Economics of Innovation and New Technology

ISSN: 1043-8599 (Print) 1476-8364 (Online) Journal homepage: www.tandfonline.com/journals/gein20

Leveraging the twin transition: the impact of green and digital investment on firms' performance

Emanuela Marrocu, Raffaele Paci & Luca Serafini

To cite this article: Emanuela Marrocu, Raffaele Paci & Luca Serafini (08 Jan 2026): Leveraging the twin transition: the impact of green and digital investment on firms' performance, Economics of Innovation and New Technology, DOI: 10.1080/10438599.2025.2612614

To link to this article: https://doi.org/10.1080/10438599.2025.2612614

Published online: 08 Jan 2026.

ECONOMICS OF INNOVATION AND NEW TECHNOLOGY
https://doi.org/10.1080/10438599.2025.2612614

Leveraging the twin transition: the impact of green and digital investment on firms' performance

Emanuela Marrocu, Raffaele Paci and Luca Serafini

Department of Economics and Business & CRENoS, University of Cagliari, Cagliari, Italy

ABSTRACT

This paper investigates the impact of green, digital, and twin transition investments on firm performance in Italy during the 2014–2020 programming period. Drawing on project level data from the OpenCoesione platform on ERDF funded initiatives, we classify investments according to their thematic focus and apply a staggered Difference-in-Differences approach to estimate their effects on value added, employment, and labour productivity. Our results show that firms supported through twin transition projects, those combining green and digital components, achieve the most substantial and sustained gains in value added and productivity. These integrated interventions appear particularly effective in enhancing firm performance and capacity utilisation, with employment effects emerging gradually. Purely green and digital projects also yield positive outcomes, though with more moderate and variable effects. We further document significant heterogeneity across regions and sectors, with stronger impacts observed among firms located in Northern and Southern Italy and in knowledge intensive sectors. Our findings highlight the importance of strategic investment design: multi-dimensional projects consistently outperform single-focus initiatives. These results suggest that EU cohesion policy plays a pivotal role in supporting structural transformation, particularly when funding is targeted to integrated projects that align with broader environmental and digital policy goals.

ARTICLE HISTORY
Received 8 August 2025
Accepted 26 December 2025

KEYWORDS
Twin transition; green policies; digital policies; innovation and firm performance; counterfactual impact analysis

JEL
R11; O47; O30

1. Introduction

The European Union (EU) has increasingly framed its Cohesion Policy around the ambition of supporting a just and inclusive transformation toward a greener and more digitally advanced economy. Central to this agenda is the concept of the 'Twin Transition', which recognises that environmental sustainability and digital innovation must proceed together. This dual transformation is not only a response to mounting ecological and technological pressures but also a strategic opportunity to modernise European industry and enhance long-term competitiveness.

CONTACT Emanuela Marrocu emarrocu@unica.it Department of Economics and Business & CRENoS, University of Cagliari, Cagliari, Italy

The green transition requires fundamental changes in how energy is produced and consumed, how resources are managed, and how firms reduce their environmental footprint. The digital transition, in parallel, is reshaping business models through automation, data analytics, artificial intelligence, and advanced connectivity. Increasingly, these two transformations are intertwined: digital tools are key enablers of green innovation, but they can also intensify environmental pressures if not managed responsibly. Effective governance of the twin transition is therefore critical to ensuring that digitalisation accelerates, rather than undermines, sustainability goals.

A growing body of research has explored the technological, organisational, and spatial dynamics underpinning the twin transition. Digital capabilities have been shown to enable green innovation by enhancing monitoring, flexibility, and supply chain transparency (Montresor and Vezzani 2023; Santoalha, Consoli, and Castellacci 2021), while regional disparities in innovation ecosystems, skills, and governance significantly shape transition readiness (Montresor and Quatraro 2020; Diodato et al. 2023; Faggian, Marzucchi, and Montresor 2024; Capello and Caragliu 2024). At the firm level, recent studies document the potential of integrated green-digital strategies (Jindra and Leusin 2022; Bellucci et al. 2023) and highlight how targeted technological investments can yield measurable performance improvements (Serafini, Marrocu, and Paci 2025).

In this context, the EU has mobilised significant structural funding to support the twin transition, notably through the European Regional Development Fund (ERDF). ERDF resources have been channelled into firm-level investments aligned with green, digital, or integrated objectives, aiming to spur innovation and accelerate structural change. Yet, despite recent advances in the literature and growing policy attention, robust causal analysis remains limited on how such investments affect firm performance and, in particular, whether integrated twin transition projects differ meaningfully from green – or digital-only initiatives, particularly in the context of EU funding programmes.

This paper contributes to addressing this gap. We provide a firm-level impact evaluation of ERDF-supported investments in Italy during the 2014–2020 programming period, with a focus on projects classified as green, digital, or twin. Using a novel text-based classification method, we identify the thematic orientation of each project and link it to administrative data on firm performance. We then estimate dynamic treatment effects using a staggered Difference-in-Differences (DiD) approach (Callaway and Sant'Anna 2021; C&S hereafter), tracking how each project type affects value added, employment, and labour productivity over time.

Our results show that twin transition projects – those combining green and digital components – are associated with larger and more persistent performance gains than digital-only, green-only, or other innovation investments. These findings offer new empirical insights into how firms operationalise the twin transition and provide actionable evidence on the value of integrated, transition-oriented industrial policy.

The remainder of the paper is structured as follows. Section 2 reviews the conceptual and policy background to the twin transition and situates our study within the existing literature. Section 3 describes the data and classification strategy. Section 4 outlines the methodology. Section 5 presents the main results on firms' outcomes, along with some robustness exercises. Section 6 examines how the impacts vary according to the project's classification (green, digital, twin, or other), while Section 7 presents an analysis by sub--sample to detect possible heterogeneity across regions, sectors, or funding sources. Section 8 discusses policy implications and concludes.

2. Literature review and framework background

The twin transition integrating green and digital transformations has emerged as a central theme in contemporary academic and policy discussions, driven by the growing recognition that environmental sustainability and digital innovation must proceed together (Diodato et al. 2023; Kostarakos, Marques Santos, and Molica 2025; Montresor and Vezzani 2023). The green dimension requires systemic changes aimed at reducing greenhouse-gas emissions, scaling renewable energy sources and promoting sustainable resource use, as the development of green inventions has been shown to rely heavily on advances in interdependent – often digitally enabled – non-green technologies (Barbieri, Marzucchi, and Rizzo 2023). Meanwhile, the digital dimension leverages Fourth Industrial Revolution tools, such as Artificial Intelligence (AI), Internet of Things (IoT), and cyber-physical systems, to optimise efficiency, enable innovation, and bolster productivity, thereby fostering economic resilience (Benassi et al. 2022).

At the European level, the green transition is framed by the European Green Deal, which the Commission describes as 'a new growth strategy' to build a resource-efficient, competitive economy with no net greenhouse gas emissions by 2050, thereby decoupling prosperity from resource use. The EU Commission promised to enshrine the neutrality goal in a European Climate Law and to tighten the 2030 target, aiming at least 50% and moving towards 55% below the 1990 levels – steps that were subsequently translated into the binding Fit-for-55 package (European Commission 2022a). To deliver these objectives, the Green Deal sets out a broad policy toolbox: carbon-pricing reform (including possible Emissions Trading System, ETS, extension and a carbon-border adjustment), a Sustainable Europe Investment Plan mobilising €1 trillion and a Just Transition Mechanism to support the regions, sectors and workers most exposed to the shift. Crucially, the Commission emphasises that digital tools are essential enablers of this agenda, embedding the twin transition logic directly into EU climate policy.

At the same time, the digital transition is structured around the Digital Compass and the broader Digital Decade programme, which establishes concrete goals for connectivity, cloud services, high-performance computing, digital skills, and business digitalisation by 2030. As stressed by the European Commission (2022b), these two transformations are deeply interconnected: digital tools can serve as powerful enablers of resource efficiency and decarbonisation, but, if poorly managed, they can also exacerbate environmental pressures through increased energy demand, critical material consumption, and electronic waste.

This recognition has led to a growing body of work framing the twin transition not simply as two parallel processes, but as a systemic transformation that must be jointly designed and governed (Muench et al. 2022). Lange, Pohl, and Santarius (2020) employ an analytical model and an extensive review of the literature to contend that the overall process of digitalisation tends to increase energy consumption, as the energy-intensive effects – both direct and those mediated through accelerated economic growth – have outweighed the energy-saving mechanisms it enables. Matthess et al. (2023) also report heterogeneous outcomes of the digitalisation process on environmental sustainability based on their analysis of 15 countries and eight manufacturing sectors. While the adoption of robotics tends to reduce energy intensity, increases in digital capital are associated with higher energy intensity.

The complexity of achieving the green-digital integration is compounded by Europe's vulnerability in global value chains. As Draghi (2024) notes, Europe remains highly exposed in both raw materials and digital technology supply, while facing a rapidly changing geopolitical environment and mounting international competition. In this context, achieving leadership in clean technologies and simultaneously excelling in digital industrial transformation is seen as essential for securing Europe's future competitiveness. At a more sector-wide vantage point, Santos et al. (2023) develop a Regional Competitive Environmental Sustainability (RCES) index that tracks the reallocation of employment toward high-productivity, low-emission NACE industries in every EU NUTS-2 region between 2008 and 2018. They show that larger stocks of European Structural Funds are linked to faster shifts into these 'green-and-competitive' sectors – especially in less developed regions – while innovation capacity and good local governance reinforce this effect.

Regional differences play a crucial role in shaping the capacity for implementing twin transition. Recent evidence reveals substantial spatial disparities in regions' ability to leverage the twin transition effectively, largely due to differences in institutional quality, technological specialisation, and innovation capabilities (Diodato et al. 2023; Faggian, Marzucchi, and Montresor 2024). Studies highlight pronounced differences in regional orientations towards green and digital transformations, driven by existing resource endowments and innovation ecosystems. Fazio, Maioli, and Rujimora (2024), for instance, demonstrate that EU regions with strong ICT specialisations are more successful in achieving twin innovations compared to those primarily oriented towards green technologies. Echoing this complementarity, Santoalha, Consoli, and Castellacci (2021) find that regions endowed with higher digital-skills stocks are markedly more capable of branching into new green technology domains, even when those lie far from their existing knowledge base, underscoring how digital capabilities can accelerate green diversification.

Regional disparities are even more pronounced at the knowledge frontier. Damioli, Bianchini, and Ghisetti (2024) find that the emergence of a 'twin knowledge base', defined as scientific research integrating green and digital themes, is heavily concentrated in a few advanced European regions. These hotspots typically already possessed strengths in both environmental and digital sciences, allowing them to specialise in enabling technologies such as AI and IoT for energy efficiency and environmental monitoring. This concentration of scientific capabilities raises concerns about uneven innovation capacities across space, which could limit the diffusion of integrated green-digital solutions to lagging firms and regions. A long-term scenario analysis by Capello and Caragliu (2024) reinforces the idea that digitalisation – while a key engine of productivity growth – risks deepening territorial disparities if not accompanied by coherent, place-sensitive policies. Their simulations for European regions over the 2021–2038 period show that even under optimistic conditions of EU-wide investment and integration, digital upgrades tend to reinforce existing advantages of already strong regions. Conversely, regions with weaker technological and infrastructural endowments benefit less, even when investment aims to reduce the digital divide. This finding highlights the limitations of 'even' investment distribution in countering market-driven divergence dynamics and calls for more targeted support aligned with local capabilities and needs.

Together, these findings highlight the importance of considering both firm-level and regional conditions in assessing the effectiveness and inclusiveness of the twin transition. A complementary regional-level perspective is offered by Marrocu, Paci, and Serafini (2025), who assess how European regions have integrated green, digital, and twin transition objectives into their smart specialisation strategies, and how this alignment shapes regional economic outcomes.

Despite growing policy interest, empirical evidence on the economic impact of the twin transition at the firm level remains relatively limited. Recent studies suggest that firms capable of integrating green and digital priorities can unlock significant advantages; however, such integration remains in its early stages. Jindra and Leusin (2022) show that digital sustainability technologies still account for only 1.6% of global patent filings, highlighting the nascent nature of the twin transition in corporate innovation portfolios.

