transformative processes of the chemicals sector toward a higher efficiency that was related to technology generation processes.

The computer, electronics and optical products sector showed one of the highest technical progresses, with a time-varying elasticity of 0.060. This suggests that there are continuous transformation in the production technology of computer, electronic and optical products affecting this sector. The main driving force of efficiency growth was fixed capital, with an elasticity of 0.550. The highest efficiency of the computer and electronics sector was in territories with high ICT exports and higher pools of workers within the relevant sector, revealing benefits of the concentration of related firms.

The motor vehicles, trailers and semi-trailers sector did not reveal a significant time trend of technological change. R&D capital elasticity was negative. It demonstrates inefficiency when higher R&D rates are not reflected in higher outputs. This shows struggles in production efficiency growth with in-house R&D investments not adding considerable value to overall sectoral performance. This may occur because of high competition in global markets affecting the output side and insufficient transformative processes in technology for changing overall performance. ICT products are usually components of motor vehicles, trailers and semi-trailers. Therefore, ICT imports positively affected production efficiency.

3.2. Comparison of production efficiency of economic sectors and countries

For the comparison of production efficiency between economic sectors and countries, we used the whole sample model in a common scale. The sector-based mean efficiency is meaningful only for the particular sector. The ratio of the highest efficiency of an arbitrary sector provided the scaling factor.

The distribution of efficiency scores reveals the different natures of inputs and outputs, the competition level within the economic sectors, and the positioning of EU countries relative to a frontier (Figure 1). The broadest distributions of efficiency scores were observed in sectors such as financial and insurance activities (D64T66), professional, scientific and technical activities (D69T75), and manufacture of machinery and equipment (D28). This suggests a wide range of activities within these sectors, leading to varying levels of productivity across countries. Conversely, sectors such as telecommunications (D61), computer programming, consultancy and related activities (D62), and information service activities (D63) exhibited the narrowest distribution in efficiency across countries. This indicates a high degree of similarity of the markets and the nature of inputs and outputs in these sectors across EU economies.

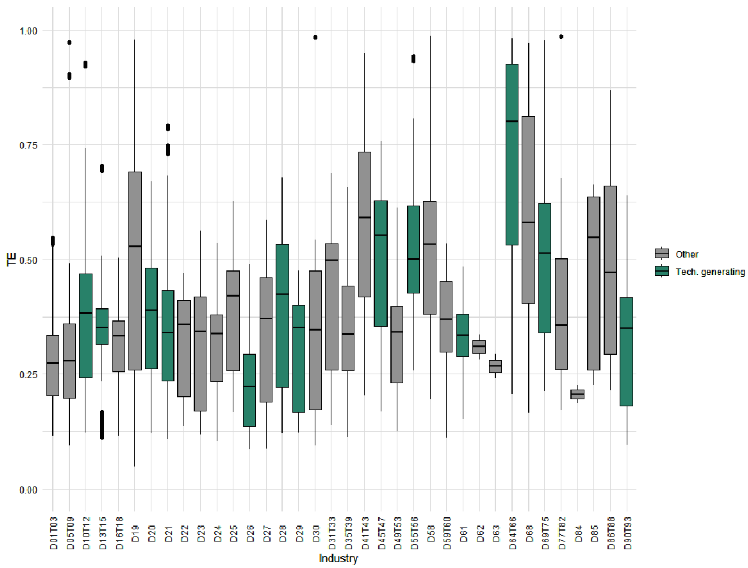

Figure 1. The distribution of efficiency scores of economic sectors (source: authors' calculations)

AT-generating sectors do not necessarily have the highest efficiency scores (Figure 1). The highest efficiency scores were in financial and insurance activities (D64T66) with median value of 0.8, while i.e. the computer, electronic, and optical products sector (D26) had comparatively lower efficiency scores with average value of 0.22. These results correspond to the previous researches that high-tech industries and innovating firms, on average, are not necessarily associated with higher efficiency levels (Liik et al., 2014; Crowley & McCann, 2018). AT-generating economic sectors usually have a diversity of firms. Firms can be divided in various categories according to their contribution to added value. This ranges from large R&D corporate performers (headquarters) that hold around 90% of world's private R&D spending and have strong financial capacities to innovate (EC, 2022), to manufacturing firms that are in locations with lower costs for production factors. Some economic sectors have high patenting intensity but at the same time are based more on continuous rather than batch production processes (Capello & Lenzi, 2021). Therefore, a diversity of economic activities within the sectors exist. These differences in industrial structure across countries and economic sectors are reflected in production efficiency scores at both sectoral (Figure 1) and country levels (Figure 2).

