Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
2022 Volume 28 Issue 6: 1854–1870
https://doi.org/10.3846/tede.2022.18005

CLUSTERS AND INNOVATION: THE RELATIONSHIP BETWEEN MEMBERSHIP IN CLUSTERS ORGANISATIONS AND TECHNOLOGICAL MATURITY OF COMPANIES IN POLAND

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Received 02 June 2022; accepted 17 October 2022

Abstract. This article aims to investigate the relationship between cluster organisation membership and the performance of companies in terms of their technological maturity. The article introduces and operationalises a new concept of technological maturity which reflects competitiveness, innovativeness, and market reputation of a company in a particular sector. To compare the technological maturity between cluster organisation members and non-members a composite index was created. The study is based on theoretical and empirical analyses. The empirical part is based on firm-level data collected in the survey from 464 companies identified in the technological fields covered by the National Smart Specializations in Poland. A set of statistical tests has been employed to assess whether (a) the indicators differ significantly between cluster organisation members and non-members (b) the composite index differs significantly between cluster organisation members and non-members. Results of the analysis show a positive relationship between being a member of the cluster organisation and the technological maturity of the company. The regression analysis proved that the relationship remains significant when controlling for the industry, geographical location, and size of a company. The article contributes to the discussion about the role of cluster organisations and their economic impact.

Keywords: cluster, cluster organization, clustering, innovation, technological maturity, technical advancement.

JEL Classification: O31, D22, D85.

Introduction

Innovation is the key factor influencing competitiveness, both in terms of the microeconomy (firm-level) and the macroeconomy. Increasing the innovativeness of companies combined with rising their technological level is crucial in the context of building their competitive advantage (Ferreira et al., 2017). Restrictions related to the COVID-19 pandemic have signifi-

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cantly changed many aspects of the economic environment and have shown the importance of the ability to innovate and adjust to new market conditions, mainly by digitizing business processes. The COVID-19 pandemic caused unprecedented growth of demand for more innovative approaches and sometimes even reinventing companies. In the rapidly changing environment, development based on innovative solutions gives chances for survival and new possibilities for development. Clusters are considered as notable platforms facilitating the creation of innovations (Künzel et al., 2016; Ferras-Hernandez & Nylund, 2019; Xu et al., 2022). For this reason, clusters have become an important research area and are considered to contribute to boosting the competitiveness of countries and regions (Porter, 1998, 2000).

In the last three decades, the popularity of clusters was rising, both as a business model used to organize economic activity, and also as an instrument of the government to increase the competitiveness of the economy. Despite many years of discussions concerning clusters and their role in the economy (Porter, 1990; Norman & Venables, 2004; Chatterji et al., 2014; Kerr & Robert-Nicoud, 2019; Ketels & Protsiv, 2021; and others) there is still insufficient empirical evidence concerning their impact on innovativeness and market performance of companies. Therefore, an increasing interest of researchers and policymakers can be noticed worldwide to explain the drivers of innovations in clusters (Chandrashekar & Bala Subrahmanya, 2019). Little research presenting evidence for the association of clusters with innovation and no comprehensive attempt has been made yet to ascertain the influence of different factors related to cluster linkages on the firm-level innovation (Chandrashekar & Bala Subrahmanya, 2019). This article addresses this research gap by examining the role of cluster organisations in the context of factors that influence the innovation level of companies like the size of a company, industry, and location.

The definition of "cluster" varies in different studies. They could be understood as "natural clusters" – shaped according to the definition by Porter (1990, 1998, 2000), or specified as "cluster initiatives", an institutionalized form of cooperation between a group of entities, including companies, public institutions, the research community, and special institutions that undertake a specific project with public funds or other formalized activities (Sölvell et al., 2003). Activities of the cluster initiative, including representing its members and managing internal and external relations, could be carried out by a legal entity called a "cluster organisation". The cluster organisation facilitates cluster management and is associated with the development of rules for participation and access to common infrastructure or activities (Furman et al., 2002; Morgulis-Yakushev & Sölvell, 2017; and others).