Montresor and Vezzani (2023) provide firm-level evidence that the bundled adoption of digital technologies – such as AI, IoT, and big data analytics – significantly increases the probability of engaging in eco-innovation. Their analysis reveals that these digital capabilities serve as 'enabling technologies' that support green innovation by enhancing process flexibility, information monitoring, and supply chain transparency. These effects are particularly pronounced when digital and environmental innovations are pursued jointly, rather than in isolation, reinforcing the idea that the twin transition offers synergistic benefits.

From a financing perspective, Bellucci et al. (2023) demonstrate that firms engaging in green patenting activities are more likely to receive venture capital funding. Using detailed data on patent citations and venture capital deals, they show that green-patenting firms signal higher innovation quality and long-term value, making them more attractive to private investors. Battisti, Stoneman, and Yuan (2025) corroborate this performance link by developing an accounting-based innovativeness index. Their cross-sector analysis reveals that the share of profit growth attributable to new ideas is economically substantial, underlining that sustained innovativeness remains a core engine of firm-level performance across diverse contexts. Importantly, Bellucci et al. (2023) and Antonioli et al. (2025) also find that these firms tend to be more mature and have stronger innovation trajectories, suggesting that successful twin transition strategies may depend not only on technology adoption but also on broader organisational readiness and innovation pathways.

In addition to these performance-related outcomes, digital preparedness has also proven essential for firm resilience. Studies by Calza, Lavopa, and Zagato (2023) and Teruel et al. (2023) show that firms with more advanced digital infrastructures were better equipped to adapt to external shocks, such as those induced by the COVID-19 pandemic, maintaining output and operational continuity. This further highlights the role of digitalisation in supporting both sustainability and robustness, reinforcing the rationale for integrated transition strategies.

Recent evidence by Serafini, Marrocu, and Paci (2025) further highlights the potential of targeted technological investments to boost firm performance. Analysing Industry 4.0 projects in Italy, their study shows that firms investing in advanced digital technologies within strategic domains recorded higher improvements in value added, employment, and labour productivity compared to those pursuing more generic innovation projects. Although their focus was primarily on digitalisation rather than the full twin transition, their findings underline the effectiveness of aligning technological investments with strategic development objectives.

Piekkola and Rahko (2024) offer complementary evidence on the productivity pay-off of eco-innovation. Merging four waves of the Finnish Community Innovation Survey with firm-level accounts, they use regional eco-innovation prevalence and organisational-capital growth as instruments to isolate the causal effect of environmental innovation. Their analysis shows that only regulation-induced green innovations translate into higher medium-term labour productivity, whereas voluntary initiatives do not. These findings emphasise how carefully designed environmental rules can unlock the productivity benefits needed to propel the twin transition.

Reshid, Svensson, and Steinbach (2025) show that competitive R&D grants can yield substantial and persistent improvements in firm performance. Drawing on a regression discontinuity design applied to the Eurostars programme, they find that subsidised SMEs recorded long-term gains in turnover, employment, and skilled labour. Their findings underline the capacity of targeted innovation funding to strengthen firm-level capabilities, a key prerequisite for advancing complex transitions such as the twin one.

Spatial dynamics also play a key role in shaping how firms engage with the twin transition. Cattani, Montresor, and Vezzani (2023) show that firms' ability to adopt eco-innovation and Industry 4.0 technologies varies systematically with their geographic context. While urban firms benefit from agglomeration economies that support the integration of digital tools into sustainable production processes, rural firms demonstrate a surprising eco-innovative edge despite generally lower levels of digital adoption. Importantly, however, the urban context appears to enhance the capacity to use digital technologies as enablers of green innovation, suggesting that spatial complementarities matter for twin transition outcomes. Extending this spatial perspective, Kriesch, Abbasiharofteh, and Losacker (2025) use novel web-scraped data and transformer-based natural language processing models to map over 678,000 firms in Germany, classifying them by their digital, green, and twin activities. Their findings reveal clear geographic asymmetries: while green firms are widespread across both rural and urban areas, twin firms are highly concentrated in urban innovation hubs, such as Berlin and Munich.

Complementing these empirical insights, Tabares, Parida, and Chirumalla (2025) propose a comprehensive firm-level framework for understanding how the twin transition is implemented within organisations. Through a systematic review of 82 studies, it is shown that green and digital projects are rarely pursued in isolation; instead, the most successful firms adopt an integrated, staged approach, from initial diagnostics and strategy design to advanced analytics and ecosystem orchestration. Their analysis reveals that digital tools frequently serve as enablers for environmental goals, with organisational capabilities, leadership, and ecosystem partnerships acting as key mediators.

Despite important conceptual and descriptive advances in the literature, key empirical gaps remain. In particular, we still lack robust causal evidence on the firm-level effects of green, digital, and integrated twin transition investments, especially in the context of public funding programmes. Prior studies have documented spatial patterns, organisational processes, and potential synergies between digital and environmental goals, but few have disentangled the economic impacts of each transition type using counterfactual methods. This paper addresses this specific gap by providing a firm-level impact evaluation of ERDF-supported investments in Italy that are explicitly classified as green, digital, or twin. Using the C&S staggered DiD estimator, we track the impacts of these investments on firms' outcomes. In doing so, we provide new evidence on how firms operationalise the twin transition in practice, and on how public policy can support this process to achieve more inclusive and sustainable growth trajectories.

3. Data

3.1. Building the dataset

This study builds on administrative project-level data from OpenCoesione, the Italian open-data platform that monitors the planning and implementation of national and EU cohesion policy plans. OpenCoesione provides detailed information on the financial, thematic, and administrative characteristics of projects financed under various financing instruments. Our analysis focuses on the ERDF projects approved in the 2014–2020 programming period.[1]

In Italy, ERDF resources are managed under the Regional Operational Programmes (ROPs) and one National Programme, each translating EU priorities into numerous specific calls for investment proposals. Over the 2014–2020 programming period, Italian regions launched several hundred calls in different years, targeting enterprises, research bodies and other local actors. These calls typically focus on innovation, digitalisation, energy efficiency, and internationalisation. Firms may apply to these calls once they open and, if selected, receive a grant that is disbursed upon project implementation. Crucially, the timing of firm participation is primarily shaped by the administrative scheduling of calls, not by firm performance or strategic timing. Since each region autonomously opens and closes its calls at different points throughout the programming period, the resulting variation in timing across firms arises mainly from institutional and procedural factors rather than endogenous firm behaviour. This feature makes the ERDF implementation context particularly suitable for a staggered DiD design, where treatment timing is plausibly exogenous to firms' underlying productivity trends.

We began with the entire universe of Italian ERDF beneficiaries recorded in OpenCoesione and progressively refined it into a firm-level panel fit for causal analysis. We first eliminate all records referring to public-sector entities like municipalities, regional administrations, universities and health authorities. Each remaining beneficiary then had to carry a valid fiscal identification number that could be matched one-to-one with AIDA, Bureau van Dijk's comprehensive database on Italian companies. AIDA combines firms' annual accounts with information on ownership, legal form and industry codes, providing nationally consistent balance-sheet, income-statement and employment series. Linking the fiscal identification number in OpenCoesione to the corresponding identifier in AIDA attaches a complete pre – and post-treatment financial history to every beneficiary, turning an administrative project register into a firm-level panel suitable for counterfactual evaluation.

Once the merge with AIDA supplied each beneficiary's ownership structure, we removed firms in which public bodies hold a majority share of equity. Although formally incorporated, these enterprises – often regional utilities or publicly controlled service companies – operate under policy mandates that differ from the market-driven incentives of fully private businesses. Excluding them keeps the analytical sample homogeneous and avoids confounding the estimated effects with behaviours shaped by public-sector objectives. We also exclude finance companies and similar holding entities, which are typically set up to administer ERDF-backed loans and guarantees. Although transfers to these funds count as programme 'spending,' the capital typically remains parked; it does not translate into the value-added or employment dynamics underpinning our outcome measures.

To maintain a clear and unique treatment definition, we limited the sample to firms that received funding only for one ERDF project. Including firms with multiple awards would blur the counterfactual comparison, because any post-treatment trajectory would mix the lingering impact of earlier funding with the incremental effect of later grants. By focusing on single-project beneficiaries, we assign each treated firm a single, unambiguous intervention date and intensity, thereby satisfying the core identification assumptions of the staggered DiD design and allowing the estimated coefficients to be interpreted as the causal effect of that specific project.[2] Moreover, we focused exclusively on firms with information on key outcome variables – value added, employment, and labour productivity – for the relevant observation period.

A staggered DiD design requires a treatment rule that is both conceptually clear and empirically sharp, as a well-defined separation of treated and control units is essential for any counterfactual exercise. Figure 1 shows that the distribution of payment ratios at the end of 2023 is strongly polarised: a dominant spike at full disbursement (100% of the committed ERDF grant), a distinct mass at zero, and only a thin scatter across the intermediate range. Notably, the second-highest bar sits in the 90-to-99% bin, indicating that most projects falling short of 100% are nevertheless very close to completion; the small residual gap usually reflects final administrative checks or minor expenditure adjustments. Moreover, the average project duration is approximately 1.38 years, indicating that

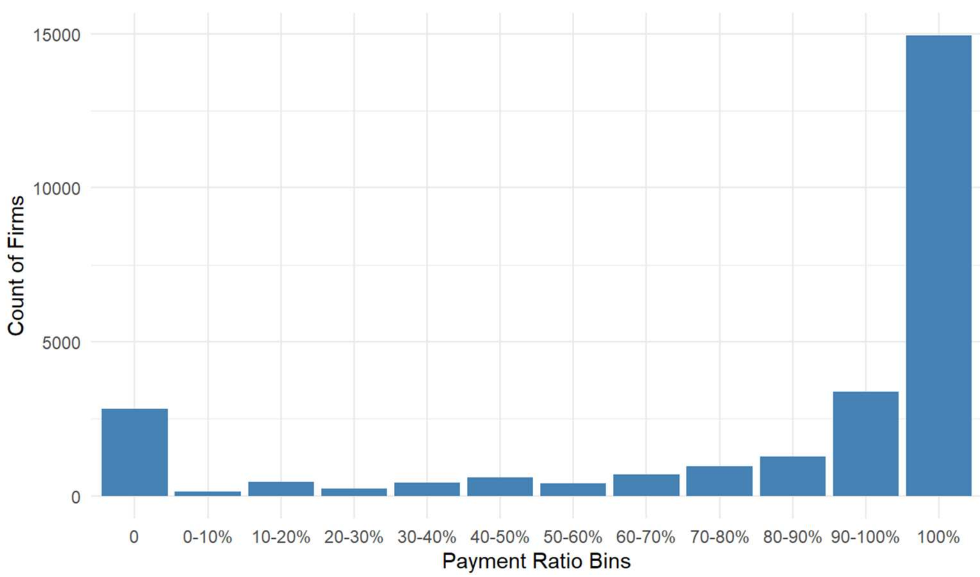

Figure 1. Distribution of ERDF payment ratios among Firms.

projects are typically completed within a period slightly extended one year. The average number of payments per project is 1.18.

Guided by these patterns, we adopt a binary rule for the treatment definition: firms are considered treated once their payment ratio reaches 90% or more, whereas firms with 0% payments constitute the control group.[3] It is important to note that in our study, the adoption of the C&S approach allows for a temporally differentiated control group as each firm eventually receives treatment. Among them, we can distinguish between the 'not-yet-treated' firms and the 'in-sample never-treated' firms. The former ones constitute the dynamic elements within the control group because they will transit to the treated group if they achieve a 90% payment ratio during this study period. The in-sample never-treated firms will complete the payments only after the study period, so that they remain consistently in the control group throughout our analysis.[4]

Note that firms in the 1-89% interval are excluded because their status is inherently ambiguous, as partial ratios may capture projects that are still under review, subject to cost revisions, suspended, or even cancelled. In each case, the funding amount and timing are uncertain, blurring any subsequent comparison of outcomes. This reasoning sets the stage for our identification strategy; its formal econometric implications, along with robustness checks using tighter or looser cut-offs, are discussed in the methodology section.