Figure 2. Average efficiency scores of economic sectors by country (source: authors' calculations)

Figure 2 shows a distribution of efficiency scores of AT-generating sectors on a country-by-country basis. Countries with the least efficiency scores were Czech Republic, Hungary and Slovakia. The gap between the most and least efficient is apparent. For example, the efficiency of financial and insurance sectors (D64T66) or pharmaceuticals (D21) may differ by four-fold between the Czech Republic and UK. Lower efficiency scores reveal a potential for efficiency growth and technology adoption, i.e. in France, and Sweden for computer, electronics and optical products or in Poland for arts, entertainment and recreation.

UK, Denmark and Belgium had a variety of sectors operating on the production possibility frontier. Other countries that were in the middle of Figure 2 also had some economic sectors operating on the production possibility frontier or close to it, i.e. accommodation and food services sector in France or professional services in the Netherlands. Due to the relatively lower efficiency of these sectors in general compared to such sectors as financial and insurance, France and the Netherlands are in the middle of the graph.

An interesting case is Estonia, which joined the EU in 2004 and is in the group of countries that are catching up with the EU average GDP per capita. Estonia's financial and insurance sector (D64T66) was operating on the production possibility frontier, with the highest margin between inputs and outputs compared to the other countries in the sample. The efficiency level of Estonia's financial and insurance sector was equal to the efficiency of the same sector in Finland, UK, Ireland or Denmark, which were operating on the production possibility frontier. The early and high-degree digitalization of traditional banking, an active FinTech sector with a vibrant start-up community and ICT development in Estonia may explain these findings (Masso et al., 2022). These findings contribute to scientific debates on catching-up economies that can have strengths in some specific fields of economic activity.

While looking at the efficiency change within five AT-generating sectors and European countries, the leaders in production efficiency remained the same in all sectors analysed during the time period. Catching-up processes between the countries analysed clearly emerged in two of five economic sectors (D20 chemicals, and D26 computer, electronic and optical products) (Figures 3, 4). Less efficient units were getting closer the efficiency frontier with a

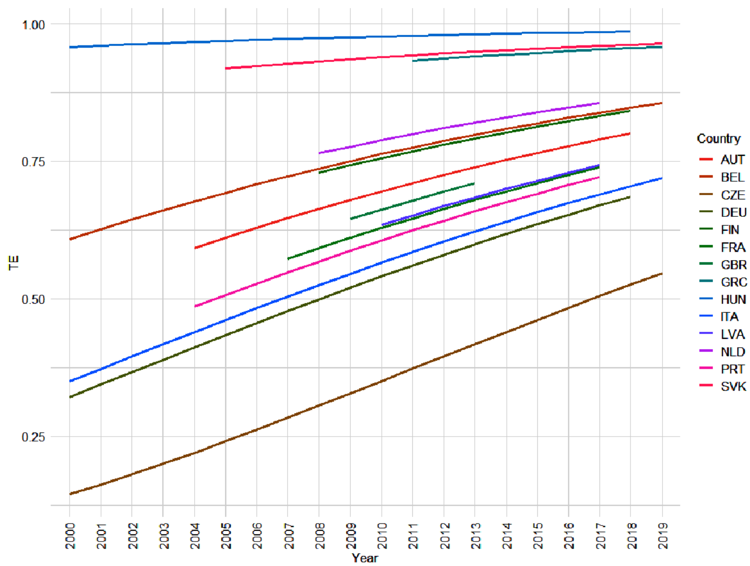

Figure 3. Efficiency scores of chemicals (D20) economic sector by country (source: authors' calculations)

