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RESEARCH PAPER

Mapping Net-Zero Technologies Through Web Scraping: Evidence from Italian Corporate Websites

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Abstract

The *Net-Zero Industry Act* (NZIA) is a key initiative of the European Union aimed at accelerating the green transition and strengthening the EU's clean-tech industrial base. However, the adoption of net-zero technologies across firms, sectors and regions remains largely undocumented, mainly due to the limitations of conventional innovation metrics. This paper addresses this gap by operationalising the NZIA technology framework at the firm level and combining structured firm-level data with unstructured information extracted from corporate websites via large-scale web scraping. Focusing on Italian companies, we map the adoption of net-zero technologies by firms and, within adopters, identify firms that are also engaged in their technological development by integrating web-based signals with patent data. We document the geographical and sectoral distribution of adopters and developers and analyse the firm-level drivers associated with technology adoption and development. Our results show that web-based data are effective in identifying the adoption of net-zero technologies, but they need to be complemented with patent information to accurately capture technological development. These findings have important implications for the design of targeted, place-based industrial policies under the NZIA framework.

Keywords Web data · Innovation · NZIA · Net-Zero technologies · Web scraping · Unconventional data · Corporate websites

JEL Classification O25 · O3 · Q55

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1 Introduction

The Net-Zero Industry Act (NZIA, henceforth), adopted as Regulation (EU) 2024/1735 and in force since 29 June 2024, plays a pivotal role in fostering innovation and accelerating the transition toward sustainable industrial practices in the European Union. As a part of the Green Deal Industrial Plan, the NZIA provides a strategic framework to expand the EU's domestic manufacturing capacity for key net-zero technologies. Together with the Critical Raw Materials Act (CRMA), the NZIA strengthens Europe's clean energy security by reducing reliance on volatile global supply chains. Beyond advancing climate neutrality, it seeks to position the EU as a global leader in the net-zero economy, fostering clean-tech industries, creating high-value jobs, and enhancing long-term competitiveness.

Despite their relatively recent embracing, these initiatives have already largely attracted scholarly attention. Existing contributions have examined the economic rationale and strategic underpinnings of European green industrial policy (Lofgren et al. 2024), the legislative architecture and pillars of the NZIA (Tagliapietra et al. 2023), its interaction with other regulatory instruments such as the CRMA (Hool et al. 2024), and its positioning relative to comparable policy frameworks, most notably the U.S. Inflation Reduction Act (Kleimann et al. 2023).

However, while a growing literature has clarified the institutional and policy design of the NZIA, much less is known about how its technological aim translates into firm-level behaviour across firms, sectors and territories. Indeed, the empirical mapping of net-zero technologies at the firm level remains undocumented. A possible reason for this shortcoming is the fact that measuring the adoption and development of net-zero technologies poses substantial challenges. These technologies are inherently interdisciplinary, evolve rapidly, and are often embedded in complex production processes that are difficult to capture by conventional indicators. Traditional tools—such as innovation surveys, financial statements, and patent statistics (Gault 2013; OECD 2015; OECD and Eurostat 2018; Hall et al. 2010; Nagaoka et al. 2010; Mairesse and Mohnen 2010)—while well established, tend to underrepresent small and medium-sized enterprises (SMEs), fail to capture early-stage or non-patentable innovations, and suffer from time lags that limit their responsiveness to fast-moving technological domains (Griliches 1990; Arundel et al. 2013; Balland and Boschma 2020).

To address these measurement challenges, this study combines structured firm-level data with unstructured (non-conventional) textual information extracted from corporate websites through large-scale web scraping. A growing literature has increasingly recognized the value of digital traces and unstructured information in capturing innovation dynamics (Nathan and Rosso 2015; Papagiannidis et al. 2018; Stich et al. 2022). In particular, web scraping can uncover firm-level innovation signals that are typically unavailable from traditional datasets (Arribas-Bel and Bakens 2019; Gentzkow et al. 2019; Ash and Hansen 2023). This method provides timely, granular, and self-reported evidence of technological engagement. Corporate websites, in particular, serve as strategic communication tools through which firms signal products, partnerships, technological capabilities, and long-term objectives, thereby offering a valuable window into the adoption of emerging technologies such as those encompassed by the NZIA.

However, web-scraped data are less informative when it comes to identifying firms that engage in the internal development of new technologies. Web-based signals primarily reflect outward-facing communication and observable technology engagement, while providing only limited and often indirect information on firms' internal R&D activities and proprietary innovation efforts. In this paper, we therefore distinguish between adoption, which reflects the broad diffusion and implementation of net-zero technologies across firms, and development, which captures the activity of the narrower subset of actors that generate proprietary technological knowledge in the net-zero technology domain. This distinction represents a central challenge for both research and policy: failing to distinguish between adopters and developers leads to misleading inferences and policy interventions that implicitly assume similar needs across fundamentally different firms. Recognizing this distinction is therefore essential for understanding the structure of innovation systems and for designing effective industrial policies in the clean technology domain.

To distinguish between adopters and developers, we explicitly integrate patent data into our empirical framework. Drawing on the innovation literature that considers patents as indicators of firms' engagement in the creation of new technological knowledge (Archibugi 1992; Peeters and Pottelsberghe de la Potterie 2007), we exploit patent information to distinguish developers from adopters within the broader population of firms exposed to net-zero technologies. Operationally, we collect firm-level patent data and determine whether patents portfolios relate to net-zero technologies by leveraging a Large Language Model (LLM) that assigns International Patent Classification (IPC) codes to NZIA technology domains. As a robustness check for the identification of technology-developing firms, we conduct an additional analysis on company websites – similar to the adoption exercise – using a set of keywords specifically related to technological development.

The focus on Italian companies is particularly well suited to this analysis because Italy represents a critical case for studying net-zero technologies and industrial policy. Indeed, its productive system is characterized by a strong manufacturing base, a dense network of industrial districts, and a predominance of SMEs, which play a central role in technology adoption but are less frequently engaged in technology development, i.e., formal R&D and patenting activities. Moreover, Italy's geographical heterogeneity and sectoral specialization patterns provide an ideal testing ground for assessing how the Net-Zero Industry Act interacts with local innovation ecosystems and existing industrial structures.

The contributions of this paper are twofold. First, we demonstrate that web-scraped data are effective in identifying firms that adopt net-zero technologies but are insufficient to detect technology developers. By integrating website information with patent data, we show that a combined data strategy is necessary to avoid misclassification. Second, we provide a firm-level mapping of adopters and developers that is explicitly aligned with the NZIA technological framework, enabling the identification of distinct firm-level drivers associated with adoption and development of net-technology, which is crucial for further research and policy analysis.

As a preview of our findings, we show that firms developing net-zero technologies differ markedly from those that merely adopt them. Developers tend to exhibit distinct financial, organizational and skill-related profiles, whereas adopters—particularly if SMEs—face more constraints related to liquidity and access to credit. Moreover, both technological roles are shaped by sectoral and territorial contexts. These results indicate that distinguishing between adoption and development is crucial for assessing the heterogeneity of the net-zero ecosystem and for informing targeted policy design.

The remainder of the paper is structured as follows. Section 2 reviews the literature. Section 3 introduces the web scraping methodology and the construction of the NZIA technology mapping. Section 4 presents the firm-level mapping of adopters and developers. Section 5 explores firm-level drivers of adoption and development. Section 6 discusses research and policy implications. Section 7 concludes.

2 Literature Review

2.1 Limitations of Conventional Approaches

Measuring innovation within firms has become an increasingly complex task, requiring the simultaneous use of both traditional and novel methods. The former have been widely discussed in the literature, with the identification of innovative firms mainly relying on surveys, financial statements, and patent data (Gault 2013; OECD 2015; OECD and Eurostat 2018; Hall et al. 2010; Nagaoka et al. 2010; Mairesse & Mohnen 2010). While these sources are acknowledged for their reliability and rigorous standards, they also reveal important shortcomings, which are particularly pronounced in contexts such as the Italian one. Surveys may be affected by response biases or fail to adequately ensure representativeness across firm size classes, particularly micro firms with fewer than ten employees, a limitation well documented in the Community Innovation Survey (Arundel et al. 2013). Financial statements also present limitations. In SMEs, for example, much of the research and development (R&D) activity is informal, often embedded within personnel expenses and protected with alternative methods, making it difficult to assess innovation through accounting data (Santarelli and Sterlacchini 1990; Holgersson 2013). Patents bring additional challenges. They often only partially capture innovation activities, do not account for the fact that the propensity to patent varies across sector (e.g., it is higher in highly specialized manufacturing) (Griliches 1990; Jaffe et al. 1993) and may exhibit distortions in informational content arising from the strategic motivations behind patent filings (Cohen et al. 2000). Additional drawbacks stem from time lags in data availability, arising from the lengthy collection and processing of survey data, the delayed disclosure of financial statements, and the time required for patent examination and granting procedures (Lanjouw and Schankerman 2004).

2.2 The Emergence of the Text Mining and Web-Scraping Approaches

The shortcomings of traditional data sources have prompted scholars to explore alternative or complementary sources, such as user-generated content, unstructured data and digital traces. Recent literature highlights the importance of these novel sources in gaining a comprehensive view of firms' innovative behaviour (Gök et al. 2015; Ojanpera et al. 2017; Antons et al. 2020; Rammer and Es-Sadki 2023). In particular, the use of large volumes of textual data, analysed through text mining techniques, has become increasingly common for extracting information on innovation-related activities (Antons et al. 2020; Rammer and Es-Sadki 2023; Marra et al. 2024a, b). In this regard, corporate websites and other online platforms have emerged as key repositories of relevant content and are increasingly used as an additional information source for innovation research (Papagiannidis et al. 2018; Stich et al. 2022; Nathan and Rosso 2015, 2022; Arora et al. 2013). Websites act as digital storefronts through which firms communicate and promote products, operational details, and strategic positioning, thus offering valuable insights into innovation dynamics (Domenech et al. 2012; Blazquez and Domenech 2018). For instance, Nathan and Rosso (2015, 2022) leverage platforms like Reuters and Yahoo! to track product launches and digital activity as proxies for innovation, while Ojanpera et al. (2017) combine data from GitHub, Wikipedia, and domain registrations to measure digital transformation. Papagiannidis et al. (2018) apply topic modelling on UK corporate websites to detect clusters of innovative firms, whereas Gök et al. (2015) extract information on R&D activities from web content. Similar approaches have been applied to US SMEs, within the Triple Helix framework (Li et al. 2018) and in studies on firms' dynamic capabilities (Arora et al. 2020).

Among these unconventional approaches, the systematic scraping of corporate websites has gained traction as a powerful tool for innovation analysis. Web-scraped textual data have been used to classify business models, construct innovation taxonomies, and assess the innovative potential of firms, particularly small and young enterprises (Libaers et al. 2016; Daas and van der Doef 2020; Kinne and Lenz 2021). Some studies also demonstrate how such data can uncover commercialization strategies and innovation pathways among SMEs (Arora et al. 2013). For example, Guzman and Li (2023) analyse the websites of over 12,000 US startups to assess strategic differentiation using textual distance measures from peer firms. Keyword-based approaches further support the construction of innovation indicators and taxonomies (Libaers et al. 2016), offering timely, scalable, accurate, and cost-efficient metrics, particularly suited to fast-evolving sectors (Daas and van der Doef 2020; Kinne and Lenz 2021).

More recent contributions extend these methods by developing web scraping tools to identify product innovation and R&D orientation (Katz & Cothey 2006; Ashouri et al. 2022) or by mapping innovation systems through hyperlink networks among corporate websites (Kinne and Axenbeck 2020; Abbasiharofteh et al. 2023). Bishop et al. (2022) and Stich et al. (2022) show how archived website data can support bottom-up classifications of economic activities and help identify firms operating in the green economy, while Marra and Baldassari (2022) and Marra et al.

(2024a, b) apply text mining and semantic algorithms to label innovative companies and examine firms in clean tech sectors.

3 Identifying Net-Zero Technologies from Company Websites

3.1 The Process of Scraping Company Websites

To gather granular, firm-level evidence on the adoption of net-zero technologies, we implement a large-scale web scraping exercise targeting the textual content of a large sample of Italian firms' websites. We collect an initial sample of 1,702,893 active Italian companies (excluding dormant, non-trading, or dissolved firms), for which we obtain the company name, VAT identification number and the link to the company's homepage. Thereafter, we identify those for which a valid and uniquely attributable corporate domain can be matched to the firm record. This step is required to ensure a reliable linkage between firm-level registry data and web-based information. The absence of a valid domain may reflect either incomplete reporting in AIDA or the firm's lack of an official website. Furthermore, to avoid misattribution of online content, we exclude domains shared by multiple firms to ensure a one-to-one matching. The resulting set comprises 477,812 companies—effectively the observable population for our web scraping procedure—without any *ex-ante* filtering. While this process may still introduce a potential selection bias, having a website is a strategic choice and is especially relevant to our focus on external communication and transparency. Firms with websites tend to be more externally oriented, and they span a wide range of sectors and firm types, ensuring sufficient heterogeneity. Including firms without websites would add no meaningful information, as no comparable online data could be collected. Thus, the sample restriction is both theoretically and empirically consistent with the chosen method. Firms included in the sample provide a partial yet meaningful representation of the national industrial landscape.

We apply a large-scale web scraping to these firms. The scraping was conducted using *beautifulsoup4* and *requests* in Python 3.11.9, hosted on a Virtual Machine for greater scalability. We begin by mapping each company's homepage (the "parent") to identify its structure and retrieve all intra-site hyperlinks, the so-called "child pages." We define depth 1 as direct links from the homepage (i.e., one click away), and depth 2 as links reachable through a child page (two or more clicks from the homepage). To minimize connection or timeout errors, we feed every web page URL to the scraping algorithm at least twice. A visual example of this hierarchy is provided in Fig. 1.

We restrict the scraping exercise to the parent page and depth-1 child pages only. We assume that firms deliberately signal their most relevant strategic initiative, such as engagement with net-zero technologies and decarbonization strategies at the upper tiers of their website hierarchy, which are specifically designed to communicate with external stakeholders. The rationale lies in the need to mitigate potential biases related to website size and structure and ensure methodological parsimony and reduce noise. To this end, we do not search for keywords across the entire

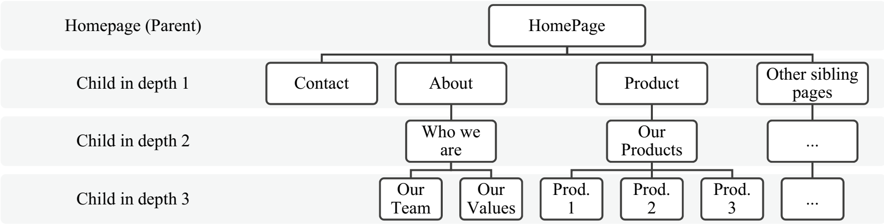


Fig. 1 Hierarchy of company's webpages. Notes: The figure illustrates the hierarchical structure of company webpages used in the analysis. Authors' elaboration

website. By excluding deeper-level pages, which are more likely to reflect heterogeneity in website length, complexity, and auxiliary content, we substantially reduce the risk that raw keyword search captures website size rather than pure technological engagement. Accordingly, our approach focuses on identifying the presence of adoption signals, rather than constructing an index of adoption intensity. This is consistent with the aim of distinguishing adopters from non-adopters, while avoiding confounding effects related to differences in firms' communication strategies or website architecture. This decision is further justified by the fact that most websites have child pages in depth 1. Figure 2 provides the distribution of the number of child pages for corporate websites included in the analysis.

Following this approach, we perform an initial data cleaning before proceeding with the keyword search within the websites. Specifically, we drop all non-functional

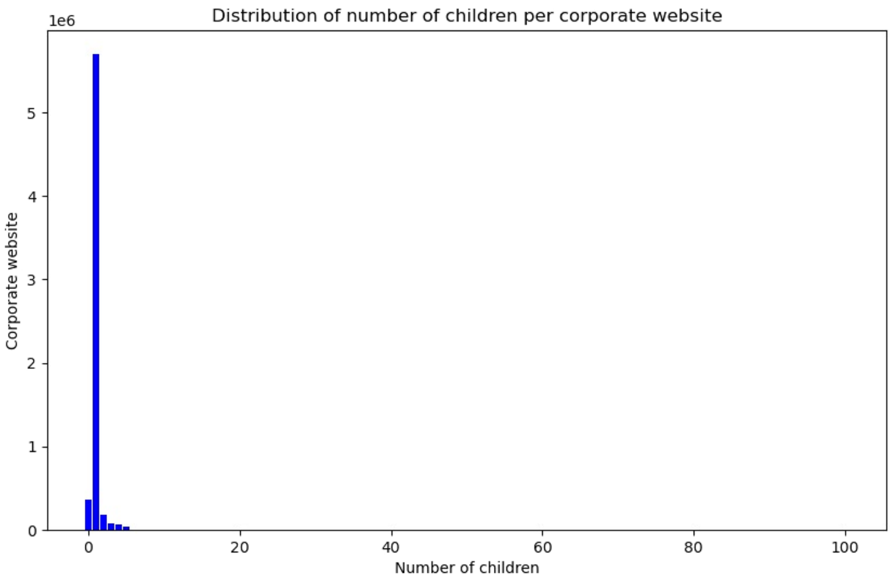


Fig. 2 Distribution of number of child pages per corporates' websites. Notes: The figure displays the distribution of the number of child pages linked to corporate websites. Authors' elaboration

URLs that produce errors such as "404 page not found." Additionally, we remove all URLs with excessive loading times (flagged via a timeout protocol) by introducing a timeout during the web scraping operations. For these URLs, we repeat the scraping to determine if the issue was temporary (related to the connection) or not. Among the functional URLs, we exclude three types of links pointing outside the company's domain or to social media platforms: a) links that, although reachable within one click, redirect users to external websites outside the company's domain, and therefore cannot be considered as part of the company's web content[1]; b) links to the company's social media sites such as Facebook, Instagram, Twitter, and others, as they are not relevant to our analysis; c) links generated by pop-ups within the web pages that appear inappropriate. Finally, we keep only unique links to remove any duplicate webpages that skew our results and increase the processing time. This rigorous filtering process results in a refined sample of 6,541,465 unique links across 366,440 companies—dropping from 477,812 companies, ready for keyword mining.

3.2 Keyword-Based Text Extraction and Processing

From each link, we extract relevant textual content and identify keywords related to net-zero technologies. We construct a tailored dictionary of keywords based on the European Commission's NZIA-related documentation (see Appendix A for details on NZIA institutional framework), encompassing technological terms, morphological variants, and broader semantic variations (see Appendix B with the full list of net-zero technology-related keywords, Table 23). For details regarding the definition of the key terms used, see *Implementing the EU's Net-Zero Industry Act,* provided by the European Parliament (Ragonnaud 2025). Moreover, any word referring to raw materials is excluded from the NZIA-keyword list as it is better covered under the CRMA.

Given the noisy and unstructured nature of web text, we develop a robust pre-processing pipeline. First, the standardization of punctuation and whitespace is crucial. Since website text often lacks consistent punctuation, we devise a strategy to standardize punctuation by replacing key characters (points, comma, dash, parentheses, etc.), the *new line symbol* *n*, and the *new tab symbol* *t* in the raw HTML output of the scraper with a space. Second, we tokenize the text into single words, bigrams and trigrams. We ensure that the entire text in the raw HTML is transformed into a list of individual words to facilitate sequential reading. Specifically, we implement an algorithm to read not only individual words (e.g., "RAN") but also bigrams (e.g., "artificial intelligence") and trigrams (e.g., "radio access network"). For instance, in the case of bigrams, we are not interested in capturing just "artificial" or just "intelligence". Instead, when the scraping algorithm reads "intelligence," it recognizes it as part of a bigram and also reads the preceding word immediately. Third, we check the position of the text and whether the word appears in the body of the website, in

[1] For example, a company may advertise a collaboration with a university and include, on its homepage, a link inviting users to apply. However, clicking on this link leads to a depth-1 page that redirects directly to the university's website rather than to a page hosted within the company's own domain.

a menu, in a link, in a disclaimer, or in irrelevant parts (e.g. footer, cookie banner). Finally, as website text is often "contaminated" with words from other languages, we follow a dual encoding (UTF-8 and UTF-16) to handle multilingual content and avoid data loss from incompatible characters.

After two rounds of scraping, we obtain information for 203,717 companies, regardless of their involvement (yet) in net-zero technologies. The results are compiled in a tabular form and aggregated at the firm level, with two post-processing refinements: morphological harmonization and semantic alignment. The first refinement refers to singular/plural forms and gendered forms. After searching for keywords in both singular/plural and masculine/feminine forms, we aggregate them into a single word and sum their frequencies. The second refinement pertains to acronyms vs. full form. After searching for both the acronyms (e.g., RAN) and the full term (e.g., radio access network), we group them and sum their frequencies. This phase yields, for each firm, the frequency with which each net-zero-related keyword appears throughout the entire company website and the total frequency count, including firms for which no such keywords are detected (i.e., the total frequency count equals zero).

