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SMART STRATEGIES, SMARTER PERFORMANCE: THE IMPACT OF S3 AND INDUSTRY 4.0 ON FIRMS' OUTCOMES

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Smart Strategies, Smarter Performance:
the Impact of S3 and Industry 4.0 on Firms' Outcomes

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Abstract

This paper focuses on the impact of the Smart Specialisation Strategy (S3) and Industry 4.0 (I4) initiatives during the 2014-2020 programming period on firms' performance in Italy. By analysing European Regional Development Fund (ERDF)-funded projects under these frameworks, we use OpenCoesione data and a Difference-in-Differences approach to assess the effectiveness of S3 and I4 initiatives. Our results reveal that projects integrating I4 technologies within the S3 framework (S3I4 projects) significantly enhance firms' performance. This is particularly evident when compared to projects funded under other ERDF initiatives. The study highlights the importance of aligning S3 and I4 strategies with regional economic profiles and innovation capacities to maximise their impact. Our analysis underscores the role of these initiatives in driving innovation and economic growth. The results offer key insights for policymakers, suggesting that focused and strategic investment in S3 and I4 can lead to more effective regional innovation and development.

Keywords: Smart Specialisation Strategy; Industry 4.0; Innovation and firm Performance; Cohesion Policy; Counterfactual Impact Analysis

Jel Classification: C21, L25, O25, O33, R58

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1. Introduction

The European Union (EU) has increasingly focused on innovation and technological advancement as pivotal drivers for economic growth and competitiveness. The Smart Specialisation Strategy (S3) and Industry 4.0 (I4) are at the forefront of this effort, two key frameworks guiding the EU's development agenda.

S3, a cornerstone of EU regional policy, aims to bolster regional innovation by encouraging regions to identify and develop their own areas of specialisation. This strategy fosters regional innovation and enables firms to capitalise on local strengths and collaborative opportunities. I4, on the other hand, represents the latest wave of the industrial revolution, emphasising integrating digital technologies into manufacturing and business processes. It lays a critical foundation for firms to evolve and remain competitive in an increasingly digitalised world.

These frameworks are integral to the EU's vision of smart, sustainable, and inclusive growth, as the Europe 2020 strategy outlines. The Regional Operational Programme 2014–2020, underpinned by the European Regional Development Fund (ERDF), has been instrumental in embedding S3 within the EU's policy mechanisms, channelling significant financial resources to support this new approach. The interplay of S3 and I4 presents a unique opportunity for firms across the EU to enhance their performance through innovation and technological adoption, thereby contributing to the region's overall economic and social cohesion.

However, while the strategic integration of S3 and I4 promises substantial benefits for EU firms, the existing body of literature reveals a complex landscape of outcomes and implementations. Studies such as Crescenzi et al. (2020) have provided valuable insights into implementing S3, particularly in the context of industrial innovation. Their findings indicate that firms in low-tech sectors, often facing greater challenges in securing credit for innovative projects, can significantly benefit from equitably structured S3 programs. This highlights the potential of S3 to level the playing field across various sectors, particularly in regions with diverse technological capabilities.

Further expanding on the regional implications of these strategies, Bachtrögler et al. (2020) investigated the impact of the EU Cohesion Policy (CP) on manufacturing firms across several member states during the 2007-2013 period. Their research points to a heterogeneous effect of policy support on firm performance, underscoring the importance of tailoring strategies to specific regional contexts. Their findings suggest that CP support has a more pronounced effect in lower-income countries and regions with limited private assets, reinforcing the need for targeted support in these areas.

The differential impacts of these frameworks are also evident in studies focusing on the effects of I4 technologies. For instance, Cirillo et al. (2023) examined the adoption of I4 technologies among Italian firms, finding positive outcomes in labour productivity, wages, and sales, particularly for smaller firms. This underscores the complex nature of technological adoption, where benefits might be unevenly distributed across different firm sizes and sectors.

Moreover, the research by Capello and Lenzi (2023) highlights the uneven regional impacts of I4 technologies. They emphasise that advanced regions in manufacturing transformation benefit more significantly from targeted I4 policies, whereas regions still adapting require broader digitalisation strategies. This finding is crucial in understanding the regional disparities in technology adoption and the corresponding economic performance.

Despite these valuable contributions, there remains a significant gap in understanding the combined effects of S3 and I4, particularly regarding firm-level impacts. This insufficient attention is critical, as the effectiveness of such policies is ultimately measured by their translation into tangible improvements in firm performance, especially in an era of rapid technological advancement.

The primary aim of this study is to deeply understand the impact of the S3 and I4 frameworks on driving innovation and, ultimately, how it translates into enhancing firm performance. Our research contributes to the existing literature by focusing on S3I4 projects, which integrate I4 technologies within the S3 framework. This distinctive approach enables us to thoroughly investigate the confluence of these frameworks at the firm level and their impact on innovation-led performance. To comprehensively analyse this, we examine ERDF-funded projects as a key measure of the effectiveness of the S3 and I4 frameworks. This analysis required extensive groundwork, as we identified and classified I4-aligned projects from the original OpenCoesione data, a key step in setting the stage for our estimations. Our study stands out not only in its targeted focus but also in its innovative methodological approach. We employ the staggered Difference-in-Differences (DiD) methodology, recently proposed by Callaway and Sant'Anna (CS, 2021), coupled with a novel procedure for identifying I4-aligned projects. Our approach allows us to uncover varied levels of effectiveness in these projects across different regions and sectors. Notably, S3I4 projects emerge as significant drivers of economic progress, outperforming other project types. The industrial sector and Northern Italy exhibit pronounced growth, while impacts in other regions and outside the industrial sphere are more heterogeneous. These findings highlight the importance of aligning ERDF investments with regional economic profiles and innovation potentials.

The remainder of the paper is organized as follows. Section 2 reviews the recent literature on S3 and I4 frameworks. Sections 3 presents the data, detailing its sources and relevance, and introduces our approach to identifying I4 projects. Section 4 provides a brief illustration of the staggered DiD methodology used in our analysis. Section 5 presents a detailed examination of the impacts of ERDF-funded projects, starting with an aggregate-level analysis and then delving into sub-sample assessments based on geographic, sectoral, and project-type disaggregations. Finally, the paper concludes with a discussion on the broader implications of our findings.

2. Literature review and theoretical background

The S3 and I4 are central to the EU's innovation landscape, each marking significant regional policy and industrial paradigm shifts. These frameworks represent transformative changes, combining regional policy development and industry advancements.

S3, guided by the insights of the "Knowledge for Growth" expert group (Foray et al., 2009) takes a place-based approach to regional development, leveraging local strengths and focusing on tailored, competitive advantages. This strategy aligns with the EU's goals of enhancing regional innovation ecosystems, as Hassink and Gong (2019) and McCann and Ortega-Argilés (2015) discussed. Central to S3 is its Entrepreneurial Discovery Process (EDP) (Foray et al., 2009, 2011; Iacobucci, 2014), which plays a crucial role in identifying regional economic specialisations involving stakeholders from public and private sectors, academia, and civil society. It is instrumental in identifying areas where a region can excel, ensuring that strategies are bottom-up and adapted to local strengths. Moreover, S3 emphasises the efficient concentration of investments, prompting regions to augment existing assets and capabilities. This approach shifts from traditional, more dispersed investment strategies, pushing technologically advanced regions to invest in General-Purpose Technologies (GPT) and Key Enabling Technologies (KET) while guiding less advanced regions to apply these technologies within their specific economic contexts.

Building on this framework, the concepts of relatedness and complexity emerge as key components within S3 (Balland et al., 2019; Balland and Rigby, 2017; Boschma, 2017; Deegan et al., 2021; Hidalgo et al., 2018; Hidalgo and Hausmann, 2009). Relatedness refers to the connection between new economic activities and a region's existing industrial and knowledge base. This concept is crucial for fostering development in areas closely linked to current economic activities, ensuring that new initiatives are relevant and supportive of the existing economic fabric. It encourages regions to capitalise on their established strengths and explore new opportunities closely aligned with their current economic ecosystem.

In contrast, complexity within S3 deals with the depth and diversity of knowledge and skills required for various economic activities. It challenges regions to develop their capacities progressively, encouraging them to engage in more sophisticated and intricate economic activities. This aspect of S3 pushes regions to evolve and adapt, ensuring that their economic development is not only based on existing strengths but is also forward-looking and ambitious. Despite its strategic approach, S3 faces challenges in implementation, such as under-theorisation and potential ineffectiveness in peripheral regions (Aranguren et al., 2019; Iacobucci, 2014; McCann and Ortega-Argilés, 2015). Empirical studies have identified a lack of consensus on measuring inter-sectoral relatedness and found that a limited number of regions have prioritized sectors in which they already have competitive advantage or in which they show clear potential to develop such, suggesting a need for more defined guidelines and robust analytical methods (D'Adda et al., 2020; Di Cataldo et al., 2021; Marrocu et al., 2022).

On the other hand, I4 signals a transformative era in manufacturing characterised by the integration of advanced digital technologies such as the Internet of Things (IoT), big data analytics, and Artificial Intelligence (AI) (De Propris and Bailey, 2020; Kagermann et al., 2013). This revolution extends beyond traditional manufacturing, redefining production processes and business models towards increased efficiency, customisation, and sustainability. The technological advancements of I4 are expected to permeate various aspects of society, transforming not only the industrial and manufacturing sectors but also impacting daily life. Applying these technologies requires careful study and attention, particularly in ensuring a smooth digital transition that supports regions and states in integrating modern technologies effectively.

The synergy between S3 and I4 creates opportunities for redefining firms' technological advance, industrial competitiveness and regional development. The alignment of S3's strategies for identifying and nurturing regional strengths with the technological advancements of I4 has the potential to accelerate regional innovation and economic growth significantly. Barzotto et al. (2020) and Lepore and Spigarelli (2020) delve into the challenges and opportunities presented by integrating I4 technologies within the framework of S3. Their research highlights the critical need for inclusive growth strategies, emphasising that the advancements brought about by I4 should be accessible and beneficial to all regions, not just the technologically advanced or economically prosperous ones.

Barzotto et al. (2020) specifically address the potential digital divide that could arise from the uneven adoption and integration of I4 technologies. They argue that without careful planning and strategic implementation, there is a risk that certain regions, particularly those that are less developed or have limited technological infrastructure, may lag behind. This could exacerbate existing disparities and hinder the overall objective of cohesive regional development.

Lepore and Spigarelli (2020) contribute to this discourse by examining the readiness of regions to embrace the technological advancements of I4. Their study suggests that strategies must be tailored to each region's unique needs and capabilities to achieve truly inclusive growth. This includes considering the current level of digital infrastructure, the availability of skilled labour, and the specific socio-economic conditions of each area.

Both contributions advocate for a comprehensive approach to policy-making encompassing the technological aspects of I4 and the broader socio-economic factors that influence regional development. They suggest policies should be designed to support regions in building the necessary infrastructure, fostering skill development, and creating conducive environments for technological adoption and innovation.

Empirical research, including studies by Crescenzi et al. (2020) and Balland et al. (2019), underscores the importance of aligning S3 priorities with the specific capabilities of each region. These studies warn against adopting generic or trendy domains without considering local conditions and stress the importance of leveraging existing capabilities in local areas for successful technological adoption and innovation. Furthermore, the work of Capello and Lenzi (2023) highlights the varying impact of I4 technologies across different regions. This suggests the necessity for tailored policies that account for different regions' unique economic, social, and geographical contexts.

The research by Ciffolilli and Muscio (2018) contributes to this discourse by highlighting the critical need for firms to adapt their business models and operational structures to the demands of I4. They emphasise the importance of strategic and organisational shifts essential for thriving in the I4 era, suggesting a holistic approach involving technological adoption, embracing advanced manufacturing processes, and fostering innovation cultures. Their study delves into the nuances of I4's influence, suggesting that firms must adopt new technologies and undergo significant strategic and structural shifts. This includes embracing advanced manufacturing processes, fostering a culture of innovation, and developing a workforce skilled in new digital technologies.