The topic discussed in this article refers to cluster organisations, providing a better recognition of their role and impact by exploring if the technological maturity of companies relates to the membership in a cluster organisation. Technological maturity is measured by indicators of i) advancement of the created or developed technologies, ii) the market readiness of technologies, iii) the achievements in the field of technology, iv) the position of the company in particular industry, and v) the patent activity, and by created composite index based on previous indicators. It has a practical dimension for providing effective public policy and support aimed at increasing the competitiveness of the economy. As noticed by Hedvičáková and Král (2021), the innovative process is so crucial for the development of the company, that it is necessary to measure performance in this area. The originality of the paper comes from analyses of firm-level data set collected in a wide-scale survey, which provides real-life evidence on how cluster organisation membership contributes to the performance of companies. A number of studies attempted to conceptualize technological maturity and operationalize it, but no attempt has been made to develop a link between the technological maturity of a company in the context of cluster organization membership. This article addresses this research gap.

The results of the analysis indicate a link between cluster organisation membership and technological maturity. The statistical tests proved that there is a clear difference between companies being cluster members and non-members as far as technological maturity is concerned.

The first section of this article presents the findings of the literature review on clusters that provided the theoretical background for development of research hypothesis. The second section presents the research methodology, details concerning the data, and the construction of the composite index used for testing the hypothesis. The third section discusses the results focusing on statistically significant differences of the composite index reflecting the technological maturity between cluster organisation members and non-members. The last section presents conclusions of the study and issues that require further exploration.

1. Theoretical background

The study builds on the innovation economics paradigm and cluster theory which is related to the agglomeration and the knowledge spillover theory. Porter (1998, p. 199) defines the cluster as "geographically proximate group of interconnected companies and associated institutions in a particular field, linked by commonalities and complementarities". Suppliers, providers of specialized infrastructure, customers, companies, governmental and other institutions such as universities, vocational training providers, and trade associations could be interconnected and collaboration and competition among them can promote growth, innovation, and competitiveness (Porter, 1998). These two factors – collaboration and competition – create an environment for innovative processes – competition drives companies to develop new solutions or more advanced products and cooperation facilitates the innovation process by learning from peers, learning by doing, knowledge flows, etc. Numerous examples, confirming the positive influence of clusters on the development of companies, the survival of start-ups and creation of innovative environment, can be found in literature, e.g. Braunerhjelm and Carlsson (1999), Lundequist and Power (2002), Lundmark and Pettersson (2012), Ahedo (2004), Konstantynova (2017), Yan et al. (2021) and others. Gupta and Subramanian (2008), Rosenfeld (1997), Chapain and Comunian (2010) and others state that the essence of a cluster is access to information and joint learning enabling the flow of knowledge. The innovation-related effects of cluster activity are supported by the cooperation between the actors of a quadruple helix model of innovation, and the flow of knowledge is a significant factor that plays a role in an informal network created by cluster members (Balland et al., 2016). As indicated by Feldman (2000), the companies located in a geographical proximity benefit from knowledge spillovers. He argues that the transfer of knowledge takes place in an environment in which interaction and communication are being facilitated.

Rodríguez-Pose and Comptour (2012) provides evidence that the presence of clusters is consequential for the economic growth of regions under the condition that there is a "social filter", which is constituted of elements creating an environment for the development of a regional innovation system. The research carried out by Rutten and Boekema (2007) also emphasizes the role of embeddedness and social capital in regional innovation networks and explains why networks of innovating firms are beneficial. Similar conclusions are drawn by Anokhin et al. (2019) who argue that industrial clusters influence regional innovation positively, and the effects of their existence are most visible in the regions with relatively high supply of qualified workers. Mackiewicz (2019) analysed the role of clusters in the Polish innovation system, emphasizing a number of functions, including technology transfer between cluster members and engagement in implementation of public tasks.