Finally, we perform manual validation to ensure the quality and reliability of the collected data. Specifically, we extract a random sample of 500 companies from the scraped population, stratified across industrial sectors to ensure representativeness. For each company, we manually verify: i) That the website is active and accessible; ii) That the content of the website corresponds to the company in the database (one-to-one matching); iii) That the presence of net-zero-related keywords, as identified by our automated search, is consistent with the company's actual activities. The results of this validation confirm that the automated keyword detection accurately reflects the firms' technological focus, supporting the reliability of the web-based identification of adopters and developers. See Table 1 for an excerpt of the keyword count matrix and Fig. 3 for an overview of the scraping methodology.

Table 1 Example of the output (table of keywords frequencies) from the web-scraping

VAT number	Word1_s	Word1_p	Word2_s	Word2_p	…	WordN_p	Tot. Keyword
AAA	0	0	0	1	…	18	$\sum_{i=1}^{n} Word_i = 19$
BBB	10	1	0	0	…	0	$\sum_{i=1}^{n} Word_i = 11$
…	…	…	…	…	…	…	…
ZZZ	1	12	3	0	…	10	$\sum_{i=1}^{n} Word_i = 26$

The table provides a generalized example of what we obtain from web scraping procedures. In each row, we provide the VAT identification number of companies. In each column, we report the keywords used. The last column, we sum up the total frequency for each company. For each company-keyword, we show the related frequency. Source: authors' elaboration

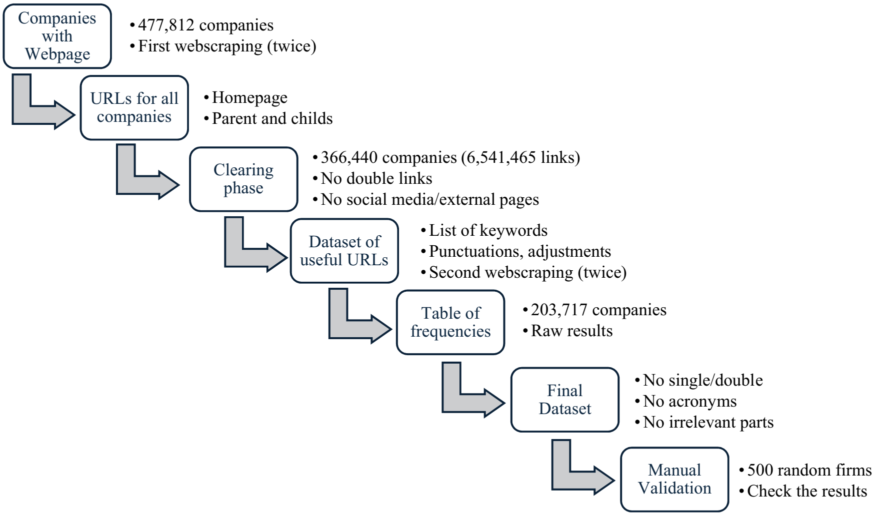


Fig. 3 Summary of the methodological framework. Notes: The figure presents a summary of the methodological framework used in the analysis, outlining the key steps and processes followed to study the adoption of NZIA-related technologies by firms. Authors' elaboration

3.3 The Final Database

The cleaned dataset contains keyword counts for all 203,717 companies. We create a dummy variable (*NZIA*) that equals one if the firm has at least one NZIA-related keyword on the website, zero otherwise. Firms with NZIA equal to one are considered adopters of technologies. Firms with NZIA equal to zero are therefore non-adopters, defined as firms whose websites do not display any reference to net-zero technologies, rather than firms for which information is missing. This approach allows us to distinguish adopters of net-zero technologies from non-adopters within a common and consistently scraped sample of firms. Then, we merge this data with those from AIDA using the VAT identification number as matching variable.[2] After this merge, 172,361 companies are successfully linked and have available financial information.

We follow Kalemli-Ozcan et al. (2024) in implementing data cleaning procedures. First, we exclude firms with negative revenue values and remove observations with leverage and/or equity ratios greater than one or lower than zero. This step ensures accounting consistency and economic interpretability, while also preventing

[2] Moody's AIDA dataset (Moody's Bureau van Dijk, 2024) is a proprietary database that includes comprehensive information on financials, ownership structure, geographic location, and sectoral classification (NACE 4-digit and ATECO 6-digit) for all Italian firms, as well as URLs of companies' websites, the BvD ID of the company and VAT identification number.

the inclusion of financially distressed firms or observations affected by data errors.[3] The final cleaned sample comprises 105,159 firms. We then check the validity of the sample to rule out potential concerns related to non-representativeness, including survivorship bias, incomplete coverage of small and young firms, and the systematic overrepresentation of large and persistent firms. Failure to address these issues may result in distorted firm-level distributions and biased estimates that are not representative of the underlying firm population. The cleaning procedure leaves the key characteristics of the sample largely unchanged, indicating that the final dataset preserves the structural features of the original data, including its sectoral composition. Moreover, because the data cleaning process does not alter the empirical patterns discussed throughout the paper—which remain stable before and after cleaning—we are confident that our findings can be generalized to the broader population of firms. Figure 4 illustrates the distributions of the sample before and after data cleaning.

Finally, we include a set of structured variables capturing firm-level characteristics commonly associated with innovation activity. These variables are grouped into two main categories: (i) Firm-internal characteristics, and (ii) Firm-external conditions, reflecting market structure and local economic context.

Regarding firm-internal characteristics, we consider four variables. First, firm size and firm age are included as standard predictors of innovation capacity (Cohen and Levinthal 1990; Huergo and Jaumandreu 2004). Firm size is measured as the natural logarithm of the number of employees (*LnEmploy*),[4] while firm age is computed as the difference between the year of analysis (2025) and the firm's year of incorporation (*Age*). Second, we control for sectoral affiliation (*Nace-2-digit*) to account for heterogeneity in technological opportunities and regulatory exposure across industries. This is particularly relevant given that some manufacturing sectors—such as chemicals, electrical and technical equipment, machinery, and automotive—are structurally more exposed to the net-zero transition (Dechezleprêtre et al. 2014; Lofgren et al. 2024). Third, we include regional location at the NUTS-2 level (*Region*) to capture geographic heterogeneity. Regional location reflects differences in institutional environments, infrastructure, and cluster dynamics that shape firms' access to knowledge, skills, and policy incentives (Boschma 2005; Crescenzi and Gagliardi 2018).

[3] We exclude firm-year observations with leverage ratios outside the (0,1) interval, equity ratios outside the (0,1) interval, and negative revenues to ensure accounting consistency and economic interpretability (Fama & French 2002; Giannetti 2003). Leverage values above unity imply negative book equity and typically characterize firms in severe financial distress, for which observed capital structures no longer reflect standard financing decisions. Similarly, extreme or negative equity values and negative revenues are commonly associated with accounting irregularities, exceptional events, or non-going-concern situations. This treatment is consistent with the established corporate finance literature, which excludes firms with equity or leverage ratios falling outside the (0,1) range (Hovakimian et al. 2001; Brown et al. 2009; Leary & Roberts 2010; Almeida & Campello 2007; Frank & Goyal 2009), as well as firms reporting non-positive revenues (Brown et al. 2009; Campello et al. 2010; Kalemli-Ozcan et al., 2024), in order to preserve the economic meaning of financial variables.

[4] For firms with one employee, the logarithm equals zero. Since all firms have at least one employee, the logarithmic transformation is well-defined. Employment data are sourced from Orbis and used as reported, without adjustment to full-time equivalent (FTE) units.

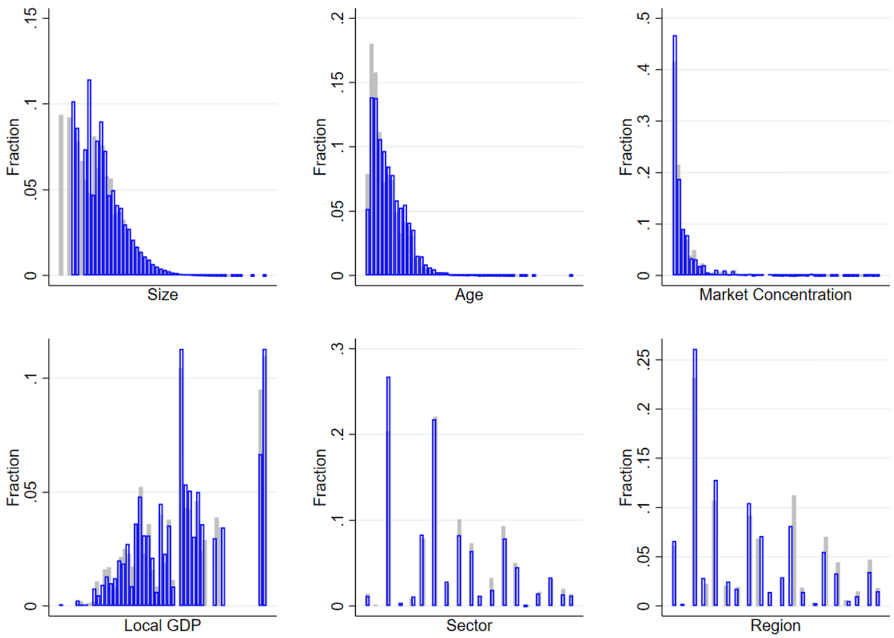


Fig. 4 Distribution of firm characteristics pre and post Kalemli-Ozcan et al. (2024) procedures. Notes: The figure illustrates the distribution of firm characteristics before and after applying the Kalemli-Ozcan et al. (2024) procedures for data cleaning. The shade bars depict the sample distribution before the employing of cleaning procedures. The blue bars show the distribution of the sample after the cleaning procedures. Authors' elaboration

Turning to firm-external conditions, we focus on market concentration and local economic condition, widely recognized as variables influencing firms' incentives to innovate (Aghion et al. 2005; Audretsch and Feldman 1996). As for the former, market concentration is measured using the Herfindahl–Hirschman Index (HHI), computed at the NACE four-digit level, with higher values indicating greater concentration within industrial sectors. Specifically, the *HHI* was computed as the sum of squared market shares, where market shares are derived from firms' revenues (sales) within each sector. As for the latter, the natural logarithm of GDP per capita at the NUTS-3 level (*LnGDP*) is included as a proxy for local economic conditions, capturing differences in wealth, demand, and market potential.

3.4 Identifying Developers of Net-Zero Technologies Using Patent Data

The final step of the analysis consists of identifying developers of net-zero technologies within the broader group of adopters. This exercise is grounded in a key conceptual distinction between technology developers—that is, firms that generate proprietary technological knowledge—and others, which may adopt, produce, manufacture, or commercialize technologies developed by third parties. In this paper, *adoption* is defined in a broad sense and refers to firms that exhibit explicit engagement with net-zero technologies, as indicated by the presence of NZIA-related keywords on their corporate websites. Such engagement may take different forms, including the use, production, sale, or internal development of net-zero technologies. While these activities differ in the degree of commitment they entail, they all imply a minimum level of awareness, exposure, and operational knowledge of net-zero technologies—ranging from deployment and commercialization to in-house production and development. Instead, *development* refers specifically to the generation of proprietary net-zero technologies and thus identifies a narrower subset of firms within the broader population of adopters.

To identify developers, we use two complementary approaches: a) An extension of the web scraping analysis targeted to search innovation-related signals, and b) An integration of the initial web scraping analysis using information from the company patent portfolio.

As for the first approach, we introduce a second dictionary of keywords aimed at capturing innovation-related signals and identifying firms potentially engaged in technological development (see Appendix B, Table 24). The methodological steps are identical to those in Fig. 3, starting from step four, but using a different set of keywords. A company is classified as a developer if its corporate website contains innovation-related terms (*Developer_Ws*). The selection of innovation-related keywords (e.g., "patent", "trademark", "research centres", "research and development", "in-house R&D", "proprietary technologies") is grounded in established practices in the innovation and text-mining literature, which has shown that references to intellectual property and R&D activities provide meaningful signals of firms' innovative engagement (e.g., Kinne and Lenz 2021; Antons et al. 2020; Leippold and Yu 2025). These approaches have been proven to offer dependable proxies for firms' engagement in innovation, especially when traditional indicators are unavailable or incomplete.

Indeed, prior studies show that references to intellectual property and R&D activities in textual sources can be effectively used as proxies to identify innovative firms. In particular, innovation indicators have been successfully extracted from firm-level textual data using keywords related to patents, trademarks, and R&D investments, capturing firms' engagement in innovative activities but not innovation intensity (Tseng et al. 2007). Moreover, web-derived indicators based on references to R&D and intellectual property have been shown to converge with traditional survey-based measures of innovation, supporting their validity as proxies for innovative activity (Héroux-Vaillancourt et al. 2020). Importantly, the inclusion of trademarks alongside patents improves the identification of innovative firms, especially in contexts where innovation is not exclusively protected through patents, reinforcing the use of intellectual property references as proxies for technological development (Morales et al. 2024).

A company is defined as a potential technology developer based on website information (D_*Ws_NZIA*) if its website contains both NZIA-related keywords and innovation-related terms. This approach leverages websites as repositories of strategic information and allows us to distinguish, within adopters, firms that are potentially involved in net-zero technological development using a single methodology.

However, information extracted from corporate websites does not allow us to determine whether the relevant technological capabilities have been developed internally or acquired from external sources. As a result, web-scraped data alone cannot clearly distinguish firms that act as technology developers from those that primarily produce, deploy, or use technologies developed elsewhere. Moreover, this approach does not indicate whether firms are specifically developing net-zero technologies, as opposed to developing other technologies that are subsequently applied or used within NZIA-relevant activities. Consequently, this strategy may over include firms whose innovative efforts fall outside the NZIA framework or whose role is limited to production or application rather than technological development.

To overcome these limitations, we complement the web-based identification strategy with patent data from the Patent Orbis (Moody's) database. Patents are widely recognized as indicators of innovation activity and are frequently used to proxy firms' technological efforts in empirical studies (Archibugi 1992; Peeters and Pottelsberghe de la Potterie 2007). Indeed, patents explicitly identify inventing firms or research organizations and thus provide a more direct proxy for internal technological development. We classify a firm as a technology *developer* if it holds at least one patent (*Developer_Orbis*). This criterion is not intended to identify net-zero developers per se, but rather to distinguish firms that generate patentable technological knowledge from those that solely produce technologies developed elsewhere. Unlike the above, the presence of patents allows us to identify companies that have developed in-house skills. Companies are then defined as *potential developers of net-zero technologies* (*D_Orbis_NZIA*) if they have at least one patent and they have keywords related to net-zero technologies on their site, but regardless of their technological domain. This approach separates technology developers from producers, but it may still include developers of technologies outside the scope of the NZIA framework.

To further refine the *D_Orbis_NZIA* indicator and isolate developers of net-zero technologies, we follow Costantini et al. (2017) and Barbieri et al. (2023) by mapping patents according to the NZIA framework using IPC codes at the highest level of granularity (14-digit). This refinement ensures that patents unrelated to net-zero technologies are excluded from the final classification. However, unlike Costantini et al. (2017) and Barbieri et al. (2023), our strategy relies on a more complex matching procedure that links highly technical IPC textual descriptions to net-zero-related technologies. For this purpose, we exploit recent advances in transformer-based textual analysis and Large Language Models (LLMs), which the literature highlights as particularly well suited for technological classifications (Colladon et al. 2025).[5] After cleaning and standardizing IPC classification data from the World

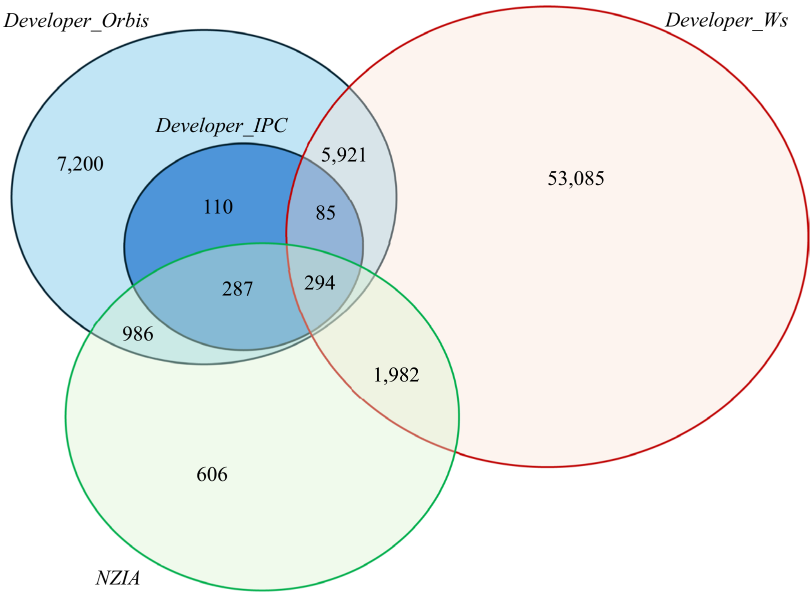
[5] In the relevant literature, green technologies have typically been identified through patent classifications based on IPC codes. Specifically, Costantini et al. (2017) employ the OECD ENV-Tech indicator, which associates selected IPC codes with seven environmental technology domains—such as renewable energy, environmental management, energy efficiency, and emissions mitigation—and complement this taxonomy with the Y02 section of the Cooperative Patent Classification (CPC) for technologies related to climate change mitigation. Similarly, Barbieri et al. (2023) rely on CPC Y02 codes to identify patents pertaining to green technologies and construct regional-level metrics of "Green Technological Fitness" and "Green Potential," based on the presence of patents within these domains.

Intellectual Property Organization (WIPO), we employ an LLM to identify the IPC codes most closely associated with net-zero technologies, based on semantic similarity between technology descriptions and IPC textual definitions. The model is prompted using structured instructions, following prompt-engineering practices established in the literature (Brown et al. 2020). The LLM is deployed locally via *Ollama*, an open-source inference framework that enables transparent and reproducible experimentation.

We report the prompt structure and technical details in Appendix C to ensure transparency and replicability. To assess the reliability and consistency of the LLM-based mapping, we replicate the same identification using alternative LLMs (ChatGPT, Google Gemini, and Microsoft Copilot). For instance, after uploading the full IPC classification and a guide explaining its structure, we employed ChatGPT in an iterative querying process to associate each NZIA-related technology with its corresponding IPC. We adopted a strategy based on repeated interactions and progressive refinement of prompts—a technique commonly referred to as "prompt engineering" or "prompt layering" in recent literature (Liu et al. 2023; Wei et al. 2023)—to ensure consistent and accurate outputs. Additional validation steps—including manual review of a random subset of IPC codes and keyword-based text-mining procedures—further confirm the reliability of the classification. This process results in the identification of 2434 IPC codes linked to net-zero technologies. Using these codes, we select a sub-sample of developer firms from the Patent Orbis (Moody's) database that hold patents aligned with NZIA-related technologies (*Developer_IPC*).

A firm is ultimately classified as a net-zero technologies developer (*D_IPC_NZIA*) only if it meets three simultaneous conditions: (i) It is an adopter of NZIA-related technologies based on web-scraped content (*NZIA* equal to 1), (ii) It holds at least one patent, signalling internal technological development (*Developer_Orbis* equal to 1), and (iii) At least one of its patents is classified as NZIA-related according to the IPC-based mapping (*Developer_IPC* equal to 1). This identification strategy isolates developers engaged in net-zero technologies (from developers of other technologies, producers, users, etc.) within the broad class of adopters of such technologies.

Figure 5 summarizes the outcomes of following the two identification strategies. It displays the number of technology-developing firms identified through each method, as well as their overlap and intersection with firms engaged in net-zero technologies. The comparison of the three identification strategies reveals substantial differences in both the number of firms classified as developers and the share of those engaged in net-zero technologies. The web scraping approach identifies a large pool of "developers" (61,367), but only a small fraction (3.7%) of them shows explicit signals of NZIA-related technologies on their websites. This confirms that keyword-based classification, while useful for mapping broad innovation activity, lacks precision in isolating net-zero technology developers, as it tends to over include producers or developers of other technologies–also far from those net-zero. By contrast, the patent-based approach using Orbis data significantly narrows the pool to 14,883 firms, yet the share of those with NZIA-related keywords on their websites increases to 8.6%. This indicates that patent holders are more likely to be engaged in net-zero technologies, and that the presence of patents serves as a



Developers:		Of which with *NZIA* keywords on site	
	Obs.	*Obs.*	*%*
Developer according to Web Scraping	61,367	2,276	3.709%
Developer according to Orbis	14,883	1,280	8.600%
Developer according to Orbis and IPC codes	776	581	74.871%
NZIA	4,155		

Notes: The figure compares NZIA developer firms identified through web scraping techniques with those identified via patent data, highlighting overlaps and differences between these two methods of firm identification. Authors' elaboration.