Building on this, a recent special issue editorial by Cefis et al. (2023) offers a broader perspective on digital transformation, discussing the importance of strategic, organisational, and technological adaptations in the face of digitalisation. This work provides a comprehensive view of the digital transformation's impact on firms, encompassing various aspects from strategy to internal structure.

Complementing these theoretical insights, Cirillo et al. (2023) and Forgione and Migliardo (2023), also part of the special issue, present empirical evidence from the Italian business sector. They show the tangible benefits of I4 for small and medium enterprises (SME), including improved labour productivity, wages, and sales growth. Additionally, their research sheds light on the regional economic implications of I4, demonstrating how advanced technological investments can reduce regional disparities and enhance operational efficiency, particularly in lagging areas.

While these studies provide a foundational understanding, a significant gap exists in comprehensively assessing how the combination of S3 and I4 strategies impacts firm performance across various regions and sectors. This present study seeks to address this gap by examining the effects of ERDF-funded S3 and I4 projects on Italian firms. It aims to uncover the variations in the effectiveness of these projects, offering a detailed analysis of their impacts across different regions and sectors. This research aims to explain how S3 and I4 can be harmoniously integrated and tailored to regions' diverse economic and innovation landscapes. The outcomes of this study are expected to offer valuable insights for business leaders and policymakers, facilitating the development of strategies that align with the transformative potential of S3 and I4, particularly in enhancing the performance and adaptability of SMEs in Italy.

3. Italian firms' ERDF projects

3.1 Building the dataset

The primary aim of this analysis is to measure the impact of ERDF-funded projects that align with I4 activities and simultaneously fall under the S3. To accomplish this objective, the study uses data from OpenCoesione, the Italian web platform that collects projects funded by EU CP funds. Our analysis targets the ERDF-funded initiative for the programming period 2014-2020, comprising 138,845 Italian projects[1]. This period is particularly significant as it marks the inaugural implementation of S3 across the European Union, with the projects funded by the ERDF being strictly related to the S3 framework. It is important to note that all firms comprising the sample had been selected for funding, but not all had received the full amount of their payment at the time of data collection. This noteworthy aspect will be elaborated upon in greater detail in the methodological section of the analysis.

Following a well-established literature (Bachtrögler et al., 2020; Cirillo et al., 2023; Crescenzi et al., 2020; Crescenzi & Giua, 2020), as the outcome variable we select Value Added (VA) which capture the value generated by a firm in the production process. This variable is widely recognised as being influenced by innovative activities and serves as a reliable indicator of a firm's economic improvement through innovation. Improvements that in our analysis are expected to be brough about by the projects aligned with the S3 strategy.

Considering this context, our dataset underwent a rigorous cleaning process to ensure the most accurate and relevant analysis (Table 1). Initially, we focused on profit-oriented entities, as these firms provide the most suitable context for assessing the impact of funding on economic performance. This focus led to the elimination of a substantial number of projects, as these were associated with public entities[2]. Subsequently, we ensured that financial statements were available for the remaining private businesses, as this data is essential for evaluating firm performance[3]. We then limited our attention to projects with a single beneficiary to eliminate ambiguity in attributing the effects of funding. Subsequently, we aligned the dataset with the 2014-2020 programming period to concentrate on the period relevant to this study. After merging the cleaned dataset with firm-level economic performance data from the ORBIS database, we had the opportunity to refine our sample further. At this stage, we excluded firms with public entity shareholders, as these firms often operate under different performance targets than purely private firms. Then, to ensure a neat identification of funding effects, we restricted our sample to firms that received funding for only one project

[1] Downloaded in December 2022.

[2] The entities excluded are mostly public bodies like regions or municipalities, plus other organisations out of the scope of the analysis (i.e. Mutual Aid Society).

[3] Entity selected: Private limited companies, Partnerships, Public limited companies, Companies with unknown/unrecorded legal form, Other legal forms, Non-profit organisations, Foreign companies.

during the study period. Lastly, to apply the DiD approach, we kept firms with at least two observations for the output variable. The final dataset comprises 22,086 projects, each corresponding to a unique firm, forming the basis of our analysis.

3.2 S3 and I4 Project Identification

Following the central aim of this study, which we reiterate is to assess the effectiveness of ERDF funding in the context of I4 and S3, it is essential to identify and categorise the projects related to these frameworks in our sample.

The OpenCoesione dataset is comprehensive, as it details the nature, finances, and stakeholders of the funded projects. Upon our request, the OpenCoesione team supplied an in-depth classification of projects aligned with S3 strategies, adding a layer of detail to the publicly available data. This allowed us to merge it with the ERDF dataset using project identification codes, thereby identifying the projects that align with regional S3.

Our refined sample has 4,808 S3 projects, making up 21.8% of the total. These S3 projects are classified according to a system encompassing regional and national strategies, shedding light on the specific areas of intervention. The predominant categories among these projects are the regional strategies "*Smart Factory*" (42.8%), followed by "*Agrifood*" (11.5%), and "*Smart, Secure and Inclusive Communities*" (10.4%), as illustrated in Table 2.

We employed a two-step procedure to identify firms undertaking projects related to I4 technologies. Initially, we classified as I4 all S3 projects categorised by OpenCoesione as "*Smart Factory*", "*Smart, Secure and Inclusive Communities*", along with the national categories of "*Smart and sustainable industry, energy, and environment*" and "*Digital Agenda, Smart Communities, Intelligent Mobility Systems*". This resulted in a partial of 2,611 S3I4 projects.

Subsequently, we extended our analysis to identify additional I4-related projects. We used a text-analysis technique using "quanteda" in R to analyse each project's denomination and description sections. The keyword list for this analysis is primarily derived from European Patent Office (EPO) documents on the Fourth Industrial Revolution (Table 3 and Table 4). The list adopts a broad approach to capturing a wide array of I4 technologies and applications, as there is no unique strict definition of what precisely constitutes an I4 technology (Chiarello et al., 2018). This list was adapted to account for the native language of the project descriptions, necessitating the translation of several terms into Italian. However, it is worth noting that not all projects had exhaustive descriptions; some included only a general aim or the firm's name. Therefore, there is a possibility that our analysis may have overlooked some I4-related projects due to insufficient information in their official descriptions.

Through this text analysis, we identified an additional 2,005 I4-related projects. Of these, 345 projects overlapped with S3 but fell outside the initially selected I4 categories, thus constituting additional S3I4 projects. The remaining 1,660 projects were identified as I4-related but not part of the S3 framework. This is unsurprising, as diverse calls exist at the regional level that promote firms' I4 innovation in areas not directly related to the regional S3 priorities.

Finally, we categorise our ERDF funded firms into four distinct, non-overlapping groups which will be the core of the econometric analysis:

- 2,956 firms (11.7%) with projects related to both S3 and I4 (S3I4)
- 1,852 firms (7.7%) with projects related to S3 but not I4 (Other S3)
- 1,660 firms (6.4%) with projects related to I4 but not S3 (Other I4)
- 15,618 firms (74.2%) with projects related to neither I4 nor S3 (Other)

3.3 Firm characteristics

Sectoral distribution

The distribution of firms with S3 and I4 projects (Table 5) across 1-digit NACE sectors in Italy provides a comprehensive insight into how various industries align with S3 and I4 objectives. The econometric analysis, given the presence of few firms in certain sectors, will focus on four macro-sectors comprising Industry, Knowledge-Intensive Services (KIS), Less Knowledge-Intensive Services (LKIS), and the Tourism and recreation sector.

Within this classification, the Industry sector encompasses 45.8% of firms, of which 18.4% are engaged in S3I4 projects. Notably, the manufacturing sector is at the forefront of S3I4 diffusion, with 20.8% of its projects linked to these initiatives. In the KIS macro-sector, where 19.6% of projects are S3I4-related, the Information and Communication sector stands out. It has a higher engagement in S3I4 projects, with 22.2% of its projects aligning with this framework. The presence of S3I4 projects is quite reduced in the remaining macro-sector. In the LKIS sector, which accounts for 20.1% of firms, 6.9% of projects align with S3I4, with the Transportation and Storage sector exhibiting the highest integration at 9.8%. Conversely, despite constituting 14.5% of firms, the Tourism and recreation sector demonstrates a notably low engagement in S3I4 projects, with a mere 2% of its projects being connected to this group.

Regional distribution

The distribution of S3 and I4 projects in Italy is represented at regional level in Table 6 and Figure 1. The North has 1,561 projects that are jointly aligned with S3 and I4, which is 17.1% of its project pool. Despite a smaller pool of projects, the Centre shows a higher proportion of such integrated projects with 1,056 S3I4 initiatives, making up 24.2% of its total. The Mezzogiorno's share of S3I4 projects is smaller at 3.9%, with 339 projects. This comparison highlights not just the raw numbers but also the relative concentration of projects, with the Centre having the highest proportion of projects that embody both S3 and I4 strategies, despite the North having more S3I4 projects in absolute terms. This two-tiered analysis allows for an understanding of the general distribution of S3 and I4 project alignment across macro-areas, and it highlights the heterogeneity across regions in the adoption and integration of the two frameworks, which can be indicative of regional priorities, the role of existing economic and industrial structure and the capacity to engage in technological advancement.

Firm dimension and legal characteristics

The distribution of S3 and S3I4 projects across firms of varying sizes (Table 7) reveals an interesting pattern: as firms' size grows, there is a discernible increase in their engagement with S3 and I4. Specifically, the share of S3I4 projects starts at 10.8% for single-employee firms and increases to 30.6% for firms with 250 or more employees. To a lesser extent, this upward trend is mirrored in the Other S3 category. Conversely, the share of projects in the Other category decreases as firm size increases, dropping from 73.9% for the smallest firms to 31.8% for the largest. This pattern suggests that larger firms tend to align more with S3 and I4 objectives, possibly due to greater resources and strategic focus. However, the predominance of smaller firms in the Other category indicates a significant opportunity for growth. Integrating I4 elements is vital for firms of all sizes, given the ongoing shift towards digitalisation in the global economy.

Finally, as for the legal characteristics of the firms in our sample (Table 8), Private Limited Companies make up the majority, accounting for 87% of the total projects. However, when it comes to engagement with S3I4 projects, Public Limited Companies exhibit a higher propensity, with a 25.6% share of their total projects falling under this category, as opposed to the 12.7% share observed among Private Limited Companies. This distinction seems to suggest that, alongside firm size, legal structure could also play a role in influencing a firm's engagement with S3I4 initiatives.

4. Methodology

4.1 Introduction to the Staggered Difference-in-Differences (DiD)

To evaluate the impact of projects funded by the ERDF on firms' VA, this study uses the staggered DiD approach, recently proposed by Callaway and Sant'Anna (2021). This methodology is selected over the classic DiD design due to the variable timing of ERDF interventions, where projects commence at different points in time. Moreover, it is worth noting that the CS approach allows for greater flexibility with respect to previous similar approaches (Athey & Imbens, 2022; De Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021) for heterogeneous treatment effects with variation in treatment time. More specifically, CS allow for minimal parallel trend assumptions to identify the average treatment effect (ATT), for the inclusion of covariates in a flexible form, different estimation procedures and different aggregation schemes to summarize the treatment effects.

The classic DiD approach typically involves two groups - treated and control- over two time periods, estimating the ATT by comparing changes in outcomes from before to after the intervention. It relies on the parallel trends' assumption, where, in the absence of treatment, the outcomes for treated and control groups would follow the same path over time. However, this traditional approach is not as well-suited to the staggered nature of ERDF project rollouts.