Knowledge flows in innovation clusters influence the competitiveness and performance of cluster members as results of cooperation, workforce mobility and geographical proximity (Fioravanti et al., 2021). These knowledge flows favour creation of innovations (Alberti et al., 2021). The concept of clustering is often used to explain why the competitiveness of some industrial regions is higher than that of others. Xu et al. (2022) provide evidence about the knowledge communication role of cluster-based technological innovations and knowledge spillover of technological innovation on efficient industrial structure. Recently scholars have tended to use the cluster theory to explain the innovative performance of companies. The role of clusters in strengthening innovation at firm level was confirmed by Ferras-Hernandez and Nylund (2019) who identified the drivers of technological change in clusters. Grashof et al. (2019) confirm ability of clusters to create a suitable environment for radical innovation. Delgado et al. (2012) provided evidence that clusters affect not only innovation but also growth and the survival rate of new companies. Li and Wang (2019) show that the development of industrial clusters attracts research institutions and service-oriented organisations, providing innovative incubation platform.

According to Wennberg and Lindqvist (2010), companies located in strong clusters create more jobs, higher tax payments, and higher wages to employees. Similar conclusions were drawn by Ketels and Protsiv (2021) who examined the impact of clusters on industry-level wages and regional prosperity. Also, it was demonstrated by Alberti and Belfanti (2021) that clusters create shared value and contribute to economic and social opportunities as cluster development variables explain much of the business and social impact variables.

Firms belonging to the cluster organization could encourage the development of practical training-oriented programs based on technical aspects and developing other skills and competences (Canet-Giner et al., 2022). The authors confirm that cluster can have an influence on firms' behaviour and facilitates knowledge-sharing processes. According Götz (2021), cluster can provide a conducive knowledge environment, simplifying and increasing the efficiency of the business processes and supporting development of I4.0 solutions and their implementation.

On the other hand, some studies provide arguments for the existence of "negative spillovers" which occur when co-location with other companies increases the risk of losing their core knowledge (Aharonson et al., 2007). They argue that location in a cluster may be a handicap as some companies face a risk of losing their competitive advantage resulting from their own knowledge. The negative aspects of networking in open innovation are noticed for example by Capone and Innocenti (2020). The authors claim that a "generic" openness is not a positive determinant for the invention capacity of the organisations. On the other hand, the depth of the openness, understood as the intensity of external network ties, has a positive influence on the innovative performance. But after a tipping point (six partnerships), the patent productivity tends to decrease due to open innovation costs. Clusters undertaking open innovation point out that it is difficult to manage joint project and companies participating are concerned about intellectual property rights (McPhilips, 2020). Aharonson et al. (2014) provide evidence that firm's innovative output measured by patent application rate is affected by location in agglomerations of companies in their technological fields. The results of the study indicate that on average companies benefit from clustering, mostly in clusters with a strong technological specialization. Cooperation in clusters facilitates development of innovations, for example, by finding and combining ideas that are complementary to existing R&D projects and the creation of cooperative relations with other cluster members (Kowalski & Mackiewicz, 2021).

Brenner and Gildner (2006) found out that although local cluster environment initially impacts the performance of a company positively, in the long run it may lead to a lag in technological advancements. Moreover, according to Simmie and Sennett (1999), the benefits of location in a cluster are not distributed evenly as some companies absorb knowledge from the network more than others. Anić et al. (2022) investigated the composition of services and firms in a wood industrial cluster based on members' interests. The research results revealed that firm's expectations regarding cluster's services may result in differences in market performance among the groups of cluster members.

Several authors of studies indicate that clustering does not necessarily lead to better innovation performance or certain conditions must be met to provide a real stimulus for innovation. For example, there should be a critical mass in terms of information sharing and sufficient interaction (Iritié, 2017). If this condition is not met, the cluster may hold back innovation in cluster companies. The European Commission (2003) also provided some arguments that in certain circumstances, clusters might hinder the development of its members. It is related to the fact, that if economies are characterized by rapid technological changes, cluster members could be less agile and more dependent on technologies used by others and less flexible to adapt themselves to technological changes. According to Marginean (2009), if cluster members rely on few buyers or on the activity of one large company, they are too dependent on the decisions of the management of the large company. Also, cluster members may become less active in a search for new technologies, as they consider that the strategy of imitating is good enough for them. Some authors indicate that the greatest positive influence of a cluster membership can be experienced by young companies (McCann & Folta, 2011). Kukalis (2010) underlines that the benefits of clustering occur when the companies have similar absorptive capacity and innovation potential. According Terstriep and Lüthje (2018), firms' absorptive capacity has positive effect on innovation cooperation, however there is no significant impact of innovation cooperation within the cluster on their innovation success.