As part of the dataset construction, we conducted a detailed review of the funding instrument adopted, which revealed the presence of a substantial number of interventions launched under special rules introduced since 2020 as a response to the COVID-19 emergency.[5] These procedures were enabled by EU Regulation 2020/460, which amended the Common Provisions Regulation to permit greater flexibility in the use of cohesion policy funds in response to the pandemic. This temporary shift allowed European member States to repurpose part of the ERDF resources toward emergency measures rather than structural investments. Projects activated under these exceptional procedures typically involved simplified implementation rules and substantially lower funding amounts, on average, about one-tenth the size of typical ERDF projects. While they formally belong to the same ERDF programming period, these interventions reflect a different policy logic, oriented toward short-term crisis response rather than long-term investment upgrading. Considering these differences, we opted to exclude the 6,027 projects identified as Covid-response from the main sample, thereby focusing on the structural effects of ERDF funding. This choice ensures consistency in treatment definition and aligns the analysis with the long-term investment rationale of cohesion policy.[6]

After applying the exclusion criteria described above, our final sample includes 14,988 one-project firms, which are evaluated in the econometric analysis presented in Section 5.

3.2. Identifying digital and green projects in OpenCoesione dataset

To assess the role of ERDF funding in supporting the green and digital transitions, we developed a classification strategy to assign each project to thematic categories aligned with the twin transition framework. Since the OpenCoesione dataset does not include explicit labels for green or digital content, we implemented a keyword-based text analysis, further refined through manual screening, to infer each project's alignment with transition objectives. In the absence of standardised classification codes – such as those used in patent databases – and given the availability of descriptive text for each project, this approach was considered the most suitable. While keyword searches are subject to limitations related to the variability of natural language, as noted by Favot et al. (2023), they offered a feasible and systematic method for thematic classification in this context.

The keyword lists were compiled from two complementary sources. For the green transition, we used the terminology developed by Jindra and Leusin (2022) in their study of sustainable digital technologies. For the digital transition, we drew on classifications developed by the European Patent Office (EPO) related to the Fourth Industrial Revolution. All terms were carefully translated into Italian to match the language used in the OpenCoesione database, preserving their semantic accuracy.

The classification was conducted using the Quanteda package in R, as explained in detail in Appendix 1, where the keywords list is reported in Table A1.1. The resulting classification distinguishes four groups:

- projects supporting the digital transition;
- projects supporting the green transition;
- projects supporting the twin transition (simultaneously digital and green);
- projects not classified in any of the above categories.

Importantly, for analytical purposes, project categories – digital, green, and twin – are not mutually exclusive, since there are overlaps between them. For example, a project tagged as both green and digital (i.e. a twin transition project) is still counted in the digital group when estimating the effects of digital projects. This decision avoids underestimating the scope and effectiveness of projects with digital traits simply because they also pursue green goals. The goal is to capture the full contribution of each thematic area, even when they intersect. Robustness checks using mutually exclusive groupings are discussed in Section 5.

After classifying projects into the four categories, we examine their distribution across Italy's macro-areas and macro-sectors (Table 1). Overall, 4,387 firms are associated with digital projects (29.3%), 2,706 with green projects (18.1%), and a smaller

Table 1. Firms by macro-sector, macro-area and projects typology (% values by rows).

	Digital	Green	Twin	Other	Total
Macro-area (a)					
North	34.7	22.1	7.9	51.1	6932
Centre	41.0	18.6	7.3	47.7	2892
Mezzogiorno	15.4	12.4	5.6	77.9	5164
Macro-sector (b)					
Industry	28.4	23.4	9.3	57.5	6856
Knowledge Intensive sectors (KIS)	44.3	14.1	7.8	49.4	3129
Low Knowledge Intensive Sectors (LKIS)	28.8	13.9	4.3	61.7	2815
Tourism & Recreation	11.2	12.3	1.9	78.5	2188
Total	4387	2706	1047	8942	

Project types are not mutually exclusive; totals exceed 100%, as Twin projects count in both Digital and Green categories.
(a) North: Piemonte, Val d'Aosta, Lombardia, Liguria, Veneto, Trento, Bolzano, Friuli Venezia Giulia, Emilia Romagna. Centre: Toscana, Umbria, Marche, Lazio. Mezzogiorno: Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna.
(b) NACE sector: Industry: A, B, C, D, E, F. KIS: J, K, L, M, N. LKIS: G, H, O, P, Q. Tourism & Recreation: I, R, S.

share, 1,047 firms (7.0%), with twin transition projects that combine both dimensions. The remaining 8,942 firms (59.7%) are linked to projects not classified under either of the transition themes. Looking at the territorial distribution, the Centre and North show comparatively high shares of digital (41.0% and 34.7%, respectively) and twin projects (7.3% and 7.9%). In contrast, the Mezzogiorno lags significantly behind, with only 15.4% of firms involved in digital projects and 5.6% in twin initiatives, while the vast majority – 77.9% – are linked to projects that are not clearly aligned with green or digital goals.

Sectoral patterns highlight distinct orientations. Knowledge-Intensive Services (KIS) lead in digital engagement, with 44.3% of firms classified under this category, followed by Industry (28.4%) and Low-Knowledge-Intensive Services (LKIS) (28.8%). Green projects are more prevalent in Industry (23.4%), consistent with eco-innovation trends in manufacturing. Twin transition projects are most common in Industry (9.3%) and KIS (7.8%), suggesting stronger integration capacity in sectors with higher technological and innovation intensity. In contrast, Tourism and Recreation and LKIS show limited involvement in transition-oriented projects and remain heavily concentrated in the 'Other' category (78.5% and 61.7%, respectively).

4. Methodology and estimation strategy

Following the staggered DiD approach proposed by C&S, we exploit variation in the timing of ERDF disbursements to identify the causal effects of funding on firms' value added, employment, and labour productivity. The staggered DiD method extends the classical two-period DiD framework to accommodate multiple periods and treatment assignments occurring at different times. At its core, it relies on the conditional parallel trend assumption: absent treatment, the evolution of outcomes for treated and untreated firms would have been comparable, once controlling for observable covariates.

The C&S method also assumes the irreversibility of treatment – once a firm receives ERDF funding, it is considered permanently treated – and limited anticipation, meaning that firms are unlikely to alter their behaviour between notification and receipt of funding. Under these assumptions, the Average Treatment Effect on the Treated (ATT) is non-parametrically identified and can be estimated through several procedures, including Outcome Regression (OR), Inverse Probability Weighting (IPW), and Doubly Robust (DR) estimation.[7] The DR estimator, which combines OR and IPW approaches and requires only one of the two models to be correctly specified for consistency, is our preferred method. However, in some sub-sample analyses – particularly when splitting the sample by project type – the DR estimator occasionally encounters convergence issues related to the construction of the IPW component, likely due to limited variation in the covariates or weighting structure within smaller groups. In such cases, we resort to the OR estimator, which remains feasible and consistent under correct specification of the outcome model. For transparency, we report which estimators are used across different specifications.[8]

The dynamic effects of ERDF funding are presented through an event-study framework, aligning firms relative to their year of treatment, and testing for pre-treatment parallel trends using pseudo-ATT estimates.

As anticipated in section 3, the treated and control groups are identified based on the payment-ratio patterns, as payments offer a consistent and verifiable administrative proxy for the implementation of funded investments. A firm is considered treated in the year in which it reaches at least 90% of the committed grant. Firms with a ratio of zero constitute the control group. This binary rule, with thresholds at zero and 90%, yields two groups that are comparable in terms of project approval but differ clearly in funding execution, satisfying the identification assumptions of the staggered DiD estimator. While alternative thresholds are possible, this definition strikes a reasonable balance between treatment precision and sample coverage. We assess the sensitivity of our findings to different cut-offs in a dedicated robustness exercise discussed in Section 5.

Because ERDF calls are implemented in successive waves across regions, firms apply at different points in time, generating a naturally staggered treatment structure. As detailed in Section 3, Italian regions autonomously manage their programmes, opening and closing calls according to their own implementation plans. The timing of firm participation and first payment, therefore, depends mainly on regional administrative schedules, not on firm performance or strategic behaviour. Accordingly, our control group comprises:

- not-yet-treated firms, i.e. firms that will receive their first ERDF payment later in the programming period (for example, a firm paid in 2018 serves as a control for firms treated in 2016, until it becomes treated itself); and
- in-sample never-treated firms, i.e. those that have been awarded funding but have not received any disbursement within the observation period. These firms are considered 'never-treated' only within our sample window, because they will receive funding later, once their projects advance through the administrative process.

This 'not-yet + in-sample never' structure follows the standard logic of staggered DiD estimators, where untreated units at time *t* are those that have not yet received treatment. Since all firms are eventual beneficiaries, those treated later provide a credible counterfactual for earlier cohorts – ensuring comparability across firms that are equally selected for funding but differ only in timing. Because this timing is driven mainly by exogenous, region-level programming factors and given the short length of projects' execution, any observed differences are reasonably due to administrative sequencing.

In the estimation stage of our analysis, we include two time-invariant covariates, namely firms' sector and geographical location. Since the C&S estimation routine tends to struggle with convergence when several covariates are included, especially in small samples, and the two covariates were effective in ensuring that the parallel-trend assumption was satisfied, we did not add other covariates. However, to further confirm the baseline comparability between treated and control groups, we also computed standardised mean differences (SMD) for key pre-treatment covariates – value added, total assets, assets per worker, R&D expenditure, and firm age – across treatment cohorts. We report SMDs, computed as Hedges' *g*, along with their 95% confidence intervals. The SMD is a unit-free measure of the distance between groups' means, and unlike *t*-tests, it does not depend on sample size; it is therefore well-suited for evaluating imbalance across variables measured in different units (Zhang et al. 2019). For each cohort, we compare firms in the year before treatment with the corresponding not-yet-treated and in-sample never-treated group, replicating the comparison underlying our identification strategy. As shown in Figure A2.1 in Appendix 2, the differences are consistently small (mostly within ±0.1). In applied work, values below approximately 0.10 are typically considered to indicate negligible imbalance, and values below approximately 0.25 are deemed acceptable. Our estimates fall comfortably within these ranges in almost all tests, confirming that treated and control firms were highly similar in their observable characteristics.[9]

As mentioned above, in our econometric analysis, we assess the effects of ERDF funding on firm-level performance, measured through value added (VA), employment, and labour productivity in line with a consolidated body of research (Bachtrögler, Fratesi, and Perucca 2020; Crescenzi, de Blasio, and Giua 2020; Crescenzi and Giua 2020; Cirillo et al. 2023). VA serves as a comprehensive measure of the economic output generated by a firm and is particularly suitable for assessing the effects of transformative investments promoted through ERDF support. We expect that such investments will have a positive influence on VA by enhancing firms' production capabilities and market competitiveness. The effect on employment, however, is less predictable and depends on the specific nature of the intervention. Innovation-related investments may lead to job creation – especially for high-skilled labour – or, conversely, result in labour displacement if the technologies adopted are labour-saving. For this reason, the direction and magnitude of employment effects remain an empirical matter. The same logic extends to productivity outcomes. While productivity gains are expected over the medium to long term, short-term adjustments may introduce delays or transitional frictions that complicate immediate improvements.

For each outcome, we report both the overall dynamic treatment effect and a set of event-time coefficients, covering the three years preceding and following the intervention. This structure enables us to assess the timing, magnitude, and persistence of the effects, while also testing for pre-treatment parallel trends. The main results are presented in Section 5, followed by analyses by project type (Section 6) and by sub-samples to detect possible heterogeneity in the estimated impacts (Section 7) across regions, sectors, and funding.

5. Results on firms' outcome variables

Table 2 presents the results of the impact analysis on firms' outcomes.[10] ERDF funding has a positive and significant effect on all firm performance indicators, as indicated by the overall dynamic coefficients – 0.193, 0.045, and 0.155 for VA, employment, and labour productivity, respectively.[11] The event study presented in Figure 2 shows that VA increases immediately upon treatment and remains significantly high throughout the three-year

Table 2. ERDF treatment effects on firms' outcomes.

All-firms sample	Overall dynamic effect	Event study			
	Single parameters	e=0	e=1	e=2	e=3
Value Added	0.193**	0.225**	0.193**	0.203**	0.150**
Employment	0.045**	0.017**	0.039**	0.056**	0.068**
Labour productivity	0.155**	0.162**	0.143*	0.150*	0.165

DR estimation. Significant level: **5%, *10% (inference based on C&S 2021 bootstrap procedure).

