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Looking at EU strategic technologies through the lens of patents: measuring, impact on productivity, and technological interdependencies

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Abstract

This study aims to provide a novel perspective on Europe's innovation landscape by offering an original, data-driven analysis of EU Strategic Technologies (EUST), assessing firm-level innovation in the EU compared to the United States and China, as well as other world regions. The purpose of the research is threefold: i) to investigate firms' innovation in EU strategic technologies (EUST) by mapping patents linked to EUST and to isolate the subgroup related to Net-Zero technologies (EUST NZ) through Large Language Models (LLMs) and scraping firms' websites; ii) to estimate the effect of strategic technologies on labour productivity at the firm level; iii) to explore technological interdependencies between strategic technologies.
The findings reveal heterogeneity in firms' innovation propensity across EU member states. At a global level, while the EU has a broad base of innovative firms, it lags in patent volume and intensity compared to its competitors. The study demonstrates the positive impact of strategic technology patents on firm-level labor productivity, particularly for Net-Zero technologies, reinforcing their strategic importance.
Additionally, the study identifies key interconnected technologies—such as Cloud Computing, AI, Cybersecurity, and Hydrogen Technologies—which act as innovation hubs, crucial for advancing EU industrial policy. These findings directly support EU policies, particularly STEP and NZIA, providing empirical evidence for optimizing investments, closing the innovation gap, and securing Europe's technological sovereignty. This research helps ensure that EU investments translate into economic growth and global competitiveness.

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Authorship contribution statement

- Marco Gentile *(Research Center "Guglielmo Tagliacarne", Italy):* Data and method, Descriptive analysis, Data visualization, Econometric analysis.

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- Paolo Righi *(Italian National Institute of Statistics):* Data and method.

- Alessandro Rinaldi *(Research Center "Guglielmo Tagliacarne", Italy):* Conceptualization, Data and method, Econometric analysis.

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1. Introduction

Within the current international landscape, increasingly oriented towards a multipolar system dominated by a few strong, progressively self-confident actors, the growing relevance of security and technological sovereignty has emerged. Given the scope and depth of the challenges, global actors have increasingly recognized the interconnections between security, strategic technologies, and economic influence. European institutions are no exception, yielding a series of strategic initiatives to tackle competitiveness, ultimately striving for Open Strategic Autonomy (Schmitz & Seidl, 2023; Guerrieri & Padoan, 2024), of which technological sovereignty and economic security are central targets (European Parliamentary Research Service, 2021; European Commission, 2023; Kroll et al. 2023; Edler, 2024).

The Letta report "Much More Than a Market" (Letta report, 2024), in providing an assessment of the European Single Market, identified the “freedom of innovation” as a necessary and fundamental addition for the EU to leverage its Single Market within the evolving global economy. Mario Draghi’s report on the "Future of European competitiveness" (Draghi report, 2024), in taking stock of the growing gap vis-à-vis the US economy, further pinpoints Europe's innovative capacity as the root cause of the EU’s weaknesses. Strategic technologies are at the heart of EU industrial policies (European Union, 2024a) as they play a pivotal role for technological sovereignty, which underlies the economic security and the ambitious environmental sustainability objectives of the Union (European Commission, 2021).

The growing gap between the EU and other global actors, particularly the US, has gained prominence in the EU policy agenda. Indeed, the EU has struggled with slow productivity growth, declining competitiveness, and lagging technological innovation, especially in more complex and high technology intensive technologies (e.g., computer technologies, digital communication optics and semiconductors), while it is relatively strong in less complex and clean technologies (Di Girolamo et al., 2023; Draghi report, 2024). Moreover, it’s worth noting that the EU’s knowledge base of digital technologies is largely placed outside the European Union (Bello et al., 2023). Considering that intellectual property is an important metric of innovation capacity (European Commission, 2025a), the EU’s share of global patent applications decreased from 30% to 17% between 2000 and 2021 (European Commission - DG RTD, 2024).

Aiming at closing the innovation gap with other global players, the European Union launched a series of industrial policies regarding technological innovation. Concerning strategic technologies that are fundamental to fulfil EU competitiveness and security ambitions, the European Commission adopted two legislative initiatives aimed at fostering their development, namely the *Net-Zero Industry Act* (European Union, 2024b) and the Regulation establishing the *Strategic Technologies European Platform* (hereinafter, STEP) (European Union, 2024a). The Net-Zero Industry Act (hereinafter, NZIA) represents the first plan set out to boost European net-zero industry by establishing a framework of measures that stimulate the manufacturing capacity and the achievement of specific targets by 2040. More recently, the Clean Industrial Deal[1] reinforced the EU's strategy on this field by providing clear business incentives for industries to decarbonize within Europe. Indeed, it proposes measures aimed at reducing energy prices, stimulating internal demand for clean technologies, and mobilizing investments towards clean-tech sectors with the twofold objective of protecting energy-intensive sectors from unfair competition and supporting the development of the European clean-tech sector. The STEP Regulation is wider in scope, as it aims to promote, develop and safeguard the uptake of critical technologies (and their value chains) not only in the clean technology realm (i.e., technologies under the NZIA) but also in advanced digital technologies and deep tech innovation.

The present study has manifold objectives. Firstly, given the importance of strategic technologies in EU policy, the main goal is to measure firms' innovation level in EU Strategic Technologies (EUST) – according to STEP and NZIA EU Regulations (Regulation EU 2024/795 and Regulation EU 2024/1735, see European Commission 2024a, 2024b) – by mapping patents in EUST. The choice of patents is based on at least two reasons: i) the recognized importance of patents for the development of strategic technologies, as underlined by the European Investments Bank (EIB, 2024); ii) the fact that in the literature, patents have long been used as one of the main indicators of innovation, as they cover several aspects of firm's innovative activity (Hall et al., 2001). Having mapped the typologies of patents linked to EUST, we then conduct a cross-country analysis both among EU countries, and between the EU and the main global actors (i.e., the US and China). Secondly, considering that productivity is one of the main elements of EU industrial policy (Draghi report, 2024), we estimate – for the Italian case – the effect of EUST on firms' labour productivity. Thirdly, since technological interdependence has long been acknowledged as a driver of innovation and technological change (Rosenberg, 1979, recently, Colladon et al., 2025), we investigate the connections between each of the EUST aimed at finding the technological interdependencies that are essential for understanding innovation dynamics and

[1] The Clean Industrial Deal: A joint roadmap for competitiveness and decarbonization, COM(2025) 85 final, Brussels, 26.2.2025.

structural (network) linkages, as progress in one sector is often influenced by developments in related domains. This applies in particular to the twin (green and digital) transition as highlighted in a recent study at EU level (Bontadini & Meliciani, 2025).

More specifically, the four objectives of the present study are as follows:

(i) measuring innovation in EUST – according to STEP and NZIA EU Regulations – through the identification of patent codes (14-digit of the International Patent Classification) linked to the EUST, by leveraging on Large Language Model (LLM) with a robustness check by scraping a sample of firms' websites;

(ii) cross-country analysis regarding: innovative firms in EUST – according to ownership of patents linked to EUST – among EU member States and comparing the EU with other global actors (namely the US and China); diffusion (i.e., number) of patents in EUST;

(iii) estimating the effect of EUST on firms' labour productivity for the Italian case through econometric analysis;

(iv) investigating the connections between each of the EUST through a network analysis (Bipartite Configuration Model (BiCM) Method) by answering the simple question: *"Given any particular technology (in our case EUST) of interest, how many other technologies (EUST) are connected to it?*

All analyses are conducted: i) on all EUST while also specifically highlighting the Net-Zero Strategic technologies (Net-Zero EUST), which are part of EUST; ii) at the firm's level while also focusing on the number of patents in EUST.

While a mapping of net-zero technologies has been performed in *The net-zero manufacturing industrial landscape across the Member States* (European Commission - DG ENER, 2024), which identifies the products linked to these technologies, and a mapping of clean-tech patents, even though not explicitly in line with the Net Zero Industry Act, was conducted by the European Investment Bank (EIB, 2024), a complete study of innovation in EUST – as defined by the EU documents – by mapping the patents related to these technologies has not yet been carried out to the best of our knowledge. Notwithstanding the long tradition of studies on the impact of patents on various dimensions of firms' performance, such as productivity (Bloom & Reenen, 2000; Bogliacino & Pianta, 2009), it is unclear whether, by focusing only on the firms with patents, a further stronger effect on firms' performance produced by EUST arises.

This study provides evidence potentially useful for EU policies in several ways. Firstly, by highlighting the heterogeneity of innovation in EUST among member states, as well as empirically measuring the gap of the EU with respect to the US and China. Secondly, by empirically demonstrating, even though only for the Italian case, how EUST act as catalysts for labour productivity at the firm level by including the key role of Capital Market. Finally, by underlining which EUST are more central, performing the highest degrees of interdependencies with other EUST.

In a nutshell, empirical evidence can support impact assessment of industrial policies enhancing technology generation in strategic areas. The remainder of the study is structured as follows: Section 2 illustrates the institutional background; Section 3 describes the data and method applied to identify the patents linked to EUST; Section 4 comments on the results of the diffusion of innovation in EUST across EU countries and global competitors, in terms of both firms and number of patents; Section 5 investigates the effect of EUST on labour productivity for Italian firms; Section 6 analyzes the technological interdependencies between each of the EUST; Section 7 concludes the paper.

2. Institutional background

2.1 Strategic technologies at the root of the new EU policy

The growing gap that has opened up between the EU and other global actors, particularly the US, has gained prominence within the European political discourse in the past several months, as emerges from the Draghi report on the *Future of European Competitiveness* (Draghi Report, 2024) and, more recently, the *EU Competitiveness Compass* (European Commission, 2025b; Zettelmeyer, 2025), among other political documents. This gap, mainly attributable to lagging advanced technological innovation and labour productivity, as well as an ageing population, comes amidst rapid change driven by the twin imperatives of the digital and green transition, on the one hand, and increasing geopolitical uncertainty, on the other.

Given the current context, European institutions have risen to the challenge of regaining competitiveness, unveiling an increasingly elaborate new policy platform inspired by a renewal of political-economic thinking with the Letta and Draghi reports. On April 14, 2024, the Letta report *Much More Than a Market* assessed the European Single Market as unfit for the current international landscape and challenges, particularly in the strategic innovation field. The report thus called for measures to enhance the functioning of the Single Market, emphasizing the role of technology and innovation, and encouraging the adoption of the "freedom of innovation". Indeed, only by implementing the proposed "fifth freedom" can the Single Market become a more dynamic environment, enabling innovators, accelerating the development and dissemination of new technologies, ultimately fostering technological progress and entrepreneurship instead of hindering it. Additionally, the report proposed the improvement of the Capital Markets Union, now the *Savings and Investments Union* (European Commission, 2025c), as the necessary condition to finance European innovation needs for digital and green transition, which is mainly driven by investments in strategic technologies (i.e., deep-tech and Net-Zero technologies), and therefore avoiding the "curse of mature technology" (Buti et al., 2025).

In this regard, the Draghi report on the *Future of European Competitiveness* (Draghi report, 2024), presented on September 9, 2024, correctly identified the linkages between strategic technologies, innovation and competitiveness, also aimed at enhancing security by reducing vulnerabilities and lessening dependencies on foreign markets (for an empirical analysis on this issue, see Arjona et al., 2023).

In the vein of the Letta and Draghi reports, the European Commission, on January 29, introduced the *Competitiveness Compass* (European Commission, 2025b), once again underscoring the urgency of revitalizing European industrial competitiveness and strengthening the manufacturing capacity needed to produce strategic technologies, among other issues. The path therefore appears clear. The growing relevance of productivity and technological innovation within the European policy discourse is unmistakable and it cannot be separated from the broader geopolitical environment. Indeed, as the international landscape, marked by increasing uncertainty and growing geopolitical competition, has evolved the European Union has progressively placed greater emphasis on security and sovereignty, marking a significant shift from its traditionally open and liberal economic stance. Nonetheless, the EU has adapted its strategic posture. Most notably, however, is the fact that, while the conceptualization of policy has evolved – from Open Strategic Autonomy to Economic security – technological sovereignty has remained fundamental to this commitment. As Europe faces the imperative of securing critical supply chains (Arjona et al., 2024), boosting technological progress, and supporting key industries (European Parliamentary Research Service, 2021; European Commission, 2023; Kroll et al. 2023; Edler, 2024), technological sovereignty has therefore emerged as critical for Europe's global standing. For this to happen, the European Union must make progress on several fronts, among which the development of strategic technologies stands out.

2.2 The EU policy on Strategic Technologies: Net Zero Industry Act and STEP

For the reasons discussed above, in 2024 the European Commission adopted two legislative initiatives aimed at fostering the development of strategic technologies that are fundamental to fulfilling the EU's ambitions, namely the *Net-Zero Industry Act* (European Union, 2024b) and the regulation establishing the *Strategic Technologies European Platform* (European Union, 2024a). The *NZIA* represents the first plan set out to boost European net-zero industry by establishing a framework of measures that stimulate the manufacturing capacity of net-zero technologies in the EU and the achievement of specific targets by 2040.[2] To deliver the results for which it has been set out, namely increasing the manufacturing capacity of net-zero technologies, the European Commission has proposed the following solutions: streamlining administrative and permit-granting procedures; the creation of a Net-Zero Europe Platform to facilitate access to finance; the stimulation of public demand for these technologies via public procurement procedures and auctions; the introduction of regulatory sandboxes for the development, testing and validation of innovative net-zero technologies; and the creation of European net-zero industry academies to develop training and education on net-zero technologies. Recently, the European Commission has also adopted the Clean Industrial Deal with the objectives of decarbonizing energy-intensive sectors and supporting the development of the European clean-tech sectors, while preserving competitiveness vis-a vis global competitors. To achieve these purposes, the plan sets out clear business incentives for industries to decarbonize within Europe by proposing a set of measures that concern the following six business drivers: affordable energy; lead markets; financing; circularity and access to materials; global markets and international partnerships and skills.

The Regulation establishing the *STEP*, despite having the same objective as the NZIA, is wider in scope as it aims to promote, develop and safeguard the uptake of critical technologies (and their value chains) not only in the clean technology realm (i.e., technologies under the NZIA) but also in the following two sectors: digital technologies and deep tech innovation, which include AI, quantum technologies, robotics and autonomous systems; and biotechnologies, such as bioinformatics, nanobiotechnologies and process biotechnology

[2] The targets are the following: to achieve a manufacturing capacity of net-zero technologies of at least 40% of the EU's annual deployment needs, necessary to reach the 2030 climate and energy targets; and to reach 15% of world production of net-zero technologies by 2040, being able to achieve the 2040 climate and energy targets (Regulation EU 2024/1735).

techniques. To stimulate investments in these technologies, the regulation advances the rationalization of eleven EU programs and funds which already exist, and which can be used to finance the uptake of critical technologies (these include for example Horizon Europe, the Innovation Fund and the European Defense Fund). Furthermore, it introduces two new instruments to attract investments in projects that are in line with STEP objectives: the Sovereignty portal,[3] i.e. a web page to help project promoters and enterprises find support and financing opportunities to develop their STEP investments; and the Sovereignty Seal, granted to projects that contribute to the STEP objectives, to help promoters gain visibility and attract public and private investments. More recently, the European Commission has also decided to allocate €1.3 billion, through the Digital Europe Programme (DIGITAL) work programme for 2025 to 2027, for the deployment of critical technologies that are strategically important for the future of Europe and its tech sovereignty, such as Artificial Intelligence, cybersecurity and high-performance computing.[4] In conclusion, the significance of strategic technologies is evident if one considers the nexus between STEP technologies, productivity and strategic autonomy (e.g., Edler, 2024). The manufacture of NZIA technologies, for instance, can reduce the EU's dependence on foreign energy sources and lower energy costs and price volatility, ultimately increasing competitiveness. Analogously, the diffusion of advanced digital technologies is critical to lifting productivity growth across industrial ecosystems.