Beaudry and Breschi (2003) claim that besides advantages, the disadvantages for non-innovative companies in the same industry are considerable. The authors argue that the positive externalities are likely to flow only from innovative firms and they explain this result by the cumulative effects of technical advancement.

2. Research methodology

As there is no consensus among scholars about the positive and negative economic effects of clusters, in this paper an attempt is made to establish empirically a link between the membership in a cluster organisation and the technological maturity of companies. Cluster organizations provide a fertile ground for the business-research cooperation and the development of technologies. According to the literature presented above, companies located in a cluster have a better access to knowledge and may benefit from technology transfer. Following hypothesis can be formulated:

Technological maturity of companies is linked with their cluster organisations' membership in a positive way.

Technological maturity is a well recognized aspect in the economic literature and there are many approaches to its measurement (Albert et al., 2015). One of popular technological maturity models was developed by Sommerlatte and Deschamps (1986). There were also other attempts to operationalize technology maturity models by Watts and Porter (1997), Haupt et al. (2007), Gao et al. (2013) and Albert et al. (2015). The main idea of these models is to overcome the necessity to re-define relevant performance measures for each new technology by using generic measures such as patent-based and other intellectual property indicators. These models are created mainly to provide a reliable and objective statement regarding the maturity of technology, compare technologies and assess their value. In these models a set of indicators reflecting the states of technology maturity, is used in the process of strategic technology management. In addition to these approaches to the assessment, in this article we explore the dimension related to innovativeness and market performance of companies and compare it between cluster organization members and non-members.

Technological maturity, defined for this article, reflects competitiveness, innovativeness and reputation of a company in a particular sector. The technological maturity is a multifaced concept and for the purpose of this research is operationalized by the following indicators: (i) company's technical advancement vs latest technological achievements on the market, (ii) technical advancement by technological readiness, (iii) number of achievements in technology development, (iv) domestic market position and (v) number of patents, trademarks and industrial designs registered or applied for by the company.

i. The advancement of the created or developed technologies in relation to the latest technologies available on the market reflects the ability of the company to compete. The more advanced the technology the better the solutions that can be offered to the customers and more opportunities to promote the brand of the company as a technology-driven and providing good quality products that meet the expectations of customers (Schacht, 2009).
ii. The level of technological readiness reflects the status of the technology, from very basic to operational. It allows the assessment of the maturity of a particular technology and comparing the maturity of different types of technologies (Mankins, 1995). According to Engel et al. (2012), technology readiness can be evaluated by dividing the process of technology development into defined stages. Each stage must be operationalized by a set of indicators to determine the readiness level of a technology. It

is widely used as the scale is universal and fits any technological field, and therefore provides a common understanding of technology status. It is often used for investment decisions or technology transfer processes (Lavoie & Tugrul, 2018).

iii. Another indicator of innovativeness and technological advancement are special achievements in the field of technology development or implementation of innovative products and services. The awards and distinctions prove that the products or services have unique features and are highly innovative. Companies with new technologies or innovative solutions often present them at fairs or other exhibition events, during which industry awards are granted. Such prizes are also awarded to start-ups, such as Positive Impact Start-ups. This indicator is linked to the technology readiness – according to the technology readiness studies, customers associate it with innovation, technology usefulness and ease of application (Parasuraman, 2000; Lin et al., 2007).

iv. It can be argued that there is a link between the advancement of technology and the market position of the company. To strengthen competitive company's market position, it is advisable to constantly evaluate and assess the development of relevant technologies (Oerlemans et al., 2005).

v. The number of patents, trademarks and industrial design reflects the performance and results of R&D activities (if produced within a company) and also shows the degree of modernity of the manufactured products. Therefore, it is one of the most frequently used measures of innovativeness (OECD/Eurostat, 2018; Chen et al., 2012; Gao et al., 2013; Gerken & Moehrle, 2012). Some companies opt for licensing instead of carrying out their own R&D works, nevertheless spending on licences also influences the potential to enhance the modernity. Contrary to the previous measure – it is an objective and easily comparable indicator.