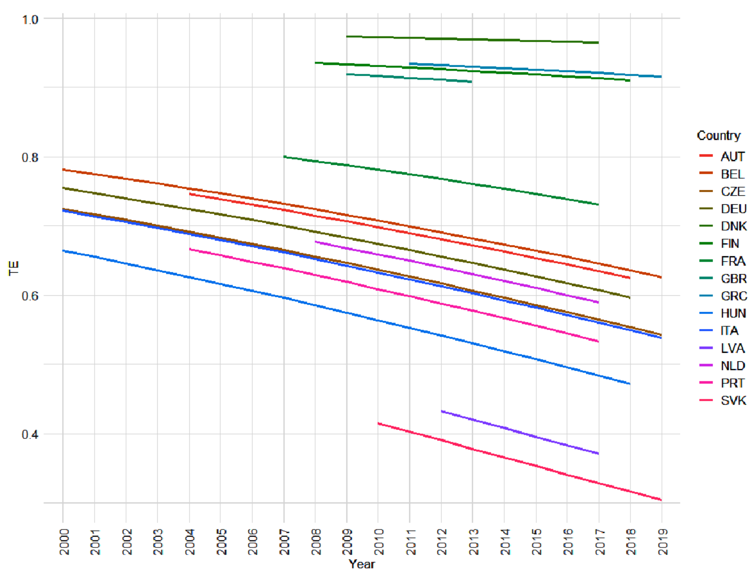

Figure 4. Efficiency scores of the pharmaceuticals (D21) economic sector by country (source: authors' calculations)

lowering efficiency gap across European countries. Two economic sectors had an efficiency growth in all countries analysed (D28 machinery, D29 motor vehicles, trailers and semi-trailers) to a lesser extent in catching-up countries. One sector (D21 pharmaceuticals) revealed decreasing efficiency and divergence among countries. This demonstrates a mixture of both convergence and divergence processes within European.

The pharmaceuticals economic sector (D21) differed from others in terms of divergence and negative changes in production efficiency (Figure 4). Leading countries showed slight decreases in production efficiency during the period analysed, while other countries revealed even sharper decreases in production efficiency. Even though the pharmaceutical industry continues to invest in R&D and is one of the top research-based areas, the sector faces considerable challenges, such as: additional regulatory hurdles, escalating R&D costs, new emerging markets for research, a highly competitive environment, and not entirely balanced property rights (European Federation of Pharmaceutical Industries and Associations [EFPIA], 2019). Back in 1990, Europe had more R&D investments in pharmaceuticals than US, while in 2017 US accounted for approximately 37% more of R&D investments than EU. The highest sales of new medicines were in the US market (65.2% of sales compared with 17.7% the European markets) during the period of 2013–2018. The Brazilian, Chinese and Indian markets grew almost two times more than EU markets in 2014–2018. With sharp global competition, the difference between inputs and outputs is decreasing and value added per employee is shrinking with lowering efficiency scores.

Conclusions

In this study, we aimed to evaluate the production efficiency of advanced-technology generating sectors in the EU and to measure the gains from technology generation (in-house R&D) and efficiency changes. Compared to previous studies on sectoral efficiency, this research employed less aggregated industry-level data and focused on technological transformations of economic sectors of high policy interest in the EU. The findings from stochastic frontier analysis of industry-level panel data suggest that technical progress in AT-generating sectors was higher than for the whole sample of economic sectors (3.2% and 1.1%, respectively) that could be expected from innovating industries.

Research results reveal that fixed capital accumulation was a driving force of production efficiency of economic sectors in the EU, stating the importance of investments, while in-house R&D contribution remained mixed. This indicates that a portion of AT-generating sectors in the EU struggle to gain higher production efficiency from technology generation processes and R&D activities, as well as, increasing productivity gap between the territories across EU, especially for pharmaceuticals industry. This shows challenges facing the sector: sharp global competition, new emerging markets, additional regulatory requirements, and reduced public spending in the EU that has affected the sector. This indicates that a broader industrial policy view on sectoral development is needed regarding regulatory framework, public spending, and other policy means depending on the sectoral and country specifics.

Research findings add to the scientific debates on the production efficiency of economic sectors in diverse territories. We can conclude that the production efficiency of economic sectors and countries cannot be boiled down to the economic development level only. Territories with lower economic development can operate efficiently in some areas of economic activities. Nevertheless, this is more an exception than a tendency. In our sample catching-up economy, Estonia, revealed high efficiency in the financial and insurance sector that was in line with other countries operating on the production possibility frontier, such as the UK, Finland or Denmark. However, other countries with lower levels of economic development within a sample (e.g. the Czech Republic, Slovakia, Hungry, Slovenia, and Portugal) revealed lower production efficiencies in all the economic sectors analysed compared to more advanced economies in the EU. Even though catching-up processes were more obvious in two economic sectors than in other AT-generating economic sectors, differences in productive efficiency reveal a remaining technological gap between countries that, without policy initiatives, could be difficult to change.