3. Data and method

3.1 The identification of patents in EU Strategic Technologies

In this section, we explain the method used to identify the patents linked to EU strategic technologies by taking into account, on the one hand, the list of strategic technologies as defined by the European Commission (Table A1 in Appendix), and on the other hand, the International Patents Classification (IPC) at the maximum level of detail (14-digit). To achieve this goal, we leveraged a Large Language Model (LLM) to streamline the identification of patent categories corresponding to the European Union Strategic Technologies. Recent literature on innovation by using patents recognized that «a newer generation of textual analysis techniques,

[3] https://strategic-technologies.europa.eu/investors_en

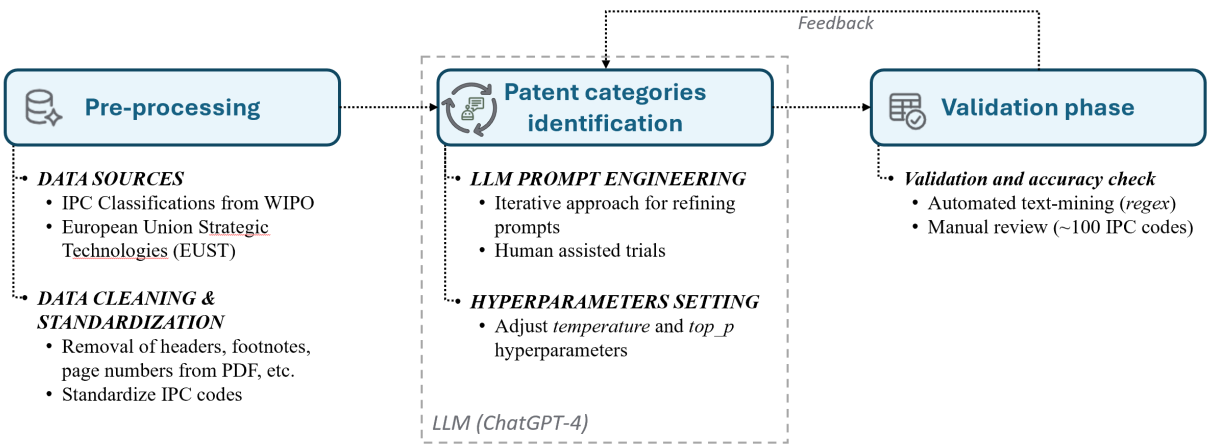
[4] COMMISSION IMPLEMENTING DECISION of 28.3.2025 on the financing of the Digital Europe Programme and the adoption of the multiannual work programme 2025-2027

for example based on transformers or large language models (ChatGPT, etc.), could be used to this purpose [analysis of patents] in light of their high potential» (Colladon et al., 2025, p. 15).

The analysis proceeded in multiple stages and relied on the content evaluation of several text files, with the goal of accurately matching these technologies to their corresponding International Patent Classification (IPC) codes at the most granular 14-digit level.

As a preliminary step, we performed data cleaning on the input files – provided as PDF documents from the official website of the World Intellectual Property Organization (WIPO) and containing the full IPC classification – to remove superfluous information such as page headers, footnotes, page numbers, and any extraneous textual elements. This pre-processing was essential to enable the LLM to focus on the core classification content, ensuring the extraction of only the semantically relevant patterns while mitigating potential misinterpretations caused by inconsistent text formatting. Additionally, we standardized the textual representation of the IPC codes, reorganizing entries to achieve a uniform data structure, thereby enhancing the efficiency of subsequent automated analyses.

Figure 1A. Workflow for patent category identification using LLM



Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

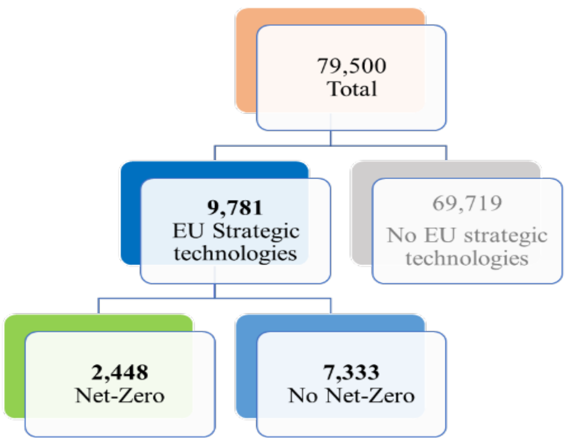
By providing the cleaned and standardized classification files to ChatGPT-4 – acknowledged at that time as a state-of-the-art multi-modal model for advanced text comprehension and classification tasks and still widely considered reliable for large-scale classification (OpenAI et al., 2023) – we adopted prompt-engineering strategies recommended by recent research (Brown et al., 2020). Specifically, after loading the complete IPC classification and a descriptive guide on how the classification system operates, we iteratively prompted

ChatGPT-4 with each target technology and requested the corresponding patent categories. We used the OpenAI API to systematically set and adjust hyperparameters such as *temperature* and *top_p*, ultimately enabling us to optimize the balance between creativity and reliability. In particular, after conducting multiple iterative trials to verify the consistency of generated results across separate runs, we settled on a *temperature* of 0.3 and a *top_p* of 0.9, since this configuration consistently yielded coherent and precise outputs. Although *fine-tuning* the model for domain specificity was initially considered, the infrastructure available in March 2024 did not yet allow for fully customized fine-tuning of ChatGPT-4; consequently, we employed repeated trials and refined prompts to achieve stable response, an approach often referred to as "prompt refinement" or "prompt stacking" in advanced prompt-engineering literature (Liu et al., 2023; Wei et al., 2023). Figure 1 displays the entire process.

In order to verify the completeness and accuracy of the LLM output, we implemented a series of validation steps. First, we conducted a manual review of approximately 100 randomly selected IPC codes to detect any anomalies or incorrect assignments to the strategic technologies; none were identified. Next, a text-mining procedure employing regular expressions on keywords relevant to each strategic technology (for instance, using "heat pump" for "Heat pumps and geothermal energy technologies") confirmed that no IPC codes identified by the LLM had been overlooked. Taken together, these measures demonstrated the robustness of the LLM's classifications.

According to the results of this analysis, we identified 9,781 patents codes (IPC codes 14-digit level) related to EUST, of which 2,448 are related to Net-Zero technologies (EUST NZ)

Figure 1B. Number of 14-digit codes of IPC classification



Note: The total number of codes (79,500) may change because of introduction of new inventions over time.

Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Once patents codes (IPC codes 14-digit level) related to EUST have been mapped, we identified firms with patents in EUST by exploiting Moody's Intellectual Property dataset. We selected, through a boolean search, the set companies holding these types of patents. The patents were filtered based on the application filing date, including only those with a filing date between 01/01/2004 and 01/01/2024. This time frame was chosen to generally exclude patents with a useful life exceeding 20 years, given that industrial property rights for invention patents extend for 20 years from the filing date.[5] No filters were applied to patent offices, so the selected patents may have been filed at any patent office worldwide. The dataset therefore includes the total patents owned directly by companies.

3.2 Robustness check: Quality survey on the ChatGPT patent mapping process

We further investigated the accuracy of the ChatGPT patent mapping process by observing a sample of websites selected from the list of 5,000 business units in the reference population. Specifically, we selected URLs (Uniform Resource Locator) and interactively observed the content of the website related to each sampled URL, searching for the presence of EU Strategic Technologies - EUST (Table A1 in Appendix).

We followed a protocol for detecting the presence of EUST. Assuming that each website has a layered structure, we determined the depth of the website beyond which the analysis will not be performed. We also did not search for the information on the linked site.

We apply these rules because the URL sample will be a ground truth sample for a future automated analysis of the full set of 5,000 business units. In this case, we perform a massive web scraping and make a prediction of technology presence using a supervised approach based on the ground truth data sample. In order to limit the computational complexity of the scraping process, automatic scraping is performed using the protocol described above.

[5] Industrial property rights last 20 years from the filing date for invention patents, 20 years from the grant date for plant variety rights, and 10 years from the filing date for utility models, starting from the filing date.

We selected the URLs according to a stratified simple random sampling without replacement, with strata given by Italian macro-regions (GEO: North, Centre, South and Islands), size classes of employees (SIZE: 5-49, 50-249, 250 or more), adopted type of technology (TYPE: EUST, EUST NZ).

The stratum sample allocation oversampled the larger economic units (strata with 50-249, 250 or more employees) with respect to the proportional population size allocation. The sample includes 627 URLs, but 52 URLs were not operational (incorrect URLs or URLs that did not correspond to the website of the business unit). Of the 575 sites examined, 544 were related to EUST, while 31 were not.

We apply a calibration estimator (Deville and Sarndäl, 1992) for producing the estimates. The calibration constraints are the marginal distributions of the number of business units by GEO, SIZE and TYPE. The calibration step also adjusted the sampling weights for non-operational URLs. Table 1 shows the relative frequencies of business units related to EU Strategic Technologies, and also the specific Net-Zero Strategic Technologies.

Table 1. Estimated relative frequencies of business units related to EU Strategic Technologies

Variable	Category	Estimate	Confidence Interval (95%) Lowerbound	Confidence Interval (95%) Upperbound
GEO	North	0.98	0.97	0.99
	Center	0.91	0.86	0.96
	South	0.84	0.75	0.92
SIZE	0-49	0.95	0.93	0.97
	50-249	0.95	0.92	0.98
	250+	0.97	0.94	1.00
TYPE	EUST NZ	0.98	0.96	1.00
	EUST	0.94	0.92	0.96
	Italy	**0.95**	**0.95**	**0.94**

Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

4. Results

In this paragraph we show descriptive statistics concerning firms with patents in EU Strategic technologies (EUST), and the related numbers of patents – also highlighting the part referred to the Net-Zero ones (EUST NZ) – among both World macro regions and EU member countries. All data refer to the limited companies.

Specifically, two indicators were developed to capture the degree and the dimensions of innovation within the entrepreneurial system: i) the first one is *Firms' propensity*, which corresponds to the number of firms with patents in EUST (and EUST NZ) per 10,000 firms, and it reflects the extent to which innovation is diffused among firms (i.e., only a few or many firms); ii) the second one is *Patent intensity*, which measures the number of patents in EUST (and EUST NZ) per 100,000 inhabitants, therefore serving as a proxy for the intensity of innovation (i.e., few or many patents). These two indicators can provide relevant insights for policy design, as they can shed light onto the trade-offs between supporting wider adoption of innovation across firms and fostering innovation intensity.

4.1 EU in the world competition

The data (Table 2, Maps 1-3, and Table A2 and Maps A1-A3 in Appendix) delivers some unexpected results. Whereas China dominates the rankings of the number of firms which own patents for both EU Strategic Technologies (EUST) and EU Strategic Net-Zero Technologies (EUST NZ), the US and the EU alternate between second and third depending on the category. Indeed, while the US outperforms the EU with regards to EUST, it lags behind the EU in terms of EUST NZ. The results differ if one takes into account the number of enterprises in the economy. When considering firms' propensity to own patents (measured as the number of firms with patents either in EUST or EUST NZ per 10,000 firms), Japan takes the lead (110 EUST and 37 EUST NZ), with China coming in second (100 and 39, respectively), Canada in third (24 and 7) and the US in fourth (22 and 5). Surprisingly, among these regions, the EU 27 come in last for strategic technologies (21) and the US drops out of the top five for Net Zero strategic technologies (5).

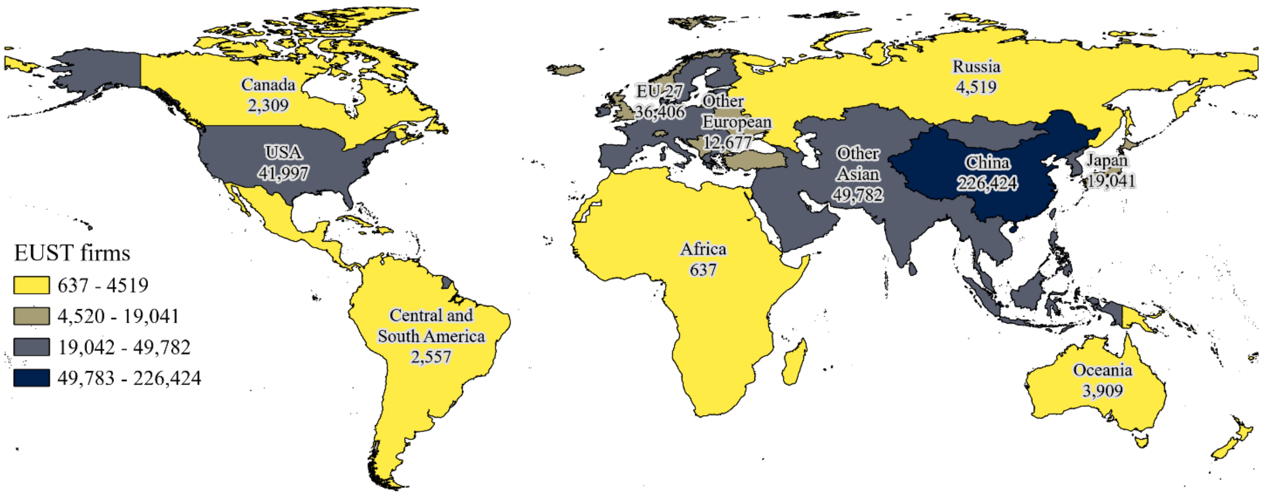
A similar trend appears when comparing the total number of patents and patent intensity (measured as the number of patents per 100,000 inhabitants). Again, while China tops the rankings in absolute terms, it is Japan that registers the highest patent intensity (2,269 patents in EUST and 422 patents in EUST NZ), followed by the US (1,002 and 110 patents respectively) and the EU (385 and 78). Focusing on a comparison with the United States, we can observe that the European Union shows a certain proximity in terms of firms' propensity to engage in strategic technologies, and an even higher propensity when it comes to firms with patents in Net-Zero technologies. However, the EU suffers from a significant gap in terms of the overall number of patents – both in absolute and relative terms. In contrast, when compared to China, the EU's position is reversed: there is a disadvantage in terms of firms' propensity, but an advantage in terms of patent intensity – this holds true for both EUST and EUST NZ.