Fig. 5 The identification of developers: comparison between web scraping and patent strategies Notes: The figure compares NZIA developer firms identified through web scraping techniques with those identified via patent data, highlighting overlaps and differences between these two methods of firm identification. Authors' elaboration

stronger signal of technological development. The most refined strategy—based on IPC code mapping aligned with the NZIA framework—further restricts the sample to 776 firms and yields the highest precision: 74.9% of these firms also display NZIA-related keywords on their websites. This high overlap confirms the robustness of the IPC-based classification and suggests that combining the classification of patent data with web-based signals provides a reliable method for identifying developers of net-zero technologies.

Accordingly, we rely on the patent-based approach to map net-zero technologies developers in the following sections of the paper and proceed by using *D_IPC_NZIA*. Descriptive statistics and detailed overview of variables construction are provided in Table 2.

Table 2 Descriptive statistics

Variable	Description	Obs	Mean	Std.Dev
Dep. Variables				
NZIA	Dummy = 1 for firm adopting net-zero technologies	105,159	0.027	0.162
D_Ws_NZIA	Dummy = 1 for developers firm according to web-scraping	105,159	0.015	0.122
D_Orbis_NZIA	Dummy = 1 for developers firm according to Patent Orbis	105,159	0.010	0.101
D_IPC_NZIA	Dummy = 1 for developers firm according to Patent Orbis and IPC	105,159	0.005	0.070
Controls				
LnEmploy	Natural logarithm of total employees	105,159	2.181	1.382
Age	Age of the firm	105,159	22.757	15.872
HHI	Herfindahl–Hirschman Index at Nace 2-digit level	105,159	0.057	0.094
LnGDP	Natural logarithm of GDP at the NUTS-3 level	105,159	10.398	1.084
Drivers				
LevRatio	Ratio of total debt to total assets	104,805	0.547	0.234
ShortDebt	Ratio of short-term debt ratio to total assets	104,805	0.426	0.218
LongDebt	Ratio of long-term debt ratio to total assets	104,805	0.121	0.153
Equity	Share of total equity over total assets	104,953	0.356	0.228
ROA	Return on Assets	105,159	8.209	14.339
ROE	Return on Equity	102,230	15.345	28.317
LnEBITDA	Log difference of revenues between year *t* and *t-1*	97,074	5.111	1.877
SalesGrowth	Natural logarithm of EBITDA	102,662	0.082	0.446
Liq_Index	Liquidity index	103,193	1.752	1.421
District	Dummy = 1 if the firm operates in an industrial district	105,159	0.296	0.456
FamilyD	Dummy = 1 if the Global Ultimate Owner (GUO) is a family	105,159	0.471	0.499
FamilyG	Dummy = 1 if the Direct Ultimate Owner (DUO) is a family	105,159	0.482	0.500
Duration	Average tenure of board members	105,159	6.636	6.851
%STEM	Average age of board members	105,159	0.003	0.042
DurationSTEM	Share of managers with a STEM degree	105,159	0.001	0.027
Age_manager	Average tenure of STEM-educated managers	62,960	56.175	10.025

The table reports descriptive statistics for the main variables used in the analysis. For each variable, we provide the number of observations, mean and standard deviation. Variables are grouped by type: dependent variables (Dep. Variable), controls, and drivers. The table provides a detailed description of the variables used in the analysis. Source: authors' elaboration

4 Mapping Net-Zero Technologies

In this section, we provide a detailed mapping of net-zero technologies. Section 4.1 focuses on firms that adopt net-zero technologies, while Sect. 4.2 focuses on the developers of such technologies. The mapping is conducted using three different lenses: geographical, sectoral, and firm level.

4.1 Mapping the Adoption of Net-Zero Technologies

4.1.1 Geographical Distribution of Net-Zero Technologies

Table 3 presents the regional distribution of firms adopting net-zero technologies across Italy. Panel A reports the percentage of NZIA- and non-NZIA-labelled firms over the total sample; Panel B displays the distribution (i.e., regional weights) only of firms adopting net-zero technologies, expressed as each region's share of total NZIA firms; and Panel C reports the within-region composition, comparing the share of NZIA adopters and non-NZIA adopters within each region.[6] Overall, the presence of such technologies remains limited: only 2.7% of firms in the sample have adopted them, despite their strategic relevance at the European level. The data reveal a clear geographical concentration with Lombardia, Veneto, and Emilia-Romagna accounting for approximately 57% of all NZIA-labelled firms. This clustering suggests that net-zero technologies are predominantly embedded within industrial ecosystems located in the North-East of Italy. This pattern closely mirrors the long-standing spatial distribution of industrial activity in Italy, where Lombardia—and, more broadly, the Northern regions—host the highest density of manufacturing firms and advanced production capabilities (Istat 2022). The prevalence of net-zero firms in Lombardia, together with significant shares in Veneto and Emilia-Romagna, appears to reflect the existing industrial structure.

Beyond absolute numbers, the relative adoption within regions confirms this asymmetry. Regions such as Trentino-Alto Adige, Lombardia, Liguria, Piemonte, Veneto, and Umbria show above-average shares of firms engaged in net-zero technologies relative to their local business population. In contrast, several southern regions report adoption rates below 1.5%, indicating not only spatial concentration but also a disparity in technological penetration across territories.

Figure 6 offers a more granular view of this pattern, mapping the distribution of adopters of net-zero technologies at both the NUTS-3 (Panel A) and municipal levels (Panel B). The visual evidence reinforces the findings from Table 3, with a clear concentration of net-zero firms in northern areas, particularly in the North-East.

Further analysis considers the relationship between the adoption of net-zero technologies and local economic conditions, proxied by the NUTS-3 level GDP. Table 4 groups provinces into GDP terciles—poor, medium, and rich—and shows that firms in wealthier areas are more likely to adopt net-zero technologies. High-income provinces host over 42% of all NZIA-labelled firms, and the adoption rate increases progressively with local wealth, from 2.2% in poor provinces to 3.2% in rich ones.

These findings suggest that a more favourable economic environment may support firms in adopting net-zero technologies. In contrast, firms located in poor regions, often characterized by weaker infrastructure, limited access to finance, and

[6] Analytically, in Panel A, the sum of the percentages reported in the two columns equals 100 percent, as they jointly account for the entire sample. In Panel B, the percentages sum to 100 percent across regions, reflecting the distribution of NZIA-labelled firms over the national total. In Panel C, percentages sum to 100 percent within each row, as they represent the composition of firms within each region.

Table 3 Distribution of firms adopting net-zero technologies within regions

	Panel A	Panel B		Panel C	
Region	%NZIA adopters over tot. sample	%No-NZIA adopters over tot. sample	% NZIA over tot. NZIA adopters	%NZIA adopters within region	%No-NZIA adopters within region
Abruzzo	0.036%	1.395%	1.339%	2.525%	97.475%
Basilicata	0.008%	0.498%	0.282%	1.504%	98.496%
Calabria	0.014%	0.999%	0.529%	1.407%	98.593%
Campania	0.106%	5.401%	3.911%	1.917%	98.083%
Emilia-Romagna	0.272%	10.200%	10.078%	2.597%	97.403%
Friuli-Venezia Giulia	0.070%	2.424%	2.607%	2.821%	97.179%
Lazio	0.177%	7.962%	6.554%	2.173%	97.827%
Liguria	0.060%	1.699%	2.220%	3.405%	96.595%
Lombardia	0.887%	25.245%	32.875%	3.395%	96.605%
Marche	0.067%	2.859%	2.467%	2.276%	97.724%
Molise	0.004%	0.287%	0.141%	1.307%	98.693%
Piemonte	0.204%	6.415%	7.541%	3.075%	96.925%
Puglia	0.049%	3.276%	1.797%	1.459%	98.541%
Sardegna	0.013%	1.499%	0.493%	0.881%	99.120%
Sicilia	0.050%	3.414%	1.868%	1.455%	98.545%
Toscana	0.163%	6.955%	6.025%	2.285%	97.715%
Trentino-Alto Adige/Südtirol	0.100%	2.749%	3.700%	3.505%	96.495%
Umbria	0.041%	1.383%	1.515%	2.872%	97.128%
Valle d'Aosta/Vallée d'Aoste	0.005%	0.219%	0.176%	2.128%	97.872%
Veneto	0.375%	12.422%	13.883%	2.928%	97.072%
Total	2.699%	97.301%	100.000%		

The table shows the geographical distribution of firms adopting net-zero technologies across Italian regions. Panel A reports the percentage of NZIA and non-NZIA adopters over the total sample. Panel B shows the share of NZIA adopters over the total number of NZIA-labelled firms. Panel C compares the weights of NZIA and non-NZIA adopters within each region. Values are expressed in percentages. Source: authors' elaboration

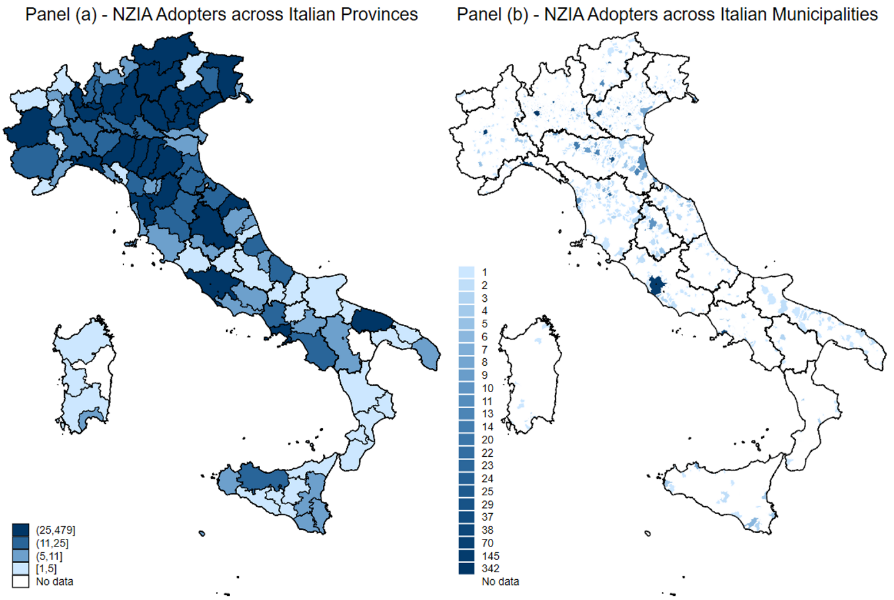


Fig. 6 Distribution of firms adopting net-zero technologies according to provinces and municipalities. Notes: The figure shows the geographic distribution of NZIA adopters across provinces (Panel A) and municipalities (Panel B), highlighting regional concentrations and spatial patterns in the adoption of NZIA-related technologies. Authors' elaboration

Table 4 Distribution of firms adopting net-zero technologies according to GDP at Nuts-3 level

	Panel A	Panel B		Panel C	
GDP Level (nuts-3)	%NZIA adopters over tot. sample	%No-NZIA adopters over tot. sample	% NZIA over tot. NZIA adopters	%NZIA adopters within region	%No-NZIA adopters within region
Poor	0.692%	31.469%	25.652%	2.153%	97.847%
Medium	0.863%	30.908%	31.959%	2.715%	97.285%
Rich	1.144%	34.923%	42.389%	3.172%	96.828%
Total	2.699%	97.301%	100.000%		

The table reports the distribution of firms adopting net-zero technologies based on GDP levels at the NUTS-3 regional classification. NUTS-3 regions are classified as *Poor*, *Medium*, or *Rich* based on the tercile distribution of regional GDP, with regions in the first tercile labelled as Poor, those in the second tercile as Medium, and those in the third tercile as Rich. Panel A shows the share of NZIA and non-NZIA adopters over the total sample, disaggregated by GDP category (Poor, Medium, Rich). Panel B displays the proportion of NZIA adopters within each GDP group relative to the total number of NZIA-labelled firms. Panel C compares the share of NZIA and non-NZIA adopters within each GDP category. Values are expressed in percentages. Source: authors' elaboration

less supportive institutional frameworks, may face additional constraints to innovation, ultimately hindering the adoption of such technologies.

4.1.2 Sectoral Distribution of Net-Zero Technologies

The sectoral dimension offers important insights into the adoption of net-zero technologies, showing whether the observed patterns align with expectations based on the sector technological characteristics. As shown in Table 5, firms adopting these technologies are predominantly concentrated in manufacturing (sector C) and wholesale and retail trade (sector G), reflecting the overall structure of the sample.[7] Together, these two sectors account for over 60% of NZIA-labelled firms, confirming their central role in the technological transition.[8]

However, the presence of net-zero technologies is not limited to traditional industrial sectors. Professional, scientific, and technical activities (sector M) also represent substantial shares of adopters (15.3%), suggesting that knowledge-intensive services play a complementary role in supporting strategic innovation. When considering the intensity of adoption within each sector, the data reveal that public administration (sector O), energy supply (sector D), and professional services (sector M) exhibit the highest relative engagement. These sectors are typically characterized by higher technological intensity and complexity, regulatory exposure, and institutional involvement—factors that may facilitate the integration of net-zero technologies. Notably, the financial and insurance activities sector (K) also emerges among NZIA adopters. This pattern may reflect investments in energy-efficient buildings, renewable energy procurement, electric vehicle infrastructure, or participation in green projects and sustainable finance initiatives. Although these activities do not constitute the core business of financial institutions, they nonetheless entail the deployment of net-zero technologies within their operational infrastructures or investment portfolios (see Figure D.1 in Appendix D for a graphical representation).

Market structure also shapes the adoption patterns. We proxy market concentration using *HHI* and classify industry sectors as follows: competitive sectors for competitive industries ($HHI \leq 0.15$), moderately concentrated sectors for industries with intermediate levels of competition ($0.15 < HHI \leq 0.25$), and highly concentrated sectors for oligopolistic or monopolistic industries ($HHI > 0.25$). Table 6 shows that while the majority of firms operate in competitive sectors (low concentration), the adoption rate of net-zero technologies is higher in moderately and highly concentrated markets. Specifically, firms in oligopolistic or monopolistic sectors show the highest intensity of adoption, suggesting that greater market power may enable firms to allocate resources toward long-term strategic investments (i.e., 3.9% in

[7] While a semantic versus substantive issue could, in theory, affect our results—similar to concerns raised in the greenwashing literature—we consider it unlikely to be relevant for several reasons. First, adoption generally involves visible investments and integration into operational processes or infrastructures (e.g., smart grids, energy storage, electric charging, renewable fuels), which are highly specific and easily verifiable. Second, our dataset relies on structured textual information and precise NZIA-related keywords, rather than generic claims of "green compliance" (such as broad references to sustainability, now common across many websites), reducing the risk of overstatement. Third, empirical evidence shows strong alignment between the sectors most involved (energy, public administration) and the types of technologies they can realistically adopt. While firms closely aligned with net-zero technologies might use varied language to signal them, these are niche technologies; if a firm adopts them, they are likely to be explicitly reported on its website, and if not, they are not claimed.

[8] For reasons of space and clarity, we use NACE Divisions.

Table 5 Distribution of firms adopting net-zero technologies according to NACE divisions

		Panel A	Panel B		Panel C	
Nace Division	Description	%NZIA adopters over tot. sample	%No-NZIA adopters over tot. sample	% NZIA over tot. NZIA adopters	%NZIA adopters within region	%No-NZIA adopters within region
A	Agriculture, Forestry, and Fishing	0.027%	1.158%	0.987%	2.247%	97.753%
C	Manufacturing	1.236%	25.521%	45.807%	4.620%	95.380%
D	Electricity, Gas, Steam, and Air Conditioning Supply	0.029%	0.341%	1.057%	7.712%	92.288%
E	Water Supply; Sewerage, Waste Management, and Remediation Activities	0.047%	1.069%	1.727%	4.177%	95.823%
F	Construction	0.167%	8.163%	6.202%	2.009%	97.991%
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	0.415%	21.352%	15.363%	1.905%	98.095%
H	Transportation and Storage	0.029%	2.825%	1.057%	1.000%	99.000%
I	Accommodation and Food Service Activities	0.069%	8.209%	2.572%	0.839%	99.161%
J	Information and Communication	0.107%	6.321%	3.946%	1.657%	98.343%
K	Financial and Insurance Activities	0.033%	1.156%	1.233%	2.798%	97.202%
L	Real Estate Activities	0.030%	1.853%	1.128%	1.615%	98.385%
M	Professional, Scientific, and Technical Activities	0.412%	7.489%	15.257%	5.212%	94.788%
N	Administrative and Support Service Activities	0.057%	4.485%	2.114%	1.256%	98.744%
O	Public Administration and Defence; Compulsory Social Security	0.001%	0.007%	0.035%	12.500%	87.500%
P	Education	0.011%	1.463%	0.423%	0.774%	99.226%
Q	Human Health and Social Work Activities	0.013%	3.329%	0.493%	0.398%	99.602%
R	Arts, Entertainment, and Recreation	0.005%	1.355%	0.176%	0.350%	99.650%
S	Other Service Activities	0.011%	1.204%	0.423%	0.939%	99.061%
Total		2.699%	97.301%	100.000%		

The table reports the distribution of firms adopting net-zero technologies across two-digit NACE divisions. Panel A shows the share of NZIA and non-NZIA adopters over the total sample. Panel B displays the percentage of NZIA adopters within each sector relative to the total number of NZIA-labelled firms. Panel C reports the proportion of NZIA and non-NZIA adopters within each NACE division. Values are expressed in percentages. Source: authors' elaboration

Table 6 Distribution of firms adopting net-zero technologies according to HHI

	Panel A	Panel B		Panel C	
HHI	%NZIA adopters over tot. sample	%No-NZIA adopters over tot. sample	% NZIA over tot. NZIA adopters	%NZIA adopters within region	%No-NZIA adopters within region
Low HHI (competitive market)	1.805%	76.741%	66.878%	2.298%	97.702%
Medium HHI (Moderate concentration)	0.572%	14.211%	21.177%	3.866%	96.134%
High HHI (high concentration)	0.322%	6.349%	11.945%	4.832%	95.168%
Total	2.699%	97.301%	100.000%		

The table shows the distribution of firms adopting net-zero technologies based on market concentration levels, as measured by the Herfindahl–Hirschman Index (*HHI*). Panel A reports the percentage of NZIA and non-NZIA adopters over the total sample. Panel B indicates the share of NZIA adopters by HHI category relative to all NZIA-labelled firms. Panel C shows the weights of NZIA and non-NZIA adopters within each HHI group. Values are expressed in percentages. Source: authors' elaboration moderately concentrated markets and 4.8% in highly concentrated ones, compared to 2.3% in competitive markets). In contrast, firms in highly competitive environments may face tighter margins and shorter strategic horizons, which limit their capacity to engage in innovation-intensive transitions.

4.1.3 Firm Characteristics and Adoption of Net-Zero Technologies

Firm-level characteristics such as size and age offer additional insights on net-zero technology adoption. Starting from size, we identify four groups based on the number of employees: micro (no more than 10 employees), small (between 11 and 50 employees), medium (between 51 and 250 employees), and large (more than 250 employees) firms. As shown in Table 7, smaller firms—particularly micro and small enterprises—represent the majority of the sample. These firms also represent a substantial share of adopters, accounting for nearly 68% of all NZIA-labelled firms. However, when looking at the adoption rates within each size category, a clear relationship emerges: the adoption of net-zero technologies increases with firm size. While only a small fraction of micro and small firms engages in these technologies (1.6% and 2.9%, respectively), the adoption rate rises significantly among medium and large firms, reaching 13.7% in the latter group. This pattern suggests that larger firms, likely due to larger financial and organizational resources, are better positioned to undertake the strategic investments required for net-zero transitions.