The staggered DiD model extends this framework by incorporating multiple periods and allowing for the varying initiation of treatments across firms. This staggered DiD analysis will compare the performance trends of firms that have received ERDF payment against those that have not yet received it, allowing for a dynamic control group that changes over time. The assumption of limited treatment anticipation underpins this model - firms do not change their behaviour significantly in the brief period between being notified of and receiving ERDF funding. It also relies on the assumption of conditional parallel trends, which asserts that the performance trends of treated and untreated firms would be similar when controlling for specific covariates before treatment. This assumption does not concern the levels of output or performance, which may naturally vary across firms of different scales, but rather focuses on the trends of these outputs over time. It assumes that, in the absence of treatment, the trajectory of change in the firms' performance would be consistent across both treated and control groups when controlling for observable covariates. This assumption is important because it allows for differences in firm characteristics and initial performance levels but posits that the rate of change in outcomes remains the same across groups prior to any intervention. In this study, the primary covariates are sector and geographical location. By controlling for these variables, we aim to isolate the impact of ERDF funding from industry-specific and regional factors that could also affect firm performance. This is crucial in ensuring that the observed effects are not conflated with external influences but are attributable to ERDF interventions.

Furthermore, this analysis incorporates the assumption of the irreversibility of treatment. Once a firm receives ERDF funding, the effects of this intervention are considered permanent. The firm's subsequent performance trajectory is analysed under the premise that the impact of the funding cannot be undone or reversed.

In the approach suggested by CS, the ATT for a specific group and period is non-parametrically point-identified under these assumptions. It can be estimated using various approaches, such as Outcome Regression (OR), Inverse Probability Weighting (IPW), and Doubly Robust (DR) methods. The ATT is calculated by comparing the changes in outcomes for the treated group with that of the control group. These ATT estimates can either serve as the final causal parameters or be aggregated to evaluate more comprehensive effects, such as those across different periods or lengths of treatment exposure.

Using firm data from 2012, even though the programming period for the ERDF projects is 2014-2020, this study ensures sufficient pre-treatment data to validate the parallel trends assumption. A varying base period specification will be employed in the pre-treatment phase to validate the parallel trends assumption. This approach computes a pseudo-ATT for each treatment period by contrasting the changes in outcomes for a specific group with that of its comparison group in the pre-treatment periods. The study aims to assess the validity of the parallel trend assumption by generating a pseudo-ATT in the period immediately preceding the treatment. If the pseudo-ATT is statistically insignificant, it would provide empirical support for the assumption that the treated and control groups were on parallel paths before the treatment, reinforcing the credibility of the subsequent DiD estimates.

In the CS (2021) framework, each group *g* is defined based on the year when treatment is first administered. The ATT for each of these groups is estimated using one of the following estimators, depending on the setup. Equations 1, 2 and 3 compare the change in the treated only against the firm that does not receive any treatment (the never-treated), while equations 4, 5 and 6 compare the change with the "not-yet treated" as well until they receive the treatment:

$$\mathrm{ATT}_{ipw}^{nev}(\mathrm{g,t}) = \mathrm{E}[\left(\frac{G_g}{E[G_g]} - \frac{\frac{p_{g,}(X)C}{1-p_{g,}(X)}}{E\left[\frac{p_{g,}(X)C}{1-p_{g,}(X)}\right]}\right)(Y_t - Y_{g-1}) \tag{1}$$

$$\mathrm{ATT}_{or}^{nev}(\mathrm{g,t}) = \mathrm{E}[\left(\frac{G_g}{E[G_g]}\right)\left(Y_t - Y_{g-1} - m_{g,t}^{nev}(X)\right)]\ ] \tag{2}$$

$$\mathrm{ATT}_{dr}^{nev}(\mathrm{g,t}) = \mathrm{E}[\left(\frac{G_g}{E[G_g]} - \frac{\frac{p_{g,}(X)C}{1-p_{g,}(X)}}{E\left[\frac{p_{g,}(X)C}{1-p_{g,}(X)}\right]}\right)\left(Y_t - Y_{g-1} - m_{g,t}^{nev}(X)\right)] \tag{3}$$

$$\mathrm{ATT}_{ipw}^{ny}(\mathrm{g,t}) = \mathrm{E}[\left(\frac{G_g}{E[G_g]} - \frac{\frac{p_{g,t}(X)(1-D_t)(1-G_g)}{1-p_{g,t}(X)}}{E\left[\frac{p_{g,t}(X)(1-D_t)(1-G_g)}{1-p_{g,t}(X)}\right]}\right)(Y_t - Y_{g-1})] \tag{4}$$

$$\mathrm{ATT}_{or}^{ny}(\mathrm{g,t}) = \mathrm{E}[\left(\frac{G_g}{E[G_g]}\right)\left(Y_t - Y_{g-1} - m_{g,t}^{ny}(X)\right)] \tag{5}$$

$$\mathrm{ATT}_{dr}^{ny}(\mathrm{g,t}) = \mathrm{E}[\left(\frac{G_g}{E[G_g]} - \frac{\frac{p_{g,t}(X)(1-D_t)(1-G_g)}{1-p_{g,t}(X)}}{E\left[\frac{p_{g,t}(X)(1-D_t)(1-G_g)}{1-p_{g,t}(X)}\right]}\right)\left(Y_t - Y_{g-1} - m_{g,t}^{ny}(X)\right) \tag{6}$$

where:

- $\boldsymbol{ATT\ (g,t)}$ represents the Average Treatment Effect on the Treated for units who are members of a particular group *g* at a particular time period *t*
- **C** is a binary variable that is equal to 1 for units that do not participate in the treatment in any time period, 0 otherwise
- $\mathbf{D_t}$ is a binary variable that is equal to 1 for unit treated at the time *t,* 0 otherwise
- $\mathbf{G_g}$ is a binary variable that is equal to 1 for units in group *g* (treatment year), 0 otherwise, distinguishing staggered treatment groups
- $\mathbf{Y_t}$ is the outcome variable measured at time *t*
- $\mathbf{Y_{g-1}}$ is the outcome variable measured at a time point defined as the group time minus one, representing the outcome at a previous time
- $\boldsymbol{m_{g,t}(X)}$ these are population outcome regressions for the never-treated group and for the "not-yet-treated" given a set of covariates X

- $\boldsymbol{p_{g,t}(X)}$ is function of the covariate group X, determining the probability of being in group *g* at time *t*, used for weighting to ensure comparability and support the parallel trends assumption

The DR estimator merges elements from the IPW and OR approaches. The IPW approach models the probability of a unit being treated (i.e. being included in group *g*), given a set of covariates X. This adjustment is crucial for aligning the distribution of covariates between the treated and control groups, thereby supporting the parallel trends assumption. The OR approach involves modelling the conditional expectation of the outcome evolution for the comparison groups. A set of X covariates X are therefore included to address potential confounding factors that might affect treatment outcomes. The DR approach combines both the OR and IPW approaches as it relies on modelling both the outcome evolution and the propensity score. Importantly, it demands accurate specification of just one of these elements — either the outcome evolution in the comparison group or the propensity score model, but not both.

In this study, while we will prioritise results from the DR estimator for its robust approach, we will consistently report estimations from all three approaches – OR, IPW and DR - for comprehensive analysis. This approach is especially pertinent as the DR estimator may not be applicable in all cases. Where DR cannot be applied, the OR and IPW approaches will be exclusively used to evaluate the treatment effects. This inclusive reporting strategy ensures a thorough and nuanced understanding of the impacts under various methodological lenses.

To construct the event study that illustrates how the average treatment effects vary with the length of exposure to the treatment, we need to focus on the aggregation of the group-time average treatment effects, ATT(g,t), over different lengths of exposure to the treatment. This is achieved through the following steps:

1. **Defining the Length of Exposure to the Treatment**: The length of exposure to the treatment is defined as $t-g+1$, where t is the current period, and g is the group time. This definition allows us to capture the varying lengths of exposure to the treatment across distinct groups and time periods.
2. **Aggregating Group-Time Average Treatment Effects**: The group-time average treatment effects, ATT(g,t), are aggregated over different lengths of exposure to the treatment using the following formula:

$$\theta_{es}(e) = \sum_{g \in G} 1\{g + e \leq T\} P(G = g \mid G + e \leq T) ATT(g, g + e) \tag{7}$$

Here:

- $\boldsymbol{\theta_{es}(e)}$ represents the event study estimate of the average treatment effect for a specific event time *e*. Let *e* denote event-time, i.e., $e = t-g$ denotes the time elapsed since treatment was adopted
- $\boldsymbol{1\{g+e \leq T\}}$ is an indicator function that takes the value 1 if the condition $g+e \leq T$ is met, 0 otherwise. This ensures that we only consider the groups that are observed at the event time *e*

- **P(G=g|G+e≤T)** is the conditional probability of being in group *g* given that the group is observed at event time *e*. This term acts as the weight in the aggregation.
- **ATT(g,g+e)** is the average treatment effect on the treated for group *g* at event time *g+e*
- **G** is the set of all groups
- **T** is the total number of time periods.

4.2 Defining treated and control groups

Applying the DiD methodology requires accurately defining the treated and control groups. In this study, the treated group consists of firms that have achieved a 100% payment ratio, indicating the full receipt of their allocated ERDF funding. The year (*t*) in which a firm reaches this 100% payment ratio is termed the treatment year, serving as a critical temporal marker for the analysis, for which the firm is associated with the group (*g*).

The control group in this study comprises firms that have been awarded ERDF funding but have not yet received the full payment. These "not-yet-treated" firms serve as a dynamic element within the control group and can be categorised based on the timing of their scheduled payments. Some are set to receive full payments within the study period, specifically from 2017 to 2021, and they transit to the treated group once achieve a 100% payment ratio. Others will only receive full payments after the study period has concluded, remaining consistently in the control group throughout the study.

Furthermore, this study's methodological approach significantly emphasises the comparability of the treated and "not-yet-treated" firms. All firms in the sample have been awarded ERDF funding, which implies a fundamental similarity in their characteristics and qualifications for treatment. This aspect substantially mitigates concerns about potential biases related to treatment timing and enhances the control group's validity as a counterfactual.

The use of the CS estimator enables the inclusion of "not-yet-treated" firms in the control group, a feature that significantly strengthens the robustness of the study's counterfactual. This methodology allows for a temporally differentiated control group, where all firms eventually receive treatment. This is a marked advantage over other methodologies like Propensity Score Matching and Synthetic Control Methods, which often rely on never-treated units selected on the basis of similarity in a set of covariates. For several reasons, such units may not have received funding, raising questions about potential selection bias. In contrast, our approach minimises this concern by focusing on firms that have all succeeded in securing ERDF funding, differing only in the timing of fund disbursement.

In addition to these methodological considerations, employing the DR estimator adds a further layer of robustness to the study. Specifically, the DR estimator controls for a set of covariates – in our case, the geographical location and the sectoral classification - in both the probability of receiving treatment and the outcome results. This dual control enhances the accuracy of the estimated treatment effects and further validates the study's counterfactual.

Two additional key criteria then shaped the final sample for the estimation. First, the study focused on firms with either a 0% or 100% payment ratio, clearly delineating the control and treated groups.

The decision to concentrate on these well-defined groups is both empirically grounded and methodologically sound. An examination of the payment ratio across all projects, as illustrated in Figure 2, revealed a prominent bimodal distribution with two distinct clusters forming at 100% and 0%. These thresholds are not arbitrary; they represent clear, definitive states of treatment. A 100% payment ratio signifies complete receipt of allocated funding, while a 0% ratio indicates no funding received. Second, only treated firms with at least complete data for the treatment year and the year before were included to ensure the possibility of estimating the ATT between at least a pre-treatment period and a post-treated period. These selection criteria led to an estimation sample of 14,631 projects.

To ensure the robustness of the findings, the study explored alternative treatment thresholds, such as varying payment ratios as the treatment threshold, and even considered firms with partial funding for the control group in additional examinations. These tests confirmed the main analysis but yielded less pronounced effects and introduced ambiguity in the treatment definition. Given these considerations, the study adheres to a binary classification of 0% and 100% payment ratios as the most methodologically sound and empirically grounded approach to capture the most significant and reliable impacts of ERDF funding instead of setting arbitrary and subjective treatment thresholds.