These challenges necessitate a more comprehensive industrial and innovation policy approach to sectoral development. Firstly, it is relevant to reevaluate regulatory frameworks, with the aim of ensuring competitiveness vis-à-vis non-EU jurisdictions where competition for EU production is emerging. Secondly, public expenditure related to advanced technology production should be strategically reviewed during the planning phase, to foster the growth of advanced technology-generating sectors within the EU. Thirdly, the establishment of conducive startup ecosystems for the development of advanced technologies across various territories appears to be a promising avenue for further exploration. Moreover, to mitigate the technology gap, particularly in the pharmaceutical sector, the networking prerequisites should be addressed in the funding schemes of scientific projects at both EU and national levels. Collectively, these measures can contribute to supporting the performance of advanced technology-generating sectors within the EU.

Limitations of the research and future research directions could be foreseen. This study aimed to give insights in the technological change and factors of efficiency mostly focusing on the EU economies. The extended analysis could include production entities from countries outside Europe with increasing R&D shares (e.g. China, India) to reveal cooperative links, potential of global knowledge transfer, meanwhile, gains and losses in a broader setting that were not covered in depth in this paper. To add to this, a case study analysis of entrepreneurial ecosystems in diverse territories could give valuable insights for a policy formation.

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Author contributions

Giedrė Dzemydaitė (GD) and Laurynas Naruševičius (LN) conceived the study and were responsible for the design, conceptualization and development of research methodology. LN was responsible for data collection and analysis. GD and LN were responsible for data interpretation. GD wrote the first draft of the article.

Disclosure statement

No competing interest to report.

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APPENDIX

Appendix 1. Statistical data sources

Table code	Table description	Source
STANI4_2020	STAN Database for Structural Analysis 1) Number of employees (EMPE); 2) Gross fixed capital formation, volumes (.GFCK); 3) Value added, volumes (.VALK)	OECD statistics
ANBERD_REV4	ANalytical Business Enterprise Research and Development (ANBERD) database; R&D expenses (national currency – 2015 prices) (.CONSTNATCUR)	OECD statistics
EAG_NEAC	Labour force status and the educational attainment level by the National Educational Attainment Categories	OECD statistics
TX.VAL.ICTG.ZS.UN	ICT goods exports (% of total goods exports)	World Bank Data
TM.VAL.ICTG.ZS.UN	ICT goods imports (% total goods imports)	World Bank Data
IT.CEL.SETS.P2	Mobile cellular subscriptions (per 100 people)	World Bank Data
IT.NET.USER.ZS	Individuals using the Internet (% of population)	World Bank Data
ert_bil_eur_a	Euro/ECU exchange rates	Eurostat

Appendix 2. Sectors (industries) involved into analysis according to ISIC Rev. 4

Industry code	Industry name	Economic sector
D10T12	Food products, beverages, and tobacco [CA]	Agro-food
D13T15	Textiles, wearing apparel, leather, and related products [CB]	Textiles
D20	**Chemicals and chemical products** [CE]	**Chemicals**
D21	**Basic pharmaceutical products and pharmaceutical preparations** [CF]	**Pharma industries, Medical devices**
D26	**Computer, electronic and optical products** [CI]	**Electronics**
D28	**Machinery and equipment n.e.c.** [CK]	**Machinery**
D29	**Motor vehicles, trailers and semi-trailers**	**Automotive**
D45T47	Wholesale and retail trade, repair of motor vehicles and motorcycles [G]	Retail and Wholesale
D55T56	Accommodation and food service activities [I]	Tourism
D61	Telecommunications [JB]	Telecommunications
D64T66	Financial and insurance activities [K]	Financial services
D69T75	Professional, scientific, and technical activities [M]	Professional services
D90T93	Arts, entertainment and recreation [R]	Tourism

Note: *According to economic sectors' names in the methodological report of EC (2021).
**In bold, economic sectors with attributed patents in advanced technologies.