Finally, firm age reveals a different pattern. Table 8 shows that the majority of adopters are among older firms, particularly those operating for more than 20 years. These incumbent firms account for over half of all NZIA-labelled adopters, while younger firms—especially those less than 10 years old—are underrepresented (only 17% and 2% of young and new firms are adopters). Yet, when considering adoption rates within each age group, a more nuanced picture emerges. Both very young and very old firms exhibit relatively higher adoption rates, suggesting a non-linear, U-shaped relationship between firm age and the net-zero technologies adoption

Table 7 Distribution of firms adopting net-zero technologies according to firms' size

	Panel A	Panel B		Panel C	
Size (N. Employees)	%NZIA adopters over tot. sample	%No-NZIA adopters over tot. sample	% NZIA over tot. NZIA adopters	%NZIA adopters within region	%No-NZIA adopters within region
Micro	0.932%	56.804%	34.531%	1.614%	98.386%
Small	0.905%	30.752%	33.545%	2.860%	97.140%
Medium	0.612%	8.177%	22.692%	6.967%	93.033%
Big	0.249%	1.567%	9.232%	13.717%	86.283%
Total	2.699%	97.301%	100.000%		

The table displays the distribution of NZIA and non-NZIA adopters by firm size, measured by the number of employees. Panel A reports the share of NZIA and non-NZIA adopters over the total sample. Panel B indicates the share of NZIA adopters by size category relative to all NZIA-labelled firms. Panel C shows the weights of NZIA and non-NZIA adopters within each size group. Values are expressed in percentages. Source: authors' elaboration

Table 8 Distribution of firms adopting net-zero technologies according to firm's age

Age	Panel A %NZIA adopters over tot. sample	Panel B %No-NZIA adopters over tot. sample	 % NZIA over tot. NZIA adopters	Panel C %NZIA adopters within region	 %No-NZIA adopters within region
New	0.047%	2.538%	1.727%	2.803%	97.197%
Young	0.455%	23.434%	16.843%	1.903%	98.097%
Mature	0.686%	25.960%	25.405%	2.573%	97.427%
Incumbent	1.512%	45.369%	56.025%	3.225%	96.775%
Total	2.699%	97.301%	100.000%		

The table reports the distribution of NZIA and non-NZIA adopters by firm age category. Panel A shows the share of NZIA and non-NZIA adopters over the total sample. Panel B indicates the proportion of NZIA adopters within each age category relative to all NZIA-labelled firms. Panel C compares the weights of NZIA and non-NZIA adopters within each age group. Values are expressed in percentages. Source: authors' elaboration

rates. On the one hand, new firms may be more agile, growth-oriented, and embedded in dynamic sectors (i.e., they are in embryonic or high-growth phases of the industry life cycle), which facilitates early adoption. On the other hand, incumbent firms benefit from accumulated knowledge, established market positions (i.e., they are in mature or declining stage of the business life cycle), and reduced competitive pressure. They can support long-term strategic investments. This duality highlights how both entrepreneurial dynamism and organizational maturity can serve as enablers of technological transition, albeit through different mechanisms.

To sum up, findings depict the adoption of net-zero technologies as phenomenon depending on both spatial and sectoral factors. High levels of GDP and technologically intensive industries, like those in the North-East of Italy, play a crucial role in enabling firms to innovate. As regards the sector, firms adopting net-zero technologies are predominant in technologically intensive industries, where the presence of existing knowledge and capabilities may facilitate the adoption of strategic ones. Moreover, the level of market competitiveness and firms' market power appear to play a role in this context. Finally, although many NZIA-labelled firms are small, their share increases with firm size. Age shows a U-shaped relationship with adoption rate.

4.2 Mapping Developers of Net-Zero Technologies

4.2.1 Geographical Distribution of Net-Zero Technologies Developers

To map the developers of net-zero technologies, we restrict the sample to firms that (i) Adopt NZIA-related technologies (i.e., *NZIA* equal to 1), and (ii) Hold at least one patent (i.e., *Developer_Orbis* equal to 1). Figure 7 provides a graphical representation of the sample selection criteria.[9] This approach ensures that the analysis

[9] We only keep the part of the sample that falls into the two darkest areas of blue.

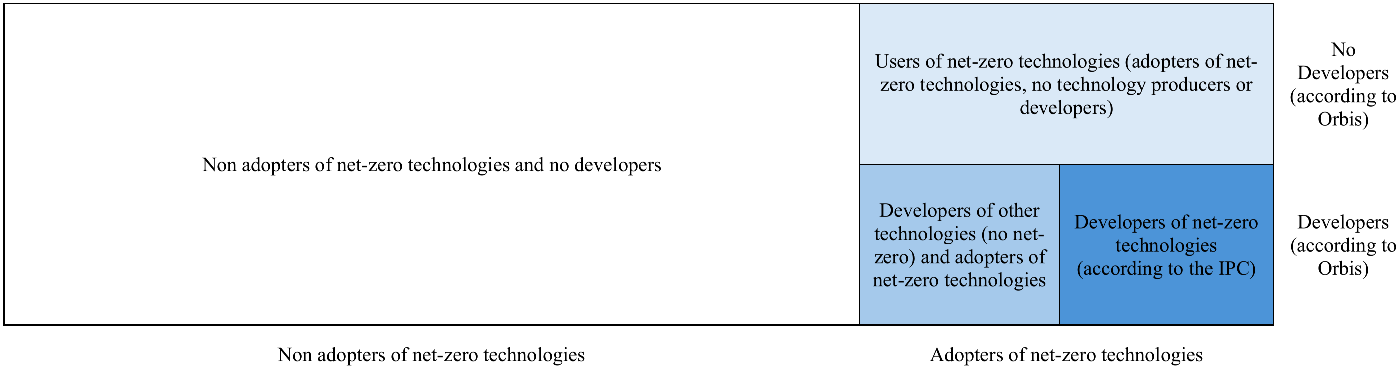


Fig. 7 Subsample of technology developers and net-zero technologies developers. Notes: The figure compares different groups of firms according to *NZIA* and *Developer_Orbis* variables. In the white areas there are firms that are not adopters of net-zero technologies. In contrast, the areas in varying shades of blue represent firms that are adopters. Light blue indicates firms that use net-zero technologies but do not hold any patents. Medium blue corresponds to firms that adopt net-zero technologies and hold patents, although in unrelated technological domains (developers of other technologies). Dark blue identifies developers of net-zero technologies. In both the mapping and the probit analysis, the sample is restricted to the two darkest blue categories. Authors' elaboration

focuses exclusively on firms that, within the group of adopters, are developers of both net-zero and other technologies, thus possessing innovative capabilities and a minimum level of technological engagement (as evidenced by their adoption of net-zero technologies).

Table 9 compares the geographical distribution of net-zero technologies developers with firms developing other technologies. Although net-zero developers represent nearly half of the sample considered (48.5%), their presence is uneven across the national territory. Northern regions—particularly Lombardia, Emilia-Romagna, and Veneto—emerge as the core hubs of development, collectively accounting for over 60% of all NZIA-labelled developers (Panel B). This concentration mirrors the industrial structure and technological endowments of these regions, where accumulated capabilities, dense innovation networks, and supporting infrastructures are more likely to sustain the development of strategic technologies.

Looking at the regional composition of developers, in regions with an extremely limited pool of technologically active firms, relative shares tend to be more polarized, reflecting the presence of only a handful of developers. In this context, Basilicata and Valle d'Aosta, while accounting for a negligible share of developers at the national level, display a high relative incidence of net-zero developers within their regional samples. By contrast, regions with a broader and more diversified industrial base—such as Lombardia and Veneto—exhibit more balanced internal distributions, with NZIA-labelled developers representing around 48% and 41% of regional developers, respectively.

Southern regions generally lag behind both in absolute and relative terms. In Calabria and Molise, firms do engage in technological development activities, but these efforts are not directed toward net-zero technologies, despite the presence of firms adopting such technologies locally. Similarly, the share of net-zero developers remains below 25% in Sicilia and Puglia. Taken together, these patterns point to a persistent gap between adoption and development in Southern regions, highlighting structural constraints that limit the transition from technology use to in-house technological development.

Figure 8 enriches the mapping of developers of net-zero technologies, focusing on provincial and municipal levels. The spatial patterns reinforce the strategic role of northern provinces, particularly in the North-East, mirroring the geography of adopters but with a more restricted numerical base.

A further layer of spatial analysis considers the relationship between development and local economic conditions. Table 10 shows that developers are more prevalent in wealthier provinces, which host over 41% of all NZIA-labelled developers (Panel B). The development rate increases with GDP levels, reaching 54.4% in high-income provinces compared to 48.4% and 41.6% in poor and medium-GDP areas, respectively (Panel C). These findings reinforce the idea that provinces with stronger financial and institutional foundations appear better equipped to support the emergence of net-zero development capabilities, offering fertile ground for net-zero technological development.

Table 9 Distribution of firms developing net-zero technologies within regions

Region	Panel A	Panel B		Panel C	
	%NZIA developers over tot. developers	%No-NZIA developers over tot. developers	% NZIA over tot. NZIA developers	%NZIA developers within region	%No-NZIA developers within region
Abruzzo	0.557%	0.464%	1.149%	54.545%	45.455%
Basilicata	0.186%	0.000%	0.383%	100.000%	0.000%
Calabria	0.000%	0.279%	0.000%	0.000%	100.000%
Campania	1.393%	0.557%	2.874%	71.429%	28.571%
Emilia-Romagna	6.778%	5.478%	13.985%	55.303%	44.697%
Friuli-Venezia Giulia	1.486%	1.486%	3.065%	50.000%	50.000%
Lazio	2.786%	1.671%	5.747%	62.500%	37.500%
Liguria	1.207%	1.393%	2.490%	46.429%	53.571%
Lombardia	16.806%	17.920%	34.674%	48.396%	51.604%
Marche	1.021%	1.486%	2.107%	40.741%	59.259%
Molise	0.000%	0.000%	0.000%	0.000%	100.000%
Piemonte	4.921%	4.921%	10.153%	50.000%	50.000%
Puglia	0.279%	0.929%	0.575%	23.077%	76.923%
Sardegna	0.093%	0.279%	0.192%	25.000%	75.000%
Sicilia	0.186%	0.650%	0.383%	22.222%	77.778%
Toscana	2.786%	2.786%	5.747%	50.000%	50.000%
Trentino-Alto Adige/Südtirol	1.300%	1.950%	2.682%	40.000%	60.000%
Umbria	0.650%	0.650%	1.341%	50.000%	50.000%
Valle d'Aosta/Vallée d'Aoste	0.093%	0.000%	0.192%	100.000%	0.000%
Veneto	5.942%	8.635%	12.261%	40.764%	59.236%
Total	48.468%	51.532%	100.000%		

The table shows the geographical distribution of firms developing net-zero technologies, among developers, across Italian regions. Panel A reports the percentage of NZIA and non-NZIA developers over the total sample of developers. Panel B shows the share of NZIA developers over the total number of NZIA-labelled developers. Panel C compares the weights of NZIA and non-NZIA developers within each region. Values are expressed in percentages. Source: authors' elaboration

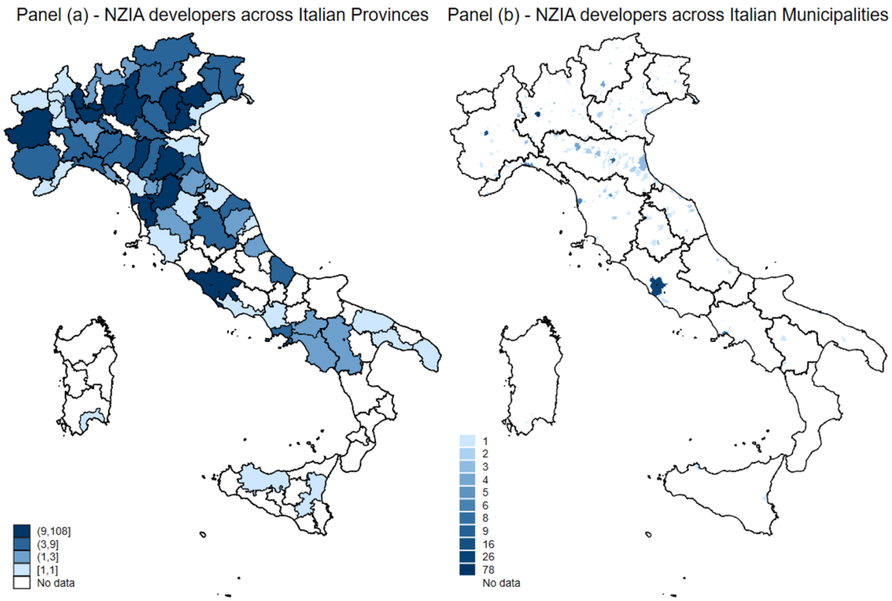


Fig. 8 Distribution of firms developing net-zero technologies according to provinces and municipalities Notes: The figure shows the geographic distribution of NZIA developers across provinces (Panel A) and municipalities (Panel B), highlighting regional concentrations and spatial patterns in the development of NZIA-related technologies. Authors' elaboration

4.2.2 Sectoral Distribution of Developers of Net-Zero Technologies

Table 11 reveals a clear concentration of net-zero technology developers in the manufacturing sector: firms in sector C account for nearly one-third of the total sample of developers (Panel A, columns 1–2) and represent almost 65% of NZIA-labelled developers (Panel B). This predominance underscores the central role of manufacturing in the development and scaling of strategic technologies. Alongside this, professional, scientific, and technical activities (sector M) emerge as significant contributors, representing 19.3% of NZIA developers, while wholesale and retail trade (sector G) plays a more marginal role (4.4%).

The share of net-zero development within sectors offers further insights. Electricity and gas supply (D), water and waste management (E), and financial services (K) exhibit particularly high engagement, with over 75% of firms in these sectors classified as developers of net-zero technologies. Transportation and storage sector (H) also shows a notable concentration, while sector M confirms its relevance with over 60% of firms involved in net-zero development. In contrast, sectors like construction (F) and wholesale trade (G), despite their presence in the sample, display lower engagement levels, suggesting more limited involvement in strategic technological development.

These patterns point to strong sectoral heterogeneity, where development is concentrated in industries characterized by high technological intensity, regulatory exposure, and strategic positioning. The ability to develop net-zero technologies

Table 10 Distribution of firms developing net-zero technologies according to GDP at Nuts-3 level

	Panel A	Panel B		Panel C	
GDP Level (nuts-3)	%NZIA developers over tot. developers	%No-NZIA developers over tot. developers	% NZIA over tot. NZIA developers	%NZIA developers within region	%No-NZIA developers within region
Poor	15.320%	16.342%	31.609%	48.387%	51.613%
Medium	13.092%	18.384%	27.011%	41.593%	58.407%
Rich	20.056%	16.806%	41.379%	54.408%	45.592%
Total	48.468%	51.532%	100.000%		

The table reports the distribution of firms developing net-zero technologies based on GDP levels at the NUTS-3 regional classification. NUTS-3 regions are classified as *Poor*, *Medium*, or *Rich* based on the tercile distribution of regional GDP, with regions in the first tercile labelled as Poor, those in the second tercile as Medium, and those in the third tercile as Rich. Panel A shows the share of NZIA and non-NZIA developers over the total sample of developers, disaggregated by GDP category (Poor, Medium, Rich). Panel B displays the proportion of NZIA developers within each GDP group relative to the total number of NZIA-labelled developers. Panel C compares the share of NZIA and non-NZIA developers within each GDP category. Values are expressed in percentages. Source: authors' elaboration

Table 11 Distribution of firms developing net-zero technologies according to NACE divisions

		Panel A	Panel B		Panel C	
Nace Division	Description	%NZIA developers over tot. developers	%No-NZIA developers over tot. developers	% NZIA over tot. NZIA developers	%NZIA developers within region	%No-NZIA developers within region
C	Manufacturing	31.383%	37.790%	64.751%	45.369%	54.631%
D	Electricity, Gas, Steam, and Air Conditioning Supply	0.836%	0.186%	1.724%	81.818%	18.182%
E	Water Supply; Sewerage, Waste Management, and Remediation Activities	1.114%	0.371%	2.299%	75.000%	25.000%
F	Construction	0.836%	2.043%	1.724%	29.032%	70.968%
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	2.136%	3.250%	4.406%	39.655%	60.345%
H	Transportation and Storage	0.371%	0.093%	0.766%	80.000%	20.000%
I	Accommodation and Food Service Activities	0.000%	0.093%	0.000%	0.000%	100.000%
J	Information and Communication	0.650%	1.114%	1.341%	36.842%	63.158%
K	Financial and Insurance Activities	1.393%	0.464%	2.874%	75.000%	25.000%
L	Real Estate Activities	0.186%	0.371%	0.383%	33.333%	66.667%
M	Professional, Scientific, and Technical Activities	9.378%	5.664%	19.349%	62.346%	37.654%
N	Administrative and Support Service Activities	0.186%	0.000%	0.383%	100.000%	0.000%
S	Other Service Activities	0.000%	0.093%	0.000%	0.000%	100.000%
Total		48.468%	51.532%	100.000%		

The table reports the distribution of firms developing net-zero technologies across two-digit NACE divisions. Panel A shows the share of NZIA and non-NZIA developers over the total sample of developers. Panel B displays the percentage of NZIA developers within each sector relative to the total number of NZIA-labelled developers. Panel C reports the weights of NZIA and non-NZIA developers within each NACE division. Values are expressed in percentages. Source: authors' elaboration appears closely tied to the structural and institutional features of the sector itself (see Fig. 10 in Appendix D for a graphical representation).

Market structure also adds further insight (Table 12). While competitive sectors host the largest number of developers overall, the development rates of net-zero technologies increase with market concentration. Firms in highly concentrated sectors—often oligopolistic or even monopolistic—exhibit the highest development rates (67.5%), followed by those in moderately concentrated markets (54.9%). This confirms that firms operating in less competitive environments may benefit from greater strategic autonomy and resource availability, enabling them to invest in capital-intensive technologies. In contrast, firms in highly competitive sectors may face tighter constraints, limiting their capacity to engage in long-term innovation.

4.2.3 The Business Profile of Developers of Net-Zero Technologies

Firm size emerges as a key factor in shaping the engagement in net-zero technology development. As shown in Table 13, medium and large firms dominate the developer landscape, together accounting for over 63% of NZIA-labelled developers (Panel B). While micro and small firms are numerically present, their contribution to net-zero development remains limited. This distribution reflects the structural advantages of larger firms, which typically benefit from greater financial capacity, organizational complexity, and access to specialized resources—conditions that are conducive to the development of strategic technologies. The intensity of development across size classes further reinforces this pattern. The share of NZIA-labelled developers increases progressively with firm size, peaking at nearly 70% among large enterprises (Panel C). Firm size not only facilitates investment in innovation but also enhances the ability to absorb the risks and complexities associated with developing advanced technologies.

Firm age offers a complementary perspective (Table 14). The majority of developers are concentrated among older firms, particularly incumbents operating for more than 20 years. These firms also represent the largest share of NZIA-labelled developers, followed by mature and young firms, while newly established firms remain a minority (Panel B). However, when examining the share of developers within each age group, the data reveal a relatively balanced distribution, with development rates hovering around 47–49% across all categories. This suggests that, unlike firm size, age does not exhibit a strictly negative or positive relationship with development propensity.

Instead, the data seem to suggest also in this case a non-linear pattern. Both very young and very old firms appear capable of engaging in net-zero development, albeit through different mechanisms. Young firms may benefit from agility, innovation-driven strategies, and positioning in emerging sectors, while incumbents leverage accumulated knowledge, stable market positions, and long-term planning horizons. This duality hints at a non-linear relationship between age and development, where both ends of the spectrum can support strategic technological engagement under the right conditions.

To conclude, the mapping of net-zero technologies developers broadly mirrors the patterns observed among adopters. The spatial distribution follows a similar

Table 12 Distribution of firms developing net-zero technologies according to HHI

	Panel A	Panel B		Panel C	
HHI	%NZIA developers over tot. developers	%No-NZIA developers over tot. developers	% NZIA over tot. NZIA developers	%NZIA developers within region	%No-NZIA developers within region
Low HHI (competitive market)	24.791%	35.469%	51.149%	41.140%	58.860%
Medium HHI (Moderate concentration)	13.649%	11.235%	20.161%	54.851%	45.149%
High HHI (high concentration)	10.028%	4.828%	28.690%	67.500%	32.500%
Total	48.468%	51.532%	100.000%		

The table shows the distribution of firms developing net-zero technologies based on market concentration levels, as measured by the Herfindahl–Hirschman Index (*HHI*). Panel A reports the percentage of NZIA and non-NZIA developers over the total sample of developers. Panel B indicates the share of NZIA developers by HHI category relative to all NZIA-labelled developers. Panel C shows the weights of NZIA and non-NZIA developers within each HHI group. Values are expressed in percentages. Source: authors' elaboration

Table 13 Distribution of firms developing net-zero technologies according to firms' size

	Panel A	Panel B		Panel C	
Size (N. Employees)	%NZIA developers over tot. developers	%No-NZIA developers over tot. developers	% NZIA over tot. NZIA developers	%NZIA developers within region	%No-NZIA developers within region
Micro	6.128%	8.542%	12.644%	41.772%	58.228%
Small	11.513%	16.527%	23.755%	41.060%	58.940%
Medium	16.806%	20.334%	34.674%	45.250%	54.750%
Big	14.020%	6.128%	28.927%	69.585%	30.415%
Total	48.468%	51.532%	100.000%		

The table displays the distribution of NZIA and non-NZIA developers by firm size, measured by the number of employees. Panel A reports the share of NZIA and non-NZIA developers over the total sample of developers. Panel B indicates the share of NZIA developers by size category relative to all NZIA-labelled developers. Panel C shows the weights of NZIA and non-NZIA developers within each size group. Values are expressed in percentages. Source: authors' elaboration

Table 14 Distribution of firms developing net-zero technologies according to firm's age

Age	Panel A %NZIA developers over tot. developers	Panel B %No-NZIA developers over tot. developers	% NZIA over tot. NZIA developers	Panel C %NZIA developers within region	%No-NZIA developers within region
New	0.093%	0.186%	10.192%	47.333%	52.667%
Young	4.178%	4.364%	8.621%	48.913%	51.087%
Mature	9.192%	10.121%	18.965%	47.596%	52.404%
Incumbent	35.005%	36.862%	62.222%	48.708%	51.292%
Total	48.468%	51.532%	100.000%		

The table reports the distribution of NZIA and non-NZIA developers by firm age category. Panel A shows the share of NZIA and non-NZIA developers over the total sample of developers. Panel B indicates the proportion of NZIA developers within each age category relative to all NZIA-labelled developers. Panel C compares the weights of NZIA and non-NZIA developers within each age group. Values are expressed in percentages. Source: authors' elaboration

trajectory showing concentration in northern and economically advanced regions, and a positive correlation with firm size and market concentration. Nevertheless, developers are concentrated high-tech industries, where firms must have specialized capabilities and domain-specific expertise. This complexity distinguishes developers from adopters and suggests that the transition from adoption to development entails not only strategic commitment but also deeper integration of technical knowledge and innovation capacity.