Table 2. Rankings of the EU, the US, China and other world regions for firms* and patents

	Firms spread	Firms' propensity	Patents spread	Patent intensity
Ranking	*N. of firms*	*Firms with patents per 10,000 firms*	*N. of patents*	*N. of patents per 100,000 inhabitants*
		with reference to EUST		
1	**China**	Japan	**China**	Japan
2	**USA**	**China**	**USA**	**USA**
3	**EU 27**	Canada	Japan	**EU 27**
4	Japan	**USA**	**EU 27**	**China**
5	Russia	**EU 27**	Canada	Canada
		with reference to EUST NZ		
1	**China**	**China**	**China**	Japan
2	**EU 27**	Japan	Japan	**USA**
3	**USA**	Russia	**USA**	**EU 27**
4	Japan	**EU 27**	**EU 27**	**China**
5	Russia	Canada	Canada	Canada

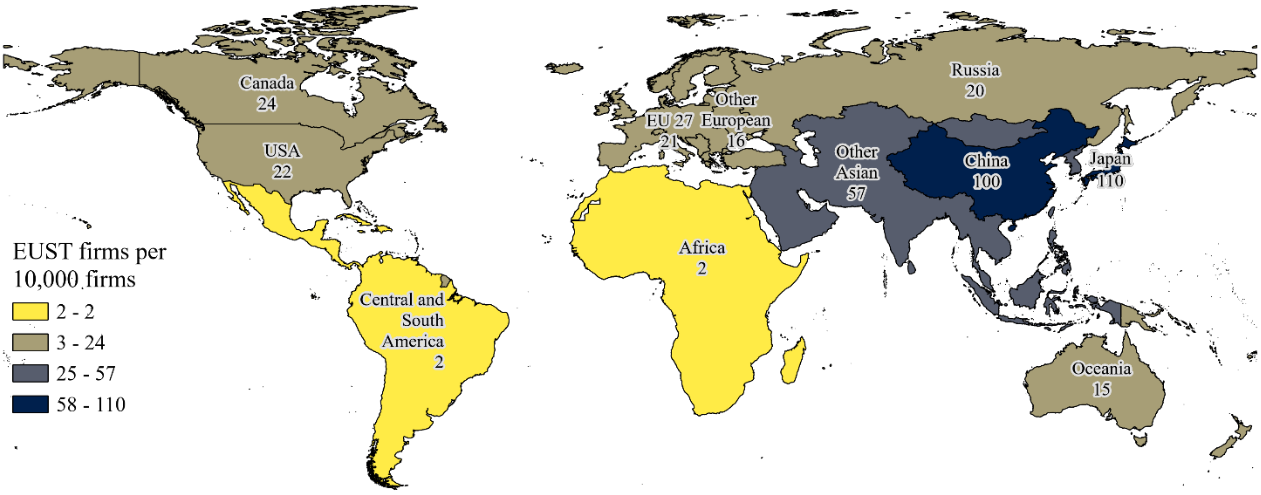
** All data refers to the limited companies.*
Note: The ranking considers EU, USA, China, and other main world countries.
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map 1. EUST firms (number)



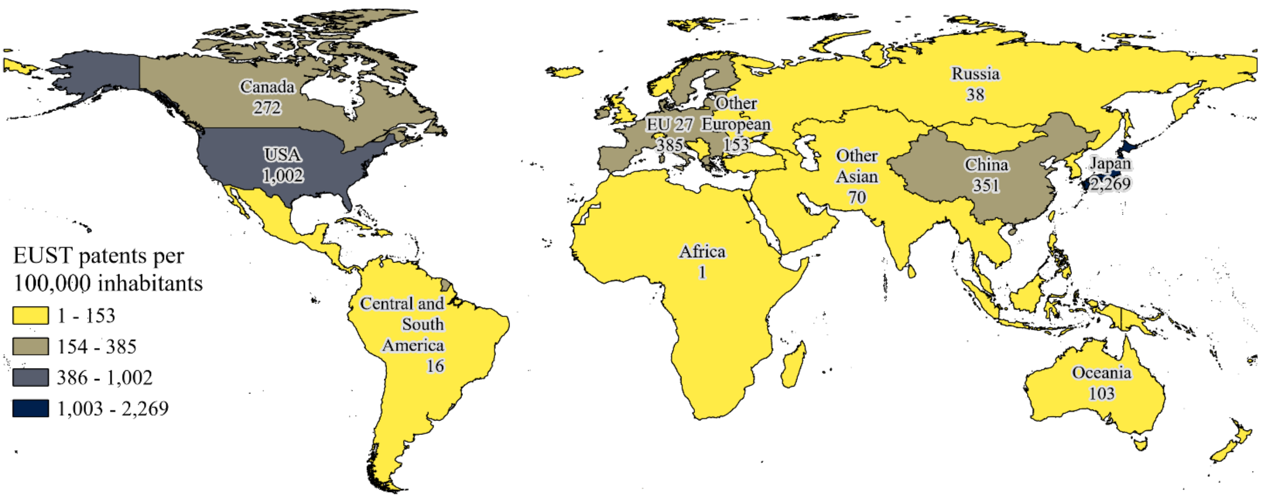
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map 2. EUST firms per 10,000 firms



Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map 3. EUST patents per 100,000 inhabitants



Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

4.2 Inside the EU: a cross-country analysis among EU countries

The results (Table 3, Maps 4-6, and Table A3 and Maps A4-A6 in Appendix), and also provide valuable insights into the innovative ecosystem within the European Union and its member states. While the larger economies – Germany, Italy, and France – tend to lead in terms of the number of strategic firms, Germany, France, and Sweden take the lead when it comes to the number of patents in strategic technologies. This could also be the result of firm size since larger firms are more likely to get patents. In Germany and Sweden, for instance, the firm's average size is higher than Italy (respectively, 12.2 and 4.8 vs 4.2 employees per enterprise) that falls in 7th place in terms of number of patents.

However, a different picture emerges when adjusting for economic and population size. In this case, Austria and Finland, along with Germany, rank highest in firms' innovation propensity, while Finland, Sweden, and Ireland stand out for their patent intensity. In this case, the smaller size of a country could amplify the intensity of innovation (indeed, among the first six countries in terms of patent intensity, only the Netherlands has a large population, i.e., in top-ten EU countries).

Once again, similar patterns emerge with regards to Net Zero strategic technologies. While Germany, France, and Italy report the highest number of firms owning patents – and Germany, France, and the Netherlands account for the largest patent volumes – it is the smaller, yet technologically advanced economies that exhibit higher firm-level innovation propensity and patent intensity. Notably, Denmark, Luxembourg, and the Netherlands stand out for their cutting-edge patent ecosystems, while Germany, Austria, and Finland lead in terms of the share of firms engaged in Net Zero strategic technologies (EUST NZ).

Table 3. Rankings of Member States of the EU, data on firms* and patents for EU Strategic technologies

	Firms Spread	Firms' Propensity	Patents Spread	Patent Intensity
Ranking	*N. of firms*	*Firms with patents per 10,000 firms*	*N. of Patents*	*N. of Patents per 100,000 inhabitants*
1	Germany	Germany	Germany	Finland
2	**Italy**	Austria	France	Sweden
3	France	Finland	Sweden	Ireland
4	Netherlands	**Italy**	Netherlands	Luxembourg
5	Spain	Ireland	Finland	Netherlands
6	Sweden	Denmark	Ireland	Denmark
7	Finland	Sweden	**Italy**	Germany
8	Poland	Luxembourg	Denmark	France
9	Austria	Malta	Spain	Austria
10	Belgium	Poland	Austria	Belgium
11	Denmark	Slovenia	Belgium	Malta
12	Czech Republic	Netherlands	Poland	Cyprus
13	Ireland	Belgium	Luxembourg	**Italy**
14	Bulgaria	France	Czech Republic	Spain
15	Romania	Czech Republic	Portugal	Estonia
16	Hungary	Cyprus	Cyprus	Lithuania
17	Portugal	Spain	Hungary	Czech Republic
18	Luxembourg	Greece	Slovakia	Slovenia
19	Slovakia	Lithuania	Romania	Slovakia
20	Slovenia	Hungary	Lithuania	Poland
21	Estonia	Bulgaria	Malta	Portugal
22	Cyprus	Slovakia	Bulgaria	Latvia
23	Greece	Croatia	Slovenia	Hungary
24	Lithuania	Latvia	Estonia	Bulgaria
25	Croatia	Estonia	Greece	Croatia
26	Latvia	Portugal	Latvia	Romania
27	Malta	Romania	Croatia	Greece

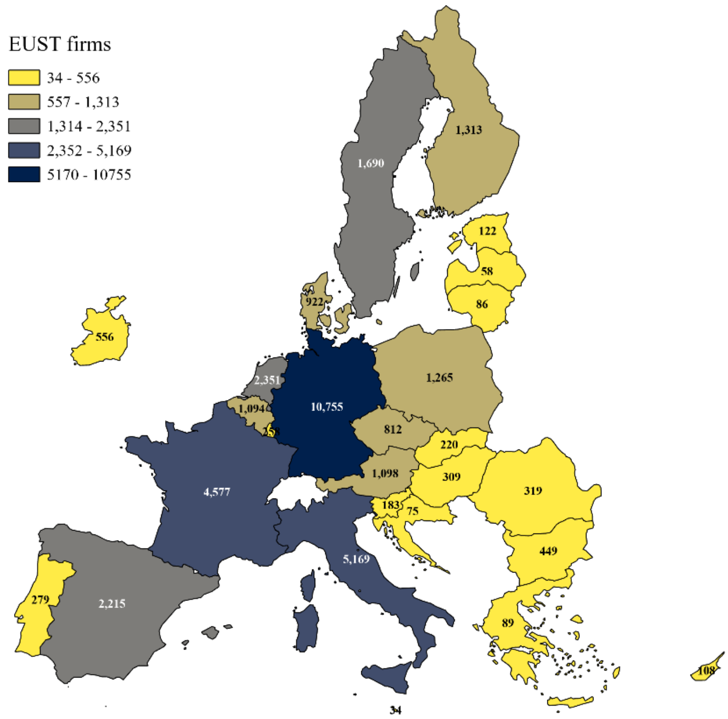
** All data refers to the limited companies.*
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Table 4. Rankings of Member States of the EU, data on firms* and patents for EU Net Zero Strategic technologies

	Firms Spread	**Firms' Propensity**	**Patents Spread**	**Patent Intensity**
Ranking	*N. of firms*	*Firms with patents per 10,000 firms*	*N. of Patents*	*N. of Patents per 100,000 inhabitants*
1	Germany	Germany	Germany	Denmark
2	France	Austria	France	Luxembourg
3	**Italy**	Finland	Netherlands	Netherlands
4	Netherlands	Denmark	Denmark	Finland
5	Spain	**Italy**	**Italy**	Germany
6	Sweden	Ireland	Spain	France
7	Poland	Poland	Belgium	Sweden
8	Denmark	Sweden	Sweden	Belgium
9	Austria	Netherlands	Finland	Austria
10	Finland	Luxembourg	Austria	Ireland
11	Belgium	Czech Republic	Poland	Spain
12	Czech Republic	Slovenia	Ireland	**Italy**
13	Ireland	Belgium	Czech Republic	Estonia
14	Bulgaria	France	Luxembourg	Cyprus
15	Hungary	Spain	Portugal	Czech Republic
16	Romania	Malta	Hungary	Slovenia
17	Slovakia	Greece	Romania	Poland
18	Luxembourg	Hungary	Slovakia	Latvia
19	Portugal	Cyprus	Slovenia	Lithuania
20	Slovenia	Slovakia	Lithuania	Portugal
21	Estonia	Lithuania	Estonia	Slovakia
22	Greece	Estonia	Cyprus	Malta
23	Cyprus	Latvia	Bulgaria	Hungary
24	Lithuania	Bulgaria	Latvia	Croatia
25	Croatia	Croatia	Croatia	Bulgaria
26	Latvia	Portugal	Greece	Romania
27	Malta	Romania	Malta	Greece

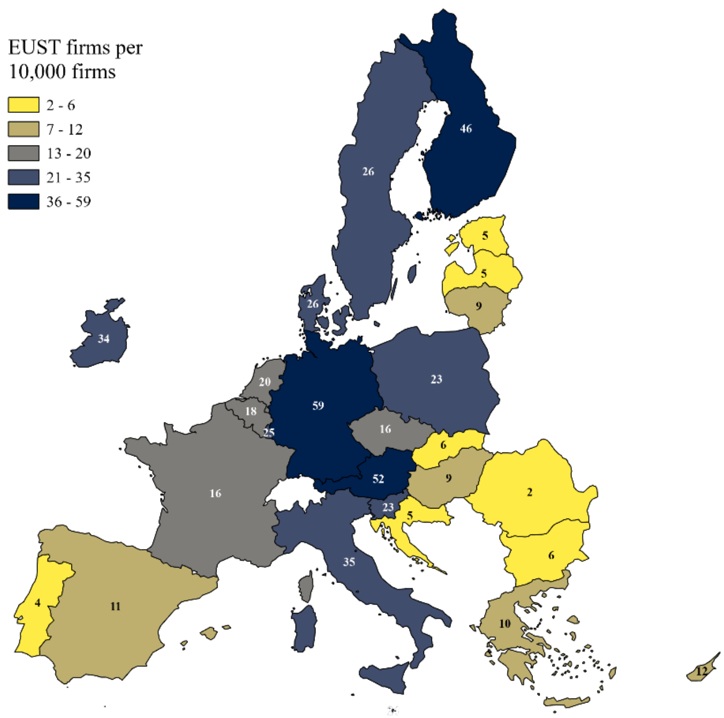
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map 4. EUST firms (number)



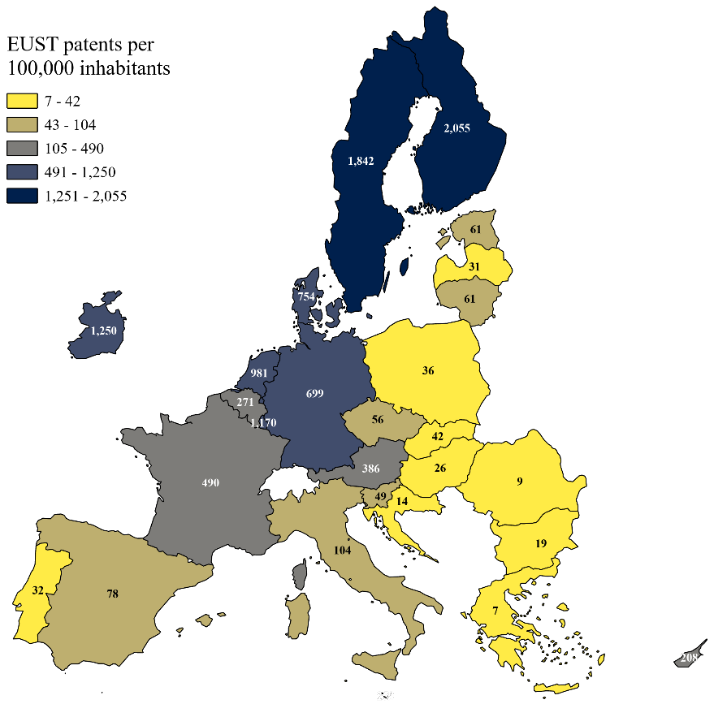
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map 5. EUST firms per 10,000 firms



Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map 6. EUST patents per 100,000 inhabitants