Poland is an example of an EU Member State struggling with a relatively low level of technological capacity of the economy and poor social capital which is reflected by low rank in the European Innovation Scoreboard – the share of innovative SMEs collaborating with others is very low in relation to the EU average. Also, patent applications are much below the EU average (European Commission, 2021). The consequence of a poor social capital is limited trust which affects cooperation. Therefore, clusters and cluster organisations are very needed to promote cooperation. Underdeveloped social capital and low ability to collaborate may be attributed to the Polish communist history and a difficult transition from a central planning to a market economy.

Poland is an example of a country that has introduced cluster policy promoting cooperation into the innovation policy mix. The history of Polish cluster policy dates back almost two decades but the financial resources dedicated to cluster policy have been modest, in particular in recent years. This has not raised a barrier for cluster development, however – there are currently 71 cluster organisations registered at the European Cluster Collaboration Platform and 15 strong cluster organisations (Key National Clusters) that play a significant role in the economy. The impact of clusters on economic development is nowadays much more important than several years ago.

The analysis is based on the data obtained as part of the questionnaire survey, which was commissioned by the Polish Ministry of Economic Development, Labour and Technology.

The survey aimed to identify key technologies for the socio-economic development of Poland examining the technological, innovation, and business activities of Polish companies. The database used for the survey encompassed 3478 entities identified in the technological fields covering the National Smart Specializations. The interviews were conducted in 2020 with the use of Computer Assisted Telephone Interviews (CATI) method. The response rate was 13% which resulted in collecting 464 responses. The surveyed entities constituted micro-enterprises (43.8%), small (27.7%), medium (16.8%), and large-sized companies (11.1%) operating in processing industries (including very diverse sample – production of machinery and equipment, chemicals and chemical products, rubber and plastic, food products, etc.). The number of medium-sized and large companies in the sample is higher than in the general population. It is explained by the fact that the sample comprised companies operating in fields covered by national smart specializations.

The questionnaire comprised 42 questions of different nature (Likert scale, single choice, and open choice) depending on the type of issue. For the article, a selection of questions was used focused on: i) the assessment of the advancement of the created or developed technologies in relation to the latest technologies available on the market (acronym TAM). Subjective assessment of the respondent was taken into account as there may be different aspects of the advancement of the created or developed technologies in relation to the latest technologies available on the market (e.g. the care for the environment or sophisticated functionalities of products created by the company); ii) the advancement of the created or developed technologies according to the level of technological readiness (acronym TAR); iii) special achievements in the field of technology development or implementation of innovative products and services (acronym ATD); iv) assessment of the position of the company in the industry on the domestic market (acronym DMP). The position of the company in the industry on the domestic market is a typical indicator based on self-assessment; v) the number of patents, trademarks, and industrial designs registered or applied for by the company in the last 5 years (acronym DMP). For calculating the indicators, we used the largest possible number of entities that responded to a given question in the survey (and for the composite index – the entities for which the whole set of data was available with no missing data).

Technological maturity was described as a composite characteristic consisting of the variables mentioned above. As a first step we tested the aspects of technological maturity separately (to examine if cluster membership is linked to the specified aspects of technological maturity), and as a second step – as a simple composite index created with all the variables listed above. As the causal relationship is not determined – the cluster membership may affect the technological maturity, or more technologically mature companies join cluster organizations – therefore the variables that proved to be not statistically significant in the first step, were also taken into account for the composite index.

As a third step, a regression was estimated explaining technological maturity index by cluster membership and control variables (size of the company, its location and NACE section) to eliminate the influence of a specific sample composition.