5. Results

5.1 Aggregate results

This section presents the empirical results of our econometric analysis, which examines the impact of ERDF funding on firm-level VA. For this analysis, VA is transformed using the inverse hyperbolic sine (IHS) method[4]. Employing the staggered DiD methodology presented above, we use DR, OR, and IPW estimators to ensure a comprehensive and robust examination of results[5]. As in CS (2021), we report the dynamic aggregated treatment effect, which captures the treatment's impact over successive periods, allowing for a more detailed understanding of how ERDF funding influences firm performance over time. This measure is

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[4] IHS: $(y) = \sinh^{-1}(x) = \ln(y + \sqrt{y^2 + 1}$

The IHS is used for its ability to handle zero and negative values. It shares equivalent properties with the logarithmic transformation, making it particularly useful in econometric analyses. Coefficients obtained from the IHS transformation can be interpreted similarly to those from a logarithmic transformation, indicating approximate percentage changes.

[5] The code and package used in this study are those provided by the original authors, available through the R package "did" on CRAN.

more informative than a simple average as it reflects the cumulative effect of funding. In addition, we provide estimates of the impacts with respect to different lengths of exposure to the treatment.

In estimating the impact of aggregate ERDF funds, all three estimators - DR, OR, and IPW - are employed to assess how results vary across the three approaches and to affirm robustness. As we said in the methodological section, the DR estimator is prioritised; however, where sample size and covariate balance preclude its use, OR and IPW estimators are used to maintain analytical consistency. Our estimation accounts for the firm's geographical location categorised as North, Centre, or Mezzogiorno, and its sector, classified into Industry, LKIS, KIS, or Tourism and Recreation.

Table 9 presents the results of the aggregate estimations. Starting with the focus on aggregate ERDF, we can see how all the estimators yield positive and significant overall effects of the funding on firm performance. Looking at the overall effect, the DR estimator shows a significant effect of 0.197, while the OR estimator indicates a slightly higher effect of 0.222, and the IPW estimator presents the highest effect of 0.244. This effect varies across the estimators, probably because the IPW, which shows the highest effect, uses the covariate only to control the probability of treatment and to adjust the control group and attributes the effect on the performance solely to the treatment effect. This pattern persists in the event study result, with IPW estimates being higher in all the periods and statistically significant more consistently across all the periods.

Figure 3 illustrates the event study estimation, providing detailed insight into the dynamic effect of projects over time. At the treatment point (e=0), we observe a positive impact on firm-level Value Added (VA), indicating a beneficial short-term effect of ERDF support. The effect does not reach statistical significance in the first and third periods post-treatment, though it comes remarkably close to being marginally significant in these periods. The reduced significance and effect observed in the last period may be attributed to decreased number of observations over time, as fewer firms are represented in the dataset further from the initial funding period. This reduction in sample size could diminish the statistical power to detect significant effects. Consequently, the absence of significant long-term effects should not be interpreted as a decline in the effectiveness of ERDF funding. The upward trend observed in the figure, despite increasing ranges of standard error leading to non-significant effects, suggests a consistent positive influence of the funding.

5.2 Geographical and sectoral focus

Focusing on the sub-sample analysis, we will now examine the differential impact of ERDF funding based on geographical and sectoral variations (Table 10). In these estimations the covariates are specific to each analysis. When examining the impact within a particular geographic area, the sector of the firm is used as the covariate. Conversely, when analysing the impact within a specific sector, the geographic area of the firm is employed as the covariate.

This ensures that while focusing on one dimension (geographical area or sector), the other dimension is accounted for as a control in our estimation.

The geographical analysis of the impact of ERDF funding, portrayed in Figure 4, reveals a differentiated effect across regions. In the North area, the DR estimator shows a consistently significant positive impact across all periods, with an overall dynamic effect of 0.360 and a peak at 0.451 in the second period post-funding. The OR and IPW estimations also indicate significant positive impacts, with the OR showing an overall effect of 0.377 and peaking at 0.469, while the IPW records 0.413 overall, peaking at 0.512. This robust positive effect could indicate a strong absorptive capacity and effective use of ERDF funds within this area, possibly due to better-developed institutional frameworks, a more competitive business environment, or greater innovation capacity. It should be noted that for this area, the parallel trends assumption is met in the third and second period before the treatment, and nearly met in the period just before the treatment.

Conversely, the Centre region has no statistically significant effect in any period and an exhibits an irregular pattern. Notably, the coefficients are first positive and not statistically significant, then negative, albeit not statistically significant, in the first and second periods following funding, suggesting that ERDF funds might not be as effectively translated into firm performance in this region. The OR and IPW estimations largely mirror this finding. This could reflect structural challenges, less effective regional policy implementation, or disparities in regional economies that affect how firms capitalise on funding.

The Mezzogiorno shows a negative, non-significant initial impact, which gradually turns positive in the subsequent periods, with all the estimators giving a similar pattern. Although not statistically significant, this delayed positive effect might suggest a slower yet eventual benefit from the interventions, possibly due to several factors, such as initial adjustment periods or slower regional economic dynamics.

The heterogeneous results across regions emphasise the complexity of the ERDF's impact and the potential influence of regional characteristics on the efficacy of funding. While the North seems to benefit consistently from the policy intervention, the Centre and Mezzogiorno regions' experiences suggest that the ERDF's influence is more complex, potentially affected by regional disparities in economic structures, governance quality, and the local business ecosystem's receptiveness to innovation and investment.

Moving from the geographical to the sectoral perspective, the analysis shifts focus to discern the differential impacts of ERDF funding between the Industry and Services sectors (Figure 5).

In the sectoral analysis of the impact of ERDF funding, the industry and services sectors exhibit distinct responses. The Industry sector demonstrates a robust response to ERDF funding. The DR estimator indicates an overall dynamic effect of 0.232, which is significant, with notable positive impacts in the second and third periods post-funding, measured at 0.218 and 0.331, respectively. Similarly, the OR and IPW estimations confirm this strong response.

The OR estimator records an overall effect of 0.238, peaking significantly at 0.333 in the third period, and the IPW estimator shows an overall effect of 0.236, reaching its peak at 0.328. This sustained positive impact highlights the sector's capacity to absorb and effectively utilise ERDF support, likely reflecting its capital-intensive and innovation-driven nature.

In contrast, the Services sector presents a less pronounced impact. The DR estimator shows an overall dynamic effect of 0.195, indicating a positive and significant trend. However, this positive trend does not translate into significant effects across individual periods, a pattern echoed in the OR and IPW estimations. The OR estimator shows an overall effect of 0.196, peaking at 0.321, and the IPW estimator records 0.195, peaking at 0.320, yet these results are not statistically significant. This pattern suggests a gradual and less immediate impact of ERDF funding in the Services sector, potentially due to the sector's emphasis on human capital and intangible assets, which often yield returns over a more extended period. Therefore, while the DR estimator's overall positive trajectory is promising, the lack of significant short-term impacts could indicate a less clear influence of ERDF funding in the Services sector.

Our sub-sample analysis resonates with the recent findings by Capello and Lenzi (2023). Their work highlighted the heterogeneous impacts of modern technologies at the regional level, which aligns with our observations of the varied effects of ERDF funding across different Italian regions and sectors.

In the geographical analysis, we observed a consistent and significant positive impact of ERDF funding in the North, possibly due to its advanced institutional frameworks, competitive business environment, and greater innovation capacity. This aligns with Capello and Lenzi's observation of selective regional growth premiums in areas with higher adoption of automation technologies. Conversely, the Centre and Mezzogiorno regions exhibited less pronounced benefits from ERDF funding, reflecting the complexities and regional disparities also noted by Capello and Lenzi (2023). Their research underscores the need for region-specific policies, resonating with our findings of the varied effectiveness of ERDF funding across Italian regions.

Our sectoral analysis is in line with Capello and Lenzi's results. The industry sector's robust response to ERDF funding mirrors the significant growth benefits seen in regions that are advanced in manufacturing transformation. In contrast, the Services sector exhibits a moderated impact, reflecting their findings about the challenges in the digital service economy, where intense competition and large digital intermediaries can moderate growth opportunities.

Thus, our combined findings suggest the necessity for meticulously tailored policies. In the context of ERDF funding, this means aligning investments with each region and sector's unique economic characteristics and technological transformation profiles.

5.3 S3I4 impact: a comparative look across ERDF projects

Moving to the core of our analysis, we explore the impacts of ERDF funding across four project types: S3I4, Other S3, Other I4, and Other projects (Table 11). Each type is analysed using OR and IPW estimators to ensure a consistent and comparative view of their effects on firm performance[6].

In defining our control group for these sub-samples, we use two different reference groups for estimation: the first compares firms within the same project category (within-category comparison), and the second includes a broader range of firms (between-category comparison), irrespective of their specific project engagements. We operate under the assumption that a firm's categorisation into specific groups (S3I4, Other S3, Other I4, or Other) is not an intrinsic characteristic of the firm itself. Rather, it is dictated by the structure and design of the ERDF projects in which they participate. For instance, integrating I4 technologies in a project, and thus a firm's classification into a specific group, is determined by the project's characteristics rather than by pre-existing attributes of the firm.

In our staggered DiD approach, we face two key complexities related to the estimation of the effects of different ERDF projects. The first challenge is the difficulty in differentiating the impacts of various projects within the same estimation. Our methodology does not allow us to distinctly attribute effects to individual projects due to their concurrent implementation.

The second issue arises when attempting to estimate the effect of a particular ERDF project. If we were to include firms involved in other ERDF projects category as part of the control group, these firms would eventually receive their respective treatments. Once treated, they would contribute to the ATT for the project under study. This overlap complicates the clear separation of effects between different projects. To circumvent this problem and accurately assess the impact of a specific ERDF project, our control group is confined to firms that have not received any ERDF treatment during our study period. This ensures that all firms in the control group remain untreated throughout, avoiding the confounding effect of treatment overlap in our staggered DiD analysis.

Our analysis of the ERDF's impact across different project types uncovers clear patterns, particularly highlighting the standout role of S3I4 projects. Focusing on these, we observe a pronounced effect on firm performance compared to other project types. The within-category comparisons for S3I4 projects reveal a significant overall dynamic effect, with the OR estimator at 0.266 (significant at 10% level) and the IPW estimator at 0.292. The effect becomes even more clear in the between-category comparisons. Here, the OR estimator indicates a significant overall effect of 0.430, while the IPW estimator shows a stronger effect at 0.484. The fact that such a pattern is evident in both within and between-category comparisons suggests that the observed effects are attributable to the projects rather than the pre-existing characteristics of the firms involved. This demonstrates the intrinsic value and effectiveness of the S3I4 projects within the ERDF framework. This persistent positive effect

[6] The application of the DR estimator is constrained by limitations in the routine handling of covariates, particularly due to the small sample size associated with specific covariate combinations.

can be appreciated even after looking at the event study estimates (visualised for the between-category comparison in Figure 6 and Figure 7).

For the S3I4 projects between comparison, we observe a clear effect during the periods, with a first effect at the time of the treatment and a significant effect after two and three periods after the treatment. The findings suggest that firms experience an immediate impact following project financing, with effects that are not only rapid but also enduring. This is evidenced by the peak values of 0.713 for the OR estimator and 0.804 for the IPW in the third period. A similar pattern, albeit of a lesser magnitude, is also observed for the within comparison.

For Other S3 projects, the within-category OR and IPW estimations reveal overall dynamic effects of 0.024 and 0.033, respectively. Notably, neither of these effects is statistically significant. The between-category comparisons produce comparable results, with the OR and IPW estimations at 0.154 and 0.168, respectively, also lacking statistical significance. Throughout the event study period, none of the effects are significant. Initially, there appears to be a positive effect, but this turns negative in the final period, indicating an unclear impact of these projects on firm performance. This trend could be due to the fact that, while the firms operate in sectors deemed strategic by the regions, they may not be benefiting from projects that substantially enhance their performance through innovation or result in significant and enduring improvements in their performance.