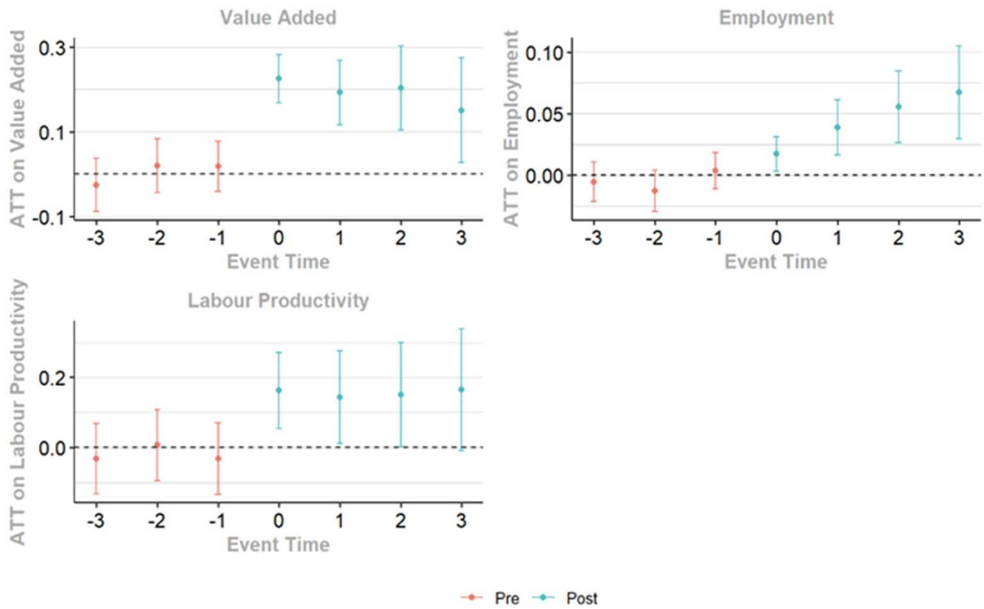

Figure 2. Event study of ERDF impact on Value Added, Employment, and Labour productivity.
DR estimation. Simultaneous 90% confidence bands – clustering at the firm level.

post-treatment window. The largest effect (0.225) occurs in the year of implementation (e = 0), followed by a gradual tapering that nonetheless maintains a clear performance improvement. This trajectory suggests an early and sustained response to cohesion policy support.

Labour productivity exhibits a similar dynamic. Gains (0.162) are already visible in the implementation year and persist across the post-treatment period. The shape and size of the effect – although less sizeable than the VA ones – suggest that the funding leads to meaningful efficiency improvements, consistent with investments in capital upgrades, technology adoption, or digital processes. The response of employment is more muted and gradual. Although the estimated effects are statistically significant from the first year after treatment onward, they remain modest in magnitude (around 0.150). This pattern aligns with an adjustment sequence in which firms initially make better use of existing inputs before expanding their workforce.

The pre-treatment period shows no evidence of diverging trends across treated and untreated firms, strengthening the causal interpretation. The estimates suggest that ERDF funding, when deployed through standard investment channels, supports firm growth primarily by increasing productivity and output.

These results align closely with findings from recent evaluations of similar innovation grant programmes. Several studies document that public support for R&D and innovation typically triggers an immediate, productivity-centred improvement in firm performance, with benefits extending beyond the initial implementation period. For instance, Reshid, Svensson, and Steinbach (2025) find sustained turnover and employment gains among Swedish SMEs funded through R&D subsidies, while Piekkola and Rahko (2024) report durable labour-productivity improvements following environmental innovations in

Finnish firms. Similarly, Serafini, Marrocu, and Paci (2025) show that ERDF-supported projects in Italy generate significant, lasting value-added increases in these dimensions, exhibiting a similar pattern.

To assess the robustness of our treatment definition, we re-estimate the value-added model using alternative thresholds for cumulative ERDF payments – 85%, 95%, and 100% of the committed amount. The results, reported in the Appendix 3 Table A3.1 and Figure A3.1 together with the baseline 90%, confirm the stability of our findings. Across all specifications, post-treatment effects remain positive and of comparable magnitude, while pre-treatment coefficients are flat and not statistically different from zero. As expected, stricter thresholds (95% and 100%) reduce the number of treated firms and slightly widen confidence intervals, whereas the 85% cutoff yields very similar estimates to the baseline. Overall, the 90% threshold provides a balanced and reliable definition of treatment, combining robust results with adequate sample coverage.

To further validate the causal interpretation of our findings, we conduct two placebo exercises, reported in Appendix 3 Figure A3.2, following the logic of placebo treatment tests discussed in Eggers, Tuñón, and Dafoe (2024). The first, which we refer to as the Early Treatment Placebo, assigns a fictitious treatment date two years prior to the actual one and restricts the sample to periods strictly preceding the actual treatment year, ensuring that no firm is ever truly treated. Estimated coefficients around this artificial treatment date are close to zero and statistically insignificant. The second, the Shuffled-Cohort Placebo, tests whether our results could arise mechanically from the staggered timing structure. Here, we preserve the original number of treated firms in each year but randomly reassign firms to treatment years, producing a dataset where treatment timing is effectively random. The resulting coefficients are again centred around zero with wide, overlapping confidence intervals. Taken together, these two exercises show that our estimated post-treatment effects are not driven by pre-existing trends, arbitrary timing patterns, or other spurious sources, reinforcing the credibility of our identification strategy.

As an additional robustness check, we re-estimate the VA model using the full sample of firms, including those supported by emergency Covid-response projects. As shown in Appendix 3, Table A3.2 and Figure A3.3, the main dynamics are preserved, although the estimated effects are somewhat attenuated – likely reflecting the inclusion of short-term, liquidity-focused interventions. To better isolate these emergency measures, we also estimate the model on the subset of Covid-related projects alone. These projects display a sharp, one-off increase in value added and labour productivity at the time of disbursement ($e = 0$), but no sustained gains over time. This pattern reflects the intention behind these projects, which were meant to provide immediate support to firms during the Covid crisis through limited-amount ERDF calls. These findings further support our decision to focus the main specification on structural investment projects, which represent the relevant policy mechanism for enhancing long-run firm performance.

6. Results by project type: the role of the twin transition

Table 3 and Figure 3 present the analysis conducted to investigate the varying impact of ERDF-supported projects with four distinct thematic orientations: Digital, Green, Twin, and Other.[12] Each category is evaluated against a common control group of in-sample

Table 3. ERDF treatment effects on Value Added by project type.

Project type	Overall dynamic effect	Event study			
	Single parameters	e=0	e=1	e=2	e=3
Digital	0.156**	0.158**	0.128	0.152	0.185
Green	0.204**	0.184**	0.207**	0.229*	0.196
Twin	0.317**	0.274**	0.362**	0.293	0.339
Other	0.167**	0.241**	0.178**	0.167**	0.083

OR estimation. Significant level: **5%, *10% (inference based on C&S 2021 bootstrap procedure).

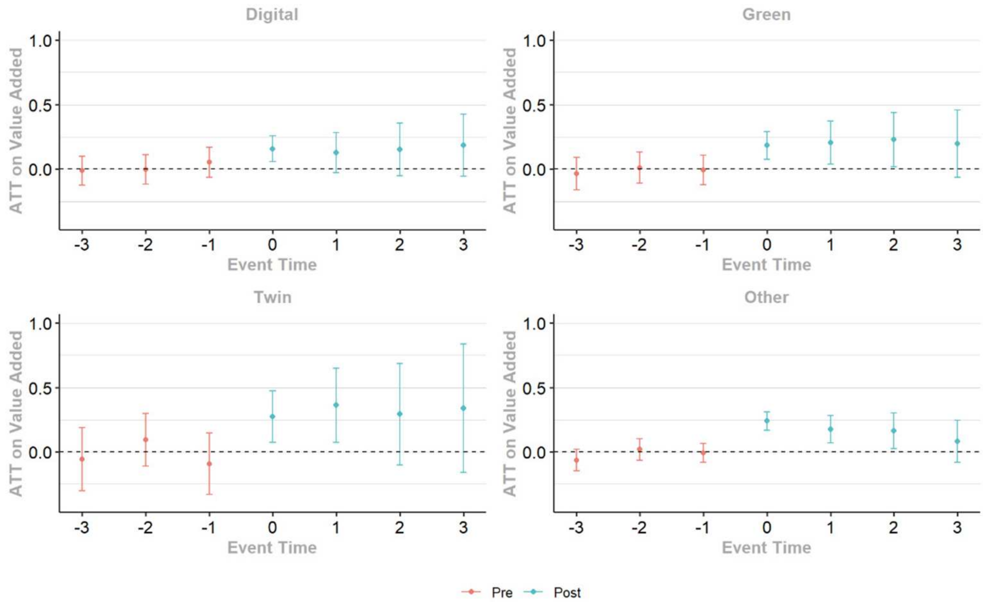

Figure 3. Event study of ERDF impact on Value Added – by project type.
OR estimation. Simultaneous 90% confidence bands – clustering at the firm level.

never-treated firms. This approach is appropriate because the classification into project types is not an intrinsic, pre-existing attribute of firms, but a result of the specific design and objectives of the funded interventions. A manufacturing firm, for instance, could undertake either a green or a digital project depending on the funding opportunity and project scope. Using a shared control group of in-sample never-treated firms ensures comparability across project types, allowing us to isolate the differential impact of the treatment content – green, digital, twin, or other – while holding the counterfactual constant. Including not-yet-treated firms in the control group would introduce bias, as these firms might eventually receive a different type of treatment, complicating the interpretation of effects.

Focusing on VA,[13] the results indicate that all four categories show positive trajectories after project implementation, confirming that ERDF funding generally enhances firm-level performance. However, the size and stability of these gains vary considerably by project type.

Projects that explicitly integrate digital and green elements – the twin category – generate the strongest and most persistent productivity improvements, with an overall dynamic effect of 0.317. These benefits emerge clearly at implementation, peak in the year immediately afterwards (0.362), and remain significantly above baseline throughout the analysis period. Although confidence intervals widen slightly due to a smaller sample, the sustained upward shift highlights the consistent productivity returns from integrated twin transition investments.

The marked and persistent effect we detect for twin projects provides novel evidence on the impact of the EU cohesion policy funding and contributes to the rapidly evolving debate that is increasingly shaping the recent literature on digital and green transitions. First, firm-level evidence shows that bundling several Industry 4.0 tools strongly amplifies eco-innovation: Montresor and Vezzani (2023) find that the eco-innovation rate rises far more when AI, IoT, or robotics are adopted together than when any single technology is used, reinforcing the idea that twin investments sit at the front line of innovation and therefore boost firm performance. Second, previous studies cast the digital and green domains as a self-reinforcing loop: sensors and analytics provide real-time resource intelligence, while green targets steer data use toward cost-saving routines, generating iterative productivity gains (Tabares, Parida, and Chirumalla 2025). Third, finance could magnify the effect: green-patenting firms are more likely to secure venture capital funding (Bellucci et al. 2023), and this Environmental, Social and Governance-plus-scalability may be stronger when digital and green upgrades are combined.

Purely Green projects achieve the second-highest average productivity gains (overall dynamic effect of 0.204), with substantial improvements evident at implementation (0.184) and continuing to increase up to two periods after the treatment (0.229). This suggests that resource-efficiency upgrades – such as energy-efficient equipment, waste reduction systems, or renewable energy installations – consistently translate into improved firm performance. The relatively tight confidence bands indicate that these benefits are robust and persistent. The pattern mirrors the Finnish evidence in Piekkola and Rahko (2024), who find that environmental innovations raise labour productivity while leaving modest employment effects, exactly the 'productivity-first' dynamic we observe here. Again, the Bellucci et al. (2023) link between green inventiveness and venture capital finance provides a plausible mechanism for the durability of these gains.

The Digital category delivers positive yet comparatively moderate productivity gains (overall dynamic effect of 0.156). Project descriptions indicate considerable internal variation: smaller-scale ICT interventions (such as enterprise resource planning – ERP – modules or basic e-commerce platforms) may deliver modest improvements, while more sophisticated digital solutions (advanced automation or analytics) can generate stronger impacts. This mixed composition likely explains both the lower average gains and the higher variability observed in digital project outcomes.