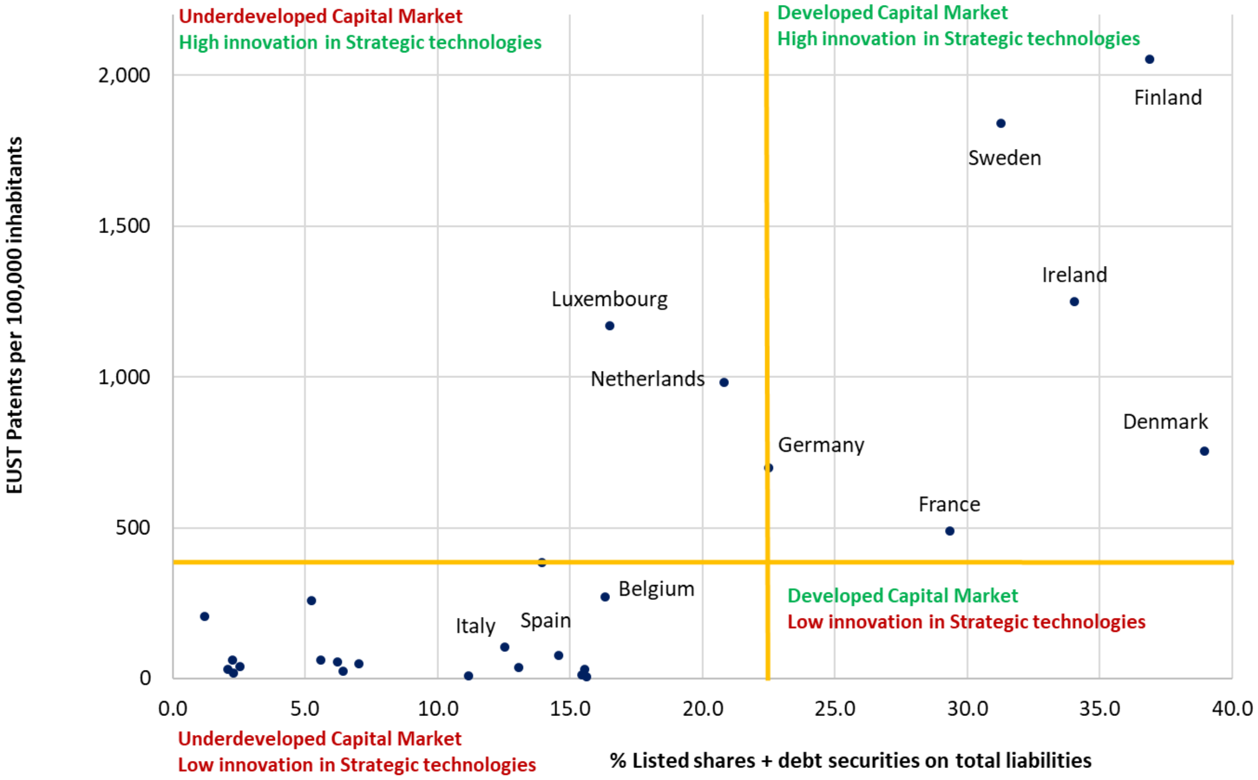


Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

4.3. Comparing Strategic technologies with Capital Market development: a cross-country analysis

The evidence from Figure 2 confirms the link between the development of a country's capital market and its degree of innovation. When investigating the number of patents in strategic technologies per 100,000 inhabitants with a measure of capital market sophistication – measured here as the share of listed shares and debt securities on total liabilities – it is clear that as the latter improves, the number of patents increase, with a correlation of 0,77. Additionally, the countries with the highest firm propensity and patent intensity all exhibit highly developed capital markets, further demonstrating the importance of closing the investment gap to foster investment in innovation (Buti et al., 2025).

Figure 2. EU Patents in Strategic technologies and EU capital market development in EU countries

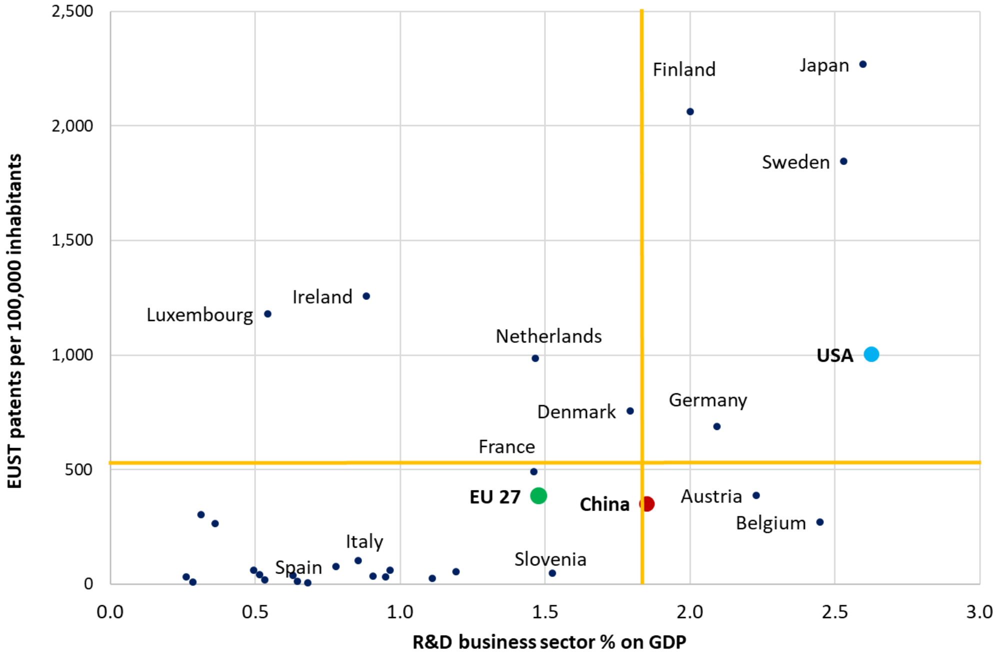


Note: Figure reports the name of the main countries, while the points refer to all countries.
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne and Eurostat

4.4. Comparing Strategic technologies with R&D: a cross-country analysis

Finally, when investigating the number of patents in EU strategic technologies and R&D within the business sector (% of GDP), clear global patterns emerge, especially regarding China, the European Union, and the United States. While American companies spend more than the global average on R&D (measured for the period 2019-2023) to obtain more EUST patents per 100,000 inhabitants than the global mean, other actors fare worse in terms of patent intensity. Among them, there are both the EU and China, although the latter spends more than the former on R&D, as shown in Figure 3.

Figure 3. Patents in EU Strategic technologies and R&D in the business sector in EU countries and major global countries



Note: a) R&D % on GDP is average for the 2019-2023 period. b) Figure reports the name of the main countries, while the points refer to all countries.
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

5. The impact of EU strategic technologies on firm's productivity: the Italian case

In this section, we investigate the effect of innovation in EU Strategic Technologies (EUST) on firms' labour productivity among Italian enterprises. Specifically, by focusing on limited companies, we contrast firms with patents in EU Strategic Technologies with firms with patents unrelated to EUST. We only consider firms with patents to better isolate the "strategic technologies effect", and also because in literature on innovation, patents are acknowledged as one of the best indicators of innovation (Colladon et al., 2025).

We measured labour productivity in terms of value added per employee – according to balance sheet data – with reference to the 2014-23 period. Concerning the latter aspect, we take into account a reference period of more than one year to capture structural relationships between the key variables of interest, thus neutralizing the business cycle effect. With regards to the dataset, we refer to the one built in this study (see Section 3): in particular, the analyses rely on the limited Italian companies with available balance sheet data for all years of the period 2014-2023.

We estimated the impact of EU strategic technologies by applying several econometric methods to have more robust results as well as to address the causality effect. We applied a large set of independent variables – besides our main variable of interest – to control for potentially confounding effects of various firm's characteristics that may influence labour productivity. The description of all variables is reported in Table 5**.**

Table 5. Variables description

Variables	Type	Description
Dependent variables		
LPmean	Continuous	Labour productivity (value added per employee), ten-year mean value for the period 2014-23, in log terms (source: elaboration on Moody's data)
Main independent variables		
EUST	Binary	1 = firm with patents in EU Strategic Technologies; 0 = otherwise (source: elaboration on Moody's data)
EUST_NZ	Binary	1 = firm with patents EU Strategic Net-Zero Technologies; 0 = otherwise (source: elaboration on Moody's data)
EUST_012	Categorical	0 = firm with patents in *non* EU-Strategic Technologies (*EUST_no*); 1= firm with patents in *non* Net-Zero EU Strategic Technologies (*EUST_noNZ*); 2= firm with Patents in EU Strategic Technologies Net-Zero (*EUST_NZ*) (source: elaboration on Moody's data)
Control variables		
Size	Continuous	Number of employees (source: elaboration on ISTAT data)
Industry	Dummies	1 = if the firm belongs to a n-sector (2-digit NACE rev.2 classification); 0 = otherwise (source: elaboration on ISTAT data)
Localization	Dummies	1 = if the firm belongs to a n-NUTS 2; 0 = otherwise.
Age	Discrete	Number of years since inception (source: elaboration on ISTAT data)
Human capital	Continuous	Share of graduates in STEM disciplines on total employees
Export	Binary	1 = if the firms exports; 0 = otherwise (source: elaboration on ISTAT data)
Foreign	Binary	1 = if the firm is a foreign-invested firm; 0 = otherwise (source: elaboration on ISTAT data)
LP_initial	Continuous	Labour productivity (value added per employee) in 2013 (source: elaboration on Moody's)
Instruments		
R&D	Continuous	R&D asset value per employee (euro) (source: elaboration on Moody's data)
High-tech sector	Dummy	1 = if the firm belongs to a high- / medium-high technology intensive sector; 0 = otherwise (source: elaboration on OECD/Eurostat data)
Capital market	Dummy	1 = if the firm is a listed company; 0 = otherwise (source: elaboration on Moody's data)

5.1. Econometric strategy

5.1.1 Cross section analysis: OLS regression

Since all independent variables are time-invariant, we conduct a cross-section analysis[6] by applying a log-linear model by Ordinary Least Square (OLS) regression.
Analytically:

$$lnLPmean_i = \beta_0 + \beta_1 EUST_i + \beta_2 C_i + \varepsilon_i \quad [1]$$

where, *LPmean* is the ten-year mean value for the period 2014-23 of the labour productivity – expressed in log terms – of the firm *i*; *EUST* is a binary variable taking value 1 if the firm holds patents in EU Strategic Technologies; *C* is the vector of controls for each firm *i*; and ε_i is the error term.

5.1.2 Deepening the causality

We address the issue of causality through three approaches. The first one is the Instrumental Variables (IV) method (Angrist et al., 1996; Wooldridge, 2010); the second one relies on a weighted regression after the nearest-neighbour matching (Abadie & Imbens, 2006, 2011) by contrasting treated firms with untreated firms of a control group; and the third one, partly linked to the second, concerns the reweighting on propensity score inverse probability (seminal paper by Rosembaum & Rubin, 1983).

5.1.2.1 Instrumental variables approach

Although our estimations control for several factors, we check for the presence of potential endogeneity of innovation in EU Strategic Technologies (i.e., the variable *EUST*) by investigating the possible presence of exogenous variables that affect firms' labour productivity through the endogenous variable *EUST*. In other words, EUST may also depend on other unobservable-to-the-analyst-factors, that is, factors correlated with the error term.

In line with the literature, we applied the method of instrumental variables approach by 2SLS (Wooldridge, 2010). The advantage of the IV approach is its capacity to restore the causal parameter consistency, also under

[6] Since the dependent variable could be time-variant, we also carried out a panel analysis (random effects model) finding similar results in terms of both magnitude and statistical significance.

selection on unobservables (Angrist & Krueger, 2001). Thus, by using the Two Stage Least Squares (2SLS) estimator, we modelled the IV approach.

The structural equation (second-stage) is the Equation [1] reported above. We considered a set of instrumental variables Z_i correlated with the potentially endogenous explanatory variable (*EUST*), but uncorrelated with the stochastic error ε in the structural equation [1].

The effects of the instruments on the endogenous variable are measured by the parameter β_{21} in the auxiliary regression (first-stage):

$$EUST_{\ i} = \beta_0 + \beta_{21} Z_i + \beta_{22} C_i + \mu_i \quad [2]$$

where *EUST* is the potentially endogenous explanatory variable in Equation [1], Z_i is the instrumental variable, and μ is the stochastic error term.

After estimating the first-stage regression (Equation 2), in the second-stage equation *EUST* is replaced by its value estimated in the first-stage – i.e. in the Equation [2]. To test if *EUST* is endogenous (test of endogeneity), we used the Wu-Hausman test: if it is significant, we reject the null hypothesis that the variable is exogenous, hence making it endogenous. Concerning the validity of the instruments, we perform two checks. First, we checked if they are correlated with the endogenous variable (instruments relevance) by calculating an F-test for the significance of the instruments' coefficients: a value above 10 means that the instruments are not weak (Stock et al., 2002, Stock & Yogo, 2005). Second, we check if they are exogenous, namely uncorrelated with the structural error term ε in the structural equation [1] by performing an overidentification restriction check by applying the Sargan test: an insignificant value means that we do not reject the null hypothesis that the instruments are exogenous.

5.1.2.2 Regression after propensity score matching and Inverse Probability Weighting

We estimated the effects of EU Strategic Technologies on firms' labour productivity also through regression after matching. Matching is a common statistical method (Stuart, 2010) for estimating treatment effects, and even more in economic and social studies (Cliendo & Kopeinig, 2008).

In our case, treated firms are the ones holding patents in EU Strategic Technologies (EUST firms). However, since this treatment isn't randomly assigned depending on several variables, and is instead probably correlated with our outcome (labour productivity), we have to build a control group of firms (untreated) having similar observable characteristics to those of the treatment group (EUST firms) while lacking, of course, patents in EU Strategic Technologies (non-EUST firms).

To identify the firms of the control group we use the nearest-neighbour matching (Abadie & Imbens, 2006, 2011), by considering nearest neighbour with replacement and a fixed number of units.

We identified the untreated companies (non-EUST firms) of the control group through the propensity score (Rosenbaum & Rubin 1983, 1985) that is the estimated probability of being treated given a set of observable characteristics at the firm level (of both treated and untreated units). Specifically, we estimate the probability of being a firm with patents in EU Strategic Technologies as a function of the following firms' characteristics: technology intensity and knowledge intensity according to OECD/EUROSTAT classification, size, geographical localization, firm age, graduated employees, governance, R&D, if firms is listed firms, total asset (description of these variables are reported in Table A4 in Appendix). The Probit model was used to estimate the propensity score (results of the probit are reported in Table A5 in Appendix).

Based on the propensity score, we match treated firms up to a maximum of 2 nearest neighbours non-EUST firms. If on the one hand a smaller number of selected nearest neighbours reduces the expected bias, on the other, it can worsen the efficiency of the estimates (Caliendo & Kopeinig, 2008). Moreover, to select the firms most similar to the treated, we also set a caliper of 0.15: this allows us to exclude the firms that are not sufficiently similar (Cocharan & Rubin, 1973) (i.e. those with a distance in terms of the estimated probability of being treated compared to the treated firm greater than 15%) even though they fall in the control group of the 2 nearest neighbours. We imposed common support which excluded treatment observations whose pscore was higher than the maximum or lower than the minimum pscore of the controls (for more details about all issues explained above, see Cerulli, 2022).

After matching, we evaluated if treated and control group were similar in observable variables (balancing). Results show that for all variables there are no statistically significant differences (Table A6 in Appendix; Figure A1 in Appendix also reports the propensity score density before and after matching).

Finally, we run the cross-sectional regression on the subsample of treated and matched control firms by applying the following OLS:

$$lnLPmean_i = \beta_0 + \beta_1 EUST_i + \varepsilon_i \quad [3]$$

As a robustness check, we also apply the inverse probability weighting (Horvitz & Thompson, 1952; Rosembaum & Rubin, 1983; Wooldridge, 2002) according to which:

- for *treated* units the inclusion probability is equal to the propensity score: $p(\mathrm{D}=1 \mid \mathbf{x})$
- for *untreated* units the inclusion probability is equal to: $p(\mathrm{D}=0 \mid \mathbf{x}) = 1-p(\mathrm{D}=1 \mid \mathbf{x})$

where **x** is the vector of observable exogenous confounding variables assumed to drive the nonrandom assignment into treatment (Cerulli, 2022 p.102-107).