Analysing the Other I4 project results, we observe distinct outcomes when comparing the within-category and between-category estimations. Within-category, the OR estimation shows an overall effect of 0.300, and the IPW estimation is slightly lower at 0.273, both significant. In contrast, the between-category comparisons present a different picture. Here, the OR and IPW estimations show no statistically significant effects, with the OR estimation at 0.154 and the IPW estimation slightly higher at 0.168. Observing the event study estimations instead, the pattern seems more similar, although the within-groups estimation presents a higher magnitude of effect. Both comparisons are significant only in the third period of the treatment, suggesting that investment in I4 may be beneficial even when operated in non-aligned sectors, but the results show a non-definitive conclusion.

Projects under the Other category demonstrate a relatively lower significant impact. The within-category analysis shows OR and IPW estimations with overall dynamic effects of 0.179 and 0.194, respectively. In the between-category comparison, the OR estimation stands at 0.186 and the IPW estimation at 0.197, with both values also achieving statistical significance. However, it is noteworthy that these results exhibit significant effect when looking at the event study dynamics. The only exception is observed in the event study for the within-category comparison, where the second period post-treatment shows a significant effect.

Our examination by type of project offers valuable insights. Primarily, S3I4 projects stand out as significant contributors to firm performance improvement within their own category and when compared with other groups. This is not a minor advancement; firms engaged in

S3I4 projects appear to be significantly outperforming others in most of the comparisons considered.

The scenario is somewhat different for Other S3 and Other I4 projects. Although Other S3 projects exhibit some positive effects, they fail to obtain statistical significance. On the contrary, Other I4 projects exhibit significant effects (overall and after 3 periods of exposure), but these are mainly confined to the within-category comparison. While these projects are beneficial, they do not achieve the same level of impact as S3I4 projects. This highlights a critical point: the effectiveness of ERDF funding varies depending on the project type. In the Other category, the impact trends are similar. Projects in this group occasionally show as opposed to the positive and perduring impact seen in S3I4 projects.

In conclusion, our analysis demonstrates that S3I4 projects make a distinct and substantial difference. This underscores the importance of focused and well-designed projects in utilising ERDF funding effectively to enhance firm performance. For policymakers, our findings emphasise the need for strategic thinking and careful selection of projects, prioritising those with the potential for significant, transformative impact. By doing so, ERDF funding can be a powerful driver for firm and regional growth and innovation.

6. Conclusions

This work has delved into the impact of ERDF-funded projects on firm performance in Italy, with a particular focus on S3I4 projects. Our comprehensive analysis contributes to demonstrating that S3I4 investment projects, which integrate Industry 4.0 technologies within Smart Specialization frameworks, stand out as effective drivers of firms performance and thus regional economic progress. The evidence clearly shows that these projects positively influence firms and surpass the impacts of other types of projects in their effectiveness.

The aggregate impact of ERDF funding, while significant, exhibits notable variations across different sectors and regions. Our analysis revealed a pronounced growth in the industrial sector and Northern Italy. In contrast, the impact in other regions, particularly in the South and sectors outside the industrial sphere, was more varied and less pronounced. This spatial divergence highlights a critical aspect of regional development: the necessity for ERDF investments to be accurately aligned with each region's distinct economic profiles and innovation potentials.

Such alignment is especially crucial when considering integrating S3 and I4 strategies. Merging these strategies with regional innovation capacities can significantly bolster firm performance and economic output. However, as our study indicates, this integration has yielded more substantial results in regions in Northern Italy, which historically have a stronger industrial base and higher innovation capabilities. In contrast, regions in the South, despite having potential growth areas, have not experienced the same level of benefit, underscoring existing regional disparities.

This North-South divide in the effectiveness of ERDF funding and the integration of S3 and I4 strategies brings to light the importance of tailoring these strategies to regional specific characteristics. It suggests that for regions with less industrial and innovation prowess, like those in Southern Italy, there is a need for strategies that not only align with their current economic realities but also provide pathways for catching up with more advanced regions. Addressing this imbalance is crucial for ensuring that the transformative potential of ERDF funding, S3, and I4 strategies is fully realised across all regions, thereby reducing regional disparities and fostering a more balanced economic development throughout Italy.

As Europe transitions into a new programming period, the insights gathered from our study can contribute critically to future policy formulation. They advocate for strategically allocating resources, highlighting the need for investment approaches in harmony with regional economic strengths and innovation potentials. Our findings reiterate the importance of specialisation and innovation as pillars of sustainable growth in the rapidly changing economic environment. For Italy, and by extension, the broader European context, supporting specialised innovation emerges as a key strategy for enduring and inclusive development.

Our investigation into S3I4 projects tackled a significant gap in our comprehension of smart specialisation strategies, offering a fresh perspective on the ongoing discourse on European economic policy and funding mechanisms. The positive outcomes witnessed in Italy through this study endorse the continued support and implementation of such initiatives. While our focus has been on Italy, the implications of our findings could have relevance beyond this specific setting. The trends and patterns observed here offer an insightful understanding of similar dynamics potentially at play in other European regions. Although direct application of these results might require adaptation to different economic and institutional conditions across Europe, the core principles unearthed through our research have broader implications. This indicates that our study, while centred on Italy, can provide valuable insights for shaping economic policies and funding strategies across diverse European landscapes.

Notwithstanding these considerations, our future research will broaden to include various EU regions, aiming to assess and generalize our findings in diverse European contexts. This step is essential given the dynamic nature of S3 strategies across Europe. Such longitudinal, empirical research is crucial for evolving and refining ERDF policies to effectively address regional disparities. Our goal is to build a robust evidence base that can guide the adaptation of smart specialisation strategies, fostering innovation and economic growth throughout the EU.

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Tables

Table 1 – Dataset cleaning procedure

Step	Excluding Criteria		No. of projects
1	All Italian ERDF projects programming period 2014-2020 (downloaded December 2022)		138,845
2	Projects of entities which do not operate on a profit-making basis (i.e. public administrations) [1]	-57,091	
			81,754
3	Projects of private businesses for which it is not possible to retrieve financial statements (i.e. individual firms) [2]	-21,813	
			59,941
4	Projects that have more than one beneficiary	-1,009	
			58,932
5	Projects with starting date <2014	-161	
			58,771
6	Projects of private businesses which do not have a matching in the ORBIS dataset	-8,718	
			50,053
7	Projects of firms controlled by public authorities/public shareholders	-602	
			49,398
8	Projects of firms with more than one project during the period	-19,777	
			29,621
9	Projects of firms with less then two values in the output variable	-7,535	
	Final sample		**22,086**

[1,2] complete list in the appendix

Table 2 – S3 and I4 projects

S3 categories description	S3 Projects	I4 identified by category	I4 identified by text analysis	S3I4 projects
Regional strategies				
Smart Factory	2057	2057		2057
Smart, Secure and Inclusive Communities	502	502		502
Agrifood	551		52	52
Health	290		33	33
Technologies for Living Environments	283		71	71
Energy and Environment	308		63	63
Design, creativity and made in Italy	281		42	42
Technologies for Cultural Heritage	211		28	28
Green Chemistry	77		15	15
Sustainable mobility	42		12	12
Blue growth	44		8	8
Aerospace	42		13	13
National strategies				
Smart and sustainable industry, energy, and environment	47	47		47
Health, Nutrition, and Quality of Life	48		5	5
Digital Agenda, Smart Communities, Intelligent Mobility Systems	5	5		5
Aerospace and defence	8		0	0
Tourism, Cultural Heritage, and Creative Industry	12		3	3
Total	**4808**	**2611**	**345**	**2956**

Table 3 - EPO Classification

Main Sector	Technology Field	Definition	Example
Core Technologies Permit the conversion of any object into a smart device connected to the internet	Hardware	Basic hardware technologies	Sensors, advanced memories, processors, adaptive displays
	Software	Basic software technologies	Intelligent cloud storage and computing structures, adaptive databases, mobile operating systems, virtualisation
	Connectivity	Basic connectivity systems	Network protocols for massively connected devices, adaptive wireless data systems
Enabling Technologies Used in combination with connected object	Analytics	Enabling the interpretation of information	Diagnostic systems for massive data
	User interfaces	Enabling the display and input of information	Virtual reality, information display in eyewear
	3D systems	Enabling the realisation of physical or simulated 3D systems	3D printers and scanners for parts manufacture, automated 3D design and simulation
	Artificial intelligence	Enabling machine understanding	Machine learning, neural networks
	Position determination	Enabling the determination of the position of objects	Enhanced GPS, device to device relative and absolute positioning
	Power supply	Enabling intelligent power handling	Situation-aware charging systems, shared power transmission objectives
	Security	Enabling the security of data or physical objects	Adaptive security systems, intelligent safety systems
Application domains The potential of connected objects is exploited	Personal	Applications pertaining to the individual	Personal health monitoring devices, smart wearables, entertainment devices
	Home	Applications for the home environment	Smart homes, alarm systems, intelligent lighting and heating, consumer robotics
	Vehicles	Applications for moving vehicles	Autonomous driving, vehicle fleet navigation devices
	Enterprise	Applications for business enterprise	Intelligent retail and healthcare systems, autonomous office systems, smart offices, agriculture
	Manufacturing	Applications for industrial manufacture	Smart factories, intelligent robotics, energy saving
	Infrastructure	Applications for infrastructure	Intelligent energy distribution networks, intelligent transport networks, intelligent lighting and heating systems

Source: Own elaboration based on EPO - Patents and the Fourth Industrial Revolution (2017)

Table 4 – I4 keywords

Category	Keywords
3D Technology	“3D laser printing”, “3D print”, “3D printing”, “3-D print”, “3-D printing”, “3D scan”, “3D scanning”, “3D simulation”, “3D user interface”, “Automated 3D”
Industry 4.0 & Advanced Systems	“4.0”, “Industry 4.0”, “Adaptive Database”, “Adaptive databases”, “Adaptive display”, “Adaptive displays”, “Adaptive security”, “Adaptive traffic control”, “Adaptive wireless”, “Computer-implemented”, “CII”
Advanced Manufacturing & Materials	“Additive manufacturing”, “Advance manufacturing”, “Advanced manufacturing”, “Advanced material”, “Advanced materials”
AI & Machine Learning	“AI”, “Artificial intelligence”, “Artificial intelligences”, “Machine learning”
Immersive & Interactive Technology	“Augmented reality”, “Virtualisation”, “Virtual reality”, “Virtual surgery”, “Augmented wearable”, “Augmented wearables”, “Multilevel customer interaction”
Automation, Robotics & Autonomy	“Automation”, “Automated generation”, “Automated system”, “Autonomous line”, “Autonomous lines”, “Autonomous office”, “Autonomous offices”, “Automated driving”, “Autonomous driving”, “Autonomous guided vehicle”, “Autonomous guided vehicles”, “Home automation”, “Greenhouse automation”, “Collaborative robot”, “Collaborative robots”, “Consumer robotic”, “Consumer robotics”, “Robotic”, “Robotics”
Data Management & Analytics	“Big analytics”, “Big Data”, “Blockchain”, “Cloud”, “Intelligent cloud”
Cybersecurity & Digital Security	“Cyber”, “Cyber-physical”, “CPS”, “Data security”, “Digital security”
Digital Healthcare	“Diagnostic system”, “Diagnostic systems”, “E-Health”, “EHealth”, “Intelligent healthcare”, “Personal health monitoring”, “Telehealth system”, “Telehealth systems”
Energy & Resource Management	“Energy efficiency monitoring”, “Energy efficiency improving”, “Energy Management”, “Shared power transmission objectives”, “Smart grid”, “Smart energy”, “Situation-aware charging”
Enterprise Solutions	“Enterprise Resource Planning”, “ERP”, “Internet of things”, “IoT”, “Mobile operating systems”, “Network Protocol”, “Network Protocols”
Smart Technology & Automation	“Smart product”, “Smart system”, “Smart services”, “Smart cities”, “Smart mobility”, “Smart building”, “Vehicle fleet navigation devices”, “Virtual commissioning”
Predictive & Neural Systems	“Neural network”, “Neural networks”, “Predictive maintenance”, “Predictive treatment”, “Predictive treatments”, “Prescriptive farming”
Product & System Optimisation	“Product’s connectivity”, “Product’s monitoring”, “Product’s control”, “Product’s optimisation”, “Product’s autonomy”