The Other category – which primarily encompasses tangible, capital-intensive interventions such as new production lines, machinery upgrades, hotel expansions, and occasional international marketing schemes – delivers a clear enhancing effect (0.167), initially even outperforming the Digital category. These gains are likely due to immediate capacity expansions and physical asset enhancements. Although the growth rate moderates over time, the post-treatment path remains solidly above zero throughout our three-year horizon.[14] A natural extension would be to classify projects into finer archetypes (e.g. capacity-expansion builds vs. outward-oriented commercial initiatives). Yet a thorough examination of the grant files shows that project descriptions vary too widely – and lack a common taxonomy – to support a reliable content-based split. Therefore, we prefer to investigate further the projects effect by means of a specific analysis at the sectoral level, which is discussed in the next section.

Taken together, our results highlight a hierarchy of effectiveness across project types: while theme-focused interventions contribute to improved firm performance, their impacts tend to be more limited in scale than those observed for Twin projects. Robustness checks using mutually exclusive groupings – where Twin projects are excluded from the Digital and Green categories – confirm the main patterns: although average effects for Digital and Green projects are slightly attenuated, the relative hierarchy of impacts remains unchanged (Table A3.3 and Figure A3.4 in Appendix 3).

In this context, the superior and more sustained gains observed for Twin projects are likely linked to their integrated design. Most projects labelled as twin transition in our dataset marry two elements: on the one hand, firms invest in a digital backbone – networked computer numerical control or robotic work-cells, IoT sensor grids, and manufacturing execution systems or ERP platforms (often cloud-based) that register production, energy, and quality metrics in real time. On the other hand, they adopt resource-efficient measures such as high-efficiency drives, heat-recovery loops, on-site renewables, or circular material inputs. Across the projects, these combinations often involve automated systems powered by renewable energy and managed through digital monitoring, where control platforms adjust speed, temperature, or load to reduce waste and downtime. Other interventions combine digital traceability and quality-control tools with cleaner, more efficient production equipment, or integrate smart management systems with energy retrofits and photovoltaic plants to optimise lighting, heating, and cooling in real time.

Taken together, these patterns suggest that digital and green components may reinforce each other in practice. Digital tools can make environmental investments more adaptable and measurable, enabling firms to monitor performance and refine their operations over time. Conversely, green technologies provide a concrete operational domain in which digital systems can generate direct efficiency gains, rather than being limited to administrative or commercial applications. This interaction may help explain why twin projects display stronger and more persistent productivity improvements, as the combination of monitoring, optimisation, and learning could extend the benefits well beyond the initial investment phase. This integrated approach provides a plausible explanation for the premium effect observed compared to purely green or purely digital interventions.

Purely green projects are typically cost-saving initiatives – such as energy-efficient equipment or renewable installations – that deliver clear but bounded productivity gains. Purely digital projects, by contrast, vary considerably: some introduce sophisticated automation and analytics, while others involve simpler interventions, such as ERP modules or e-commerce platforms. This variation explains both their lower average and greater outcome variability. Twin projects may thus outperform because their structure consistently combines substantial tangible resource savings with meaningful digital enhancements – avoiding both the narrower scope of green-only interventions and the uneven effectiveness of digital-only ones. This balanced integration likely contributes to their stronger and more sustained firm-level performance gains.

From a policy perspective, our novel evidence emphasises the value of explicitly promoting integrated twin transition investments. Encouraging firms to design and implement projects that jointly leverage digital upgrades and sustainability measures appears particularly effective in maximising the impact of cohesion policy. Policymakers might therefore consider specifically incentivising twin projects, recognising their capacity to deliver robust and persistent production gains. Moreover, even for interventions initially focused solely on digitalisation or sustainability, targeted incentives or advisory support to incorporate complementary elements from the other domain could significantly amplify their overall economic return.

7. How the impacts change across regions, sectors and funding

In this section we investigate how the average effects discussed in section 5 change along three intuitive dimensions: where firms operate, which sector they belong to, and how much funding support they receive. In these cases, we estimate separate staggered DiD models using stratified control groups – that is, treated firms are matched only to untreated or not-yet-treated firms within the same region, sector, or funding amount class. This ensures that comparisons are made among observationally similar firms and avoids conflating structural differences that could bias the estimates. For example, it would not be meaningful to compare a treated firm in the North with an untreated firm in the South, or a manufacturing firm with one in tourism.

The logic of the estimation changes accordingly: rather than identifying the effect of project type across a shared baseline, these models evaluate whether treated firms perform better than comparable untreated firms within the same contextual environment. The resulting coefficients reflect within-stratum treatment effects and should not be directly compared across rows, as each estimate is based on a different underlying control group.

Focusing on VA, Table 4 and Figure 4 show that firms located in the North exhibit a clear and persistent improvement (overall dynamic effect of 0.189); the post-treatment line rises at implementation and remains positive three years later. The Mezzogiorno

Table 4. ERDF treatment effects on Value Added by macro-area, macro-sector, and funding.

	Overall dynamic effect	Event study			
Macro-area	Single parameters	e=0	e=1	e=2	e=3
North	0.189**	0.174**	0.210**	0.224**	0.150
Centre	0.174**	0.281**	0.116	0.122	0.177
Mezzogiorno	0.193**	0.251**	0.204**	0.198**	0.118
Macro-sector					
Industry	0.138**	0.122**	0.140**	0.167**	0.122
KIS	0.418**	0.476**	0.443**	0.483**	0.271
LKIS	0.101	0.115	0.093	0.132	0.064
Tourism and recreation	0.087	0.277**	0.052	-0.102	0.119
Funding class					
Low	0.157**	0.107**	0.113*	0.206**	0.203*
Medium	0.196**	0.271**	0.226**	0.168	0.118
High	0.218**	0.287**	0.215**	0.228**	0.143

DR (area) and OR (Sector/Funding) estimation.
Significant level: **5%, *10% (inference based on C&S 2021 bootstrap procedure).
Funding class by tertiles: <€20,000 (low), €20,000–65,000 (medium), >€65,000 (high).

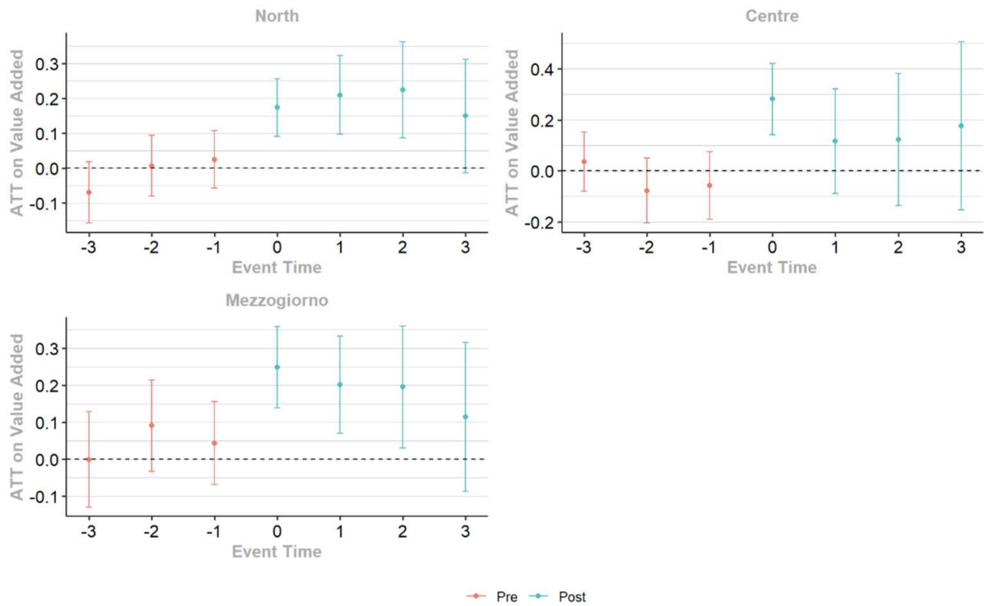

Figure 4. Event study: ERDF impact on Value Added – by macro area.
DR estimation. Simultaneous 90% confidence bands – clustering at the firm level.

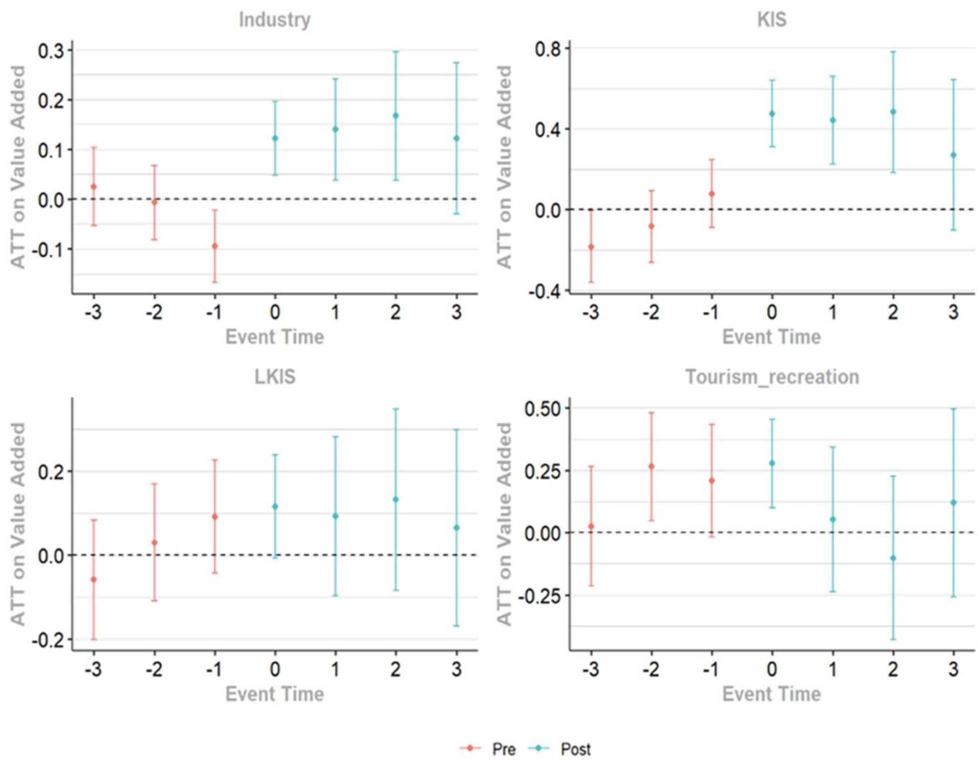

Figure 5. Event study: ERDF impact on Value Added – by macro-sector.
OR estimation. Simultaneous 90% confidence bands – clustering at the firm level.

registers an even larger overall gain (0.193), although its confidence intervals are wider, indicating more dispersion across cohorts. This stronger Mezzogiorno effect is achieved because we exclude Covid-related grants, which were heavily concentrated in the Mezzogiorno and, by design, were not intended to raise long-term productivity. Once those relief operations are set aside, the structural component of ERDF funding appears to translate into tangible performance gains for southern firms. The Centre sits in between: it records a sizeable jump in the treatment year (0.281), but the line flattens thereafter, suggesting that the initial impulse dissipates more quickly.

On the activity side, Table 4 and Figure 5 show a clear ranking across sectors. KIS display the largest within-sector improvement (overall dynamic effect: 0.418): their post-treatment line stays well above zero for the entire three-year window. Industry follows, with a smaller but still noticeable gain (0.138); a slight dip below zero indicates a mild pre-trend, so results for Industry should be interpreted with some caution. LKIS register no significant impact, while tourism-related activities exhibit a positive effect only in the treatment year. However, no parallel trend issues make a causal interpretation misleading. Overall, sectors richer in human capital and intangible assets appear better positioned to turn ERDF support into sustained increases in value added.