5 Drivers of Adoption of Net-Zero Technologies

In this section, we investigate potential drivers that affect the likelihood of adopting (developing) net-zero technologies. As no empirical evidence exists on the role of these drivers in the NZIA framework, their effects are not assumed ex-ante, i.e., they may enable or hinder the adoption of net-zero technologies (Dosi 1988; Roper et al. 2008). In Sect. 5.1 we introduce the empirical strategy, whereas in Sects. 5.2 and 5.3 we discuss the results for adopters and developers, respectively. Finally, in Sect. 5.4, we explore the heterogeneity across SMEs and large companies.

5.1 Empirical Strategy

Our analysis focuses on a set of explanatory variables—referred to as drivers—that may influence the adoption and development of net-zero technologies (Laursen and Salter 2006; Cefis & Marsili 2006; Cainelli et al. 2015; Balland & Boschma 2020). These drivers are clustered in four distinct groups: (1) Financial constraints, (2) Profitability, (3) Organizational and relational features, and (4) Knowledge intensity. Financial and profitability-related drivers affect the availability of resources and risk tolerance, which are crucial for investing in technologies. Organizational and relational drivers influence internal decision-making and external collaborations, both of which can influence innovation processes. Knowledge and human capital drivers determine the firm's ability to understand and implement complex technologies, making them essential for effective engagement with NZIA-related innovation.

Under financial drivers, we include capital structure indicators as enablers or constraints for risky investment (Hall and Lerner 2010; Hottenrott and Peters 2012). Specifically, we measure the firm's debt exposure, distinguishing between long-term and short-term debt. We measure the firm's indebtedness using leverage as the ratio of total debt to total assets (*LevRatio*). We further compute the short-term debt ratio (*ShortDebt*) and long-term debt ratio (*LongDebt*). In addition, we calculate the equity ratio as the share of total equity over total assets (*Equity*).

Regarding the profitability drivers, we include return on assets (*ROA*) and return on equity (*ROE*), which capture operational and financial performance, respectively. We also include the natural logarithm of EBITDA as a proxy for operating profit (*LnEBITDA*), and the firm's liquidity ratio (*Liq_Index*). Finally, we define firm's revenue growth rate as the logarithm difference of revenues between year *t* and *t-1* (*SalesGrowth*). Profitability can be a signal of good performance and investment potential (Savignac 2008).

As for organizational and relational drivers, we focus on two relevant features in the Italian context: family ownership and affiliation to industrial districts. Family ownership and local embeddedness are central for their influence on long-term orientation, risk aversion, and path dependence (Anderson and Reeb 2003). For family firms, we construct two dummy variables: *FamilyD* and *FamilyG*: *FamilyD* equals one if the direct ultimate owner (DUO) is a family, and zero otherwise, whereas *FamilyG* equals one if the global ultimate owner (GUO) is a family, and zero otherwise. As for industrial districts, we create a dummy variable (*District*) equal to one if the firm is in an industrial district, officially recognized by ISTAT, and zero otherwise. Classification is based on a match between the firm's provincial location and the XV ISTAT Census of Population and Housing.

Finally, knowledge- and human capital-related drivers refer to the composition of the firm's managerial board. STEM qualifications and managerial characteristics are indicators of absorptive capacity and innovation propensity (Grimpe and Hussinger 2013; Huergo 2006). Indeed, we consider the percentage of managers with a STEM degree (*%STEM*), the average tenure of board members (*Duration*), the average tenure of STEM-educated managers (*DurationSTEM*), and the average age of managers (*Age_manager*). Data have been drawn from the AIDA dataset.

We estimate the following probit model to test the association of these drivers with NZIA outcomes:

$$NZIA_{i,t} = \alpha_r + \alpha_s + \beta * Driver_{i,t-1} + \gamma * Controls_{i,t-1} + \varepsilon_i$$

where $i = 1 \ldots 105,159$ corresponds to the number of firms and t = 2024. The dependent variable is the dummy *NZIA*. The main coefficient of interest is β that measures the effect of each driver, included individually in the specification, on the likelihood of adopting net-zero technologies. Vector *Controls* include the set of variables we used in the mapping: *LnEmploy*, *Age*, *Age*^{2}, *HHI*, and *LnGDP*. Firm age is modelled in quadratic form – consistent with both the evidence emerging from the univariate descriptive analysis and the firm-level literature – to account for a non-linear relationship between firm age and innovation or technology adoption (Evans 1987; Coad et al. 2018; López-Delgado et al. 2024).[10] To avoid simultaneity bias, the controls are one-year lagged. We saturate our model including sectors (α_s) and regions (α_r) fixed effects. According to the mapping evidence, we expect firms operating in specific sectors, such as advanced manufacturing or professional, scientific, and technical activities or energy, to be more likely to adopt NZIA-related technologies due to greater environmental exposure. Similarly, firms located in regions with stronger environmental regulations or incentive policies may face higher pressure, or find more support, to adopt these technologies.[11] ε_i is the error term. Standard errors are clustered at firm level.

5.2 Drivers of Net-Zero Technologies Adoption

We first test our baseline specification looking at the effect of *Controls* on net-zero technologies adoption (Column 1 of Table 15): the signs of their coefficients (γ) are coherent with the evidence stemming from the mapping of firms adopting net-zero technologies (see Sect. 4.1).[12] Moreover, the coefficients' signs remain consistent across different model specifications and estimators, confirming the stability of our model specification (see Appendix E).

Focusing on financial drivers (columns 2–5), the increase in debt exposure (*LevRatio*) significantly decreases the likelihood of adopting net-zero technologies. Specifically, both short-term (*ShortDebt*) and long-term (*LongDebt*) debt have a negative effect, but the short-term debt tends to reduce the likelihood of adopting net-zero technologies more than the long-term debt does. Conversely, an increase in equity (*Equity*) fosters innovation activities related to net-zero technologies. The results show that higher debt exposure amplifies firms' financial constraints, particularly when funding innovative-related projects. These constraints—combined with the higher cost of debt—reduce the likelihood that firms will be able to finance risky investments, such as those required for technological innovation. By contrast, firms with higher internal resources, i.e., equity, tend to adopt these technologies more easily.

The different behaviour of firms in financing innovation is further supported by the coefficients in columns 6–10. Although *ROA, SalesGrowth* and *Liq_Index* are not statistically significant, higher profitability–proxied by *ROE* and *LnEBITDA*–is positively associated with the likelihood of adopting net-zero technologies. Greater profitability enhances internal cash flows that can be reinvested in innovation.

[10] To improve interpretability, we rescale firm age in decades (age/10).

[11] While the inclusion of sector and region fixed effects necessarily absorbs part of the cross-sectoral and spatial variation in net-zero adoption, their use is motivated by the sectoral and geographical concentration documented in the descriptive analysis. Controlling for these dimensions allows us to identify firm-level correlates net of heterogeneity, while ensuring that estimated associations are not driven by compositional effects across industries or regions.

[12] The estimated coefficients do not change the signs and significance, and the magnitudes remain close to those presented in Table 15 even when the pre-clean procedure sample is not used.

Table 15 Financial drivers and profitability-related drivers of firms adopting net-zero technologies

Dep.Variable	(1) NZIA	(2) NZIA	(3) NZIA	(4) NZIA	(5) NZIA	(6) NZIA	(7) NZIA	(8) NZIA	(9) NZIA	(10) NZIA
Driver =		*LevRatio*	*ShortDebt*	*LongDebt*	*Equity*	*ROA*	*ROE*	*LnEBITDA*	*SalesGrowth*	*Liq_Index*
Driver		−0.0101***	−0.0086***	−0.0077**	0.0178***	0.0001	0.0001**	0.0055***	0.0016	0.0005
		(0.0023)	(0.0025)	(0.0038)	(0.0022)	(0.0000)	(0.0000)	(0.0005)	(0.0013)	(0.0004)
LnEmploy	0.0104***	0.0107***	0.0105***	0.0104***	0.0105***	0.0104***	0.0103***	0.0050***	0.0105***	0.0106***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0004)	(0.0004)
Age	−0.0031***	−0.0033***	−0.0036***	−0.0032***	−0.0038***	−0.0031***	−0.0027***	−0.0035***	−0.0026***	−0.0032***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Age^2	0.0003***	0.0003***	0.0004***	0.0004***	0.0004***	0.0003***	0.0003***	0.0004***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HHI	0.0267***	0.0267***	0.0279***	0.0286***	0.0264***	0.0266***	0.0282***	0.0220***	0.0249***	0.0286***
	(0.0046)	(0.0042)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0047)	(0.0051)	(0.0047)	(0.0046)
LnGDP	0.0031***	0.0031***	0.0031***	0.0030***	0.0032***	0.0031***	0.0033***	0.0029***	0.0029***	0.0030***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Obs	105,159	104,798	104,798	104,798	104,953	105,159	102,223	97,068	102,658	103,187
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.127	0.132	0.129	0.129	0.130	0.127	0.127	0.133	0.127	0.129
Mean VIF	2.01	2.02	2.02	2.01	2.01	2.01	2.03	2.13	2.01	2.02

The table reports the marginal effects from Probit regressions where the dependent variable is a dummy equal to 1 if a firm adopts NZIA-related technologies, and 0 otherwise. Columns (2) to (10) include different financial and performance-related drivers: leverage ratio (*LevRatio*), short-term debt (*ShortDebt*), long-term debt (*LongDebt*), equity (*Equity*), return on assets (*ROA*), return on equity (*ROE*), sales growth (*SalesGrowth*), logarithm of EBITDA (*LnEBITDA*), and liquidity index (*Liq_Index*). All regressions control for firm size (*LnEmploy*), firm age and its square (*Age*, Age^2), market concentration (*HHI*), and GDP at the regional level (*LnGDP*). Sector and regional fixed effects are included throughout. Standard errors (in brackets) are robust. Pseudo R^2 statistics and mean variance inflation factors (*VIF*) are reported at the bottom of the table. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

Moving to the organizational drivers (Table 16), operating in an industrial district (*District*) does not significantly influence the likelihood of adoption (Column 1). While this result may appear at odds with the traditional view of Italian industrial districts as engines of open and diffuse innovation (Giunta and Rossi 2017), it is consistent with the idea that district-based innovation has historically been rooted in sector-specific, incremental, and path-dependent technological trajectories. In this context, districts may remain highly innovative within traditional production domains, while being less directly involved in the development or early adoption of net-zero technologies, which often require cross-sectoral knowledge, new scientific competences, and substantial coordination across actors.[13] In contrast, being a family-owned firm, *FamilyD* and *FamilyG,* negatively affects the probability of adopting net-zero technologies (Columns 2–3). This result reflects the more conservative management approach and long-term orientation of family-owned firms compared with non-family firms, which often prioritize stability and intergenerational continuity over the adoption of innovative technologies such as those promoted by the NZIA framework.

Finally, longer managerial tenures (*Duration*) are associated with a lower probability of adoption (Column 4): managers with extended tenure are more reluctant to embrace changes, preferring to avoid disruptive and high-risk investments. In contrast, shorter tenures are often linked to a greater openness to strategic transformation, as newly appointed managers may be more inclined to introduce changes and demonstrate value in the short run. Moreover, a higher share of managers with STEM degrees (*%STEM*) and long-tenure managers with STEM backgrounds (*DurationSTEM*) are positively associated with the adoption of net-zero technologies (Columns 5–6). These findings suggest that a stronger base of technical knowledge boosts managerial awareness and responsiveness to structural change, acting as a key enabler for the uptake of innovative technologies. Lastly, managerial age (*Age_manager*) does not show a statistically significant effect.

5.3 Drivers of Net-Zero Technologies Development

To investigate the drivers of net-zero technologies development, we re-estimate Eq. 1 by replacing the dependent variable *NZIA* with *D_IPC_NZIA*. Furthermore, as

[13] The lack of statistical significance suggests that districts are not systematically disadvantaged in absolute terms, but rather that they do not represent the primary organizational locus of innovation for NZIA-related technologies. In other words, the competitive and innovative advantages of industrial districts may operate through channels that are only weakly connected to the technological and organizational requirements of the net-zero transition. This interpretation is consistent with a view of districts as innovation-intensive structures whose strengths are concentrated in established technological paradigms, rather than in radical and transversal green technologies. This pattern may also reflect the fact that net-zero technologies often involve higher coordination requirements, longer investment horizons, and complementarities across firms and institutions, which are not always easily accommodated within fragmented district structures. While these coordination issues are not always directly testable, they are consistent with the idea that district-based innovation may be less effective in supporting radical and cross-cutting technological transitions. Importantly, this does not imply that industrial districts are inherently less innovative, but rather that their traditional sources of competitive advantage may be less closely aligned with the specific technological and organizational demands of NZIA-related innovations.

Table 16 Organizational and relational drivers, knowledge and human capital drivers of firms adopting net-zero technologies

Dep.Variable	(1) NZIA	(2) NZIA	(3) NZIA	(4) NZIA	(5) NZIA	(6) NZIA	(7) NZIA
Driver =	*District*	*FamilyD*	*FamilyG*	*Duration*	*%STEM*	*DurationSTEM*	*Age_manager*
Driver	−0.0016	−0.0059***	−0.0049***	−0.0006***	0.0409***	0.0475***	0.0001
	(0.0013)	(0.0010)	(0.0010)	(0.0001)	(0.0060)	(0.0088)	(0.0001)
LnEmploy	0.0104***	0.0100***	0.0101***	0.0095***	0.0101***	0.0101***	0.0026***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0006)
Age	−0.0031***	−0.0032***	−0.0032***	−0.0021***	−0.0030***	−0.0030***	−0.0027***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0009)
Age^2	0.0003***	0.0003***	0.0003***	0.0002***	0.0003***	0.0003***	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HHI	0.0267***	0.0266***	0.0266***	0.0265***	0.0260***	0.0261***	0.0288***
	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0048)
LnGDP	0.0028***	0.0030***	0.0031***	0.0030***	0.0029***	0.0030***	0.0019***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)
Obs	105,159	105,159	105,159	105,159	105,159	105,159	60,017
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.129	0.128	0.129	0.129	0.128	0.0862	0.129
Mean VIF	2.02	2.01	2.01	2.02	2.01	2.01	2.08

The table reports marginal effects from Probit regressions where the dependent variable is a dummy equal to 1 if a firm adopts NZIA-related technologies, and 0 otherwise. Each column includes a different driver: presence in an industrial district (*District*), ownership by a family group (*FamilyG*), direct family ownership (*FamilyD*), duration of employee tenure (*Duration*), share of STEM graduates among employees (*%STEM*), duration of STEM employees (DurationSTEM), and age of the manager (*Age_manager*). All regressions include controls for firm size (*LnEmploy*), firm age and its square (*Age*, Age^2), market concentration (*HHI*), and regional GDP (*LnGDP*). Sector and regional fixed effects are included in all specifications. Standard errors (in brackets) are robust. Pseudo R^2 statistics and mean variance inflation factors (*VIF*) are reported at the bottom of the table. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively done in Sect. 4.2, we limit the sample to companies that, among adopters, are also technology developers.

Within this restricted sample, the dependent variable *D_IPC_NZIA* allows us to isolate firms that go one step further, namely those that adopt and develop technologies that are specifically aligned with the NZIA framework. In other words, we aim to identify factors that drive firms, already equipped with innovation capacity and exposed to net-zero technologies, to become actual developers of them.

The column 1 of Table 17 reports the coefficients of the control variables: their signs are consistent with the evidence from the mapping discussed in Sect. 4.2. The short-term debt significantly reduces the probability of developing net-zero technologies, whereas the long-term debt and equity increase it. These results suggest that lower short-term financial distress and stronger capital buffers are critical for funding the up-front R&D and capital-intensive activities required for technological development. On the other hand, the presence of long-term debt may facilitate the undertaking of substantial investments in net-zero technologies, by allowing firms to operate under extended repayment horizons. This financial structure can ease liquidity constraints and align investment timelines with the long-term nature of technological development.

Profitability appears to have a differentiated effect on the likelihood of developing net-zero technologies. While *ROA* and *SalesGrowth* negatively affect development propensity, the coefficient of *LnEBITDA* is positive and statistically significant. In fact, developers may not prioritize short-term profitability in terms of asset efficiency but rather rely on operational cash flow as a more relevant indicator of their capacity to engage in strategic investments. In this context, firms may tolerate lower accounting returns (as captured by ROA) while leveraging stronger internal cash generation (as proxied by EBITDA) to support long-term technological commitments.

Organizational and human-capital drivers suggest that certain structural configurations may hinder the likelihood of engaging in net-zero technology development. Specifically, firms located within industrial districts show a statistically significant negative association with NZIA-labelled development (Column 1, Table 18). District-based firms often operate within tightly knit networks and established organizational routines, which, while beneficial for incremental innovation and efficiency, may limit the flexibility and autonomy required for investing in disruptive or capital-intensive technologies. Moreover, while districts foster innovation in traditional domains, they can be less directly involved in the development of net-zero technologies.

Similarly, family-owned firms are negatively associated with net-zero development (Columns 2–3). This could be attributed to more conservative strategic orientations, lower risk tolerance, and a preference for preserving financial stability over long-term technological bets. In both cases, the organizational context may constrain the firm's capacity or willingness to undertake the additional technological and managerial complexity required for developing strategic net-zero technologies.