3. Research results

The results of tests examining whether a significant difference between the answers of members and non-members can be detected are presented in Table 1. All, but one variable, are ordinal. The only exception is the number of actual outcomes of companies' innovation efforts, defined as the sum of the numbers of registered patents, trademarks, and industrial designs. For the ordinal variables the Mann-Whitey test was used (Conover, 1980). This test could be applied as all the observations from both groups (cluster members and non-members) are independent of each other and it is always possible to say which observation (response) is greater in value.

The null hypothesis that the distributions of responses of members and non-members don't differ could not be rejected in the case of two out of five variables (TAM, TAR) (p-values in Table 1 of 0.18 and 0.46 respectively). In case of the remaining three variables (ATD, DMP, and PTD) statistically significant differences between both of groups were indicated (percentages of particular responses of cluster members or non-members differ). They are also clearly visible in Figure 1.

Table 1. The results of Mann-Whitney and t-test (source: own research)

Variable	Description	Test used	Statistic	P-value
TAM	Technical advancement vs market	Mann-Whitney	5742	0.17684
TAR	Technical advancement by technological readiness	Mann-Whitney	6366	0.45589
ATD	Achievements in technology development	Mann-Whitney	11620	0.00581
DMP	Domestic market position	Mann-Whitney	6549	0.0003
PTD	Patents, trademarks, designs	t-test	3.771	0.00019

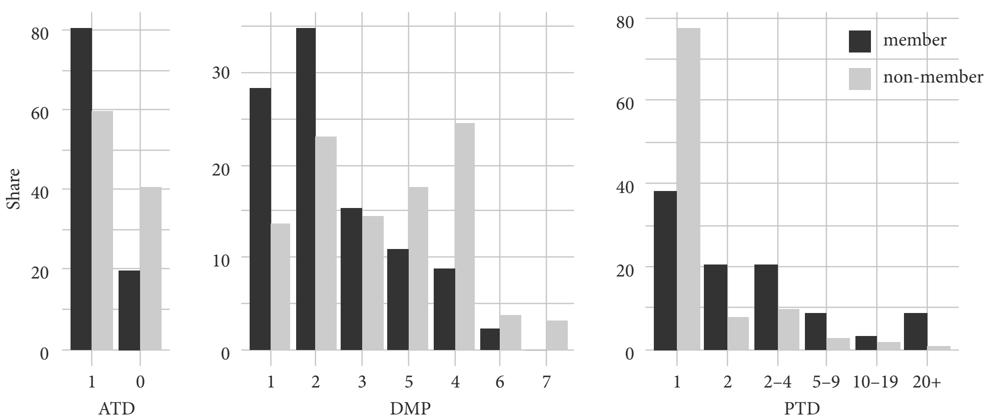

Figure 1. Survey results-responses by cluster members (n = 46) and non-members (n = 418), in % (source: own research)

In the subsequent step, a simple composite measure of technological maturity was created and compared between cluster members and non-members. For each respondent, a composite index was calculated as an arithmetic mean of responses to the aforementioned survey questions (variables). Each variable was first recoded so that higher values (understood as the position of the response on Likert scale or 0/1 for binary variables) were expected to associate with greater technological maturity. PTD was converted to an ordinal variable with six levels as depicted on Figure 1. The responses to questions other than binary ones where then standardized within <0,1> range. Recoding was straightforward apart from DMP, where answers ranged from "just have started a business" to "we are a domestic market leader". One can argue that a start-up could be a technologically mature company and a future market leader. But according to the Eurostat data, the majority of start-ups does not survive (Eurostat, 2021). Their performance depends on the competitive environment and the business environment (Dvorský et al., 2021). Therefore, in this article start-ups are treated as companies with a small market share. As all variables are ordinal in their nature, the index reflects (standardized) company position across all the variables. The resulting measure varies between 0.125 and 1.0, with a mean of 0.586. The standard two-sample means test has been employed to assess whether achieved measures differ significantly between cluster members and non-members. Averages for members and non-members were correspondingly 0.680 and 0.572. The calculated test value was 3.15. At 323 degrees of freedom, it was significant at the most conventionally used levels (p-value 0.0018).