Finally, we examine whether the effectiveness of ERDF varies with the funding scale of supported projects.[15] Table 4 and Figure 6 present results based on a tertile classification of public funding. The low tertile includes projects with relatively modest grants (mostly under €20,000), the medium tertile ranges from around €20,000 to €65,000, while the high tertile encompasses larger projects with grants starting above €65,000 and extending over a broad range. All three groups show positive and statistically significant effects

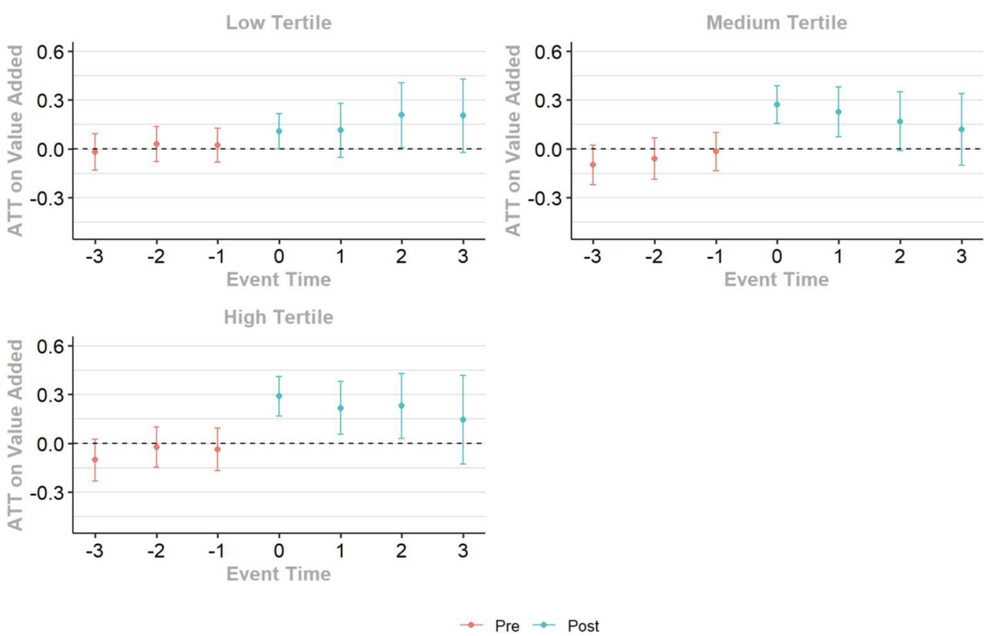

Figure 6. Event study: ERDF impact on Value Added – by funding classes.
OR estimation. Simultaneous 90% confidence bands – clustering at the firm level.

on value added, though the timing and magnitude differ. High-funded projects exhibit the strongest immediate gains (0.287), medium-funded ones generate robust and sustained improvements (overall dynamic effect: 0.196), and lower-funded projects display more gradual effects (overall dynamic effect: 0.157) that build over time.[16]

8. Conclusions

This study has evaluated the impact of ERDF-funded projects on firm-level performance in Italy during the 2014–2020 programming period, with a particular focus on investments supporting the green, digital, and twin transitions. Using a staggered DiD framework, we examined how these interventions influenced firms' value added, employment, and labour productivity.

Our findings provide robust and novel evidence that ERDF funding generates significant positive impacts across all three outcomes. The estimated gains are particularly notable for value added and labour productivity, which rise immediately after funding and remain substantially elevated over a three-year horizon. Employment effects are more moderate and unfold with a delay, confirming that initial productivity improvements precede job creation. This sequencing could indicate that ERDF support primarily enhances firm efficiency and capacity utilisation before translating into broader employment gains.

An essential insight of our analysis is the marked heterogeneity in outcomes based on the thematic orientation of projects. Investments explicitly addressing the twin transition stand out clearly, delivering the largest productivity improvements. The integrated nature of these twin transition projects, pairing digital monitoring and automation systems with resource-efficient technologies, could be crucial for their superior performance. Despite their relatively small number, the strength and consistency of these effects underline the strategic advantage of pursuing integrated, multi-dimensional interventions. Single-focus projects, by comparison, display more varied outcomes. Purely green investments yield significant and stable performance improvements, confirming that resource-efficiency measures reliably translate into firm-level productivity gains. Purely digital interventions, while generally positive, exhibit greater variability, reflecting differences in project complexity and scope, ranging from basic ICT upgrades to advanced analytics and automation.

Moreover, the study reveals substantial heterogeneity across regions and sectors. Firms in Northern Italy experience clear and persistent performance enhancements. Interestingly, firms in the Mezzogiorno also show significant improvements once short-term COVID-19 relief projects are excluded, highlighting the structural potential of ERDF funding in southern regions. Firms in the Centre exhibit more modest and less persistent gains. Sectoral analysis confirms that KIS achieve the highest returns, followed by Industry. Firms in the LKIS and tourism sectors benefit the least, suggesting that absorptive capacity and innovation intensity are critical determinants of success. Notably, the positive effects of ERDF support are evident across the entire funding-size distribution, demonstrating that even modest funding can yield meaningful performance improvements.

Overall, our results strongly indicate that the efficacy of cohesion policy hinges not merely on funding availability but on the strategic orientation of investments and the regional-sectoral contexts in which they are deployed. Transition-oriented initiatives, particularly those that integrate green and digital objectives, emerge as effective instruments for sustainable structural change.

Although our findings are derived from the Italian context, they are consistent with evidence from comparable studies conducted in other European countries – such as Piekkola and Rahko (2024) for Finland and Reshid, Svensson, and Steinbach (2025) for Sweden – as well as with global analyses, exemplified by the semi-structured literature review of Tabares, Parida, and Chirumalla (2025). Hence, the results presented here bear broader implications for European regions engaged in the ongoing twin transition.

Policies promoting integrated and strategically targeted investments can substantially enhance firm performance by fostering inclusive and sustainable growth, as well as advancing territorial cohesion. The successful advancement of the digital transition is contingent upon firms' capacity to adopt, assimilate, and effectively deploy new technologies. Consequently, policy interventions should prioritise the enhancement of human capital formation and the stimulation of R&D investment, thereby augmenting the intensity of firms' intangible assets and strengthening their capability to capitalise on the transformative potential of digitalisation. More broadly, supporting green and digital transitions holds significant promise not only for improving firm-level outcomes but also for addressing urgent environmental challenges and achieving wider societal benefits.

Future research could further explore the longer-term dynamics of twin transition investments, including potential spillover effects on supply chains, regional ecosystems, and workforce composition. As more data become available, it may also be possible to examine whether the observed firm-level gains translate into broader macroeconomic outcomes such as regional productivity convergence or sectoral transformation. Additionally, complementary qualitative analyses could shed light on implementation processes, organisational change, and firm-level decision-making, dimensions that remain difficult to capture through administrative data alone. Finally, future research could strengthen the analysis by incorporating measures of actual environmental impact, thereby allowing a more accurate assessment of the potential trade-offs between investments aimed at improving project quality and the effective achievement of environmental benefits.

Notes

1. The projects' data was downloaded from the OpenCoesione platform (https://opencoesione.gov.it/en/) in September 2024.
2. In our sample, single- and multi-project firms are broadly comparable in their main characteristics, although the latter tend to be slightly larger and more R&D-active. If we assume that multi-project firms, due to their characteristics, are among the best performers, then their exclusion strengthens the internal validity of our estimates.
3. We have estimated the model with different thresholds for the completion rate: 85%, 95%. Results are discussed in section 5.1 and reported in Table A3.1 in the Appendix 3.
4. It is worth remarking that in the general C&S framework, there also exist 'true' never-treated units, which are the ones that always belong to the control group because they will never receive any treatment.
5. Typical 'COVID calls' financed emergency liquidity micro-grants and soft loans for firms hit by lockdowns, small-scale investments to meet health-safety requirements (personal protective

equipment, sanitation, distancing), rapid digitalisation/e-commerce vouchers, and, in a few cases, new production lines for medical or protective equipment.

6. The potential implications of including Covid-related projects are examined in a robustness check presented in Section 5.
7. The OR approach models the conditional expectation of the outcome evolution for the comparison groups (i.e. firms treated in the same period), a set of covariates can be included to address possible confounding factor issues. The IPW approach models the probability of a unit being treated at a given, conditional on a set of covariates. This adjustment is crucial for aligning the distribution, conditional on pre-treatment covariates, between the treated and control groups, thereby supporting the parallel trends assumption. The DR approach combines OR and IPW, modelling both the outcome evolution and the propensity score.
8. Serafini, Marrocu, and Paci (2025) conduct a comprehensive analysis on the performance of the three different estimation approaches that revealed that the IPW one tends to yield the highest impacts, followed by the OR and the DR ones. As we prefer to take a cautious stand, our estimation strategy is based on the DR estimator, we resort to the OR one only when small size issues impede the use of the DR approach.
9. The comparison is conducted at t-1, between treated firms in each cohort and the corresponding not-yet-treated and in-sample never-treated firms observed in the same year. This approach assesses whether the groups are similar in observable characteristics prior to treatment.
10. It is important to note that the estimates for employment and labour productivity are based on a smaller sample than those for value added, due to missing data in the employment variable. Since labour productivity is calculated as value added per employee, the same sample reduction applies to that outcome as well.
11. VA and labour productivity are inverse hyperbolic sine (HIS) transformed (Bellemare and Wichman 2020). This transformation allows us to handle few zero values. Estimated coefficients are interpreted as those from logarithmic transformations as they indicate approximate percentage changes. Employment is log-transformed.
12. Note that some projects may overlap across categories, as discussed in Section 3.2. For estimation purposes, we allow these overlaps to ensure that the full scope of each thematic area – digital, green, and twin – is captured, even when objectives intersect.
13. We focus on VA to ensure a sufficient number of observations within each project-type subsample, as the overall sample size decreases when considering employment and labour productivity due to missing employment data.
14. Projects in the ‘Other’ category show slightly longer implementation times (≈1.7 years on average), suggesting that their tangible investments may require a longer horizon for effects to fully materialise beyond the observed evaluation window.
15. Although using funding amounts as a continuous treatment variable may seem preferable, the standard C&S estimator does not accommodate treatment intensity. A new companion package (contdid) introduces this functionality but currently lacks key features, such as support for covariates, flexible base periods, and unbalanced panels, which are essential in firm-level applications, where data gaps and firm entry/exit are common. Therefore, to address treatment intensity in a tractable way, we adopt a tertile-based approach that maintains comparability across groups while preserving the core strengths of the DiD framework.
16. As a robustness check, we replicate the analysis using fixed thresholds (€20,000 and €100,000). The overall patterns remain consistent, although the high-funding group, defined by the >€100,000 cutoff, includes fewer projects and shows somewhat smaller effects, reflecting differences in group composition and sample size.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by European Union Horizon Project ESSPIN 'Economic Social and Spatial Inequalities in Europe in the Era of Global Mega-Trends' [grant number 101061104]; European Union – NextGenerationEU, Mission 4, Component 2, in the framework of the GRINS – Growing Resilient, INclusive and Sustainable – project [grant number GRINS PE00000018].

ORCID

Emanuela Marrocu http://orcid.org/0000-0002-7436-0055
Raffaele Paci http://orcid.org/0000-0003-0301-438X
Luca Serafini http://orcid.org/0009-0002-6477-5270

References

EU Regulation 2020/460 of the European Parliament and of the Council. 30 March 2020.

Antonioli, D., C. Ghisetti, M. Mazzanti, F. Nicolli, and M. Quatrosi. 2025. "Twin Transition" and HRM Practices: Empirical Evidence from Italian Firms." *Industry and Innovation*, https://doi.org/10.1080/13662716.2025.2516036.

Bachtrögler, J., U. Fratesi, and G. Perucca. 2020. "The Influence of the Local Context on the Implementation and Impact of EU Cohesion Policy." *Regional Studies* 54 (1): 21–34.

Barbieri, N., A. Marzucchi, and U. Rizzo. 2023. "Green Technologies, Interdependencies, and Policy." *Journal of Environmental Economics and Management* 118:102791.

Battisti, G., P. Stoneman, and Y. Yuan. 2025. "Measuring Firm Innovativeness across Countries, Sectors and Time." *Economics of Innovation and New Technology* : 1–23.

Bellemare, M. F., and C. J. Wichman. 2020. "Elasticities and the Inverse Hyperbolic Sine Transformation." *Oxford Bulletin of Economics and Statistics* 82 (1): 50–61.

Bellucci, A., S. Fatica, A. Georgakaki, G. Gucciardi, S. Letout, and F. Pasimeni. 2023. "Venture Capital Financing and Green Patenting." *Industry and Innovation* 30 (7): 947–983.

Benassi, M., E. Grinza, F. Rentocchini, and L. Rondi. 2022. "Patenting in 4IR Technologies and Firm Performance." *Industrial and Corporate Change* 31 (1): 112–136.

Callaway, B., and P. H. Sant'Anna. 2021. "Difference-in-differences with Multiple Time Periods." *Journal of Econometrics* 225 (2): 200–230.