Finally, only *%STEM* and *DurationSTEM* are statistically significant (Columns 5–6). The positive effect of *%STEM* highlights the centrality of technical expertise within the workforce, suggesting that a higher share of employees with scientific and

Table 17 Financial drivers and profitability-related drivers of firms developing net-zero technologies

Dep.Variable	(1) D_IPC_ NZIA	(2) D_IPC_ NZIA	(3) D_IPC_ NZIA	(4) D_IPC_ NZIA	(5) D_IPC_ NZIA	(6) D_IPC_ NZIA	(7) D_IPC_ NZIA	(8) D_IPC_ NZIA	(9) D_IPC_ NZIA	(10) D_IPC_NZIA
Driver =		*LevRatio*	*ShortDebt*	*LongDebt*	*Equity*	*ROA*	*ROE*	*LnEBITDA*	*SalesGrowth*	*Liq_Index*
Driver		−0.0052	−0.1312*	0.2788***	0.0455	−0.0026**	−0.0010	0.0276**	−0.0540*	0.0017
		(0.0677)	(0.0751)	(0.1065)	(0.0668)	(0.0011)	(0.0007)	(0.0140)	(0.0305)	(0.0115)
LnEmploy	0.0574***	0.0570***	0.0581***	0.0558***	0.0577***	0.0576***	0.0572***	0.0373**	0.0603***	0.0578***
	(0.0090)	(0.0091)	(0.0091)	(0.0091)	(0.0090)	(0.0089)	(0.0091)	(0.0178)	(0.0093)	(0.0094)
Age	−0.0437**	−0.0417*	−0.0412*	−0.0352	−0.0435**	−0.0391*	−0.0359*	−0.0547**	−0.0459**	−0.0340
	(0.0212)	(0.0215)	(0.0215)	(0.0215)	(0.0213)	(0.0206)	(0.0214)	(0.0246)	(0.0211)	(0.0211)
Age^2	0.0045**	0.0044**	0.0043**	0.0039*	0.0045**	0.0040**	0.0040*	0.0059**	0.0044**	0.0034
	(0.0021)	(0.0022)	(0.0022)	(0.0022)	(0.0021)	(0.0020)	(0.0021)	(0.0026)	(0.0021)	(0.0021)
HHI	0.4099***	0.3992***	0.3835***	0.3875***	0.3939***	0.3982***	0.4005***	0.3763***	0.3749***	0.4180***
	(0.0965)	(0.0964)	(0.0967)	(0.0971)	(0.0963)	(0.0971)	(0.0965)	(0.1163)	(0.1001)	(0.0995)
LnGDP	0.0367*	0.0338*	0.0357*	0.0350*	0.0347*	0.0384**	0.0357*	0.0397**	0.0354*	0.0310
	(0.0188)	(0.0189)	(0.0190)	(0.0188)	(0.0189)	(0.0187)	(0.0189)	(0.0201)	(0.0190)	(0.0191)
Obs	1071	1063	1063	1063	1066	1071	1046	930	1040	1045
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.064	0.062	0.064	0.066	0.064	0.068	0.066	0.075	0.064	0.060
Mean VIF	1.76	1.88	1.88	1.88	1.73	1.73	1.87	2.09	1.73	1.87

The table reports the marginal effects from Probit regressions where the dependent variable is a dummy equal to 1 if a firm develops NZIA-related technologies, and 0 otherwise. Columns (2) to (10) include different financial and performance-related drivers: leverage ratio (*LevRatio*), short-term debt (*ShortDebt*), long-term debt (*LongDebt*), equity (*Equity*), return on assets (*ROA*), return on equity (*ROE*), sales growth (*SalesGrowth*), logarithm of EBITDA (*LnEBITDA*), and liquidity index (*Liq_Index*). All regressions control for firm size (*LnEmploy*), firm age and its square (*Age*, Age^2), market concentration (*HHI*), and GDP at the regional level (*LnGDP*). Sector and regional fixed effects are included throughout. Standard errors (in brackets) are robust. Pseudo R^2 statistics and mean variance inflation factors (*VIF*) are reported at the bottom of the table. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

Table 18 Organizational and relational drivers, knowledge and human capital drivers of firms developing net-zero technologies

Dep.Variable	(1) D_IPC_NZIA	(2) D_IPC_NZIA	(3) D_IPC_NZIA	(4) D_IPC_NZIA	(5) D_IPC_NZIA	(6) D_IPC_NZIA	(7) D_IPC_NZIA
Driver =	*District*	*FamilyD*	*FamilyG*	*Duration*	*%STEM*	*DurationSTEM*	*Age_manager*
Driver	−0.0842**	−0.0610*	−0.0583*	−0.0022	0.3056***	0.6746**	0.0049
	(0.0376)	(0.0325)	(0.0319)	(0.0037)	(0.1172)	(0.2874)	(0.0043)
LnEmploy	0.0571***	0.0539***	0.0543***	0.0550***	0.0522***	0.0494***	0.0232
	(0.0089)	(0.0092)	(0.0091)	(0.0098)	(0.0093)	(0.0096)	(0.0314)
Age	−0.0420**	−0.0418**	−0.0420**	−0.0427**	−0.0403*	−0.0388*	0.0872
	(0.0211)	(0.0210)	(0.0210)	(0.0212)	(0.0211)	(0.0212)	(0.0568)
Age^2	0.0043**	0.0043**	0.0043**	0.0044**	0.0043**	0.0042**	-0.0060
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0064)
HHI	0.4057***	0.4165***	0.4155***	0.4100***	0.3946***	0.3846***	0.3128**
	(0.0967)	(0.0962)	(0.0963)	(0.0963)	(0.0969)	(0.0973)	(0.1502)
LnGDP	0.0183	0.0363*	0.0362*	0.0372**	0.0337*	0.0319*	0.0057
	(0.0204)	(0.0187)	(0.0187)	(0.0188)	(0.0187)	(0.0187)	(0.0397)
Obs	1071	1071	1071	1071	1071	1071	225
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.068	0.067	0.067	0.065	0.069	0.071	0.092
Mean VIF	1.79	1.74	1.74	1.75	1.74	1.75	2.29

The table reports the marginal effects from Probit regressions where the dependent variable is a dummy equal to 1 if a firm develops NZIA-related technologies, and 0 otherwise. Each column includes a different driver: presence in an industrial district (*District*), ownership by a family group (*FamilyG*), direct family ownership (*FamilyD*), duration of employee tenure (*Duration*), share of STEM graduates among employees (*%STEM*), duration of STEM employees (DurationSTEM), and age of the manager (*Age_manager*). All regressions include controls for firm size (*LnEmploy*), firm age and its square (*Age*, Age^2), market concentration (*HHI*), and regional GDP (*LnGDP*). Sector and regional fixed effects are included in all specifications. Standard errors (in brackets) are robust. Pseudo R^2 statistics and mean variance inflation factors (*VIF*) are reported at the bottom of the table. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively engineering backgrounds enhances a firm's capacity to engage in complex technological development. Likewise, the positive coefficient for *DurationSTEM* indicates that longer tenures of STEM-trained managers contribute positively to development outcomes. This underscores the importance of accumulated experience and domain-specific knowledge in overseeing innovation-driven processes, where strategic decisions and technical oversight must be integrated.

5.4 Large Companies vs. SMEs

Within the Italian context, distinguishing between large enterprises and SMEs is essential to better understand how the drivers influencing adoption operate differently across firm size categories. Firms with different sizes may have distinct developmental trajectories, strategic objectives, and technological capabilities. We identify SMEs following the standard European Commission's definition, while large companies are defined as all firms not classified as SMEs.[14] See Tables 19 and 20 for SMEs (Panel A) and large companies (Panel B).

First, we focus on controls across SMEs and large companies. The coefficients of *LnEmploy* and *LnGDP* are both positive and statistically significant. Further, firm age confirms a U-shaped relationship in both cases. By contrast, while *HHI* does not significantly affect the likelihood of adopting net-zero technologies in SMEs, its coefficient is positive and significant in large companies. The latter are more likely to innovate when operating in less competitive markets.

When disaggregating the analysis, some differences emerge in the financial and organizational drivers. The most notable distinction concerns the role of debt maturity. For SMEs, long-term debt is negatively and significantly associated with the likelihood of adopting net-zero technologies, suggesting that financial rigidity or limited access to long-term financing may constrain their capacity to adopt these technologies. In contrast, for large firms, short-term debt shows a significant negative effect, reflecting heightened rollover risk and liquidity pressures that discourage long-horizon technological commitments.

Further differences are observed in profitability. While *ROE* does not appear to influence adoption among SMEs, it has a negative and significant effect for large firms, indicating that higher equity returns may be associated with more conservative investment strategies in this group.

Organizational characteristics also show divergent patterns (Table 20). District membership does not exhibit a significant effect on the likelihood of adoption among large enterprises, potentially because these firms benefit from broader relational networks. In contrast, SMEs display a negative and statistically significant coefficient for district affiliation. This evidence is particularly relevant as it indicates that industrial districts act as a constraint on the adoption of net-zero technologies. Industrial district membership is negatively associated with adoption only among SMEs, possibly reflecting structural rigidities or path dependencies within localized networks. Conversely, *DurationSTEM* is significant only for large firms, suggesting

[14] We label firms as SMEs if the number of employees is lower than 250 and the value of total assets is lower than €43 million.

Table 19 Financial drivers and profitability drivers of firms adopting net-zero technologies (SMEs versus Large Companies)

Dep.Variable	(1) NZIA	(2) NZIA	(3) NZIA	(4) NZIA	(5) NZIA	(6) NZIA	(7) NZIA	(8) NZIA	(9) NZIA	(10) NZIA
Driver =		*LevRatio*	*ShortDebt*	*LongDebt*	*Equity*	*ROA*	*ROE*	*LnEBITDA*	*SalesGrowth*	*Liq_Index*
PANEL A: SMEs										
Driver		−0.0066***	−0.0007	−0.0166***	0.0108***	−0.0001	−0.0001	0.0032***	0.0019	0.0006
		(0.0026)	(0.0028)	(0.0043)	(0.0025)	(0.0000)	(0.0000)	(0.0006)	(0.0012)	(0.0004)
LnEmploy	0.0085***	0.0087***	0.0085***	0.0085***	0.0085***	0.0085***	0.0084***	0.0053***	0.0087***	0.0086***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0008)	(0.0005)	(0.0005)
Age	−0.0029***	−0.0031***	−0.0030***	−0.0030***	−0.0033***	−0.0029***	−0.0029***	−0.0028***	−0.0023**	−0.0030***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0009)
Age^2	0.0003**	0.0003**	0.0003**	0.0003**	0.0003**	0.0003**	0.0003**	0.0003**	0.0002	0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HHI	0.0059	0.0056	0.0046	0.0047	0.0047	0.0059	0.0046	0.0073	0.0064	0.0060
	(0.0061)	(0.0060)	(0.0062)	(0.0062)	(0.0062)	(0.0061)	(0.0063)	(0.0065)	(0.0062)	(0.0062)
LnGDP	0.0029***	0.0030***	0.0029***	0.0028***	0.0029***	0.0029***	0.0030***	0.0030***	0.0027***	0.0028***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Obs	70,815	70,762	70,762	70,762	70,762	70,815	68,740	65,341	68,869	69,723
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.104	0.106	0.104	0.105	0.105	0.104	0.103	0.106	0.103	0.104
Mean VIF	2.11	2.08	2.07	2.06	2.07	2.06	2.07	2.17	2.09	2.07
PANEL B: LARGE COMPANIES										
Driver		−0.0156***	−0.0237***	0.0098	0.0288***	−0.0001	−0.0001**	0.0090***	0.0010	0.0001
		(0.0047)	(0.0052)	(0.0075)	(0.0045)	(0.0001)	(0.0000)	(0.0009)	(0.0031)	(0.0008)
LnEmploy	0.0137***	0.0146***	0.0142***	0.0139***	0.0140***	0.0136***	0.0136***	0.0061***	0.0139***	0.0141***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0011)	(0.0008)	(0.0008)

Table 19 (continued)

Dep.Variable	(1) NZIA	(2) NZIA	(3) NZIA	(4) NZIA	(5) NZIA	(6) NZIA	(7) NZIA	(8) NZIA	(9) NZIA	(10) NZIA
Age	−0.0032**	−0.0035**	−0.0042***	−0.0029**	−0.0045***	−0.0032**	−0.0025*	−0.0040***	−0.0029**	−0.0031**
	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Age^2	0.0004***	0.0004***	0.0005***	0.0004**	0.0004***	0.0004***	0.0003*	0.0004***	0.0003**	0.0004**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
HHI	0.0408***	0.0422***	0.0439***	0.0458***	0.0413***	0.0403***	0.0452***	0.0356***	0.0379***	0.0470***
	(0.0080)	(0.0074)	(0.0082)	(0.0081)	(0.0082)	(0.0080)	(0.0082)	(0.0093)	(0.0082)	(0.0083)
LnGDP	0.0038***	0.0036***	0.0039***	0.0037***	0.0040***	0.0038***	0.0043***	0.0028**	0.0036***	0.0038***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Obs	33,371	33,068	33,068	33,068	33,218	33,371	32,558	30,851	32,841	32,512
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.153	0.160	0.157	0.156	0.157	0.153	0.153	0.165	0.153	0.156
Mean VIF	1.95	1.97	1.97	1.95	1.93	1.91	1.93	2.00	1.92	1.96

The table reports the marginal effects from Probit regressions where the dependent variable is a dummy equal to 1 if a firm adopts NZIA-related technologies, and 0 otherwise. Columns (2) to (10) include different financial and performance-related drivers: leverage ratio (*LevRatio*), short-term debt (*ShortDebt*), long-term debt (*LongDebt*), equity (*Equity*), return on assets (*ROA*), return on equity (*ROE*), sales growth (*SalesGrowth*), logarithm of EBITDA (*LnEBITDA*), and liquidity index (*Liq_Index*). All regressions control for firm size (*LnEmploy*), firm age and its square (*Age, Age^2*), market concentration (*HHI*), and GDP at the regional level (*LnGDP*). Sector and regional fixed effects are included throughout. Standard errors (in brackets) are robust. Pseudo R^2 statistics and mean variance inflation factors (*VIF*) are reported at the bottom of the table. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

Table 20 Organizational and relational drivers, knowledge and human capital drivers of firms adopting net-zero technologies (SMEs versus Large Companies)

Dep.Variable	(1) NZIA	(2) NZIA	(3) NZIA	(4) NZIA	(5) NZIA	(6) NZIA	(7) NZIA
Driver =	*District*	*FamilyD*	*FamilyG*	*Duration*	*%STEM*	*DurationSTEM*	*Age_manager*
PANEL A: SMEs							
Driver	−0.0028**	−0.0035***	−0.0028**	−0.0004***	0.0281***	0.0123	0.0001
	(0.0014)	(0.0011)	(0.0011)	(0.0001)	(0.0095)	(0.0143)	(0.0001)
LnEmploy	0.0085***	0.0083***	0.0084***	0.0079***	0.0084***	0.0085***	0.0037***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0008)
Age	−0.0029***	−0.0030***	−0.0030***	−0.0019*	−0.0029***	−0.0029***	−0.0031**
	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0013)
Age^2	0.0003**	0.0003**	0.0003**	0.0002	0.0003**	0.0003**	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
HHI	0.0058	0.0058	0.0058	0.0057	0.0059	0.0059	0.0096
	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0069)
LnGDP	0.0025***	0.0029***	0.0029***	0.0029***	0.0029***	0.0029***	0.0022***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
Obs	70,815	70,815	70,815	70,815	70,815	70,815	42,461
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.104	0.104	0.104	0.105	0.104	0.104	0.0823
Mean VIF	2.11	2.06	2.07	2.12	2.06	2.06	2.11
PANEL B: LARGE COMPANIES							
Driver	0.0010	−0.0115***	−0.0097***	−0.0011***	0.0565***	0.0758***	0.0002
	(0.0027)	(0.0023)	(0.0022)	(0.0002)	(0.0097)	(0.0149)	(0.0001)
LnEmploy	0.0137***	0.0131***	0.0132***	0.0121***	0.0131***	0.0131***	0.002
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0016)

Table 20 (continued)

Dep.Variable	(1) NZIA	(2) NZIA	(3) NZIA	(4) NZIA	(5) NZIA	(6) NZIA	(7) NZIA
Age	−0.0032**	−0.0035***	−0.0035***	−0.0025*	−0.0031**	−0.0031**	−0.0033*
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0017)
Age^2	0.0004***	0.0004***	0.0004***	0.0003**	0.0004***	0.0004***	0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
HHI	0.0408***	0.0407***	0.0408***	0.0402***	0.0394***	0.0394***	0.0409***
	(0.0080)	(0.0080)	(0.0080)	(0.0081)	(0.0080)	(0.0080)	(0.0081)
LnGDP	0.0039***	0.0036***	0.0037***	0.0036***	0.0035***	0.0035***	0.0010
	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0015)
Obs	33,371	33,371	33,371	33,371	33,371	33,371	15,816
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.153	0.155	0.155	0.155	0.155	0.155	0.114
Mean VIF	1.95	1.91	1.91	1.93	1.91	1.91	1.97

The table reports the marginal effects from Probit regressions where the dependent variable is a dummy equal to 1 if a firm adopts NZIA-related technologies, and 0 otherwise. Each column includes a different driver: presence in an industrial district (*District*), ownership by a family group (*FamilyG*), direct family ownership (*FamilyD*), duration of employee tenure (*Duration*), share of STEM graduates among employees *(%STEM*), duration of STEM employees (DurationSTEM), and age of the manager (*Age_manager*). All regressions include controls for firm size (*LnEmploy*), firm age and its square (*Age, Age^2*), market concentration (*HHI*), and regional GDP (*LnGDP*). Sector and regional fixed effects are included in all specifications. Standard errors (in brackets) are robust. Pseudo R^2 statistics and mean variance inflation factors (*VIF*) are reported at the bottom of the table. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively that the accumulation of technical leadership experience plays a more decisive role in complex adoption environments typical of larger organizational structures.

Tables 21 and 22 report additional results for large firms vs. SMEs developing NZIA-related technologies. While SMEs represent the majority of firms in the overall sample, developers are concentrated among large companies. This size asymmetry already suggests that engaging in the development of net-zero technologies—rather than their mere adoption—requires organizational and financial capacities that are more frequently observed among larger firms.

Indeed, the estimated patterns largely mirror those observed in the full sample of developers, but the disaggregation by firm size reveals important nuances. In particular, financial and profitability drivers play a limited role for SMEs, whereas they are central for large firms. Among SMEs, none of the financial variables, including leverage, debt maturity, equity, or profitability indicators, significantly affects the probability of developing net-zero technologies. This suggests that, for smaller firms, financial constraints or performance do not systematically translate into development engagement, possibly reflecting structural barriers that go beyond balance-sheet conditions.

By contrast, for large companies, several financial and performance-related variables emerge as significant. *LongDebt* and *LnEBITDA* are positively associated with the likelihood of developing net-zero technologies, indicating that access to stable financing and higher operating margins support long-horizon, innovation-intensive investments. At the same time, return on assets (*ROA*) displays a negative and significant effect, pointing to a trade-off between short-term asset efficiency and engagement in complex technological development. Altogether, these results reinforce the idea that net-zero development requires financial slack and long-term planning capacities that are primarily available to large firms, while SMEs appear largely excluded from this margin.

A similar size-dependent pattern emerges when considering organizational, relational, and human capital drivers (Table 22). For large firms, both *%STEM* and *DurationSTEM* exert a positive and significant effect on the probability of being net-zero developers. This finding is fully consistent with the results observed for adopters and with the aggregate developer sample, but it is clearly driven by large firms. Economies of scale, economies of scope, and internal labour markets allow these firms to accumulate and retain specialized skills, which in turn increase their ability to develop net-zero technologies. For SMEs, by contrast, human capital variables do not display statistically significant effects.

One result that clearly differentiates SMEs from large firms concerns industrial district membership. For SMEs, belonging to an industrial district is negatively and significantly associated with the probability of developing NZIA-related technologies. This finding strengthens the interpretation already discussed above and indicates that industrial districts do not represent the primary organizational locus of innovation for net-zero technology development. This pattern further suggests a misalignment between the organizational and coordination requirements of NZIA-related technological development and the traditional innovation mechanisms characterizing industrial districts.

Table 21 Financial drivers and profitability drivers of firms developing net-zero technologies (SMEs versus Large Companies)

Dep.Variable	(1) D_IPC_NZIA	(2) D_IPC_NZIA	(3) D_IPC_NZIA	(4) D_IPC_NZIA	(5) D_IPC_NZIA	(6) D_IPC_NZIA	(7) D_IPC_NZIA	(8) D_IPC_NZIA	(9) D_IPC_NZIA	(10) D_IPC_NZIA
Driver =		*LevRatio*	*ShortDebt*	*LongDebt*	*Equity*	*ROA*	*ROE*	*LnEBITDA*	*SalesGrowth*	*Liq_Index*
PANEL A: SMEs										
Driver		−0.0555	−0.0021	0.1338	−0.0356	−0.0005	−0.0008	−0.0050	−0.0672	0.0194
		(0.1137)	(0.1288)	(0.1802)	(0.1136)	(0.0015)	(0.0010)	(0.0263)	(0.0625)	(0.0181)
LnEmploy	0.0290	0.0254	0.0256	0.0273	0.0256	0.0296	0.0268	0.0350	0.0319	0.0294
	(0.0202)	(0.0206)	(0.0204)	(0.0206)	(0.0204)	(0.0203)	(0.0206)	(0.0346)	(0.0208)	(0.0209)
Age	−0.0064	−0.0033	−0.0039	−0.0040	−0.0045	−0.0049	−0.0004	−0.0071	−0.0105	0.0023
	(0.0422)	(0.0419)	(0.0420)	(0.0421)	(0.0420)	(0.0425)	(0.0429)	(0.0445)	(0.0432)	(0.0421)
Age^2	0.0003	0.0004	0.0004	0.0004	0.0005	0.0001	−0.0002	0.0006	0.0004	−0.0003
	(0.0049)	(0.0048)	(0.0049)	(0.0049)	(0.0049)	(0.0050)	(0.0050)	(0.0051)	(0.0050)	(0.0048)
HHI	0.4106*	0.3275	0.3415	0.3328	0.3346	0.4163*	0.3391	0.3995*	0.4451*	0.3612
	(0.2291)	(0.2274)	(0.2291)	(0.2303)	(0.2303)	(0.2305)	(0.2313)	(0.2397)	(0.2353)	(0.2291)
LnGDP	0.0167	0.0096	0.0099	0.0111	0.0091	0.0178	0.0153	0.0139	0.0204	0.0089
	(0.0288)	(0.0292)	(0.0291)	(0.0290)	(0.0289)	(0.0289)	(0.0291)	(0.0299)	(0.0292)	(0.0295)
Obs	433	429	429	429	429	433	417	394	425	423
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0483	0.0483	0.0477	0.0486	0.0479	0.0486	0.0498	0.0483	0.0525	0.0455
Mean VIF	2.18	2.14	2.14	2.14	2.14	2.15	2.16	2.33	2.15	2.19
PANEL B: LARGE COMPANIES										
Driver		−0.0238	−0.1504	0.2816**	0.0696	−0.0041**	−0.0009	0.0404**	−0.0510	0.0087
		(0.0847)	(0.0930)	(0.1340)	(0.0834)	(0.0019)	(0.0009)	(0.0172)	(0.0335)	(0.0156)

Table 21 (continued)