5.2. Results

5.2.1 Baseline results

The results of the cross-section analysis show that patents in EUST have a positive impact on labour productivity. Indeed, firms with patents in EU Strategic Technologies (*EUST*) have a statistically significant ($p<0.01$) 3.8% higher labour productivity compared to the firms with patents which don't correspond to EUST. (Table 6, Model A). When considering exclusively firms with patents in Net-Zero technologies (*EUST_NZ*) – a subset of EU strategic technologies – we discover that their labour productivity is significantly ($p<0.01$) higher by 7.3%, compared to other firms (Table 6, Model B).

Table 6. OLS regression

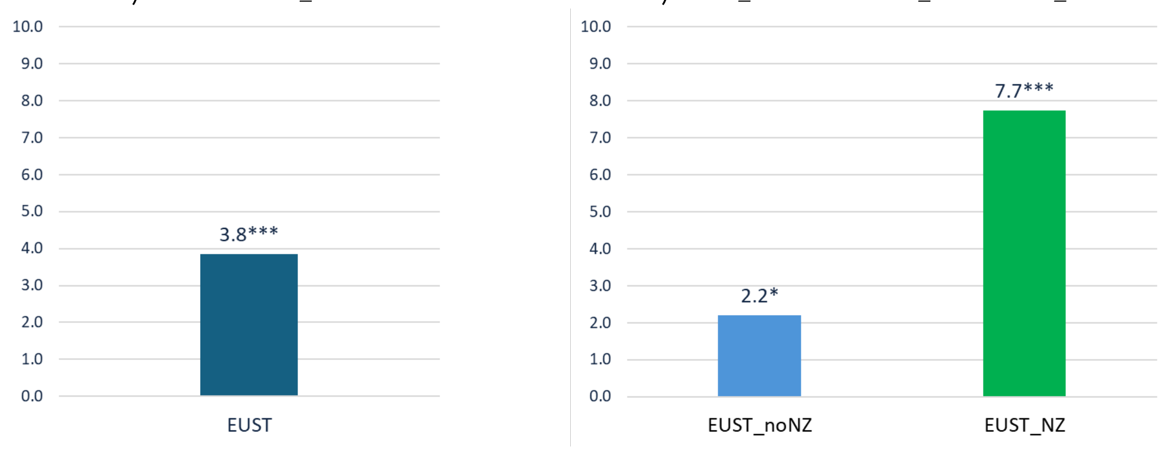
	lnLPmean **(A)**	*lnLPmean* **(B)**	*lnLPmean* **(C)**
EUST	0.038***		
	(0.011)		
EUST_NZ		0.073***	
		(0.018)	
EUST_012			
EUST_noNZ			0.022*
			(0.013)
EUST_NZ			0.077***
			(0.019)
+ controls			
Observations	8,669	8,669	8,669

Note: i) the dependent variable is reported at the top of the column. EUST_012; ii) EUST_no as reference category (see Table 5 Variables description); iii) standard errors in parentheses.
**** p < 0.01, ** p < 0.05, * p < 0.1.*

These results are further confirmed when we consider simultaneously Net-Zero and non-Net-Zero strategic technologies through a categorical variable (*EUST_012*) taking value 0 if the firm has patents in *non EUST*, value 1 if the firm has patents in *EUST* but not in Net-Zero technologies, and value 2 if the firm has patents specifically in *Net-Zero EUST* (see Table 5 Variables description). Indeed, we find that the effect of strategic technologies is most pronounced in the case of *Net Zero EUST*. In particular, by setting the *non-EUST* firms as a reference category, those with patents in *non-Net-Zero EUST* have a 2.2% higher labour productivity (p<0.10), while firms with patents in *Net-Zero EUST* demonstrate an even greater 7.7% increase (Table 6, Model C and Figure 3), however with a higher degree of statistical significance (p<0.01).

Figure 3. Percentage difference of labour productivity of firms with patents in EU Strategic Technologies (EUST) compared to firms with patents in non-EU Strategic technologies (*EUST_no*)

A): *EUST* vs *EUST_no*   **B): *EUST_noNZ* and *EUST_NZ* vs *EUST_no***



Note: A) refers to results in Table 6 column A; B) refers to results in Table 6 column C.
**** p < 0.01, ** p < 0.05, * p < 0.1.*

5.2.2 Addressing the causality

The findings explained above are also validated by further analyses that tackle the issue of causality. By comparing the firms with patents in EUST (treated) with a control group of firms having the same characteristics (untreated matched) – through regression after matching – we find a positive and statistically significant effect of Strategic Technologies (*EUST*) that is even greater in the case of Net-Zero Strategic Technologies (*EUST_NZ*) (Table 7, Model A, B). This was also achieved by using the inverse probability weighting technique (Table 7, Model D, E).

Table 7. OLS regression after Propensity Score Matching (PSM) and Inverse Probability Weighting (IPW)

	OLS after PSM		IPW	
	lnLPmean	*lnLPmean*	*lnLPmean*	*lnLPmean*
	(A)	**(B)**	**(D)**	**(E)**
EUST	0.037**		0.026**	
	(0.018)		(0.013)	
EUST_NZ		0.129***		0.084***
		(0.025)		(0.031)
+ controls				
Observations	3,863	3,863	8,667	8,663

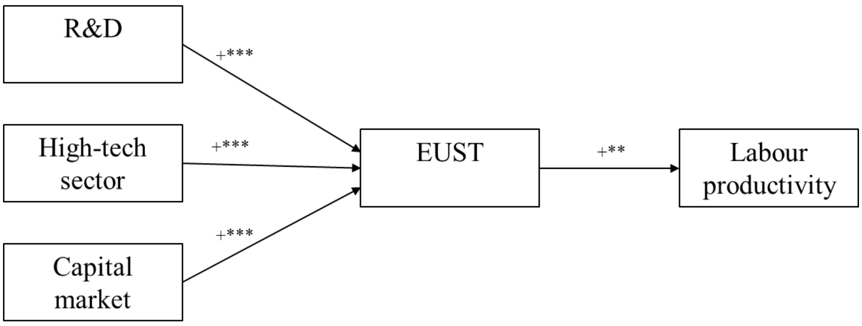
*Note: i) the dependent variable is reported at the top of the column; ii) standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.*

Even more interesting results arise from the instrumental variables estimation. In this case, we address the causality issue by considering innovation in EU Strategic Technologies (*EUST*) endogenous by depending on other factors (exogenous variables). More specifically, considering *EUST* endogenous (instrumented variable), we can argue that the probability of holding patents in EU Strategic Technologies is likely to be determined by other factors, that are the instruments. We identify three instruments. The first one is *R&D* (R&D asset value per employee) in line with the literature about R&D as an important input of innovation (recently, Dong et al. 2024; on the specific case of Italian firms, Hall et al. 2013).

The second one refers to the capital market, captured here by a binary variable (*Capital market*) taking a value of one if the firm is a listed company. This stems from the growing importance of the capital market, especially the Capital Markets Union in the case of the EU, in supporting innovation, particularly in terms of innovation at the frontier (as referenced in Letta's Report, Chapter 2, 2024, and Draghi Report, Part B, Section 2, Chapters 1 and 3, 2024). The third variable concerns the technological intensity at the sector level by assuming that operating in a higher technological intensity sector may affect the probability of investing in EU strategic technologies. Basically, we constructed a variable (*High-tech sector*) taking value 1 if the firm belongs to a high or medium-high technological intensity sector.[7]

The results of the IV estimation confirm the positive and statistically significant ($p<0.01$) effect of *EUST* on labour productivity (Table 8, column B), and the larger effect of *EUST_NZ* (Table 8, column D). Interestingly, looking at the first stage, we find a positive, and statistically significant ($p<0.01$) relationship between each instrument (*R&D*, *High-Tech*, *Capital market*) and innovation in EU Strategic Technologies (*EUST*).

Figure 4. Framework of the IV estimation



Note: the figure displays the sign and the related statistical significance of the coefficient (details in Table 8).
**** p < 0.01, ** p < 0.05, * p < 0.1.*

This demonstrates the validity of instruments: more technically, F statistics for the instruments' relevance is over 10 (43.435, $p<0.01$, Table 8), indicating that the instruments are not weak.

With regards to the endogeneity of the instrumented variable, the Wu-Hausmann test rejects at the 5% the null hypotheses of exogeneity (4.284, $p<0.05$, Table 8), ultimately proving that *EUST* is endogenous. Finally, concerning the exogeneity of the instruments, the Sargan test is not significant (0.750, $p>0.10$, Table 8). We can thus assume the instruments to be exogenous. These tests are further confirmed in the IV estimation focusing on the *EUST_NZ* as the main independent variable (Table 8, columns C-D).

[7] According to the OECD/EUROSTAT taxonomy. Specifically (in parentheses 2-digit level of Nace Rev.2): Manufacture of basic pharmaceutical products and pharmaceutical preparations (21); Manufacture of computer, electronic and optical products (26); Manufacture of chemicals and chemical products (20); Manufacture of electrical equipment (27); Manufacture of machinery and equipment n.e.c. (28); Manufacture of motor vehicles, trailers and semi-trailers (29); Manufacture of other transport equipment (30).

Table 8. Instrumental variables approach

	IV-2SLS		IV-2SLS	
	1st Stage	**2nd Stage**	**1st Stage**	**2nd Stage**
	EUST	*lnLPmean*	*EUST_NZ*	*lnLPmean*
	(A)	**(B)**	**(C)**	**(D)**
EUST		0.217**		
		(0.095)		
EUST_NZ				0.366**
				(0.168)
+ controls				
#R&D	0.002***		0.001***	
	(0.000)		(0.000)	
#High Tech sector	0.082***		0.036***	
	(0.010)		(0.006)	
#Capital market	0.217***		0.166***	
	(0.035)		(0.021)	
Endogeneity: Wu Hausmann (F-test)	4.284**		2.845*	
Instruments relevance: F-test	43.435***		37.910***	
Instruments exogeneity: Sargan test Chi2	0.750		1.290	
Observations	8,669		8,669	

*Note: i) the dependent variable is reported at the top of the column; ii) standard errors in parentheses; iii) the symbol # indicates the instrumental variable; iv) the table reports also the following tests: Endogeneity test Wu-Hausman (if we reject the Hypothesis the variable EUST and EUST_NZ are endogenous); F-test for instruments relevance (statistical significant with a F-value > 10 means to reject the hypothesis of irrelevance of the instrumental variables); Sargan test Chi2 for the overidentification restriction (no statistical significant means to not reject the hypothesis of exogeneity of the instrumental variables). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Finally, it is important to underline that the instrumental variables choice might be problematic in terms of their exclusion restrictions because the instruments (*R&D, High-tech sector, Capital market*) may be highly correlated with the dependent variable (*lnLPmean*) of the selection model. In Table 9 we show that the variables related to the exclusion restriction (*R&D, High-tech sector, Capital market*) are significant at the first stage and loss significance at the second stage in the selection model.

Table 9. Check on exclusion restriction

	First stage (***EUST***)	Second stage Selection model (***lnLPmean***)
	(A)	(B)
R&D	0.002***	0.001
	(0.000)	(0.000)
High-Tech sector	0.082***	0.014
	(0.010)	(0.010)
Capital market	0.217***	0.032
	(0.035)	(0.038)
+ other variables		
Observations	8,669	8,669

Note: i) the table displays coefficients; ii) standard errors in parentheses. Iii) dependent variable at the top of the column in bold.
*** p < 0.01, ** p < 0.05, * p < 0.1.

6. The EU Strategic Technologies interdependencies through a network analysis

The analysis of technological interdependencies is essential for understanding the direction of technological change (Rosenberg, 1979; Colladon et al., 2025) and they matter for sectoral innovation, also including twin transition in EU (Bontadini & Meliciani, 2025). The modern industrial system increasingly relies on intersectoral connections (Acemoglu et al., 2016), since as progress in one sector is often influenced by developments in related domains. Thus, in line with the literature investigating the technological trajectories through the ties among the technological fields in which firms invest (Breschi et al., 2003), by using network analysis we identify the connections between each of the EU Strategic Technologies, aimed at identifying those that serve as central hubs, facilitating innovation across multiple sectors (Pichler et al., 2020).

In other words, we try to answer the simple question: *"Given any particular technology (in our case EUST) of interest, how many other technologies (EUST) are connected to it?*

6.1 Network analysis: Bipartite Configuration Model (BiCM) Method

A bipartite network, also referred to as a two-mode network, consists of two distinct layers of nodes, where connections occur solely between nodes of different types**.** In other words, nodes within the same layer do not directly connect to one another, but only to nodes in the other layer. These networks are widely utilized to model the affiliation of economic actors, such as firms, with specific groups, such as technological categories (Newman, 2018). The most important information in a bipartite network is encapsulated in the rectangular matrix *T* with dimensions *nxm*, commonly known as the incidence matrix, where *n* is the number of EU Strategic Technologies (58 strategic EU technologies) on one layer and *m* is the number of International Patent Classification (IPC) on the other layer. Each element T_{ij} is assigned a value:

$$T_{ij} = \begin{cases} 1 \text{ if IPC } i \text{ belongs to technology } j \\ 0 \text{ otherwise} \end{cases} \quad (1)$$

The development of strategies and economic policies aimed at gaining a competitive advantage in the technological domain requires the identification of core and emerging technologies, which respectively represent established technological foundations and promising innovations for the future (Cho et al., 2011). Hence, to simplify our analysis, we apply a one-mode projection that transforms the bipartite network into a monopartite one (Newman, 2018), i.e. we created a technology-technology network, linking two technologies based on the number and type of IPC categories they share. For example, if Cloud and edge computing and AI-enabled systems both share IPC categories, they will be linked in the monopartite network, with the strength of their connection proportional to the number of IPC categories they share.

In summary, finding a monopartite network that most accurately depicts the bipartite one while preserving as much information as possible is the basic objective; therefore, using the one-mode projection is an efficient way to reduce complexity (Newman, 2018).

To achieve this, we followed the methodology proposed by Saracco et al. (2015), implementing appropriate null models to detect statistically relevant patterns in real bipartite networks. Specifically, we use the Bipartite Configuration Model (BiCM). The model generates a probability distribution over possible bipartite networks, preserving the observed degree sequences (the number of connections each node has), while treating the links as independent. As a result, we obtain a monopartite network where nodes of the same layer are connected based on their co-occurrence in the original bipartite structure. This allows us to create a $V_{jj}{}'$ matrix connecting the j_{th} technology to the j'_{th} technology.

As highlighted by Saracco et al. (2015), these projections can be used to compute topological measures, such as degree centrality and other metrics that capture the structure of the original bipartite network while reducing its complexity.

In the context of graph theory and network analysis, various measures are used to evaluate the centrality and connectivity of the nodes within a graph. These measures can be divided into two categories: direct and indirect measures.

Direct measures are computed directly from the graph based on the nodes and edges (links). These measures do not require additional computations and are simple to derive from the graph structure itself. Degree centrality is the most basic statistic in network analysis because it basically answers the simple question: *"Given any particular technology of interest (in our case EUST), how many other technologies (EUST) are connected to it?"*. The degree of a technology-node v_j represents the number of adjacent nodes, indicating how well-connected the node is in the graph. A more advanced indirect centrality measure is shown in Appendix, providing consistent results with the simple degree centrality.

6.2 Results

We constructed the bipartite network introduced in 6.1, using IPCs categories (4-digit level[8]) and the 58 EUST identified by the European Union (Table A1 in Appendix). From this, we derived the technology-technology network, which has 58 nodes, where each node represents a strategic EUST, and connections between them are established based on shared IPC categories. We then computed the degree centrality of this network, identifying the top 10 EUST with the highest degree. A higher degree centrality indicates that a technology is strongly interconnected with many others, suggesting that the capabilities required to innovate in that field are also relevant to multiple other technologies. These highly connected technologies act as technological pivots, facilitating advancements not only within their domain but also across diverse and potentially unrelated sectors (Pichler et al., 2020, Tseng et al., 2016).