Calza, E., A. Lavopa, and L. Zagato. 2023. "Advanced Digitalisation and Resilience during the COVID-19 Pandemic: Firm-Level Evidence from Developing and Emerging Economies." *Industry and Innovation* 30 (7): 864–894.

Capello, R., and A. Caragliu. 2024. "Digital Transition in a Turbulent World: European Regional Growth Opportunities in 17 Years' Time." *Economics of Innovation and New Technology* 34 (7): 997–1015.

Cattani, L., S. Montresor, and A. Vezzani. 2023. "Firms' eco-Innovation and Industry 4.0 Technologies in Urban and Rural Areas." *Regional Studies* 59 (1).

Cirillo, V., L. Fanti, A. Mina, and A. Ricci. 2023. "New Digital Technologies and Firm Performance in the Italian Economy." *Industry and Innovation* 30 (1): 159–188.

Crescenzi, R., G. de Blasio, and M. Giua. 2020. "Cohesion Policy Incentives for Collaborative Industrial Research: Evaluation of a Smart Specialisation Forerunner Programme." *Regional Studies* 54 (10): 1341–1353.

Crescenzi, R., and M. Giua. 2020. "One or Many Cohesion Policies of the European Union? On the Differential Economic Impacts of Cohesion Policy across Member States." *Regional Studies* 54 (1): 10–20.

Damioli, G., S. Bianchini, and C. Ghisetti. 2024. "The Emergence of a 'Twin Transition' Scientific Knowledge Base in the European Regions." *Regional Studies* 59(1).

Diodato, D., E. Huergo, P. Moncada-Paternò-Castello, F. Rentocchini, and B. Timmermans. 2023. "Introduction to the Special Issue on "the Twin (Digital and Green) Transition: Handling the Economic and Social Challenges"." *Industry and Innovation* 30 (7): 755–765.

Draghi, M. 2024. *The Future of European Competitiveness – a Competitiveness Strategy for Europe*. Brussels: European Commission.

Eggers, A. C., G. Tuñón, and A. Dafoe. 2024. "Placebo Tests for Causal Inference." *American Journal of Political Science* 68 (3): 1106–1121.

European Commission. 2022a. *Cohesion Policy: Over €1 Billion from REACT-EU to Support Recovery and the Green and Digital Transition in Italy*. https://ec.europa.eu/commission/presscorner/detail/en/ip_22_1467.

European Commission. 2022b. *Strategic Foresight Report: Twinning the Green and Digital Transitions in the New Geopolitical Context*. https://publications.jrc.ec.europa.eu/repository/handle/JRC129319.

Faggian, A., A. Marzucchi, and S. Montresor. 2024. "Regions Facing the 'Twin Transition': Combining Regional Green and Digital Innovations." *Regional Studies* 59(1).

Favot, M., L. Vesnic, R. Priore, A. Bincoletto, and F. Fabio Morea. 2023. "Green Patents and Green Codes: How Different Methodologies Lead to Different Results." *Resources, Conservation & Recycling Advances* 18:200132.

Fazio, G., S. Maioli, and N. Rujimora. 2024. "The Twin Innovation Transitions of European Regions." *Regional Studies* 59 (1).

Jindra, B., and M. Leusin. 2022. *The Development of Digital Sustainability Technologies by top R&D Investors*. Brussels: Publications Office of the European Union.

Kostarakos, I., A. Marques Santos, and F. Molica. 2025. "Regional Resilience in the Era of Climate Change and Digitalization," *JRC Working Papers on Territorial Modelling and Analysis*, 08/2025, European Commission, Seville, 2025, JRC139516.

Kriesch, L., M. Abbasiharofteh, and S. Losacker. 2025. "The Geography of Digital and Green (Twin) Firms in Germany." *Regional Studies, Regional Science* 12 (1): 513–516.

Lange, S., J. Pohl, and T. Santarius. 2020. "Digitalization and Energy Consumption: Does ICT Reduce Energy Demand?" *Ecological Economics* 176:106760.

Marrocu, E., R. Paci, and L. Serafini. 2025. *Smart and Green. The Uneven Effects of the Twin Transition in EU Regions*. Cagliari: WP Crenos, 25/10.

Matthess, M., S. Kunkel, M. F. Dachrodt, and G. Beier. 2023. "The Impact of Digitalization on Energy Intensity in Manufacturing Sectors – a Panel Data Analysis for Europe." *Journal of Cleaner Production* 397:136598.

Montresor, S., and F. Quatraro. 2020. "Green Technologies and Smart Specialisation Strategies: A European Patent-Based Analysis of the Intertwining of Technological Relatedness and Key Enabling Technologies." *Regional Studies* 54 (10): 1354–1365.

Montresor, S., and A. Vezzani. 2023. "Digital Technologies and eco-Innovation. Evidence of the Twin Transition from Italian Firms." *Industry and Innovation* 30 (7): 766–800.

Muench, S., E. Stoermer, K. Jensen, T. Asikainen, M. Salvi, and F. Scapolo. 2022. *Towards a Green and Digital Future*. Luxembourg: Publications Office of the European Union.

Piekkola, H., and J. Rahko. 2024. "The Effects of Environmental Innovations on Labor Productivity: How Does It pay to Be Green." *Economics of Innovation and New Technology* 34 (7): 1122–1143.

Reshid, A., P. Svensson, and N. Steinbach. 2025. "The Long-Term Effects of R&D Subsidies on Firm Performance: Evidence from a Regression Discontinuity Design." *Economics of Innovation and New Technology* 34 (3): 469–492.

Santoalha, A., D. Consoli, and F. Castellacci. 2021. "Digital Skills, Relatedness and Green Diversification: A Study of European Regions." *Research Policy* 50 (9): 104340.

Santos, A., J. Barbero, S. Salotti, O. Diukanova, and D. Pontikakis. 2023. "On the Road to Regional 'Competitive Environmental Sustainability': The Role of the European Structural Funds." *Industry and Innovation* 30 (7): 801–823.

Serafini, L., E. Marrocu, and R. Paci. 2025. "Smart Strategies, Smarter Performance: The Impact of S3 and Industry 4.0 on Firms' Outcomes." *Industrial and Corporate Change*, https://doi.org/10.1093/icc/dtaf010.

Tabares, S., V. Parida, and K. Chirumalla. 2025. "Twin Transition in Industrial Organizations: Conceptualization, Implementation Framework, and Research Agenda." *Technological Forecasting and Social Change* 213:123995.

Teruel, M., S. Amaral-Garcia, P. Bauer, A. Coad, C. Domnick, P. Harasztosi, and R. Pál. 2023. "Productivity and HGEs: Resilience and Recovery from the COVID-19 Pandemic." *Industry and Innovation* 30 (7): 895–918.

Zhang, Z., H. J. Kim, G. Lonjon, and Y. Zhu. 2019. "Balance Diagnostics After Propensity Score Matching." *Annals of Translational Medicine* 7 (1): 16.

Appendices

Appendix 1. Keywords classification of digital and green projects

The keyword matching was case-insensitive and applied to stemmed unigrams – trigrams to capture multi-word expressions (e.g. 'renewable energy', 'smart grid'). Using bigrams and trigrams helped avoid false positives from single generic words; for example, the phrase 'smart sensor' was counted as 'digital,' but the unigram 'smart' alone, often used in non-technological contexts, was ignored.

During development, we first ran the keyword search only on project titles and descriptions to test coverage. Comparing these results with projects listed under clearly themed administrative categories (e.g. environmental protection, digital technologies) revealed that several relevant projects were not captured. We examined these excluded cases to identify how digital or green elements were described in practice and added the missing expressions to our dictionaries, ensuring that the automated tags consistently reflected substantive project content.

For the final classification, the refined dictionaries were applied to a broader search that also included other descriptive fields – such as the funding instrument, expenditure category, priority axis, and classification codes. These fields served as additional text sources, not filters, ensuring that projects with digital or green content were detected even when funded under broader or mixed-purpose calls. Projects were tagged as green or digital based on the presence of at least one corresponding keyword across any of these fields, and those matching both were classified as twin transition projects. In a final residual step, a Large Language Model (LLM) was used to review unclassified projects and flag possible remaining digital or green cases. These were manually checked before inclusion, confirming that only a very small number of relevant projects were missed by the main automated procedure. This step helped reduce false negatives and ensured greater consistency across the dataset.

Table A1.1. Keyword list.

Category	Representative keywords
DIGITAL	
Advanced Manufacturing & Industry 4.0	additive/advanced manufacturing; advanced materials; Industry 4.0; 3D printing/scanning/simulation; smart factory; autonomous line
Automation & Robotics	Automation; robotics; adaptive robotics; drones; autonomous driving; cyber-physical systems; automated systems
Cybersecurity & Data Protection	cybersecurity; digital/data security; adaptive security
Smart Devices & IoT Systems	Internet of Things (IoT); smart product/system/services/building; wearables; virtual/augmented reality; multichannel interaction; virtual commissioning; smart sensors; smart homes; product control/monitoring/optimisation/connectivity; traffic optimisation
Digital Business & Infrastructure	ERP / enterprise resource planning; mobile operating systems; network protocols; cloud/fog/mobile/social computing; blockchain; digitalisation; digital transformation; virtualisation; quantum/distributed computing
Healthcare & Diagnostics (Digital)	smart healthcare; health monitoring; diagnostic systems; telemedicine; virtual surgery; e-health
Predictive & AI-enhanced Systems	predictive treatment; artificial intelligence; machine learning; neural networks; prescriptive agriculture; product autonomy

(*Continued*)

Table A1.1. Continued.

Category	Representative keywords
Data Analytics & Data Science	big data; analytics; data science; business analytics; data collaboration; natural language processing (NLP); semantic web; climate data analytics
Digital Services & Applications	e-commerce; e-banking; e-learning; e-business; ICT; ICT-enabled applications
Digital-Green Crossover	digital twin(s); twin transition; smart grid(s); smart energy (system); smart mobility; smart cities; precision farming; smart agriculture; demand response systems; distributed energy resources
GREEN	
Pollution, Monitoring & Emissions	pollution control; air pollution/quality; CO_2 levels; GHG emissions; carbon footprint (reduction/tracking/reporting); methane management/storage; carbon capture; environmental monitoring; ozone depletion
Circular Economy & Resource Management	waste management; recycling; e-waste; organic waste valorisation; biodegradable plastics; reuse; solid/food/agri waste; waste collection optimisation; sharing economies; lifecycle transparency; sustainable packaging; waste-to-energy; wastewater treatment; sustainable materials; green chemistry; environmental technologies; resource efficiency/depletion/reduced consumption
Sustainable Urban Development & Mobility	sustainable buildings/cities; urban regeneration; climate-resilient infrastructure; urban green spaces; electric vehicles; sustainable mobility; green transport; low-emission fuels; micromobility; charging infrastructure; multimodal mobility; hybrid vehicles
Climate Change & Adaptation	climate change; adaptation; disaster management; coastal/flood protection; CO_2 storage; nature-based solutions; environmental/climate impact
Renewable Energy	solar energy/power; wind energy; geothermal energy; hydro energy; marine/tidal energy; biofuels; green hydrogen; photovoltaic; renewable/clean energy; clean fuels
Energy Efficiency	energy efficiency/retrofitting; HVAC efficiency; energy conservation; energy storage; heat pumps; efficient lighting; energy-efficient appliances; energy management; aware charging; LED; cogeneration; thermal insulation
Biodiversity & Ecosystems	biodiversity; conservation; rewilding; forests; nature-based solutions; ecological restoration; ecosystems; habitat; toxic-free environment; forest management
Sustainable Agriculture & Food Systems	sustainable agriculture; agroecology; sustainable consumption; short supply chains; smart nutrition; agricultural adaptation; preventing food losses
Green Governance & Finance	green finance; ESG investing; environmental reporting/certification; sustainable investment; climate finance; green procurement; ISO 14001; EMAS; green technologies; sustainable industry
Water Resources Management	water resources/scarcity; clean water & sanitation; water efficiency; water treatment; efficient water use; desalination; rainwater harvesting; natural resources management
Sustainability (General Concepts)	sustainability; sustainable development/production/supply chain; sustainable industry/consumption/mobility/technology; green transition; restoring ecosystems
Digital-Green Crossover	smart grid(s); smart energy (system); smart mobility; smart cities; precision farming; smart agriculture; demand response systems; distributed energy resources

The operational dictionaries used for automated classification contained entries in both English and Italian. Matching was case-insensitive and applied to stemmed tokens with n-grams (unigrams – trigrams) to harmonise morphological variants and capture multi-word expressions (e.g. 'solar energy', 'smart grids'). The table above is illustrative rather than exhaustive: near-duplicate forms, plural variants, and direct Italian translations were omitted for readability. Where semantically distinct phrasings are common (e.g. 'renewable energy', 'clean energy'), multiple variants were retained in the operational dictionaries to ensure coverage. Generic single-word tokens that can cause false positives (e.g. only 'smart') were not included.