The results of both steps indicate that a link between cluster organisation membership and technological maturity exists. However, the possibility that the link is spurious cannot be ruled out yet. Particularly, such a bogus relationship might be a reflection of particular composition of companies in cluster organisations in the sample. For example, average company sizes of cluster members and non-members might systematically differ, and one could ask a question if such a difference affects average technical maturity. Therefore, one more step was taken to at least partially eliminate such a possibility. Available data on companies within the sample were used to control for size (micro, small, medium and large enterprises), industry (NACE), and region of their operation (16 voivodships). The purpose of introducing those variables was to control for possible sources of variation of the composite index other than being or not being a cluster member. As in the example above, it can be reasonably argued that technological maturity might be related to those characteristics. Therefore, a regression explaining technological maturity index by cluster membership and aforementioned variables was estimated. The reasoning is as follows: if the relationship between membership and technological maturity is a spurious one and results from a specific sample composition it should disappear in presence of those additional control variables. Table 1A in the Appendix presents the results of the estimation, explanatory variables are categorical.

The estimation confirms the previous findings. Among considered additional variables company size affects positively the index of technological maturity. The larger the company, the higher the index. This is to some extent an expected result as the index includes variables that might be affected by a company's size such as domestic market position. Other variables seem not to affect the index or affect it incidentally only. Finally, and most importantly, variable referring to the non-membership of a cluster organisation is statistically significant at level of 0.01. Being a non-member results in values of composite index lower of around

0.098 (see Table 1A in Appendix) comparing to a member, which amounts to 17% of the sample mean (on average the composite index is lower for non-members). Therefore, one can tentatively state that the link between cluster organisation membership and technological maturity exists. The findings point to members being more technologically mature companies. However, it should be stated once more, that assumption of direction of causality is neither made nor derived. It is possible that companies that are more technologically mature in the first place congregate in clusters and that being a member of a cluster organisation allows faster technological advancement compared to non-members.

The findings are consistent with much of the existing literature but provide new input to the discussion on the economic role of clusters and their influence on the innovative performance of cluster organisation members. In particular, our research results support the findings by Ketels and Protsiv (2021) mentioned in the literature review. According to Kowalski (2013) clusters matter for the innovativeness of business activity, but their role is quite limited due to relatively low level of cluster development. Results of meta-analysis of the firm-specific cluster effect provided by Grashof and Fornahl (2021) indicate a rather significant positive effect of location in a cluster, but negative firm-specific cluster effect can occur in low-tech industries. The study by Pavelková et al. (2021) which presents the data from 2009 through 2016, did not discover any meaningful influence of firm localisation in a natural cluster or membership in the cluster organisation on financial performance for companies in the selected sectors within the Czech Republic. This may lead to a conclusion that the stage of cluster development matters for the technological maturity of companies operating in a cluster. At the time of the research by Kowalski (2013) clusters in Poland were emerging and the level of their professionalisation was rather low. This situation has changed over recent years and a group of mature clusters emerged in Poland (Mackiewicz, 2019). A similar conclusion was drawn by Bittencourt et al. (2022) who claim that the cluster's influence on firm innovation varies according to its development stage. The more mature the cluster is, the higher the positive externalities resulting from its critical mass and a collective strategy.

The research findings are also in line with the study conducted by Aharonson et al. (2014) which shows a positive relation between location in a cluster and the firms' innovativeness, in particular, if the cluster has a strong technological specialization. The analysis supports conclusion that cluster organisation membership is meaningfully and positively related to technological maturity of a company. This extends the findings of Aharonson et al. (2014) based on the data collected in Canada and measuring innovativeness of a company by the patent application rate. This study confirmed that a similar relationship can be found in Poland – the number of patents is significantly higher in companies that operate in a cluster organisation than in the general population. Moreover, we provide evidence that cluster organisation membership is linked to the achievements in technology development and the position in the domestic market. The statistical tests have not proved that the technical advancement measured by the technology readiness level is related to the membership in a cluster organisation. Also, there is no relation with the higher technical advancement in comparison to other companies in the sector of operation.

The main limitation of this research is the samples' size. The share of cluster organization members is about 5% in the general population and when comparing cluster members and non-members, the first group will always be relatively small.