Dep.Variable	(1) D_IPC_NZIA	(2) D_IPC_NZIA	(3) D_IPC_NZIA	(4) D_IPC_NZIA	(5) D_IPC_NZIA	(6) D_IPC_NZIA	(7) D_IPC_NZIA	(8) D_IPC_NZIA	(9) D_IPC_NZIA	(10) D_IPC_NZIA
LnEmploy	0.0541***	0.0539***	0.0554***	0.0513***	0.0556***	0.0547***	0.0558***	0.0306	0.0571***	0.0543***
	(0.0110)	(0.0113)	(0.0111)	(0.0112)	(0.0111)	(0.0109)	(0.0111)	(0.0209)	(0.0117)	(0.0116)
Age	−0.0345	−0.0318	−0.0331	−0.0257	−0.0360	−0.0305	−0.0260	−0.0555*	−0.0381	−0.0252
	(0.0260)	(0.0270)	(0.0264)	(0.0261)	(0.0262)	(0.0249)	(0.0263)	(0.0329)	(0.0259)	(0.0256)
Age^2	0.0038	0.0036	0.0036	0.0031	0.0039	0.0034	0.0033	0.0064*	0.0039	0.0027
	(0.0025)	(0.0026)	(0.0026)	(0.0025)	(0.0025)	(0.0023)	(0.0025)	(0.0034)	(0.0024)	(0.0024)
HHI	0.3520***	0.3545***	0.3244***	0.3354***	0.3387***	0.3290***	0.3553***	0.3580***	0.3208***	0.3674***
	(0.1050)	(0.1102)	(0.1064)	(0.1059)	(0.1052)	(0.1056)	(0.1053)	(0.1298)	(0.1092)	(0.1088)
LnGDP	0.0471*	0.0460*	0.0474*	0.0466*	0.0470*	0.0465*	0.0470*	0.0572**	0.0430*	0.0434*
	(0.0247)	(0.0246)	(0.0248)	(0.0246)	(0.0248)	(0.0246)	(0.0249)	(0.0269)	(0.0252)	(0.0250)
Obs	629	625	625	625	628	629	620	528	606	613
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0713	0.0677	0.0708	0.0724	0.0719	0.0782	0.0736	0.0932	0.0675	0.0674
Mean VIF	1.78	1.91	1.91	1.91	1.76	1.75	1.90	2.08	1.75	1.88

The table reports the marginal effects from Probit regressions where the dependent variable is a dummy equal to 1 if a firm develops NZIA-related technologies, and 0 otherwise. Columns (2) to (10) include different financial and performance-related drivers: leverage ratio (*LevRatio*), short-term debt (*ShortDebt*), long-term debt (*LongDebt*), equity (*Equity*), return on assets (*ROA*), return on equity (*ROE*), sales growth (*SalesGrowth*), logarithm of EBITDA (*LnEBITDA*), and liquidity index (*Liq_Index*). All regressions control for firm size (*LnEmploy*), firm age and its square (*Age*, Age^2), market concentration (*HHI*), and GDP at the regional level (*LnGDP*). Sector and regional fixed effects are included throughout. Standard errors (in brackets) are robust. Pseudo R^2 statistics and mean variance inflation factors (*VIF*) are reported at the bottom of the table. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

Table 22 Organizational and relational drivers, knowledge and human capital drivers of firms developing net-zero technologies (SMEs versus Large Companies)

Dep.Variable	(1) D_IPC_NZIA	(2) D_IPC_NZIA	(3) D_IPC_NZIA	(4) D_IPC_NZIA	(5) D_IPC_NZIA	(6) D_IPC_NZIA	(7) D_IPC_NZIA
Driver =	*District*	*FamilyD*	*FamilyG*	*Duration*	*%STEM*	*DurationSTEM*	*Age_manager*
PANEL A: SMEs							
Driver	−0.1627***	−0.0449	−0.0349	−0.0031	0.0706	0.3462	0.0085
	(0.0559)	(0.0477)	(0.0475)	(0.0048)	(0.2194)	(0.7067)	(0.0057)
LnEmploy	0.0315	0.0265	0.0273	0.0231	0.0298	0.0303	0.0125
	(0.0199)	(0.0205)	(0.0205)	(0.0224)	(0.0204)	(0.0204)	(0.0458)
Age	−0.0087	−0.0023	−0.0038	−0.0025	−0.0075	−0.0087	0.1215
	(0.0422)	(0.0425)	(0.0424)	(0.0428)	(0.0424)	(0.0425)	(0.0899)
Age^2	0.0004	−0.0002	−0.0001	−0.0001	0.0004	0.0005	−0.0126
	(0.0049)	(0.0050)	(0.0050)	(0.0050)	(0.0049)	(0.0049)	(0.0124)
HHI	0.4122*	0.4257*	0.4234*	0.4205*	0.4094*	0.4088*	−0.0146
	(0.2289)	(0.2305)	(0.2305)	(0.2289)	(0.2293)	(0.2294)	(0.3912)
LnGDP	−0.0136	0.0180	0.0179	0.0170	0.0171	0.0175	−0.0301
	(0.0299)	(0.0287)	(0.0287)	(0.0288)	(0.0288)	(0.0288)	(0.0483)
Obs	433	433	433	433	433	433	113
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0621	0.0499	0.0493	0.0491	0.0485	0.0487	0.101
Mean VIF	2.20	2.15	2.14	2.17	2.14	2.15	2.44
PANEL B: LARGE COMPANIES							
Driver	−0.0473	−0.0401	−0.0508	−0.0007	0.3937**	0.7029*	−0.0056
	(0.0498)	(0.0457)	(0.0441)	(0.0062)	(0.1676)	(0.3768)	(0.0080)
LnEmploy	0.0535***	0.0525***	0.0523***	0.0535***	0.0472***	0.0442***	0.0464
	(0.0110)	(0.0111)	(0.0111)	(0.0120)	(0.0115)	(0.0119)	(0.0482)

Table 22 (continued)

Dep.Variable	(1) D_IPC_NZIA	(2) D_IPC_NZIA	(3) D_IPC_NZIA	(4) D_IPC_NZIA	(5) D_IPC_NZIA	(6) D_IPC_NZIA	(7) D_IPC_NZIA
Age	−0.0330	−0.0347	−0.0343	−0.0344	−0.0337	−0.0323	0.1752**
	(0.0258)	(0.0260)	(0.0259)	(0.0260)	(0.0258)	(0.0260)	(0.0793)
Age^2	0.0037	0.0038	0.0038	0.0038	0.0038	0.0037	-0.0143*
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0079)
HHI	0.3478***	0.3570***	0.3572***	0.3515***	0.3285***	0.3205***	0.2449
	(0.1050)	(0.1048)	(0.1047)	(0.1049)	(0.1059)	(0.1063)	(0.1833)
LnGDP	0.0356	0.0458*	0.0450*	0.0474*	0.0418*	0.0397	0.0684
	(0.0274)	(0.0247)	(0.0247)	(0.0248)	(0.0245)	(0.0246)	(0.0737)
Obs	629	629	629	629	629	629	108
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0723	0.0722	0.0728	0.0713	0.0803	0.0818	0.129
Mean VIF	1.82	1.76	1.76	1.77	1.76	1.77	2.95

The table reports the marginal effects from Probit regressions where the dependent variable is a dummy equal to 1 if a firm develops NZIA-related technologies, and 0 otherwise. Each column includes a different driver: presence in an industrial district (*District*), ownership by a family group (*FamilyG*), direct family ownership (*FamilyD*), duration of employee tenure (*Duration*), share of STEM graduates among employees *(%STEM)*, duration of STEM employees (DurationSTEM), and age of the manager (*Age_manager*). All regressions include controls for firm size (*LnEmploy*), firm age and its square (*Age, Age^2*), market concentration (*HHI*), and regional GDP (*LnGDP*). Sector and regional fixed effects are included in all specifications. Standard errors (in brackets) are robust. Pseudo R^2 statistics and mean variance inflation factors (*VIF*) are reported at the bottom of the table. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

6 Research and Policy Implications

6.1 Discussion

Based on these findings, this paper contributes to the growing literature that exploits corporate websites to study firms' engagement with innovation and emerging technologies. A central insight of this strand of research is that web-based data provide timely and granular information on technological engagement that often remains invisible to conventional indicators such as financial data, patents, or surveys. Consistent with this literature (e.g., Kinne et al. 2024; Kinne and Lenz 2021; Ashouri et al. 2022), our large-scale mapping of NZIA-related technologies shows that web-scraped signals are particularly effective in capturing technology adoption, revealing a broad layer of firms interacting with net-zero technologies that would otherwise remain unobserved. This evidence aligns with the notion of "local digital footprints" proposed by Nathan and Rosso (2015) and further developed by Stich et al. (2022).

At the same time, our results highlight an important limitation of relying on web-based indicators alone. While corporate websites are well suited to identifying adoption and outward-facing technological engagement, they provide limited information on firms' involvement in the development of new technologies. A key contribution of this study is therefore the explicit distinction between adopters and developers, a taxonomy that remains largely underdeveloped in the existing literature. Although previous contributions have proposed alternative firm classifications (e.g., manufacturers versus service providers in Schwierzy et al. (2022), or product versus process digitalization in Ashouri et al. (2022)), web-based signals are often treated as an exhaustive proxy for innovation activity. By integrating patent data, we show that while the web "unhides" a vast population of adopters, patent-based indicators remain essential to identify firms engaged in the development of proprietary technological knowledge (Tseng et al. 2007).

This distinction proves to be economically meaningful. Firm-level patterns among adopters broadly align with earlier findings in the web-based innovation literature, notably the positive association with firm size and the non-linear relationship with firm age. However, once the focus shifts to developers, these turn out to be firms that tend to be more established, better capitalized, and endowed with stronger internal capabilities. This result underscores that adoption and development respond to different constraints and incentives and should not be mixed, either empirically or conceptually.

Our geographical and sectoral evidence further reinforces this interpretation. The strong concentration of NZIA-related development activities in Northern Italian regions mirrors patterns documented in the literature on green and digital innovation systems, where innovation tends to cluster in areas characterized by dense industrial ecosystems and accumulated technological capabilities. For instance, Kriesch et al. (2025) show that German green-digital firms tend to co-locate in specific regional clusters. Similarly, the prominence of the Italian North-East reflects the role of historical industrial specialization and pre-existing manufacturing capabilities, in line with studies on spatially embedded innovation processes. This finding aligns with the literature on innovation clusters and spatially embedded innovation processes (Singh et al. 2023; Schwierzy et al. 2022), which highlights the importance of proximity to technical universities, lead users, and specialised supply chains. However, our findings also indicate that the mere presence of industrial districts is not sufficient to foster net-zero technology development, particularly for SMEs. These challenges simplified cluster-based views of innovation and suggest that firm-specific internal resources—rather than local spillovers alone—are decisive for engagement in high-risk, capital-intensive net-zero technologies.

From a sectoral perspective, manufacturing firms play a central role in technological development, while service firms are more prevalent among adopters. This asymmetry is consistent with evidence showing that manufacturing firms tend to signal technical competences through their websites, whereas service firms more often communicate adoption of advanced technologies (Bottai et al. 2024). Overall, these results confirm that web-based indicators capture meaningful heterogeneity in firms' modes of engagement, but also that such heterogeneity must be interpreted carefully when inferring innovative roles.

The firm-level patterns identified among NZIA adopters are largely consistent with earlier web-based studies. In line with Mazzoni et al. (2024) and Thonipara et al. (2023), we find a strong positive association between adoption and firm size, reflecting greater digital visibility and communication capacity among larger firms. Moreover, the relationship between adoption and firm age displays a non-linear (U-shaped) pattern, suggesting that both young and incumbent firms engage with emerging technologies through distinct channels. Younger firms benefit from agility and strategic positioning in dynamic markets, while older firms rely on accumulated resources and established market positions. These findings are consistent with studies using website-based indicators to detect engagement with advanced technologies. However, this pattern does not extend to technological development. Focusing on developers reveals a markedly different firm profile: they are generally more established and capital-intensive, indicating that the development of net-zero technologies is concentrated among firms with the financial capacity to sustain long and risky R&D activities, while younger firms tend to be adopters.

Financial conditions play a central role in shaping this divide. Our findings show that leverage and economic performance exert a decisive, albeit contrasting, effect on adoption and development, highlighting capital constraints as a primary bottleneck for investments related to the green transition. This result challenges approaches that treat web signals as a comprehensive indicator of innovation (e.g. Ashouri et al. 2024), as it demonstrates that a visible "green" digital presence must be supported by solid financial fundamentals to translate into genuine technological advancement.

A further contribution of our study concerns the role of industrial districts and regional specialization. While the literature often emphasizes the innovation-enhancing role of clusters through shared infrastructures and knowledge spillovers (Singh et al. 2023; Kriesch et al. 2025), our evidence finds that district affiliation does not significantly increase the likelihood of being a developer, particularly for SMEs. This complements traditional cluster-based narratives (e.g. Kinne et al. 2024; Wildnerova et al. 2024; Schwierzy et al. 2022) and suggests that, in the context of high-tech NZIA development, geographical proximity alone is insufficient. Instead, development appears to be driven primarily by firm-specific internal capabilities rather than by potential localized spillovers.

Human capital represents a key component of these internal capabilities. While a basic level of digitalization may be sufficient to support adoption (Mazzoni et al. 2024), the availability of high-skilled human capital—especially STEM competencies—emerges as a critical determinant of technological development. This finding extends the insights of Bottai et al. (2024), indicating that innovativeness is not only signalled by the firm's digital presence, but depends on the quality of its internal knowledge base and its ability to transform information into patentable innovation.

These results are particularly relevant for SMEs. While some studies suggest that the innovative activity of manufacturing SMEs can be effectively captured through digital traces (Bottai et al. 2024 among others), Thonipara et al. (2023) point to a persistent "digital divide" driven by resource constraints. Our evidence reconciles these views by showing that SMEs may appear as adopters of net-zero technologies in web-based data yet remain structurally constrained in moving towards development due to limited access to finance and shortages of specialized skills.

Taken together, our findings support and extend the web-based innovation literature by confirming both its strengths and its limitations. Website data provide a timely and scalable tool to map technology adoption and to identify spatial and sectoral patterns of engagement with emerging technologies. Nevertheless, they remain an imperfect proxy for technological development, reinforcing the need for multi-source approaches that combine unstructured web information with structured indicators such as patents. We show that this combination yields a more nuanced and accurate picture of firms' engagement with net-zero technologies. Further, we demonstrate that distinguishing between adoption and development is crucial for understanding green innovation systems and for designing effective industrial policies, as policies aimed at accelerating adoption cannot be expected to automatically foster domestic technological development.

6.2 Policy Implications

Our insights have direct and policy-relevant implications for both research and policy. From a research perspective, we highlight four main contributions. First, we demonstrate how the integration of unconventional web-based indicators with structured firm-level data is particularly valuable in emerging technological domains, where traditional indicators often fail or are delayed. Second, our contribution highlights that the web scraping methodology provides a valuable tool for mapping firms adopting net-zero technologies, but it falls short when it comes to identifying developers. The use of patent data is necessary to better identify developers of net-zero technologies. Third, we discover the existence of geographical, sectoral, and organizational patterns: this confirms the relevance of place-based and path-dependency perspectives in regional and innovation studies and highlights the role of local ecosystems, sectoral specialization, and firm structures in enabling the net-zero transition. Fourth, our evidence outlines how the same factors act differently when firms engage in adoption of net-zero technologies rather than development.

From a policy view, a central message emerging from our analysis is that engagement with net-zero technologies is highly heterogeneous, and that policies aimed at accelerating the net-zero transition should explicitly distinguish between technology adoption and technological development. First, policies supporting the adoption of net-zero technologies should move beyond uniform and technology-neutral measures. Firms participate in the net-zero transition through different roles, face distinct constraints, and respond to different incentives. Treating adopters and developers as a homogeneous group risks generating ineffective or misdirected interventions. Instead, an effective policy mix requires differentiated and coordinated instruments tailored to firms' technological roles, financial structures, and local production environments.

Second, the financial dimension emerges as a key axis for policy differentiation. Developers rely more heavily on long-term and equity-based financing, reflecting the capital intensity, risk exposure, and long investment horizons associated with the creation of new net-zero technologies. By contrast, adopters tend to face tighter financial constraints and depend more strongly on standard debt instruments. This heterogeneity implies that financial policies should be explicitly role-specific. Patient capital, equity-like instruments, and blended public–private financing schemes are better suited to support developers, while loan guarantees, subsidized long-term credit, and adoption-linked tax incentives are more appropriate for facilitating technology uptake among adopters, particularly SMEs.

These insights are especially relevant in light of recent developments in the European monetary, supervisory, and banking framework, which increasingly emphasize the role of sustainable finance in supporting the green transition. As climate-related risks and sustainability considerations are progressively integrated into banking regulation, financial institutions are becoming more inclined to provide long-term financing for green investments—especially when supported by public guarantees or aligned with EU standards. Our results suggest that this evolving financial landscape can be effectively leveraged to support NZIA objectives, provided that financial instruments are aligned with firms' roles within the net-zero ecosystem. While developers require long-term capital and risk-sharing mechanisms to address technological uncertainty, adopters—particularly SMEs—benefit most from policies that ease access to long-term bank credit and reduce adoption risk.

Third, financial constraints are closely intertwined with human capital bottlenecks. Technological development is significantly more skill-intensive than adoption, underscoring the central role of STEM-related competencies and advanced managerial capabilities. This evidence speaks directly to the human capital pillar of the Net-Zero Industry Act, including the establishment of Net-Zero Industry Academies and EU-wide reskilling and upskilling initiatives. Importantly, our results suggest that investments in STEM education and managerial reskilling should be viewed as targeted complements to financial support instruments. By alleviating skill constraints, such initiatives enhance firms' capacity to absorb public funding, scale up production, and translate financial support into effective technological development and deployment.

Fourth, our evidence on industrial districts highlights a more nuanced role for place-based policies. While districts are often considered engines of innovation due to localized spillovers and shared infrastructures, district membership alone does not increase the likelihood of developing net-zero technologies, especially for SMEs. This suggests the presence of technological lock-ins, whereby existing production structures and competences are misaligned with the requirements of the net-zero transition. In this context, place-based policies should not simply reinforce existing district configurations, but actively support their upgrading and transformation. Investments in shared R&D, testing and certification facilities, collective training programs, and the modernization of district-level infrastructure are crucial to prevent district membership from becoming a constraint. Such interventions can help turn districts into platforms for coordinated adoption of NZIA-compliant technologies, particularly benefiting SMEs.

Finally, while the Net-Zero Industry Act is primarily a supply-side industrial policy, it explicitly acknowledges the role of public demand in supporting the scale-up and deployment of net-zero technologies. In this context, green public procurement can act as a lead-market mechanism, reducing demand uncertainty and facilitating the transition from development to large-scale adoption. Our results indicate that this channel is particularly relevant given firms' heterogeneous roles. For developers, procurement contracts can provide stable long-term demand, complementing equity-based and long-horizon financing. For adopters—especially SMEs—public procurement can lower adoption risks by setting technical standards and providing predictable market signals. Moreover, procurement aligned with NZIA objectives can function as a coordination device within production networks, encouraging large firms to act as anchor buyers and technology integrators, thereby fostering adoption along supply chains.

Overall, the policy implications of our findings point to the need for a differentiated and coordinated policy mix. Accelerating the net-zero transition requires policies that explicitly recognize the distinction between adoption and development, align financial and human capital instruments accordingly, and combine place-based and demand-side interventions to support the net-zero industrial ecosystems.

7 Conclusion

This paper provides a firm-level analysis of the adoption and development of net-zero technologies in Italy within the policy framework of the Net-Zero Industry Act (NZIA). By combining unstructured textual information from corporate websites with structured patent and firm-level data, we propose a scalable and policy-relevant approach to observe technological engagement in contexts where conventional innovation indicators are insufficient.

From a methodological perspective, our results highlight a clear distinction between adoption and development and contribute to the growing literature on the use of digital traces in innovation studies by demonstrating both the potential and the limits of web-based data. While web scraping proves highly effective in identifying firms that adopt net-zero technologies, only the integration of web-based information with patent data allows a precise and conceptually consistent identification of net-zero developers. This integrated framework offers a novel and scalable tool for mapping firms' innovative roles in emerging technological domains.

Empirically, we show that adoption is relatively widespread but unevenly distributed across territories (e.g., Northern Italy), industry sectors (e.g., technologically intensive industries, specialized manufacturing and energy), and firm characteristics (e.g., larger ones), whereas development is concentrated among a narrower group of firms characterized by stronger financial capacity, larger size, and higher levels of human capital (e.g., high-skilled environments, managers with STEM backgrounds).

Importantly, SMEs show distinct patterns. While smaller firms are less likely to engage in development compared with larger, resource-rich companies, they can be highly agile adopters of net-zero technologies, particularly when supported by targeted policies. This suggests that SME-oriented policies should focus on reducing adoption barriers through subsidized credit, fiscal incentives, and knowledge-sharing networks, while development-oriented support (such as equity-like financing and specialized training programs) may be crucial to enable SMEs to move from adoption toward technology development.