Among the technologies with the highest degree, we find Cloud and edge computing (9), Cyber security technologies inc. cyber- surveillance, security and intrusion systems, digital forensics (8) and Hydrogen and new fuels (7) (Table 10). The high degree centrality of Cloud and Edge Computing suggests that patent-holding firms investing in this area may also engage with other EUST. Some technologies have no significant

[8] In line with the approach proposed in Bumbea et al. (2025), we constructed the incidence matrix at the 4-digit IPC level by aggregating the 14-digit IPC codes. This aggregation reduced sparsity and enhanced connectivity, allowing for more reliable inferences on technological interrelationships, within the graphs.

connection to other technologies; this will be referred to as isolated technologies. (For each technology, we have created tables linking the EU Strategic Technologies, which are provided in Appendix, Table A7).

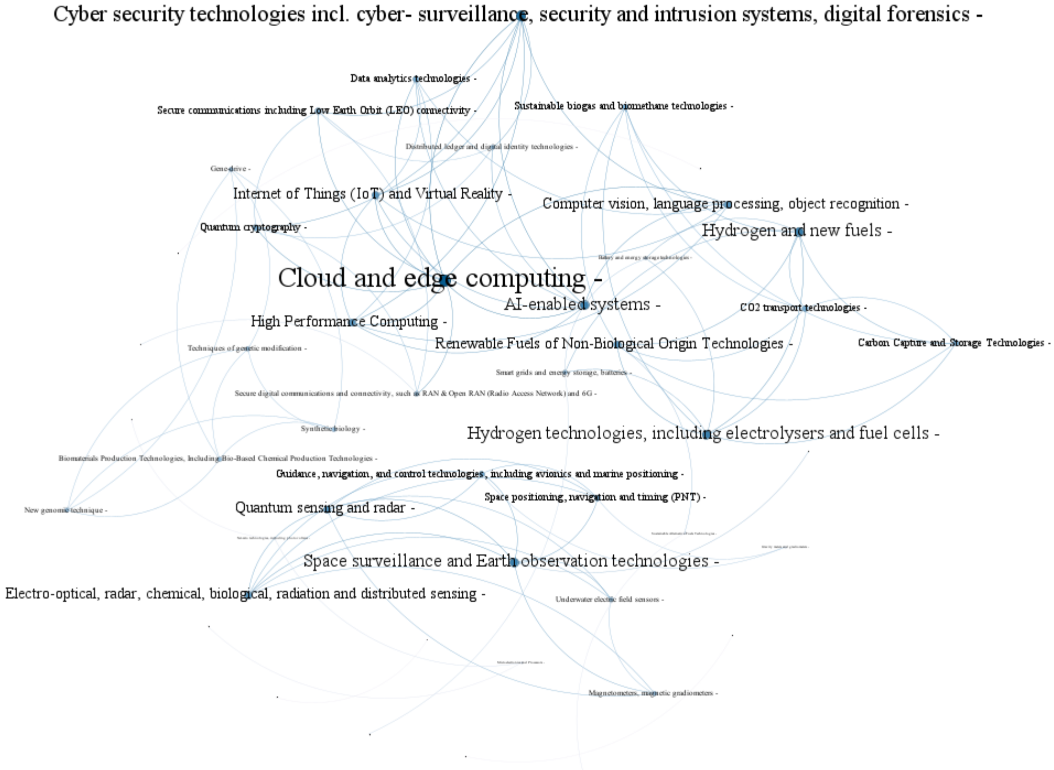
We are able to visualize the statistically significant connections between technologies in Figure 5. The nodes with higher degrees are highlighted within the graph, with larger nodes representing higher degrees and smaller nodes indicating lower degrees.

Table 10 Ranking (top-10) of strategic EU technologies, extracted from the BiCM, ordered by degree centrality

Technologies	Degree
Cloud and edge computing	9
Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics	8
Hydrogen and new fuels	7
Hydrogen technologies, including electrolysers and fuel cells	7
AI-enabled systems	7
Space surveillance and Earth observation technologies	7
Computer vision, language processing, object recognition	6
High Performance Computing	6
Internet of Things (IoT) and Virtual Reality	6
Renewable Fuels of Non-Biological Origin Technologies	6

Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne, Universitas Mercatorum

Figure 5. The technology-technology network.
The size of each node depends on the number of links it has, therefore, nodes with 0 links, representing isolated technologies, disappear.



Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne, Universitas Mercatorum

7. Conclusion

The current EU policy agenda has now placed technological sovereignty and economic security at its very core, recognizing the indispensable need to close the innovation gap vis-à-vis other global actors, namely the US, so as to safeguard the Union's economic resilience. In practice, this has been translated into an ambitious industrial policy platform, encompassing several programmes (in particular, STEP and NZIA EU Regulations) aimed at supporting investments in strategic technologies under the umbrella of Economic Security. This framework, which has now replaced the earlier paradigm of Open Strategic Autonomy, further stresses the strategic value of technological sovereignty for both competitiveness and safety and security, while preserving the EU's commitment to an open, rule-based order (Edler, 2024).

The Letta and Draghi reports both highlighted the urgency of accelerating the uptake of advanced technologies (i.e., deep-tech, net-zero technologies) by also leveraging a well-functioning Single Market, which is a crucial condition for European firms to scale up, innovate and invest in these types of technologies.

The present study has many objectives. First, it aims to provide empirical evidence on firms' degree of innovation in EU strategic technologies (EUST) – also highlighting the Net-Zero technologies (EUST NZ) – both among global actors, above all the US and China, and across EU member states. To do this, the study measures innovation by mapping the patent codes (IPC classification) linked to EUST by applying Large Language Model (LLM) with a robustness check by scraping a sample of firms' websites. Second, it investigates whether there is a positive effect between innovation in EUST and labour productivity at the firm level, although for Italian firms only. Finally, it investigates the interdependencies between each EUST through network analysis.

In the face of these aims, results shows that: i) there is a high heterogeneity of firms' innovation propensity in EUST among EU Member States; ii) compared to the US, the EU shows a more widespread distribution of firms with patents in EUST but suffers a gap in terms of number of patents; iii) with regards to China, the EU's position is reversed in light of a drawback in terms of firms' propensity but an edge in terms of patent diffusion; iv) there a positive effect of innovation in EUST on firm's labour productivity, which further increases in the case of Net-Zero technologies; v) R&D and a developed capital market further support EUST innovation; vii) some strategic technologies, such as those related to Cloud computing, Cyber security, Hydrogen, Artificial Intelligence, Space surveillance and Earth observation technologies, demonstrate higher degrees of connection with other EUST. The empirical evidence in this study is intended to provide useful information for the EU's industrial policy design. The contribution to industrial policy is twofold. First, at a geographical level, it aims at favouring an entrepreneurial convergence in terms of innovation in EUST – including EUST NZ – between member states. Second, technologically, it seeks to incentivise "trigger" technologies, i.e., those showing higher degrees of interdependence with other strategic technologies (namely, degree of centrality), therefore facilitating the identification of those technologies which can contribute the most to the technological sovereignty of the EU.

Notwithstanding, the present study also shows some limitations. Firstly, the study investigates innovation only through patents. Secondly, the identification of patent codes needs further robustness checks, such as web scraping on all firms owning EUST patents besides on only a sample of firms. Thirdly, we consider patents with a filing date of the last 20 years, so further analysis by changing the time period could be useful. Fourthly, with regards to the econometric analysis, which is based on the average level of labour productivity of the last ten years, further robustness checks by changing the time period may be needed, as well as taking into account the time variation besides the levels. The analysis inquiring into the causal relationship should be strengthened through specific types of analyses such as difference-in-difference.

Along with the network analysis, fitness and complexity analyses would also be of great value for policymakers. Future developments of this study will extend to labour force skill mismatches, with a particular focus on advanced digital competencies. Finally, given the gap between knowledge generation and commercial exploitation of patents, future developments will empirically investigate the nexus between patenting and its exploitation by firms (i.e., manufacturing, selling, licensing, or distributing the patented product or process).

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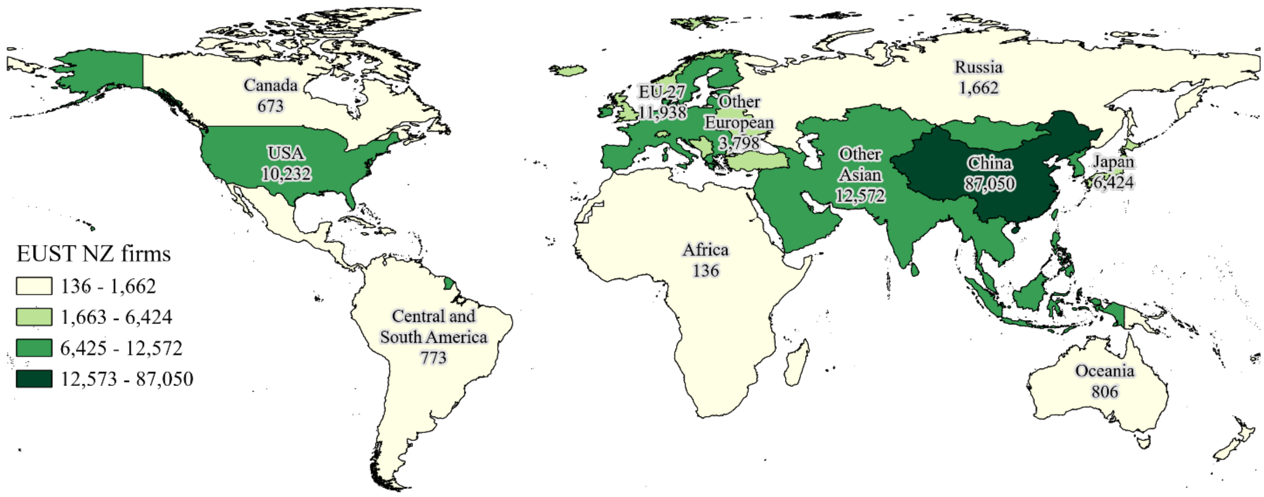
Appendix

Table A1. List of EU Strategic Technologies divided into non Net-Zero (EUST_noNZ) and Net-Zero (EUST_NZ)

Net-Zero type	Description
EUST_noNZ	Smart grids and energy storage, batteries
EUST_noNZ	Additive manufacturing, including in the field
EUST_noNZ	AI-enabled systems
EUST_noNZ	Cloud and edge computing
EUST_noNZ	Computer vision, language processing, object recognition
EUST_noNZ	Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics
EUST_noNZ	Data analytics technologies
EUST_noNZ	Dedicated space-focused technologies
EUST_noNZ	Digital controlled micro-precision manufacturing and small-scale laser machining/welding
EUST_noNZ	Distributed ledger and digital identity technologies
EUST_noNZ	Electro-optical, radar, chemical, biological, radiation and distributed sensing
EUST_noNZ	Exoskeletons
EUST_noNZ	Gene-drive
EUST_noNZ	Gravity meters and gradiometers
EUST_noNZ	Guidance, navigation, and control technologies, including avionics and marine positioning
EUST_noNZ	High frequency chips
EUST_noNZ	High Performance Computing
EUST_noNZ	Hydrogen and new fuels
EUST_noNZ	Internet of Things (IoT) and Virtual Reality
EUST_noNZ	Magnetometers, magnetic gradiometers
EUST_noNZ	Microelectronics and Processors
EUST_noNZ	Net-zero technologies, including photovoltaics
EUST_noNZ	New genomic technique
EUST_noNZ	Nuclear fusion technologies, reactors and power generation, radiological Conversion/Enrichment/Recycling Technologies
EUST_noNZ	Photonics (including high energy laser) technologies
EUST_noNZ	Propulsion technologies, including hypersonics and components for military use
EUST_noNZ	Quantum communications
EUST_noNZ	Quantum computing
EUST_noNZ	Quantum cryptography
EUST_noNZ	Quantum sensing and radar
EUST_noNZ	Robotics and Autonomous Systems
EUST_noNZ	Robots and robot-controlled precision systems
EUST_noNZ	Secure communications including Low Earth Orbit (LEO) connectivity
EUST_noNZ	Secure digital communications and connectivity, such as RAN & Open RAN (Radio Access Network) and 6G
EUST_noNZ	Semiconductor manufacturing equipment at very advanced node sizes
EUST_noNZ	Space positioning, navigation and timing (PNT)
EUST_noNZ	Space surveillance and Earth observation technologies

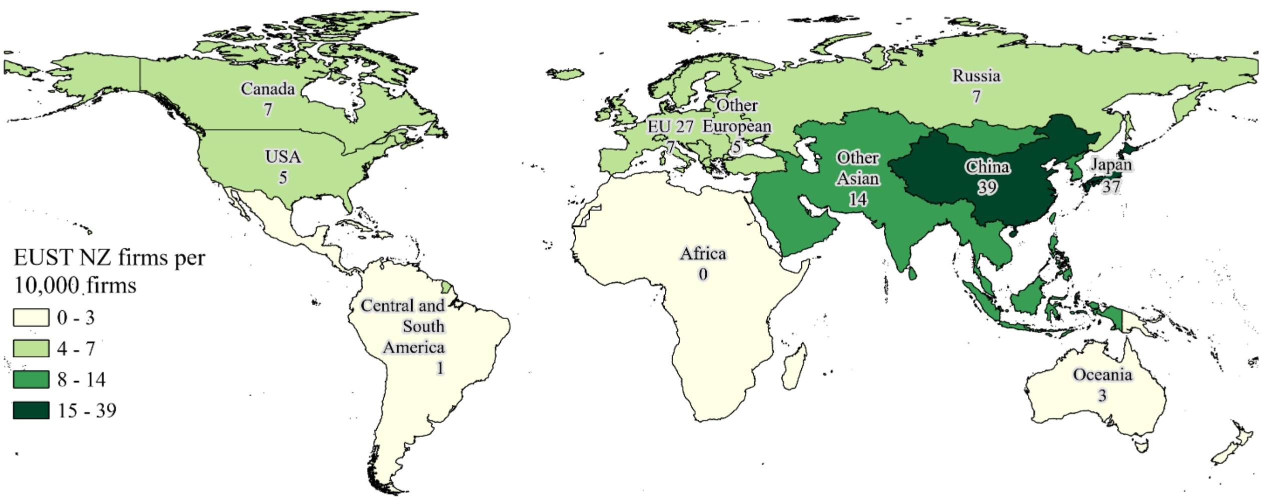
EUST_noNZ	Synthetic biology
EUST_noNZ	Techniques of genetic modification
EUST_noNZ	Technologies for extraction, processing and recycling of critical raw materials
EUST_noNZ	Technologies for nanomaterials, smart materials, advanced ceramic materials, stealth materials, safe and sustainable by design materials
EUST_noNZ	Underwater electric field sensors
EUST_NZ	Battery and energy storage technologies
EUST_NZ	Biomaterials Production Technologies, Including Bio-Based Chemical Production Technologies
EUST_NZ	Carbon Capture and Storage Technologies
EUST_NZ	CO2 transport technologies
EUST_NZ	Electricity Grid Technologies, Including Electric Charging Technologies for Transportation and Technologies to Digitalize the Grid
EUST_NZ	Energy System-Related Energy Efficiency Technologies
EUST_NZ	Heat pumps and geothermal energy technologies
EUST_NZ	Hydrogen technologies, including electrolysers and fuel cells
EUST_NZ	Nuclear Fission Energy Technologies, Including Nuclear Fuel Cycle Technologies
EUST_NZ	Onshore Wind and Offshore Renewable Technologies
EUST_NZ	Sustainable Propulsion Technologies for Transportation
EUST_NZ	Renewable energy technologies not covered under the previous categories (osmotic energy technologies, ambient energy technologies, hydropower technologies, biomass technologies, landfill gas technologies, sewage treatment plant gas technologies, biogas technologies, thermal energy technologies including heat grid technologies)
EUST_NZ	Renewable Fuels of Non-Biological Origin Technologies
EUST_NZ	Solar technologies
EUST_NZ	Sustainable Alternative Fuels Technologies
EUST_NZ	Sustainable biogas and biomethane technologies