Source: Own elaboration based on EPO - Patents and the Fourth Industrial Revolution (2017)

Table 5 - Firms by NACE sectors

NACE main section	Macro Sector	% S3I4	% Other S3	% Other I4	% Other	Total
A - Agriculture, forestry and fishing	Industry[1]	6.4	19.2	10.3	64.1	78
B - Mining and quarrying	Industry	12.7	1.6	14.3	71.4	63
C - Manufacturing	Industry	20.8	8.7	9.7	60.8	7921
D - Electricity, gas, steam and air conditioning supply	Industry	17.9	21.4	7.1	53.6	28
E - Water supply; sewerage, waste management and remediation activities	Industry	12.4	13.3	8.6	65.7	233
F - Construction	Industry	8.8	9.5	5.7	76.0	1781
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	LKIS[2]	6.4	5.1	6.8	81.7	3202
H - Transportation and storage	LKIS	9.8	6.9	6.4	76.9	451
I - Accommodation and food service activities	Tourism & Recreation	1.6	4.0	5.4	89	2578
J - Information and communication	KIS	22.2	13.5	9.8	54.4	1655
K - Financial and insurance activities	KIS	16.3	4.7	2.3	76.7	43
L - Real estate activities	KIS	7.0	5.5	6.0	81.5	200
M - Professional, scientific and technical activities	KIS	18.1	16.9	6.5	58.5	1452
N - Administrative and support service activities	KIS	8.0	6.5	2.6	82.9	973
O - Public administration and defence; compulsory social security	LKIS	100	0.0	0.0	0.0	1
P - Education	LKIS	13.5	7.5	3.8	75.2	133
Q - Human health and social work activities	LKIS	5.7	7.7	5.4	81.3	652
R - Arts, entertainment and recreation	Tourism & Recreation	3.5	8.3	5.6	82.5	372
S - Other service activities	Tourism & Recreation	3.4	3.8	3.8	89.0	264
NA[3]		16.7	16.7	0.0	66.7	6

[1] Agriculture is included in Industry macro-sector due to the nature of the projects, mostly involving food transformation processes, aligning it with manufacturing activities.

[2] LKIS: Low Knowledge Intensive Sectors – KIS: Knowledge Intensive Sectors

[3] No available data for the period selected

Table 6 – Regional share of firms per type of project

Macro area	**% S3I4**	**% Other S3**	**% Other I4**	**% Other**	**Total projects**
North	17.1	8.0	9.0	65.9	9118
Centre	24.2	9.2	9.1	57.6	4370
Mezzogiorno	3.9	8.4	5.1	82.5	8598
Region					
Piemonte	7.7	9.5	7.4	75.5	929
Valle D'Aosta	39.5	2.6	5.3	52.6	21
Lombardia	17.7	5.2	11.6	65.5	2621
Trentino-Alto Adige	11.1	12.0	26.9	50.0	86
Veneto	18.6	7.1	3.8	70.6	2169
Friuli-Venezia Giulia	26.6	26.0	11.2	36.2	795
Liguria	0.2	0.4	4.8	94.6	1485
Emilia-Romagna	12.7	8.2	9.3	69.8	1012
Toscana	34.1	6.6	9.2	50.0	2135
Umbria	31.9	13.4	3.8	50.9	499
Marche	14.0	8.3	8.8	68.9	748
Lazio	6.7	12.6	8.9	71.8	988
Abruzzo	10.0	8.7	6.2	75.1	222
Molise	0.3	0.8	2.2	96.7	400
Campania	7.4	8.2	17.7	66.7	941
Puglia	1.2	1.9	0.3	96.6	4761
Basilicata	4.1	46.8	12.6	36.5	466
Calabria	12.4	15.4	4.4	67.7	392
Sicilia	4.8	8.1	5.7	81.4	991
Sardegna	15.4	29.2	10.5	45.0	425
Total	**11.7**	**7.7**	**6.4**	**74.2**	**22086**

Table 7 – Firms by size

Employees	% S3I4	% Other S3	% Other I4	% Other	% on total firms	Total
1	10.8	9.9	5.4	73.9	15.4	3403
2-5	9.4	6.8	5.1	78.6	29.6	6544
6-10	10.9	7.8	7.0	74.4	17.8	3932
11-20	14.9	8.1	10.5	66.5	17.4	3835
21-50	20.9	9.3	10.5	59.2	12.6	2788
51-249	24.8	11.4	10.6	53.2	5.8	1271
250+	30.6	22.5	15.0	31.8	0.8	173
NA*	12.9	8.6	5.7	72.9	0.6	140
Total firms	**2,956**	**1,852**	**1,660**	**15,618**		**22086**

*No available data for employment for the period selected

Table 8 – Firms by legal form

Legal form	S3I4	Other S3	Other I4	Other	% on total firms	Total
Private limited companies (Società a responsabilità limitata)	2436	1530	1424	13822	87.0	19212
Partnerships (Società Semplice)	102	120	59	930	5.5	1211
Public limited companies (Società per azioni)	406	184	175	821	7.2	1586
Other legal forms	11	18	2	45	03	76
Foreign companies	1	0	0	0	0.0	1
Total firms	**2,956**	**1,852**	**1,660**	**15,618**		**22086**

Table 9 - Value Added aggregated ATT estimations

Group	*Overall dynamic effect*	*Event study*			
Aggregate	Single parameters	e=0	e=1	e=2	e=3
DR estimation	0.197*	0.150*	0.120	0.304*	0.213
OR estimation	0.222*	0.153*	0.159	0.331*	0.245
IPW estimation	0.244*	0.163*	0.176	0.363*	0.276

**Significant level 5% (inference based on C&S 2021 bootstrap procedure)*

Table 10 - Value Added geographical and sectoral ATT estimations

Group	*Overall dynamic effect*	*Event study*			
Area	Single parameters	e=0	e=1	e=2	e=3
North					
DR estimation	0.360*	0.303*	0.330*	0.451*	0.357
OR estimation	0.377*	0.303*	0.362*	0.469*	0.374
IPW estimation	0.413*	0.322*	0.401*	0.512*	0.417*
Centre					
DR estimation	-0.036	0.187	-0.210	-0.281	0.159
OR estimation	-0.018	0.187	-0.196	-0.271	0.206
IPW estimation	-0.014	0.188	-0.194	-0.265	0.215
Mezzogiorno					
DR estimation	0.103	-0.048	0.024	0.344	0.094
OR estimation	0.111	-0.048	0.034	0.356	0.101
IPW estimation	0.127	-0.045	0.042	0.379	0.133
Sector					
Industry					
DR estimation	0.232*	0.131	0.218*	0.331*	0.249
OR estimation	0.238*	0.132	0.232*	0.333*	0.254
IPW estimation	0.236*	0.137	0.238*	0.328*	0.243
Services					
DR estimation	0.195*	0.169	0.044	0.324	0.243
OR estimation	0.196	0.169	0.050	0.321	0.245
IPW estimation	0.195	0.171	0.051	0.320	0.237

**Significant level 5% (inference based on C&S 2021 bootstrap procedure)*

Table 11 - Value Added project category ATT estimations

Category	*Overall dynamic effect*	*Event study*			
S3I4	Single parameters	e=0	e=1	e=2	e=3
Within group					
OR estimation	0.266	0.218	0.033	0.180	0.632
IPW estimation	0.292*	0.211	0.022	0.226	0.709*
Between groups					
OR estimation	0.430*	0.253*	0.288	0.466*	0.713*
IPW estimation	0.484*	0.273*	0.331	0.530*	0.804*
Other S3					
Within group					
OR estimation	0.024	0.171	0.194	0.397	-0.665
IPW estimation	0.033	0.196	0.195	0.361	-0.618
Between groups					
OR estimation	0.154	0.332	0.291	0.342	-0.349
IPW estimation	0.168	0.345	0.316	0.360	-0.348
Other I4					
Within group					
OR estimation	0.300*	0.125	0.242	0.315	0.519*
IPW estimation	0.273*	0.118	0.229	0.282	0.462*
Between groups					
OR estimation	0.165	0.060	0.145	0.157	0.296*
IPW estimation	0.184	0.066	0.163	0.186	0.321*
Other					
Within group					
OR estimation	0.179*	0.077	0.089	0.284	0.265
IPW estimation	0.194*	0.072	0.086	0.315*	0.302
Between groups					
OR estimation	0.186*	0.123	0.083	0.265	0.271
IPW estimation	0.197*	0.127	0.082	0.285	0.294