Appendix 2. Covariate balance assessment

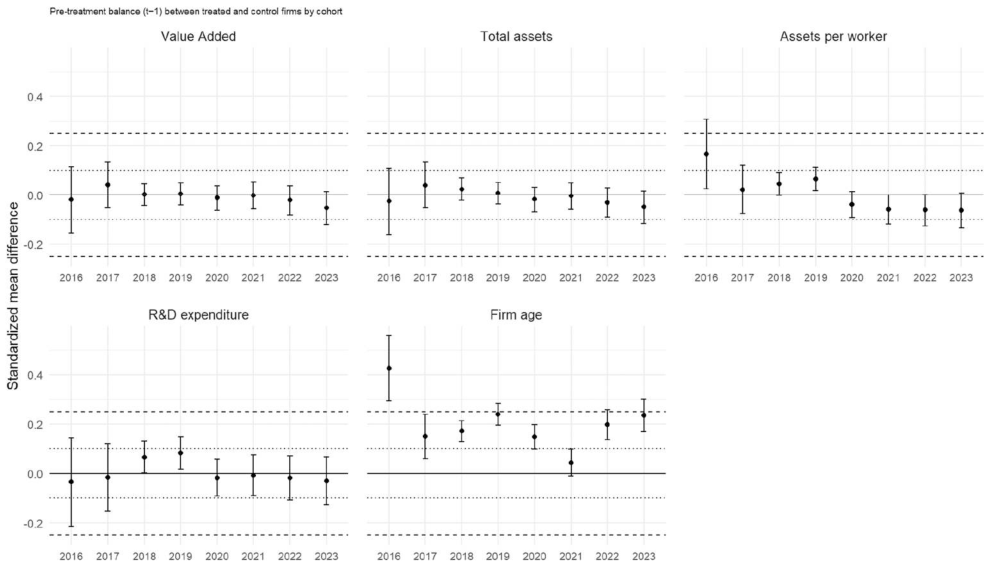

Figure A2.1. Standardised mean differences for pre-treatment covariates across treatment cohorts

Appendix 3. Robustness estimation

Table A3.1. Event study: ERDF impact on Value Added – Different thresholds treatment.

Threshold	Overall dynamic effect	Event study			
	Single parameters	e=0	e=1	e=2	e=3
85%	0.201**	0.232**	0.201**	0.215**	0.158**
90% (baseline)	0.193**	0.225**	0.193**	0.203**	0.150**
95%	0.181**	0.211**	0.178**	0.191**	0.145*
100%	0.133**	0.188**	0.129**	0.145**	0.068

DR estimation. Significant level: **5%, *10% (inference based on C&S 2021 bootstrap procedure).

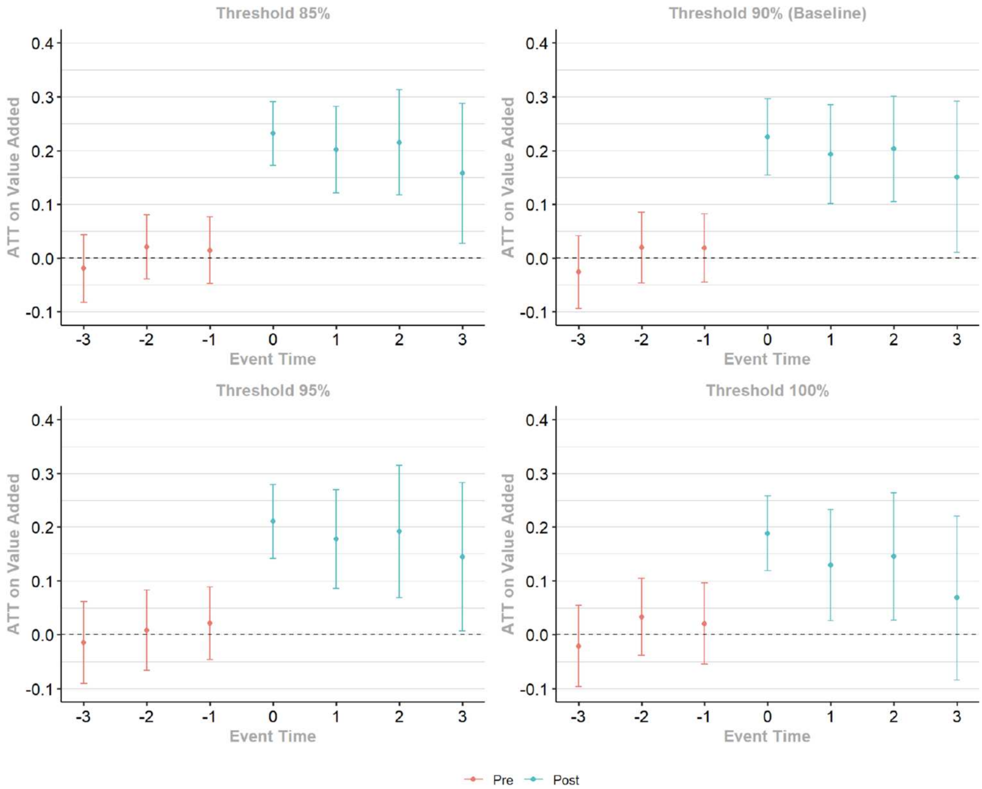

Figure A3.1. Event study: ERDF impact on Value Added – Different thresholds treatment.
DR estimation. Simultaneous 90% confidence bands – clustering at the firm level.

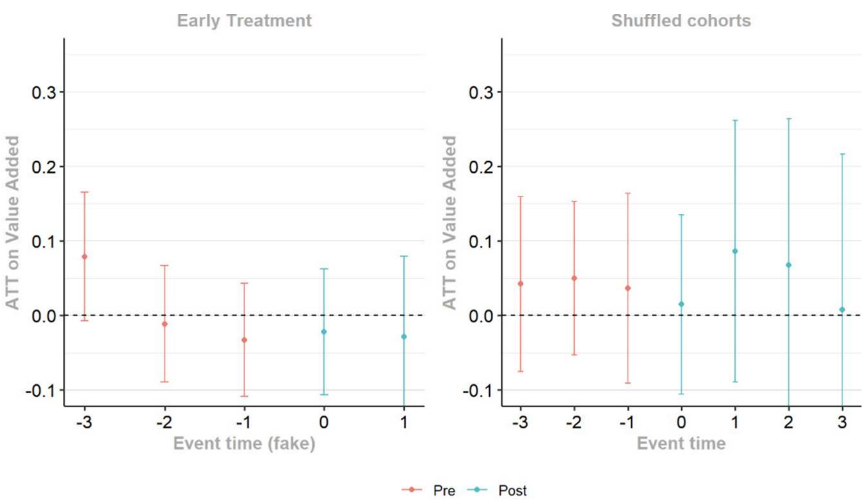

Figure A3.2. Event-study placebo tests for the ERDF impact on Value Added.
DR estimation. Simultaneous 90% confidence bands – clustering at the firm level.

Table A3.2. ERDF treatment effects on firms' outcomes – Covid analysis.

	Overall dynamic effect	Event study			
	Single parameters	e=0	e=1	e=2	e=3
Baseline	0.192**	0.224**	0.192**	0.202**	0.149**
Full sample - Covid included	0.151**	0.193**	0.169**	0.128**	0.114*
Covid only	0.292	0.331**	0.247	0.299	--

DR estimation. Significant level: **5%, *10% (inference based on C&S 2021 bootstrap procedure).

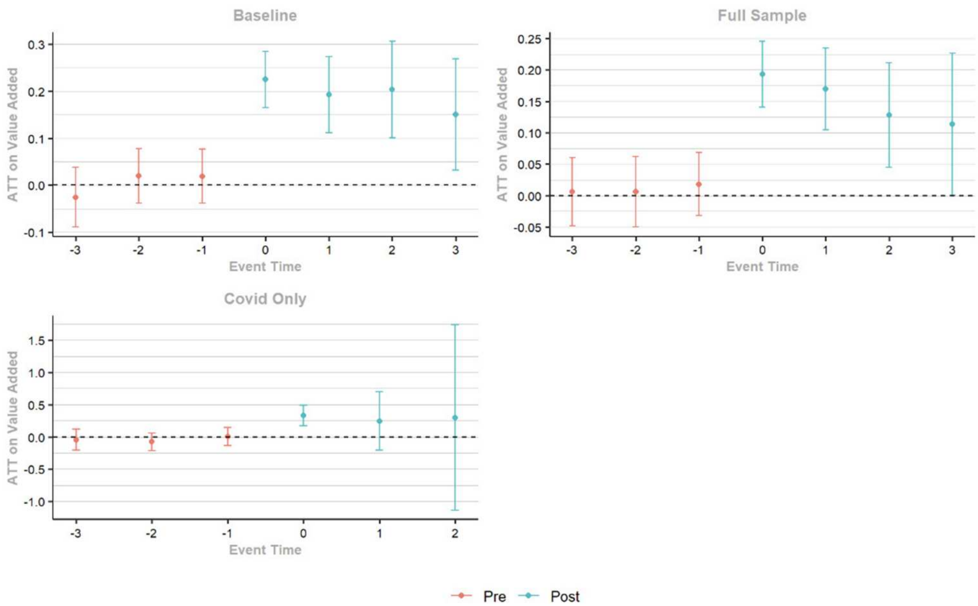

Figure A3.3. Event study: ERDF impact on Value Added – Covid analysis.
DR estimation. Simultaneous 90% confidence bands – clustering at the firm level.

Table A3.3. Event study: ERDF impact on Value Added – by project type, no overlap.

Project type	Overall dynamic effect	Event study			
	Single parameters	e=0	e=1	e=2	e=3
Digital	0.121**	0.132**	0.081	0.127	0.143
Green	0.145**	0.136**	0.131	0.198	0.117

OR estimation. Significant level: **5%, *10% (inference based on C&S 2021 bootstrap procedure).

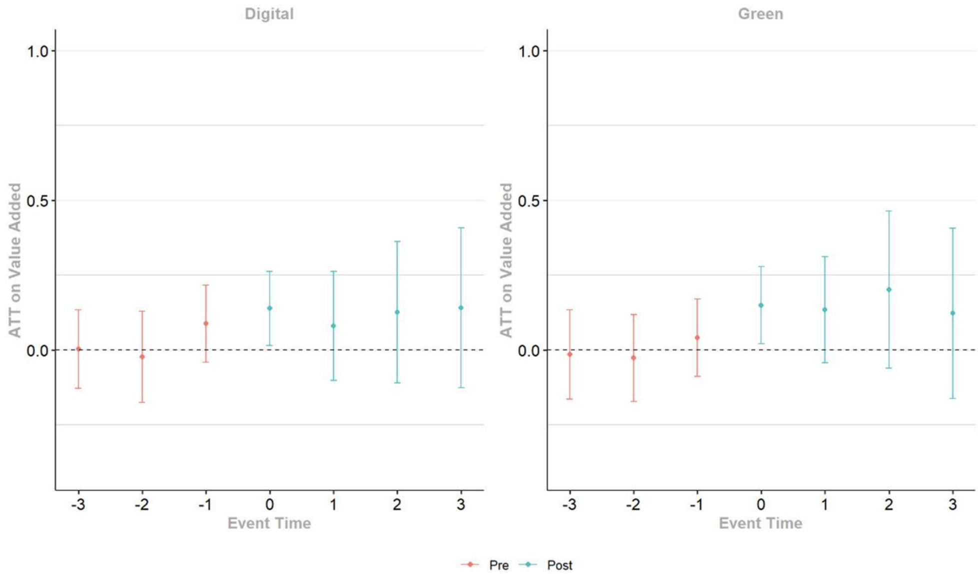

Figure A3.4. Event study: ERDF impact on Value Added – by project type, no overlap.
OR estimation. Simultaneous 90% confidence bands – clustering at the firm level.