Map A1. EUST NZ firms (number)



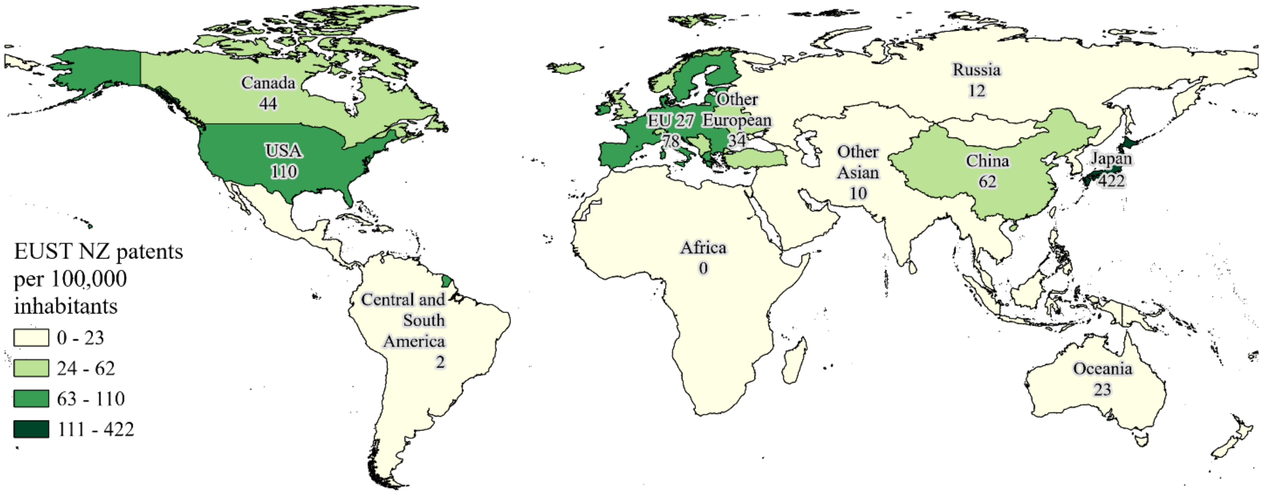
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map A2. EUST NZ firms per 10,000 firms



Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map A3. EUST NZ patents per 100,000 inhabitants



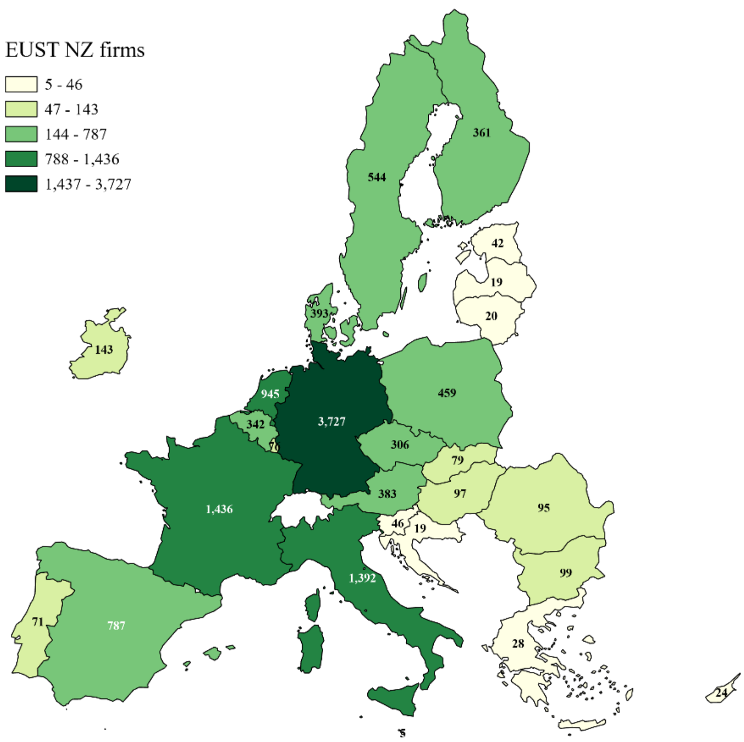
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Table A2. Macro regions

	Firms*				Patents			
Macro regions	**N. firms with patents in EUST**	**of which with patents in EUST NZ**	**EUST firms per 10,000 firms**	**EUST NZ firms per 10,000 firms**	**N. patents in EUST**	**N. patents in EUST NZ**	**EUST patents per 100,000 persons**	**EUST NZ patents per 100,000 persons**
EU 27	36,406	11,938	21	7	1,726,337	348,279	385	78
USA	41,997	10,232	22	5	3,354,968	369,110	1,002	110
China	226,424	87,050	100	39	4,953,288	868,339	351	62
Japan	19,041	6,424	110	37	2,825,736	525,122	2,269	422
Canada	2,309	673	24	7	108,928	17,502	272	44
Russia	4,519	1,662	20	7	54,022	16,938	38	12
Central and South America	2,557	773	2	1	102,261	10,668	16	2
Africa	637	136	2	0	10,018	4,930	1	0
Oceania	3.909	806	15	3	46,325	10,225	103	23
Other European	12,677	3,798	16	5	359,932	80,055	153	34
Other Asian	49,782	12,572	57	14	2,209,069	323,814	70	10
World	***400,258***	***136,064***	***41***	***14***	***15,750,884***	***2,574,982***	***195***	***32***

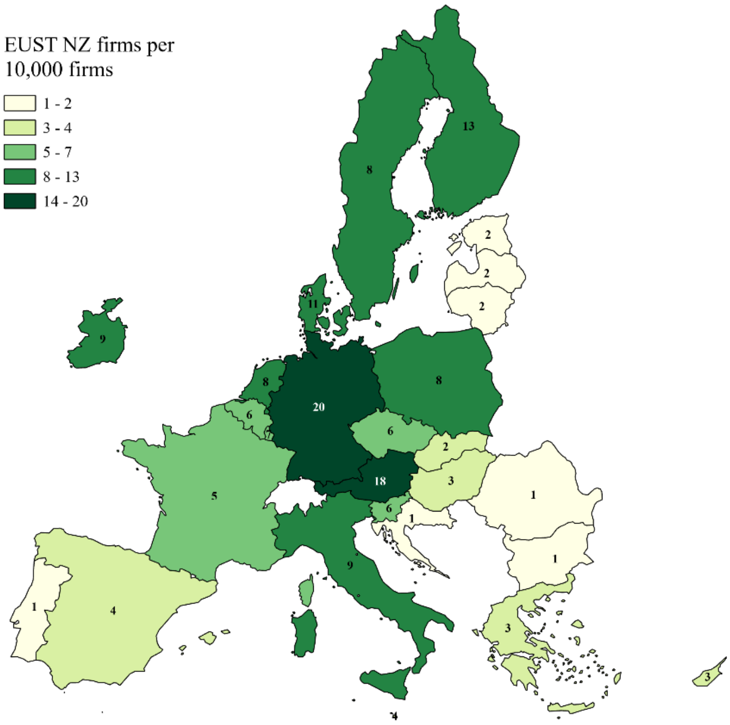
** All data refers to the limited companies.*
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map A4. EUST NZ firms (number)



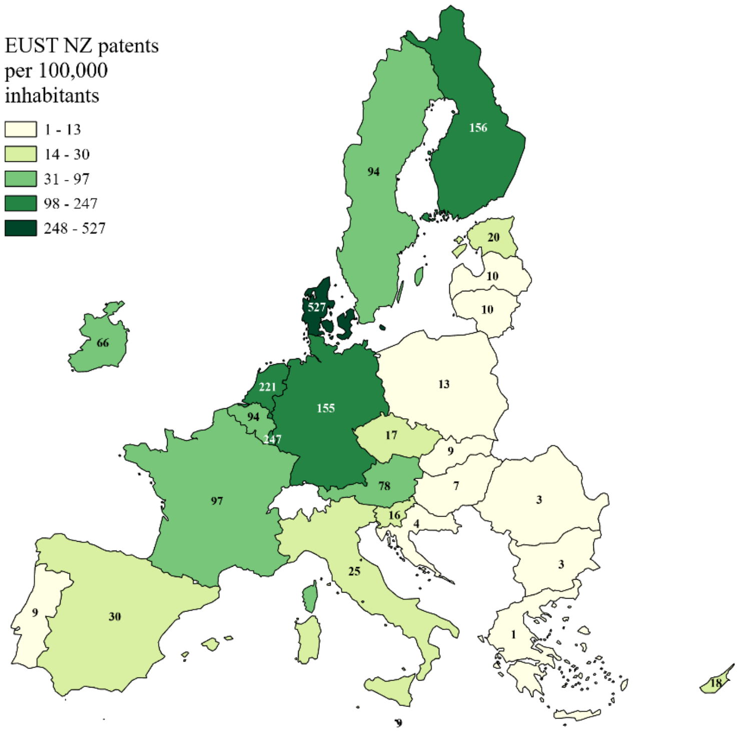
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map A5. EUST NZ firms per 10,000 firms



Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Map A6. EUST NZ patents per 100,000 inhabitants



Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Table A3 European Union countries

	Firms*				Patents			
EU Regions	**N. firms with patents in EUST**	**of which with patents in EUST NZ**	**EUST firms per 10,000 firms**	**EUST NZ firms per 10,000 firms**	**N. patents in EUST**	**N. patents in EUST NZ**	**EUST patents per 100,000 persons**	**EUST NZ patents per 100,000 persons**
Austria	1,098	383	52	18	35,227	7,143	386	78
Belgium	1,094	342	18	6	31,958	11,050	271	94
Bulgaria	449	99	6	1	1,193	225	19	3
Croatia	75	19	5	1	529	149	14	4
Cyprus	108	24	12	3	2,795	240	208	18
Czech Republic	812	306	16	6	6,053	1,884	56	17
Denmark	922	393	26	11	44,860	31,312	754	527
Estonia	122	42	5	2	833	272	61	20
Finland	1,313	361	46	13	114,728	8,716	2055	156
France	4,577	1,436	16	5	334,723	66,092	490	97
Germany	10,755	3,727	59	20	581,786	129,472	699	155
Greece	89	28	10	3	759	111	7	1
Hungary	309	97	9	3	2,494	687	26	7
Ireland	556	143	34	9	66,346	3,504	1250	66
Italy	5,169	1,392	35	9	61,605	14,529	104	25
Latvia	58	19	5	2	576	196	31	10
Lithuania	86	20	9	2	1,741	297	61	10
Luxembourg	258	76	25	7	7,795	1,647	1170	247
Malta	34	5	24	4	1,434	47	259	9
Netherlands	2,351	945	20	8	175,334	39,488	981	221
Poland	1,265	459	23	8	13,302	4,588	36	13
Portugal	279	71	4	1	3,415	903	32	9
Romania	319	95	2	1	1,759	489	9	3
Slovakia	220	79	6	2	2,255	462	42	9
Slovenia	183	46	23	6	1,035	335	49	16
Spain	2,215	787	11	4	37,696	14,519	78	30
Sweden	1,690	544	26	8	194,106	9,922	1842	94
EU 27	***36,406***	***11,938***	***21***	***7***	***1,726,337***	***348,279***	***385***	***78***

** All data refers to the limited companies.*
Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne

Table A4. Variables description of the propensity score

Variables	Type	Description
Dependent variables		
EUST	Binary	1 = firm with patents in EU Strategic Technologies; 0 = otherwise (source: elaboration on Moody's data)
Independent variables		
Industry tech	Dummies	1 = if the firm belongs to a n-sector according to the OECD/EUROSTAT technology and knowledge intensity classification (high/medium-high technology intensive manufacturing; low/medium-low technology intensive manufacturing; high knowledge intensity services; low knowledge intensive services); sectors not elsewhere classified (*Industry n.e.c.*); 0 = otherwise (source: elaboration on ISTAT data)
Size	Dummies	1 = if the firm belongs to a n-size class: less than 10 employees (*Micro*); 10-49 employees (*Small*); 50-249 employees (*Medium*); 250 and over employees (*Large*); 0 = otherwise (source: elaboration on ISTAT)
Localization	Dummies	1 = if the firm belongs to a n-NUTS 1 (North-West, North-East, Center, South*); 0 = otherwise.
Age	Discrete	Number of years since inception (source: elaboration on ISTAT)
Graduates	Continuous	Share of graduated employees of total employees
Governance	Dummies	1 = if the firm belongs to a n-type of governance: Foreign-invested firms with foreign control (*FI foreign control*); Foreign-invested firm with Italian control (*FI Italian control*); Italian corporate group (*Corporate group*); Independent firm (*Independent*); not classified (*Gov nc*) (source: elaboration on ISTAT)
R&D	Continuous	R&D asset value per employee (euro) (source: elaboration on Moody's data)
Capital market	Dummy	1 = if the firm is a listed company (source: Moody's)
Asset	Continuous	Total asset (thousand euro) (source: elaboration on Moody's data)

* South includes also the Islands.