**Significant level 5% (inference based on C&S 2021 bootstrap procedure)*

Figures

Figure 1 – Regional share of firms per project category

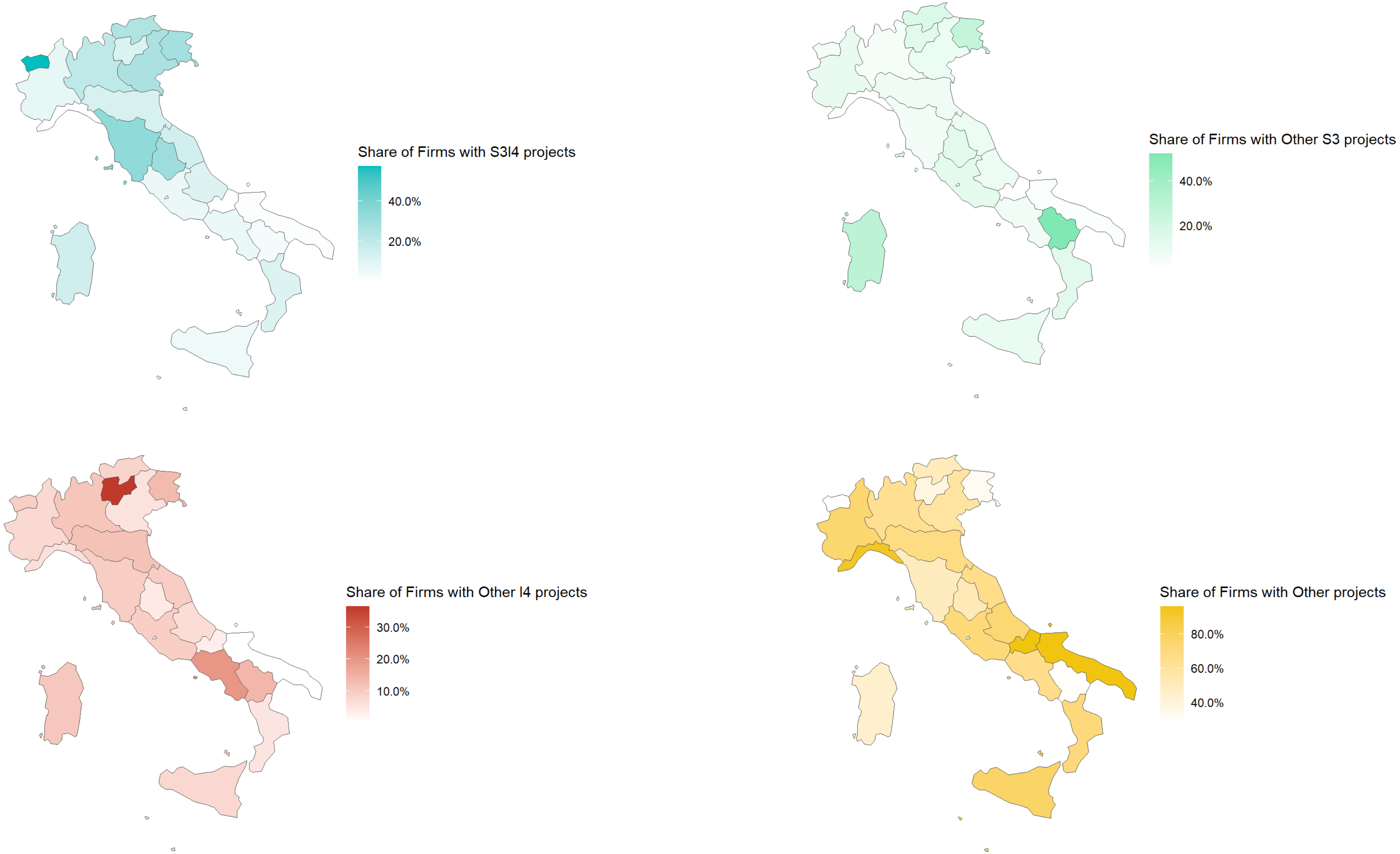


Figure 2 - Firm's max payment ratio

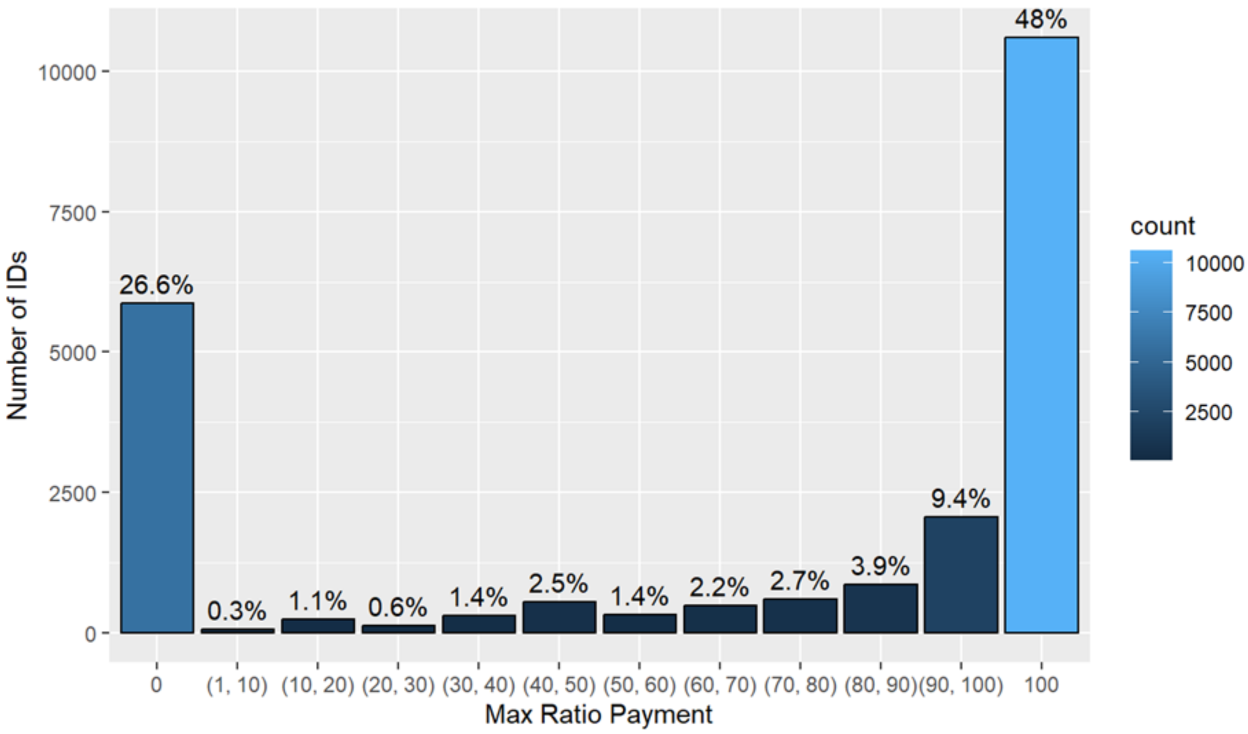
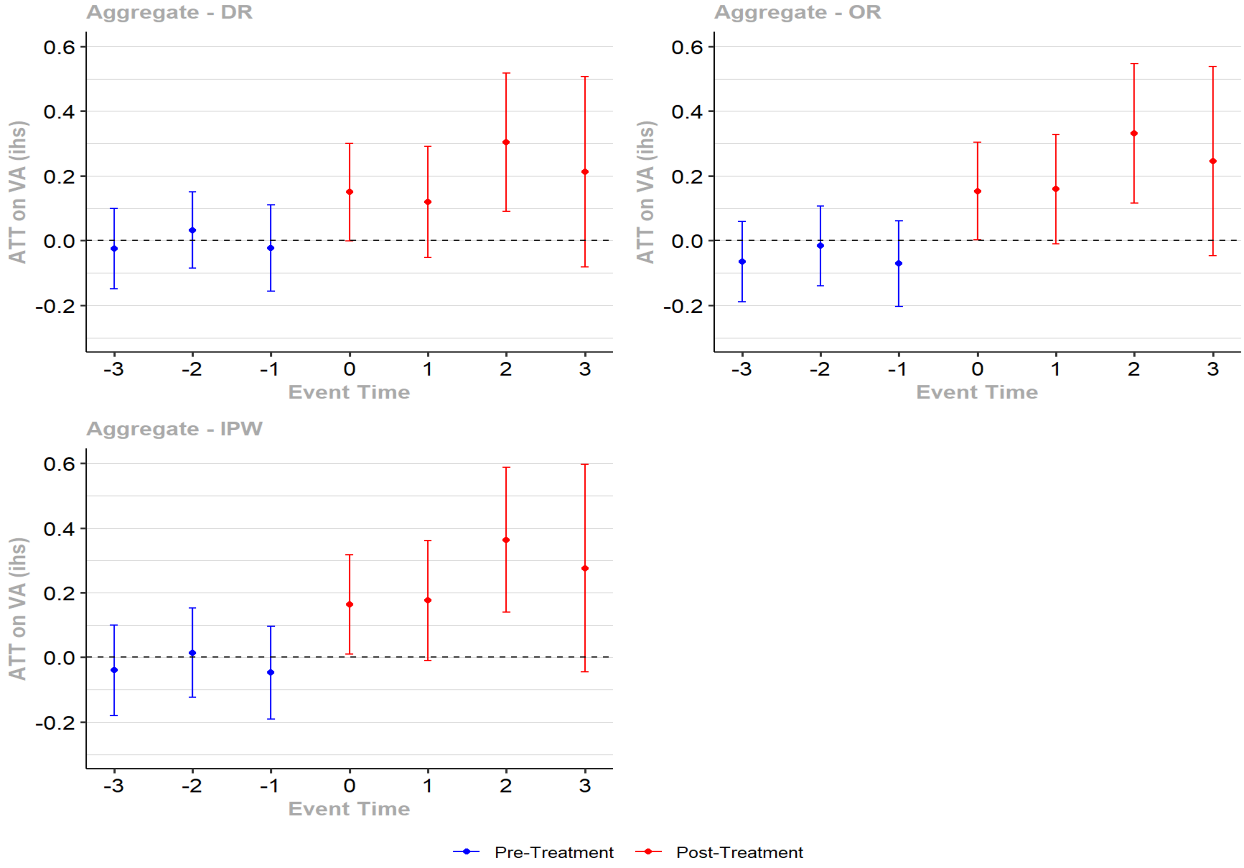
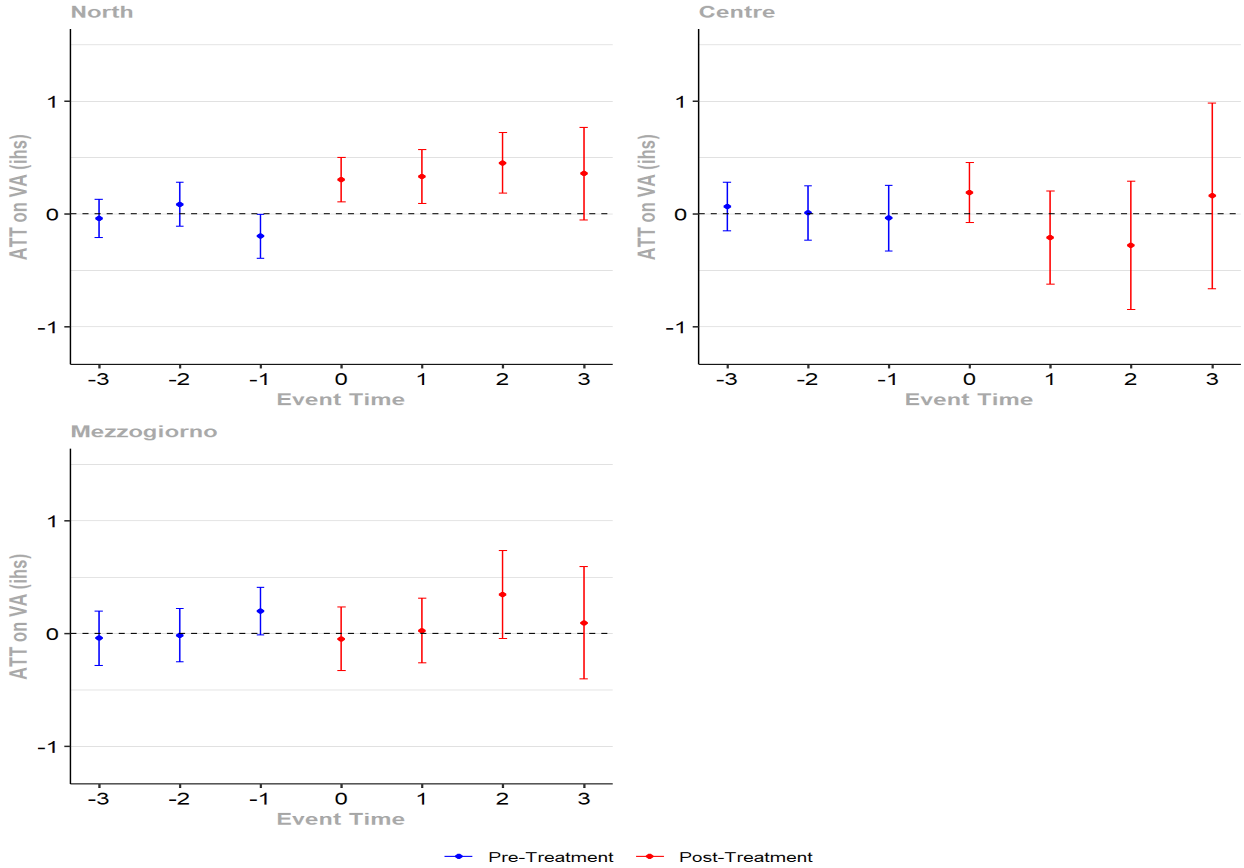


Figure 3 - Event Study: Impact of ERDF Projects on Firm Value Added (Aggregate)