Conclusions

The purpose of the article is to enrich the state-of-the-art knowledge on the benefits of clustering by investigating the relationship between cluster organisation membership and the performance of companies in terms of technological maturity. Our results demonstrated that technological maturity of companies is linked with their cluster organisations' membership in a positive way. This can be associated to the fact that cluster membership brigs many advantages related to knowledge transfer and collaboration opportunities. Clusters create an environment conducive to collaboration between different types of entities on research and development projects which can influence the number of patents, trademarks, designs and technology achievement. The study has a practical dimension, and its findings can serve for the promotion of clustering among enterprises and policymakers.

The study revealed some issues that require further exploration. First, the direction of causal relationship between cluster organisation membership and technological maturity of companies asks for a further investigation. The study proves that companies being members of a cluster organisation are more technologically mature. It may be linked to the fact, that the membership in a cluster organisation helps to become more technologically mature or vice versa – more technologically mature companies may be more likely to join cluster organisations. Additional regression analysis shows that the relationship under study exists even when controlling for variables such as geographical location, industry (NACE) or company size.

Author contributions

MM conceived the study and was responsible for the design of the study, MM and DP conducted literature review, MM was responsible for development of the data analysis and data analysis. MM was responsible for data interpretation. MM wrote the first draft of the article, DP improved the draft. MM and DP revised the article.

Disclosure statement

No potential conflict of interest was reported by the authors.

Acknowledgements

This paper was enriched thanks to the Ministry of Economic Development and Technology – the owner of the database resulting from a survey with managers of companies which was used for the analysis.

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APPENDIX

Table 1A. Results of the estimation of control variables (source: own calculation)

Variable	Estimate	Std. Error	t-value	Pr(>|t|)	Significance
(Intercept)	0.963942	0.210494	4.579	6.91e-06	***
CL non-member	–0.097631	0.034961	–2.793	0.00557	**
IND3	–0.348893	0.202551	–1.722	0.08604	.
IND4	–0.470896	0.234075	–2.012	0.04517	*
IND5	–0.407627	0.215475	–1.892	0.05951	.
IND6	–0.413966	0.214050	–1.934	0.05408	.
IND7	–0.373193	0.207421	–1.799	0.07302	.
IND8	–0.585218	0.285989	–2.046	0.04162	*
IND10	–0.305496	0.205424	–1.487	0.13805	
IND11	–0.252840	0.219355	–1.153	0.25000	
IND12	–0.627029	0.288549	–2.173	0.03058	*
IND13	–0.348728	0.204748	–1.703	0.08959	.
IND14	–0.076446	0.282633	–0.270	0.78698	
IND16	–0.423230	0.223153	–1.897	0.05887	.
IND19	–0.132730	0.288972	–0.459	0.64635	
VOI2	–0.039988	0.063585	–0.629	0.52991	
VOI3	0.052721	0.064799	0.814	0.41653	
VOI4	0.219212	0.081219	2.699	0.00736	**
VOI5	–0.056428	0.057483	–0.982	0.32709	
VOI6	–0.046964	0.050881	–0.923	0.35676	
VOI7	0.010135	0.040419	0.251	0.80218	
VOI8	0.035884	0.095081	0.377	0.70615	
VOI9	–0.013993	0.055209	–0.253	0.80009	
VOI10	–0.168118	0.200552	–0.838	0.40256	
VOI11	–0.013482	0.058815	–0.229	0.81886	
VOI12	–0.002174	0.047361	–0.046	0.96342	
VOI13	–0.082258	0.079638	–1.033	0.30250	
VOI14	–0.176598	0.077750	–2.271	0.02385	*
VOI15	0.041023	0.053875	0.761	0.44701	
VOI16	0.012041	0.076660	0.157	0.87530	
SOC2	0.075335	0.027533	2.736	0.00660	**
SOC3	0.098677	0.032882	3.001	0.00292	**
SOC4	0.121177	0.040495	2.992	0.00300	**

Note: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1; IND – industry (according to NACE); VOI – voivodeship (region); SOC – size of a company (according to the number of employees); CL non member – cluster non-member N = 325.