Table A5. Probit of propensity score

	Pr(Treatment)
HM	0.572***
	(0.085)
HKIS	0.395***
	(0.040)
LKIS	0.640***
	(0.073)
Industry n.e.c.	0.194***
	(0.057)
Small	0.107*
	(0.060)
Medium	0.326***
	(0.066)
Large	0.738***
	(0.079)
North-East	0.029
	(0.037)
Center	0.007
	(0.051)
South	0.115
	(0.073)
Age	-0.000
	(0.001)
Graduates	1.041***
	(0.098)
FI foreign control	0.028
	(0.062)
FI italian control	0.128***
	(0.049)
Corporate group	-0.005
	(0.044)
Gov n.c	-0.068
	(0.534)
R&D	0.005***
	(0.001)
Capital market	0.403***
	(0.118)
Asset	0.000
	(0.000)
Pseudo R^2	0.097
LR chi2	824.63***
Observations	8,710

Note: i) Treatment refers to the variable *EUST*. ii) standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

Figure A1. Propensity-score density before and after matching

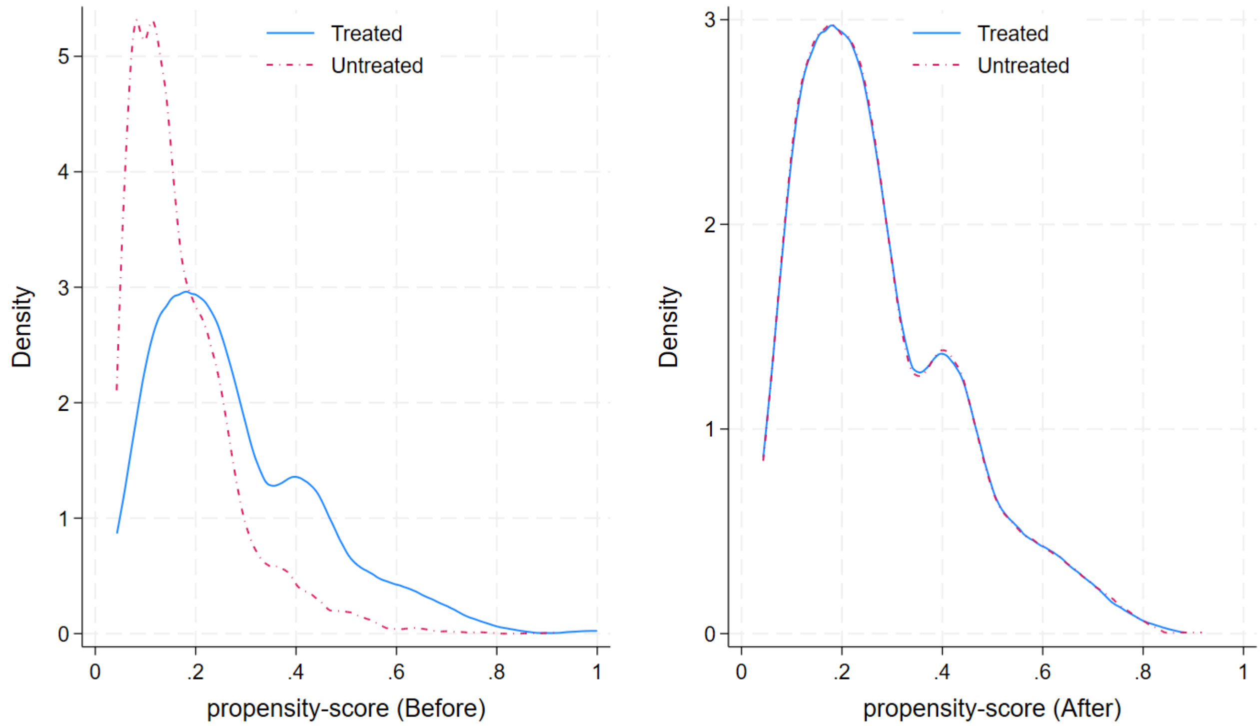


Table A6. Balancing properties of the matched sample

	Treated	*Matched control*	*t-test*	*p-value*
HM	0.450	0.424	1.63	0.103
HKIS	0.171	0.181	-0.77	0.440
LKIS	0.122	0.136	-1.34	0.180
Industry n.e.c.	0.051	0.053	-0.26	0.796
Small	0.311	0.313	-0.07	0.944
Medium	0.380	0.374	0.40	0.686
Large	0.215	0.219	-0.24	0.812
North-East	0.363	0.366	-0.20	0.839
Center	0.139	0.144	-0.47	0.639
South	0.062	0.064	-0.27	0.788
Age	38.822	35.144	-0.60	0.546
Graduates	0.286	0.284	0.34	0.731
FI foreign control	0.149	0.157	-0.68	0.496
FI italian control	0.353	0.343	0.63	0.526
Corporate group	0.255	0.2654	-0.67	0.503
Gov n.c	0.005	0.007	-0.31	0.756
R&D	2.266	2.791	-0.81	0.420
Capital market	0.046	0.051	-0.68	0.495
Asset	137.15	116.51	0.76	0.446

Table A7. Technological interdependencies: Technologies ordered by Degree centrality.
For each EU strategic technology, we report the list of the other EU strategic technologies most connected by technological interdependencies

1. **Cloud and edge computing (9)**
Secure communications including Low Earth Orbit (LEO) connectivity
Secure digital communications and connectivity, such as RAN & Open RAN (Radio Access Network) and 6G
Computer vision, language processing, object recognition
High Performance Computing
Internet of Things (IoT) and Virtual Reality
Data analytics technologies
Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics
AI-enabled systems
Quantum cryptography

2. **Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics (8)**
Quantum cryptography
Secure communications including Low Earth Orbit (LEO) connectivity
Distributed ledger and digital identity technologies
High Performance Computing
Internet of Things (IoT) and Virtual Reality
AI-enabled systems
Computer vision, language processing, object recognition
Cloud and edge computing

3. **Hydrogen and new fuels (7)**
Hydrogen technologies, including electrolysers and fuel cells
Renewable Fuels of Non-Biological Origin Technologies
Sustainable biogas and biomethane technologies
Smart grids and energy storage, batteries
Battery and energy storage technologies
CO2 transport technologies
Carbon Capture and Storage Technologies

4. **Hydrogen technologies, including electrolysers and fuel cells (7)**
Renewable Fuels of Non-Biological Origin Technologies
Sustainable biogas and biomethane technologies
Smart grids and energy storage, batteries
Battery and energy storage technologies
CO2 transport technologies
Carbon Capture and Storage Technologies
Hydrogen and new fuels

5. **AI-enabled systems (7)**
Cloud and edge computing
Computer vision, language processing, object recognition
High Performance Computing
Internet of Things (IoT) and Virtual Reality

Data analytics technologies
Cyber security technologies, incl. cyber- surveillance, security and intrusion systems, digital forensics
Distributed ledger and digital identity technologies

6. Space surveillance and Earth observation technologies (7)

Underwater electric field sensors
Dedicated space-focused technologies
Electro-optical, radar, chemical, biological, radiation and distributed sensing
Guidance, navigation, and control technologies, including avionics and marine positioning
Magnetometers, magnetic gradiometers
Quantum sensing and radar
Space positioning, navigation and timing (PNT)

7. Computer vision, language processing, object recognition (6)

High Performance Computing
Internet of Things (IoT) and Virtual Reality
Data analytics technologies
Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics
AI-enabled systems
Cloud and edge computing

8. High Performance Computing (6)

Internet of Things (IoT) and Virtual Reality
AI-enabled systems
Cloud and edge computing
Computer vision, language processing, object recognition
Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics
Data analytics technologies

9. Internet of Things (IoT) and Virtual Reality (6)

AI-enabled systems
Cloud and edge computing
Computer vision, language processing, object recognition
Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics
Data analytics technologies
High Performance Computing

10. Renewable Fuels of Non-Biological Origin Technologies (6)

Sustainable Alternative Fuels Technologies
Sustainable biogas and biomethane technologies
CO2 transport technologies
Carbon Capture and Storage Technologies
Hydrogen and new fuels
Hydrogen technologies, including electrolysers and fuel cells

11. Electro-optical, radar, chemical, biological, radiation and distributed sensing (6)

Space positioning, navigation and timing (PNT)
Guidance, navigation, and control technologies, including avionics and marine positioning

Quantum sensing and radar
Space surveillance and Earth observation technologies
Underwater electric field sensors
Magnetometers, magnetic gradiometers

12. Quantum sensing and radar (6)

Space surveillance and Earth observation technologies
Underwater electric field sensors
Electro-optical, radar, chemical, biological, radiation and distributed sensing
Guidance, navigation, and control technologies, including avionics and marine positioning
Magnetometers, magnetic gradiometers
Underwater electric field sensors

13. Data analytics technologies (5)

High Performance Computing
Internet of Things (IoT) and Virtual Reality
AI-enabled systems
Cloud and edge computing
Computer vision, language processing, object recognition

14. CO2 transport technologies (5)

Sustainable biogas and biomethane technologies
Carbon Capture and Storage Technologies
Renewable Fuels of Non-Biological Origin Technologies
Hydrogen and new fuels
Hydrogen technologies, including electrolysers and fuel cells

15. Sustainable biogas and biomethane technologies (5)

CO2 transport technologies
Carbon Capture and Storage Technologies
Hydrogen and new fuels
Hydrogen technologies, including electrolysers and fuel cells
Renewable Fuels of Non-Biological Origin Technologies

16. Carbon Capture and Storage Technologies (5)

Renewable Fuels of Non-Biological Origin Technologies
Sustainable biogas and biomethane technologies
Hydrogen and new fuels
Hydrogen technologies, including electrolysers and fuel cells
CO2 transport technologies

17. Secure communications including Low Earth Orbit (LEO) connectivity (5)

Secure digital communications and connectivity, such as RAN & Open RAN (Radio Access Network) and 6G
Cloud and edge computing
Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics
Distributed ledger and digital identity technologies
Quantum cryptography

18. Quantum cryptography (5)

Secure communications including Low Earth Orbit (LEO) connectivity
Secure digital communications and connectivity, such as RAN & Open RAN (Radio Access Network) and 6G
Cloud and edge computing
Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics
Distributed ledger and digital identity technologies

19. Space positioning, navigation and timing (PNT) (5)

Space surveillance and Earth observation technologies
Electro-optical, radar, chemical, biological, radiation and distributed sensing
Gravity meters and gradiometers
Guidance, navigation, and control technologies, including avionics and marine positioning
Quantum sensing and radar

20. Guidance, navigation, and control technologies, including avionics and marine positioning (5)

Space positioning, navigation and timing (PNT)
Quantum sensing and radar
Space surveillance and Earth observation technologies
Electro-optical, radar, chemical, biological, radiation and distributed sensing
Gravity meters and gradiometers

21. Smart grids and energy storage, batteries (4)

Battery and energy storage technologies
Hydrogen and new fuels
Hydrogen technologies, including electrolysers and fuel cells
Electricity Grid Technologies, Including Electric Charging Technologies for Transportation and Technologies to Digitalize the Grid

22. Distributed ledger and digital identity technologies (4)

Quantum cryptography
Secure communications including Low Earth Orbit (LEO) connectivity
AI-enabled systems
Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics

23. Biomaterials Production Technologies, Including Bio-Based Chemical Production Technologies (4)

Gene-drive
Synthetic biology
Techniques of genetic modification
New genomic technique

24. Gene-drive (4)

Synthetic biology
Techniques of genetic modification
New genomic technique
Biomaterials Production Technologies, Including Bio-Based Chemical Production Technologies

25. Synthetic biology (4)

Techniques of genetic modification
Biomaterials Production Technologies, Including Bio-Based Chemical Production Technologies
Gene-drive
New genomic technique

26. Techniques of genetic modification (4)

Biomaterials Production Technologies, Including Bio-Based Chemical Production Technologies
Gene-drive
New genomic technique
Synthetic biology

27. New genomic technique (4)

Synthetic biology
Techniques of genetic modification
Biomaterials Production Technologies, Including Bio-Based Chemical Production Technologies
Gene-drive

28. Secure digital communications and connectivity, such as RAN & Open RAN (Radio Access Network) and 6G (4)

Cloud and edge computing
Quantum communications
Quantum cryptography
Secure communications including Low Earth Orbit (LEO) connectivity

29. Underwater electric field sensors (4)

Electro-optical, radar, chemical, biological, radiation and distributed sensing
Magnetometers, magnetic gradiometers
Quantum sensing and radar
Space surveillance and Earth observation technologies

30. Magnetometers, magnetic gradiometers (4)

Quantum sensing and radar
Space surveillance and Earth observation technologies
Underwater electric field sensors
Electro-optical, radar, chemical, biological, radiation and distributed sensing

31. Battery and energy storage technologies (3)

Hydrogen and new fuels
Hydrogen technologies, including electrolysers and fuel cells
Smart grids and energy storage, batteries

32. Gravity meters and gradiometers (2)

Space positioning, navigation and timing (PNT)
Guidance, navigation, and control technologies, including avionics and marine positioning

33. Microelectronics and Processors (2)

Semiconductor manufacturing equipment at very advanced node sizes
Net-zero technologies, including photovoltaics

34. Net-zero technologies, including photovoltaics (2)

Solar technologies

Microelectronics and Processors

35. Sustainable Alternative Fuels Technologies (2)

Renewable Fuels of Non-Biological Origin Technologies

Renewable energy technologies not covered under the previous categories

36. Electricity Grid Technologies, Including Electric Charging Technologies for Transportation and Technologies to Digitalize the Grid (1)

Smart grids and energy storage, batteries

37. Dedicated space-focused technologies (1)

Space surveillance and Earth observation technologies

38. Exoskeletons (1)

Robots and robot-controlled precision systems

39. Robots and robot-controlled precision systems (1)

Exoskeletons

40. Semiconductor manufacturing equipment at very advanced node sizes (1)

Microelectronics and Processors

41. Solar technologies (1)

Net-zero technologies, including photovoltaics

42. Nuclear Fission Energy Technologies, Including Nuclear Fuel Cycle Technologies (1)

Nuclear fusion technologies, reactors and power generation, radiological Conversion/Enrichment/Recycling Technologies

43. Nuclear fusion technologies, reactors and power generation, radiological Conversion/Enrichment/Recycling Technologies (1)

Nuclear Fission Energy Technologies, Including Nuclear Fuel Cycle Technologies

44. Onshore Wind and Offshore Renewable Technologies (1)

Sustainable Propulsion Technologies for Transportation

45. Sustainable Propulsion Technologies for Transportation (1)

Onshore Wind and Offshore Renewable Technologies

46. Quantum communications (1)

Secure digital communications and connectivity, such as RAN & Open RAN (Radio Access Network) and 6G

47. Renewable energy technologies not covered under the previous categories (1)

Sustainable Alternative Fuels Technologies

Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne, Universitas Mercatorum

Other centrality measure: The Betweenness centrality

Indirect measures capture the global behaviour of the nodes within the network, reflecting their role in the overall connectivity. For example, betweenness centrality is an indirect measure that quantifies the extent to which a node acts as an intermediary in the shortest paths between other pairs of nodes. Specifically, it calculates the number of shortest paths that pass through a given node, indicating how central a node is in connecting different parts of the network. The betweenness centrality is given by Eqs A1.

$$Bet_w = \Sigma_{u \neq v,\ w \notin \{u,v\}} \frac{n_w\,(u,v)/n(u,v)}{(n-1)(n-2)} \quad \text{(A1)}$$

Let n(u,v) represent the total number of shortest paths $P *_{uv}$ from node u to node υ, and let $n_w\,(u,v)$ =$|\{P *_{uv}\ \mid w\ \notin\ P *_{uv}\}|$ represent the number of shortest paths from node u to node υ that pass-through node ω. The betweenness centrality of node ω can then be calculated as the fraction of shortest paths between all pairs of nodes that pass-through ω, which provides a measure of the importance of node ω in connecting different parts of the network. We also computed the Betweenness centrality.

Table A8. The Betweenness centrality

Technologies	Betweenness
Renewable Fuels of Non-Biological Origin Technologies	0,0155
Cloud and edge computing	0,0148
Secure digital communications and connectivity, such as RAN & Open RAN (Radio Access Network) and 6G	0,0099
Smart grids and energy storage, batteries	0,0087
Hydrogen and new fuels	0,0087
Hydrogen technologies, including electrolysers and fuel cells	0,0087
Space surveillance and Earth observation technologies	0,0087
Sustainable Alternative Fuels Technologies	0,0087
Cyber security technologies incl. cyber- surveillance, security and intrusion systems, digital forensics	0,0052
Space positioning, navigation and timing (PNT)	0,0029

Source: Research Center of the Chambers of Commerce Guglielmo Tagliacarne, Universitas Mercatorum

Having a high betweenness centrality means that a particular technology plays a crucial role in the interconnection of other technologies or concepts in the overall system. Technologies with high betweenness are those that act as 'intermediaries' or 'connectors' for many other technologies. For example, Renewable Fuels of Non-Biological Origin Technologies and Cloud and Edge Computing are among the most central in the network, suggesting that they are connected to many other technologies or could serve as hubs for future technological developments. Technologies with high betweenness centrality are critical for the network: if these intermediary nodes were removed, the graph could fragment, disrupting many connections between other technologies. In practice, without these nodes, the network would become less connected, compromising the diffusion of innovations. Therefore, these technologies are essential for maintaining the integrity and cohesion of the entire system, and their absence could lead to a 'collapse' of the graph.