Appendix 3. Evaluation of R&D capital stock by perpetual inventory method

R&D capital stock in time period *t* is derived from the perpetual inventory method (Hall et al., 2010), as follows:

$$R\,\&\,Dcapital_t = R\,\&\,Dcapital_{t-1}\left(1-\delta\right) + R\,\&\,D_t\,, \tag{5}$$

where δ is the depreciation rate; $R\&D_t$ – R&D expenses at period t. Additionally, a stating value of R&D capital at a first period of a panel (t_0) is as follows:

$$R\,\&\,D\,capital_{t0} = \frac{TA_{t0}}{\left(\varrho+\delta\right)}, \tag{6}$$

where ϱ is the growth rate of R&D expenses. The depreciation rate can vary between technologies and industries (Severgnini, 2009). Differences between depreciation rates are based on the idea that more advanced and emerging technologies have shorter average life cycles. For example, Kumbhakar et al. (2012) applied the following depreciation rates for R&D capital: high-tech industries = 20%, medium-tech industries = 15%, and low-tech industries = 12%. Similarly, for the calculation of fixed capital, the depreciation rates of 8%, 6%, and 4% were applied, respectively. Our sample included economic sectors that had been developing diverse sets of technologies and countries with different intensities of R&D within the same economic sector. Due to heterogeneity of the sample, we opted to use the average depreciation rate of 15% for R&D capital and 6% for gross fixed capital.

Appendix 4. Robustness check of the evaluation of production efficiency

For the robustness check, we aimed to show that the key results of the paper hold true even if we estimate efficiency with methods other than an SFA. To do this, we applied Data Envelopment Analysis (DEA). DEA is widely applied for the estimation of the efficiency of various economic systems (Sickles & Zelenyuk, 2019). It is a non-parametric technique, and its results are determined without choosing a parametric model for the production function (Schaffer et al., 2011). Efficiency scores are estimated with linear programming techniques that consist of a set of mathematical formulations designed to imitate a technology set from the production process. DEA can evaluate efficiency scores of units analysed, but it does not evaluate elasticities of different factors, as in an SFA. Therefore, we calculated efficiency scores by DEA and compared them with efficiency scores calculated by SFA.

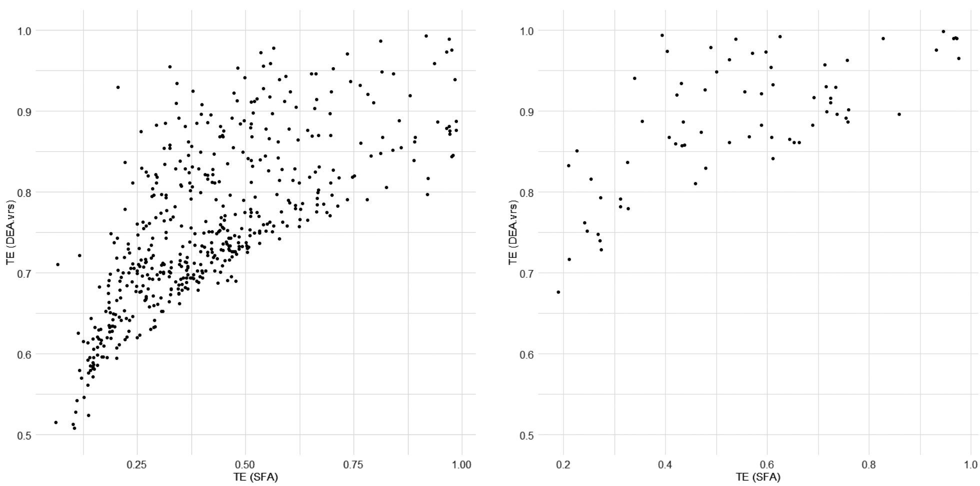

Figure A1. A scatter plot of efficiency scores of all economic sectors (left) and economic sectors that generally patent new technologies (right) by SFA and DEA (source: authors' calculations)

Results reveal the distribution of efficiency scores of economic sectors evaluated by parametric (SFA) and non-parametric (DEA) techniques (Figure A1). The correlation of efficiency scores by DEA and SFA affirm the similar tendencies of the estimation of efficiency scores. The relationship of efficiency scores evaluated by SFA and DEA had a non-linear form. Non-linearity of the relationship indicates that the SFA exposed a broader distribution of efficiency scores than the DEA. More efficient units evaluated by the DEA (which varied from 1.00 to 1.25) had a broader spread of scores than by SFA. This is due to the SFA's framework, which has more properties than DEA, evaluating time series and slacks, and is supposed to be more appropriate for panel data treatment (Coelli et al., 2005). We may assume that SFA is able to estimate technical efficiency more precisely.