This paper highlights key policy implications. Failing to distinguish between developers and adopters may lead to misdirected and less effective interventions. Developers face distinct constraints, requiring targeted support such as long-term and equity-like finance, advanced STEM skills (and initiatives like the Net-Zero Industry Academies), and attention to territorial and sectoral contexts. By contrast, adoption benefits more from subsidised credit, guarantees, fiscal incentives, and demand-side measures. The findings support place-based and technology-specific policies tailored to firms' roles within the NZIA ecosystem.

This study represents a first empirical contribution to the study of the adoption and development of net-zero technologies in Italy and opens several avenues for future research. Extending the analysis to a cross-country setting would allow comparative assessments of how different productive structures and policy environments shape adoption and development patterns. Further, exploiting the longitudinal dimension of corporate websites could offer new insights into the dynamics of technological transition. Lastly, while our web scraping strategy is designed to capture the presence of net-zero technology adoption rather than its intensity, future research could exploit information on website size and structure to construct normalised, intensity-based indicators, potentially in combination with patent data. Overall, this paper offers a first tool for researchers and policymakers for monitoring and supporting the engagement of net-zero technologies in an increasingly dynamic industrial landscape.

Appendix

Appendix A – NZIA – Net-Zero Industry Act

The *Net-Zero Industry Act* (NZIA)–formally adopted as Regulation (EU) 2024/1735 and in force since 29 June 2024–constitutes a part of the European Green Deal

Industrial Plan.[15] As a regulatory instrument, it reflects a paradigm shift in EU climate and industrial policy: from fostering early-stage innovation to promoting the large-scale deployment of net-zero technologies. The NZIA seeks to bolster the EU's strategic autonomy in the clean tech sectors, enhance economic resilience, and support the industrial dimension of the green transition. It mirrors global efforts such as the United States' *Inflation Reduction Act* (IRA), underlining the increasingly geopolitical nature of clean technology leadership.[16]

The NZIA was introduced alongside the *Critical Raw Materials Act* (CRMA)[17] and the reform of the EU electricity market design,[18] within a broader policy package aimed at strengthening the competitiveness and technological sovereignty of the European cleantech industry. Its regulatory rationale is grounded in the rapid expansion of the global market for net-zero technologies–which reached an estimated value of $700 billion in 2023 and is projected to almost triple by 2035.[19] Within this context, the NZIA functions both as a policy signal and as an institutional framework guiding public and private investment toward a more geographically balanced industrial base for net-zero technologies across Europe.

A central feature of the NZIA is its explicit focus on industrial development, which directly positions firms as the primary agents of technological upgrading. The regulation identifies nineteen categories of net-zero technologies: solar photovoltaic and solar thermal technologies, onshore and offshore renewable technologies, battery/storage technologies, heat pumps and geothermal energy technologies, hydrogen technologies (including electrolysers and fuel cells), sustainable biogas/biomethane technologies, carbon capture and storage (CCS) technologies, grid technologies, nuclear fission energy technologies (including nuclear fuel cycle technologies), sustainable alternative fuels technologies, hydropower technologies, other renewable energy technologies, energy system-related energy efficiency technologies (including heat grid technologies), renewable fuels of non-biological origin

[15] Regulation (EU) 2024/1735 of the European Parliament and of the Council of 13 June 2024 on establishing a framework of measures for strengthening Europe's net-zero technology manufacturing ecosystem and amending Regulation (EU) 2018/1724. (see: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32024R1735). For technical details about the European Green Deal Industrial Plan see the *Communication from the commission to the European parliament, the European council, the council, the European economic and social committee and the committee of the regions* (https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52023DC0062).

[16] The *Net-Zero Industry Act* (NZIA) and the U.S. *Inflation Reduction Act* (IRA) both aim to accelerate the clean energy transition but differ in approach. The IRA provides substantial federal-level financial incentives, such as tax credits and subsidies, to stimulate clean technology markets. In contrast, the NZIA focuses on regulatory simplification, domestic production targets, and coordination of national funding, without major new EU financial commitments. While the IRA offers greater financial certainty to investors, the NZIA addresses structural barriers like permitting and skills gaps. Both prioritize key net-zero technologies but reflect distinct policy models: market-driven in the IRA and planning-oriented in the NZIA.

[17] For details about the CRMA see: https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2024)766253

[18] Reform of the electricity market design: https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2023)745694

[19] For further details, see the World Energy Outlook 2023 provided by International Energy Agency (https://www.iea.org/reports/world-energy-outlook-2023).

technologies, biotech climate and energy solutions, other transformative industrial technologies for decarbonization, CO2 transport and utilization technologies, wind propulsion and electric propulsion technologies for transport, other nuclear technologies.

Moreover, the regulation also establishes quantitative manufacturing benchmarks, such as the target of producing 40% of deployment needs domestically by 2030. These targets are not merely aspirational: they are supported by a suite of regulatory instruments designed to "download" the policy ambition onto firms, requiring them to adapt innovation processes, scale production capacity, and align with sustainability and resilience criteria in procurement markets.

From a sectoral perspective, the official policy documentation does not identify specific industrial sectors as eligible or ineligible for the programme, nor does it impose access restrictions based on sectoral classification. Rather than targeting predefined industries, the NZIA adopts a technology-based approach: while the regulation formally covers nineteen categories of net-zero technologies, it is highly restrictive in defining which technologies fall within the net-zero scope. Within this framework, particular emphasis is placed on a subset of technologies that are both commercially mature and critical for achieving the EU's 2030 climate and energy targets. These include, in particular, solar photovoltaic technologies, wind technologies (onshore and offshore), battery and storage technologies, heat pumps, electrolysers and fuel cells for hydrogen, grid technologies, and carbon capture and storage (CCS). These sectors are explicitly identified as strategic due to their high contribution to decarbonization, their relevance for energy security, and the EU's current or growing dependence on extra-EU suppliers. As a result, these technology domains constitute the core industrial targets of the NZIA and provide the main sectoral reference for our empirical analysis.

The NZIA also introduces complementary institutional mechanisms aimed at addressing structural bottlenecks. *Net-Zero Industry Academies* are designed to support workforce development through standardized training and credentialing, with Member States encouraged to mobilize resources from the European Social Fund Plus (ESF+). At the same time, the regulation promotes the creation of *Net-Zero Acceleration Valleys*—regionally concentrated industrial clusters in which permitting, infrastructure provision, and investment support are streamlined. These valleys are formally recognized as projects of public interest, reinforcing the spatial dimension of industrial transformation and the relevance of firm-level location data.

In addition, the NZIA regulation promotes regulatory sandboxes to support the testing and development of innovative technologies that are not yet commercially viable. These instruments are especially relevant for SMEs and start-ups, offering administrative assistance and regulatory flexibility and administrative support in controlled environments, potentially with cross-border collaboration. The inclusion of sandboxes underscores the NZIA's intention not only to support established firms but also to stimulate the emergence of new cleantech actors within the broader industrial ecosystem.

Consistent with the official regulatory framework set out in Regulation (EU) 2024/1735 and the Commission's explanatory memorandum, the NZIA is structured around a limited number of interrelated policy pillars that jointly define its industrial strategy. These pillars provide the analytical backbone of the regulation and clarify how regulatory simplification, market creation, and investment coordination are expected to translate into firm-level behavioural responses. Making these pillars explicit is essential for understanding both the scope of the policy intervention and the empirical strategy adopted in this paper.

Operationally, the implementation of the NZIA rests on four pillars (Tagliapietra et al. 2023), each of which has direct implications for firm behaviour and territorial dynamics:

1. Strategic Technology Prioritization, whereby a subset of technologies is designated as "strategic" based on their relevance for decarbonization, competitiveness, and supply security. This designation shapes the allocation of support and regulatory focus.
2. Manufacturing Benchmarks and Investment Signalling: by setting measurable targets, including CCS storage capacity, the regulation provides coordination tools for Member States and private investors.
3. Project-Based Governance and Spatial Targeting: Member States are required to identify Net-Zero Strategic Projects (NZSPs), which must involve near-market technologies and are expected to contribute both to EU climate goals and economic security. These projects are inherently territorial—as the policy explicitly seeks to create geographically anchored industrial clusters—and often embedded in existing or emerging industrial ecosystems.
4. Support Instruments and Incentive Alignment: the NZIA mandates administrative simplification (e.g., permitting acceleration, one-stop-shop procedures), incorporates sustainability criteria into public procurement (with preferential treatment for domestic suppliers), and promotes blended finance through existing instruments such as the EU Innovation Fund.[20] However, the regulation does not create new EU funding lines, relying instead on national support schemes within the updated *Temporary Crisis and Transition Framework* (TCTF).[21]

Public procurement plays a central role within this fourth pillar. The NZIA mandates the integration of sustainability and resilience criteria into public procurement procedures and renewable energy auctions, allowing such criteria to account for a substantial share of award scores. Procurement rules are explicitly designed to

[20] Specifically, this pillar focuses on three key areas: a) Permitting Acceleration – Simplified procedures with time limits and one-stop-shop authorities to speed up approvals; b) Market Access and Procurement – Public procurement must consider sustainability and resilience, with up to 30% weighting; bids relying heavily (> 65%) on non-EU technologies may be penalized; c) Funding Coordination – An estimated €92 billion is needed by 2030, mostly from private sources. While no new EU-level funds are introduced, existing tools like the EU Innovation Fund (financed through the EU Emissions Trading System) are leveraged, and national governments play a central funding role.

[21] The TCTF enables a) Enhanced support for disadvantaged regions, with caps adjusted based on location and firm size; b) Broader eligibility of aid forms, including tax benefits and guarantees, allowing coverage of operational expenditures (OPEX); c) Matching aid, to compete with foreign subsidies and attract investment within the EU, particularly in cohesion regions or cross-border projects. These provisions reflect a strategic response to global competition in cleantech and signify a more flexible European state aid regime.

favour suppliers whose production processes align with the NZIA's strategic objectives, including reduced environmental impact, enhanced supply-chain resilience, and lower dependence on non-EU technologies. This makes public procurement a central channel through which the NZIA shapes market access and competitive conditions for firms operating in targeted net-zero sectors.

Together, these four pillars summarise the NZIA's strategic rationale as identified in the policy debate (Tagliapietra et al. 2023) and operationalised in Regulation (EU) 2024/1735. While analytically distinct, they are mutually reinforcing and jointly define the technological, spatial, and institutional scope of the regulation.

APPENDIX B – List of keywords

See appendix Tables 23 and 24

APPENDIX C – Details about the LLM

LLM environment and model: The classification task is conducted using *Ollama*, an open-source framework for running Large Language Models locally. This choice ensures full control over model versions, prompts, and inference parameters, thereby enhancing reproducibility. The embedding model used for semantic matching is nomic-embed-text, which is specifically designed for high-quality text embeddings and semantic similarity tasks (see: *ollama pull nomic-embed-text*).

IPC preprocessing: IPC classification files were obtained from the World Intellectual Property Organization (WIPO) and provided in text format. After removing non-informative elements (headers, footnotes, page numbers), IPC codes and their official descriptions were extracted and stored in a structured text format. Each IPC entry consists of a 14-digit code and its corresponding textual definition.

Prompt structure: The LLM is prompted to match NZIA-related technologies with IPC codes based on official textual descriptions. A simplified version of the description from the official website is reported below:

While the general structure of the prompt is the following:

NZIA technology description:

"[Insert official NZIA technology definition]"

IPC descriptions:

"[Insert list of IPC codes with official descriptions]"

Question:

Which IPC codes are directly related to this NZIA technology?

Return a list of IPC codes and a short justification for each.

Robustness checks: To verify consistency, the same prompt was (i) repeated multiple times using the *Ollama* environment and (ii) replicated without modification using ChatGPT, Google Gemini, and Microsoft Copilot. The overlap in selected IPC codes across models exceeded 95%, and discrepancies were limited to marginal or borderline cases, which were resolved through manual inspection.

Table 23 List of net-zero technologies-related keywords used in the web scraping procedure

Net-zero technologies (EU Commission)	Keywords related to net-zero technologies
1) Solar photovoltaic and solar thermal technologies	solar; solar photovoltaics; solar thermal
2) Onshore and offshore renewable technologies	offshore renewable; onshore wind; ambient energy; osmotic energy
3) Battery/storage technologies	batteries; energy storage; battery technologies; storage technologies
4) Heat pumps and geothermal energy technologies	thermal energy; geothermal energy; heat pumps
5) Hydrogen technologies (including electrolysers and fuel cells)	hydrogen; fuel cells; electrolysers;
6) Sustainable biogas/biomethane technologies	sustainable biogas; biogas; biomethane; landfill gas; sewage gas
7) Carbon capture and storage (CCS) technologies	carbon capture; carbon storage; CCS; CCU
8) Grid technologies	smart grids; electricity grid; power generation
9) Nuclear fission energy technologies (including nuclear fuel cycle technologies)	nuclear fuel; nuclear fusion; nuclear fission; radiological enrichment; radiological recycling
10) Sustainable alternative fuels technologies	new fuels; sustainable alternative fuels; sustainable propulsion
11) Hydropower technologies	hydropower technologies
12) Other renewable energy technologies	renewable energy; biomass
13) Energy system-related energy efficiency technologies (including heat grid technologies)	heat grid; sewage treatment plant; energy efficiency technologies
14) Renewable fuels of non-biological origin technologies	renewable fuels
15) Biotech climate and energy solutions	energy efficiency technologies; bio-based chemical production; biomaterials production technologies
16) Other transformative industrial technologies for decarbonization	decarbonisation; net-zero technologies; safe and sustainable
17) CO_2 transport and utilization technologies	CO_2 transport technologies
18) Wind propulsion and electric propulsion technologies for transport	wind propulsion; electric charging; electric propulsion
19) Other nuclear technologies	nuclear reactor; reactors; radiation sensing; radiological conversion

Table reports the list of keywords related to net-zero technologies that were used in the web scraping procedure. Each keyword is presented in its singular and plural form to ensure comprehensive coverage of variations that may appear in online content

Table 24 List of innovation-related keywords used in the web scraping procedure

Keywords related to development (innovation) capabilities	
Patent	trademark
Research centre	research and development (R&D)
Technology innovation	in-house R&D
Proprietary technologies	patented
Utility model	intellectual property

Table reports the list of keywords related to development capabilities (to identify developers) that were used in the web scraping procedure. Each keyword is presented in its singular and plural form to ensure comprehensive coverage of variations that may appear in online content

APPENDIX D – Sectoral details

See appendix Fig. 9

APPENDIX E – Net-zero adoption process: different specifications and estimators

See appendix Figs. 9, 10 and Table 25

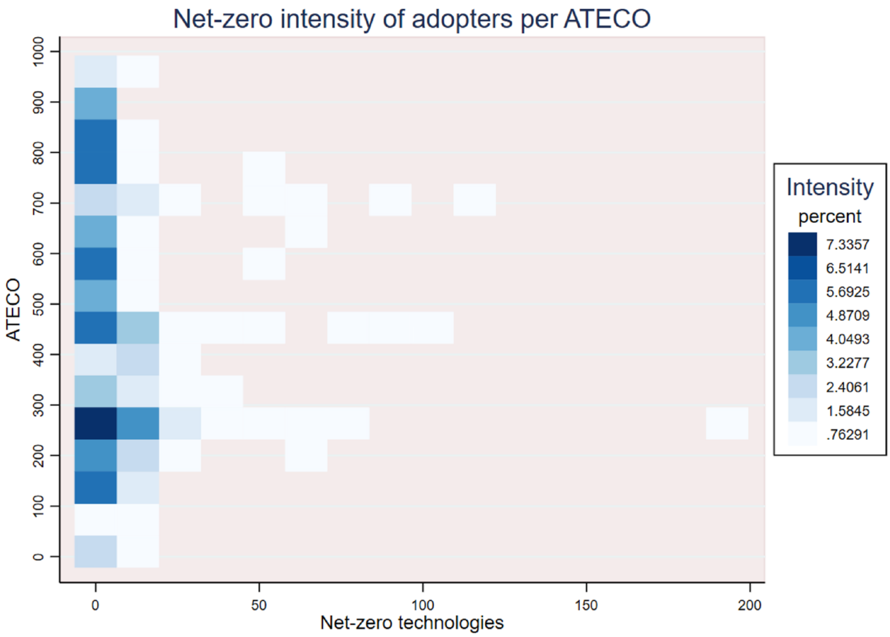


Fig. 9 Distribution of net-zero technologies adoption according to the ATECO classification. Notes: The figure illustrates the distribution of firms adopting net-zero technologies according to industry sector at ATECO level. Authors' elaboration

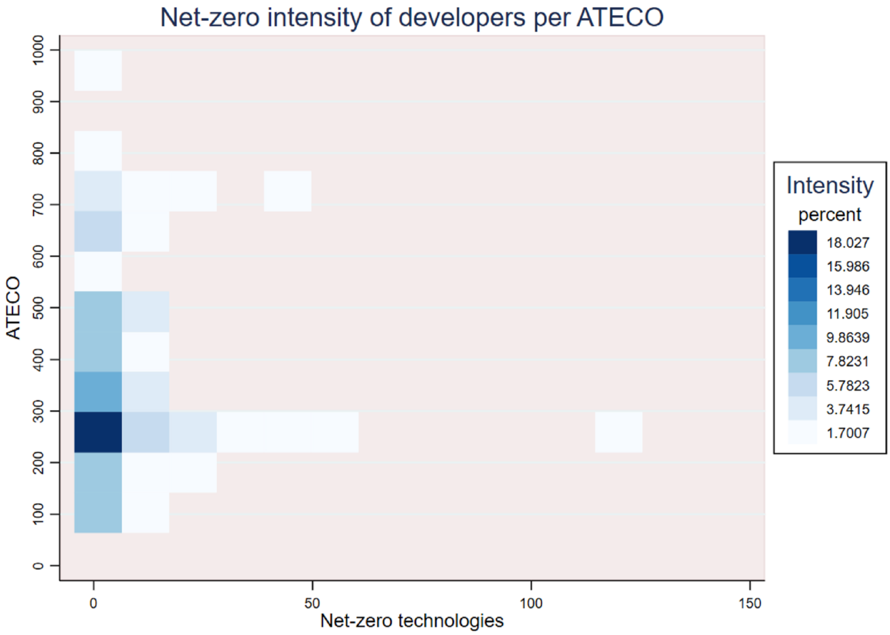


Fig. 10 Distribution of net-zero technologies development according to the ATECO classification. Notes: The figure illustrates the distribution of firms developing net-zero technologies according to industry sector at ATECO level. Authors' elaboration

Table 25 Net-zero adoption process using different models and estimators

Dep.Variable	(1) NZIA	(2) NZIA	(3) NZIA	(4) NZIA	(5) NZIA	(6) NZIA
(Model)	*Probit (benchmark)*	*Probit*	*Probit*	*Probit*	*OLS*	*Logit*
LnEmploy	0.0104***	0.0105***	0.0104***	0.0104***	0.0129***	0.0106***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)
Age	−0.0031***	−0.0007	−0.0029***	−0.0012*	−0.0050***	−0.0027***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0011)	(0.0007)
Age^2	0.0003***	0.0001*	0.0003***	0.0002**	0.0007***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
HHI	0.0267***	0.0487***	0.0267***	0.0496***	0.0490***	0.0258***
	(0.0046)	(0.0038)	(0.0046)	(0.0038)	(0.0084)	(0.0042)
LnGDP	0.0031***	0.0036***	0.0030***	0.0034***	0.0032***	0.0031***
	(0.0006)	(0.0004)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Constant					-0.0353***	
					(0.0079)	
Obs	105,159	105,607	105,159	105,607	105,601	105,159
Sector FE	Yes	No	Yes	No	Yes	Yes
Regional FE	Yes	No	No	Yes	Yes	Yes
Pseudo R^2	0.127	0.0534	0.126	0.0572		0.130
R^2					0.0402	
Mean VIF	2.01	3.16	2.08	2.00	2.01	2.01

The table reports the marginal effects from various model specifications and estimators examining the adoption of NZIA-related technologies. Columns (1) to (4) report Probit models with varying inclusion of sector and regional fixed effects: (1) benchmark, (2) no fixed effects, (3) sector fixed effects only, (4) regional fixed effects only. Column (5) shows an OLS regression with both sector and regional fixed effects. Column (6) reports a Logit model with both sector and regional fixed effects. Standard errors (in brackets) are robust. Pseudo R^2 statistics and mean variance inflation factors (*VIF*) are reported at the bottom of the table. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively

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Data Availability The data that support the findings of this study are available from Università Politecnica delle Marche (UNIVPM), but restrictions apply to the availability of these data, which were used under licence and so are not publicly available. The data are, however, available from the authors upon reasonable request and with the permission of Università Politecnica delle Marche (UNIVPM).

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