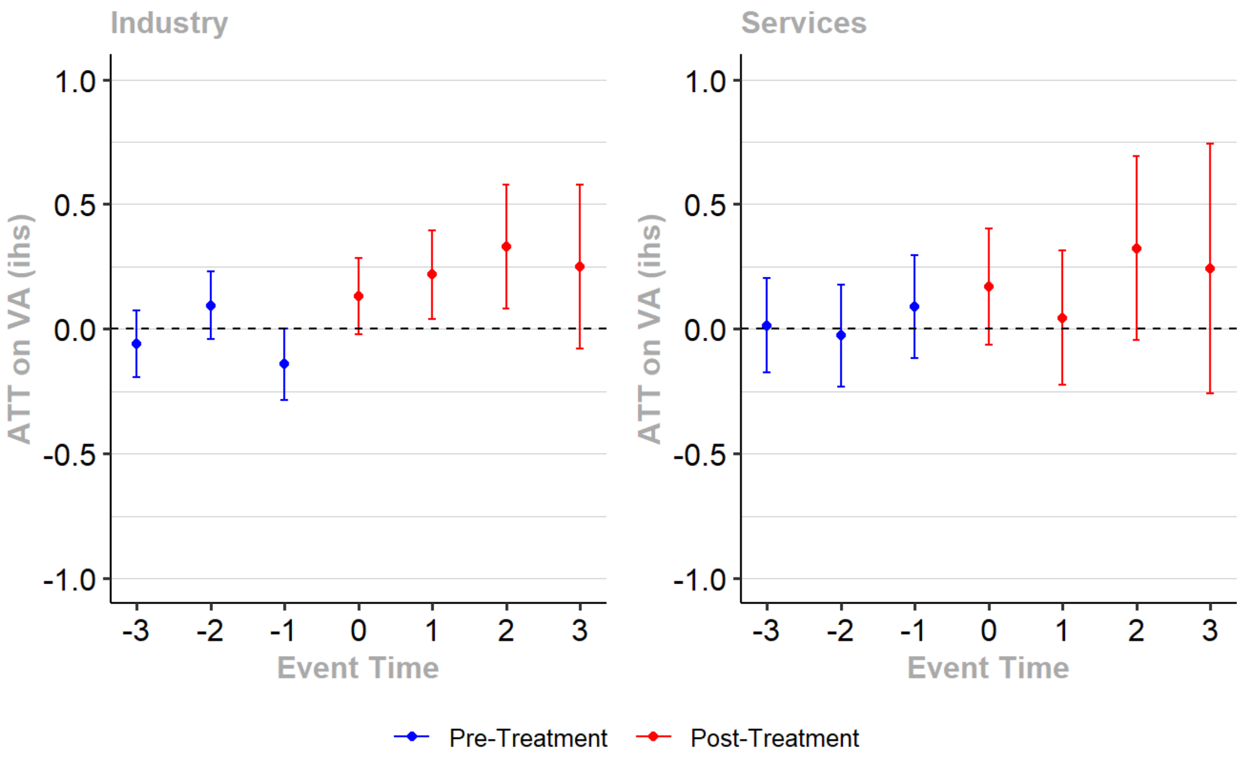
Simultaneous 95% confidence bands – clustering at the firm level

Figure 4 - Event Study: Impact of ERDF Projects on Firm Value Added – by Area (DR)



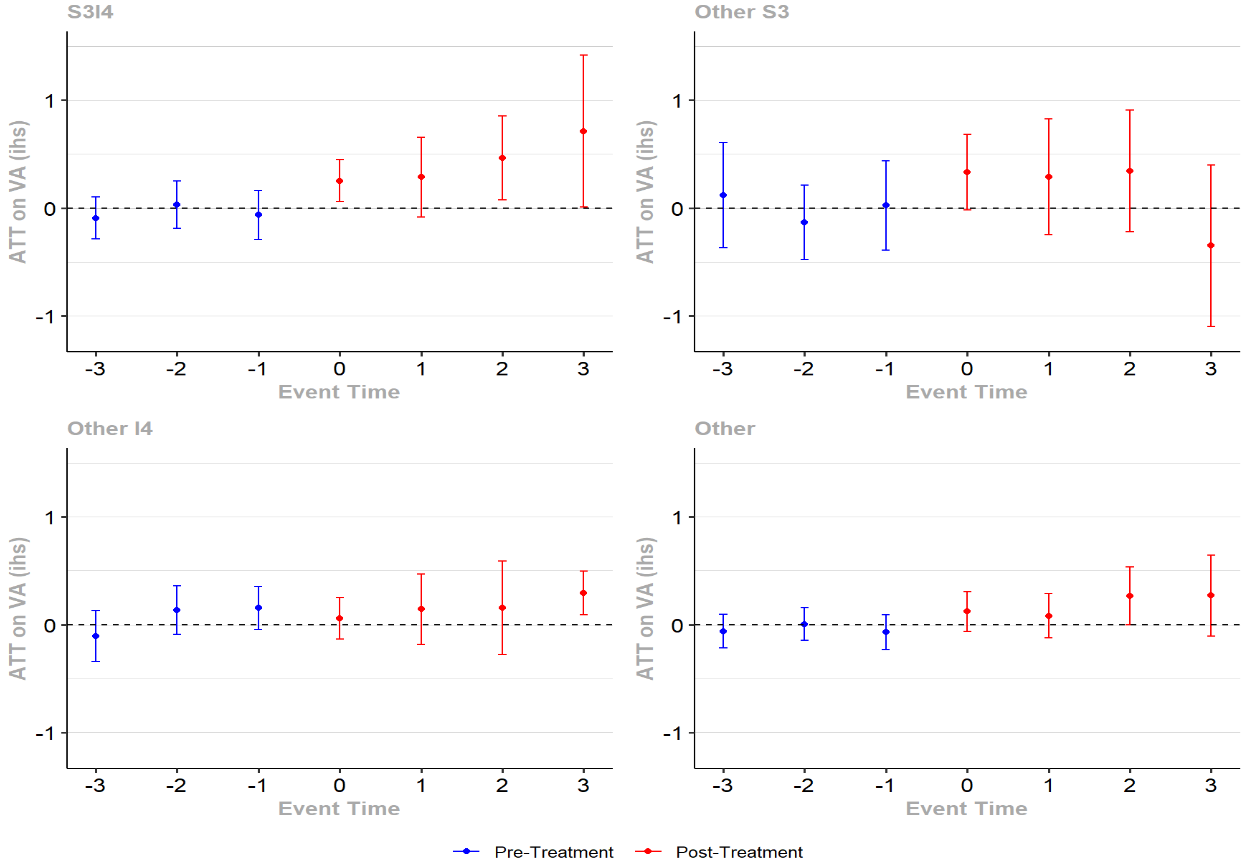
Simultaneous 95% confidence bands – clustering at the firm level

Figure 5 - Event Study: Impact of ERDF Projects on Firm Value Added - by Sectors (DR)



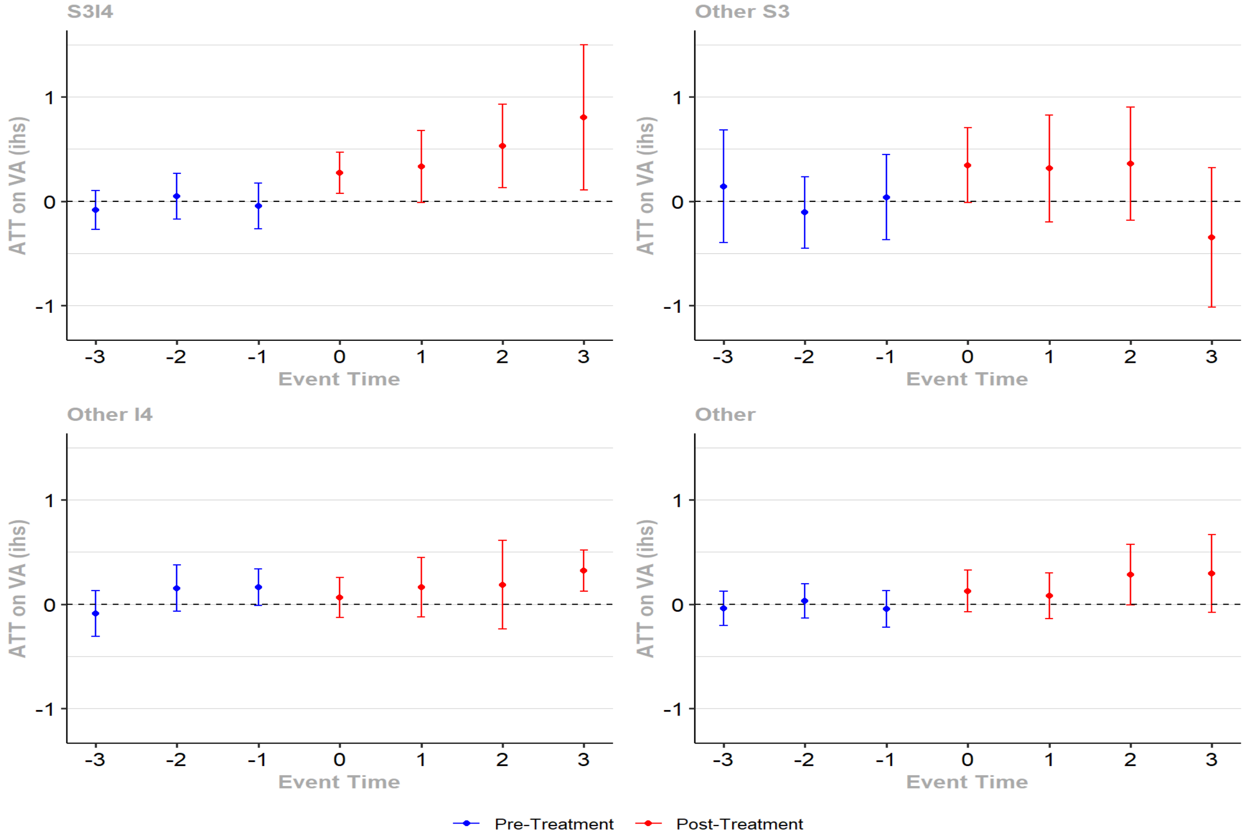
Simultaneous 95% confidence bands – clustering at the firm level

Figure 6 - Event Study: Impact of ERDF Projects on Firm Value Added – by category, between categories (OR)



Simultaneous 95% confidence bands – clustering at the firm level

Figure 7 - Event Study: Impact of ERDF Projects on Firm Value Added – by category, between categories (IPW)



Simultaneous 95% confidence bands – clustering at the firm level

Appendix – Excluded entities for DiD analysis

Entities which do not operate on a profit-making basis

- Agenzia dello Stato
- Altra forma di ente privato con personalità giuridica
- Altra forma di ente privato senza personalità giuridica
- Altro ente pubblico non economico nazionale
- Associazione non riconosciuta
- Associazione o raggruppamento temporaneo di imprese
- Associazione riconosciuta
- Autorità indipendenti
- Azienda o ente del servizio sanitario nazionale
- Azienda pubblica di servizi alle persone ai sensi del d.lgs n. 207/2001
- Azienda speciale ai sensi del t.u. 267/2000
- Camera di commercio
- Città metropolitana
- Comune
- Comunità montana o isolana
- Consorzio di diritto privato
- Consorzio di diritto pubblico
- Ente ambientale regionale
- Ente di sviluppo agricolo regionale o di altro ente locale
- Ente ecclesiastico
- Ente o autorità portuale
- Ente parco
- Ente per il turismo
- Ente per la ricerca e per l'aggiornamento educativo
- Ente pubblico economico
- Fondazione (esclusa fondazione bancaria)
- Fondazione bancaria
- Imprenditore individuale agricolo
- Imprenditore individuale non agricolo
- Istituto e scuola pubblica di ogni ordine e grado
- Istituto o ente pubblico di ricerca
- Istituto pubblico di assistenza e beneficenza
- Lavoratore autonomo
- Libero professionista
- Ministero
- Ordine e collegio professionale
- Organo costituzionale o a rilevanza costituzionale
- Persona Fisica
- Presidenza del consiglio
- Provincia
- Regione
- Studio associato e Società di professionisti
- Società di mutuo soccorso
- Unione di comuni
- Università pubblica

Entities without financial statements on ORBIS

- Altra forma di ente privato con personalità giuridica
- Altra forma di ente privato senza personalità giuridica
- Imprenditore individuale agricolo
- Imprenditore individuale non agricolo
- Lavoratore autonomo
- Libero professionista
- Persona Fisica
- Studio associato e Società di professionisti

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