Balancing Productivity and Employment in the Digital Age: Empirical Evidence from Italy's Transition 4.0 Program

Abstract

This study evaluates the impact of the Italian National Recovery and Resilience Plan (NRRP) funds targeting the Transition 4.0 on firm-level productivity and employment. Leveraging firm-level data and employing a combination of panel event studies and continuous two-way fixed effects models, we find evidence that NRRP funds positively influence both total factor productivity (tfp) and employment. Firms receiving Transition 4.0 support experience an average tfp increase of 16.9–17.8% and an employment growth of around 15.2–15.8%. We also discuss that investments in employee training and upskilling may represent the mechanism through which firms achieve tfp and employment gains. Sectoral heterogeneity reveals that ICT and Wholesale Trade firms benefit the most. Importantly, machine learning-based feature importance analyses validate the role of NRRP funding as a key driver of performance improvements. These findings challenge the trade-off between automation and employment, showing that the Transition 4.0 can boost both competitiveness and employment. The results offer policy-relevant insights for designing inclusive and productivity-enhancing digital transformation strategies.

Keywords:— Transition 4.0, NRRP funds, total factor productivity, employment, panel event study.

1 Introduction

The Transition 4.0, commonly referred to as the Fourth Industrial Revolution or Industry 4.0, represents a paradigm shift in industrial practices, driven by the integration of advanced digital technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), robotics, and big data analytics into manufacturing and business processes. This transformation is poised to redefine the competitive landscape by enabling firms to achieve significant productivity gains, operational efficiencies, and innovation capabilities (Fragapane et al., 2022, Delke et al., 2023, Guo, 2025). However, while the Transition 4.0 offers immense opportunities, it also presents substantial challenges, particularly in terms of its implications for human capital and workforce dynamics (Margherita and Braccini, 2021, Ayhan and Elal, 2023, Rikala et al., 2024).

On one hand, Transition 4.0 technologies have the potential to revolutionize business performance by automating repetitive tasks, optimizing supply chains, and enabling real-time decision-making (Song et al., 2022, Guimarães et al., 2025). For instance, the adoption of autonomous mobile robots and smart intralogistics has been shown to increase flexibility and productivity in production networks (Fragapane et al., 2022). Similarly, green technology advancements have contributed to enhancing total factor productivity while addressing environmental concerns (Song et al., 2022). These advancements underscore the promise of the Transition 4.0 as a driver of sustainable economic growth.

On the other hand, the rapid adoption of these technologies raises critical concerns about employment and workforce adaptability. Automation and robotics can displace jobs traditionally performed by humans, particularly those involving routine or manual tasks (Abeliansky et al., 2024, Bettiol et al., 2024, Sharfaei and Bittner, 2024). Moreover, the increasing reliance on digital tools necessitates a workforce equipped with advanced technical skills, thereby exposing significant skill gaps and creating barriers to employability for certain segments of the labor market (Rikala et al., 2024). These challenges highlight the need for a balanced approach that ensures the sustainability of this digital transformation.

The Transition 4.0 is not merely a technological endeavor but also a socio-economic challenge that requires careful consideration of its broader implications. Researchers have emphasized the importance of adopting sustainable strategies that align technological advancements with workforce development and ethical considerations (Margherita and Braccini, 2021, Peerally et al., 2022). For example, implementing fair policies for workforce reskilling and upskilling can mitigate the adverse effects of automation on employment while fostering inclusive growth.

Despite extensive theoretical discussions on these issues, empirical evidence remains scarce regarding the simultaneous effects of the Transition 4.0 on firm-level productivity and employment outcomes. Despite progress, some critical gaps persist. First, most studies analyze productivity and employment impacts in isolation, neglecting their systemic interplay (Bettiol et al., 2024, Cattani et al., 2024). Second, they tend to analyse past initiatives, failing to capture the impact of more recent programmes fostering the Transition 4.0, which introduce advanced technologies. Third, current studies inadequately clarify the mechanisms that moderate Transition 4.0 outcomes (Khanna and Sharma, 2024).

Against this background, we aim to bridge this gap by providing empirical insights into how Transition 4.0 technologies influence both productivity and employment at the firm level. In particular, we use data from Italy's National Recovery and Resilience Plan (NRRP), specifically from Mission 1, Component 2 (Transition 4.0), since it provides a unique opportunity to study the impact of Transition 4.0-related investments on firm-level employment and productivity over the period 2021-2024. Indeed, this initiative represents one of the most financially significant components of the NRRP, with 13.4 billion euros allocated to support the digital and technological transformation of Italian firms, particularly through tax credits for investments in advanced machinery, software, and training.[1] Importantly, the NRRP's Transition 4.0 program enables a more precise identification of projects explicitly linked to Transition 4.0 objectives, addressing a key limitation in earlier research. Previous studies often struggled to distinguish whether firms' investments were genuinely aligned with digital transition goals or were part of broader, less targeted Transition 4.0 initiatives. In contrast, the administrative structure of the NRRP, with well-defined eligibility criteria, detailed classification of supported investments, and clear timelines, allows researchers to more accurately trace the causal effects of Transition 4.0 support. This clear project definition and precise targeting represent a methodological advance as it reduces the risk of treatment misclassification and strengthens identification strategies credibility. Furthermore, the substantial financial scale of the program ensures both a wide coverage across firms and sufficient variation in treatment intensity, which enhances the robustness of empirical analyses.

To assess the impact of this initiative on firms' productivity and employment while addressing potential endogeneity threats, we adopt a staggered difference-in-differences approach. We leverage this method since it accounts for the fact that projects start in different years. In practice, we compare the dynamics in total factor productivity (tfp) and employment of firms benefiting from the intervention (treated units) both before and after the intervention with firms that did not receive such funds (control units). We estimate the impact of such funds on tfp and employment using two measures: a dummy variable indicating fund receipt (extensive margin) and the funding amount (intensive margin). For the extensive margin, we employ the (Callaway and Sant'Anna, 2021) estimator. This aligns us with recent advancements in the literature on treatment effect heterogeneity across cohorts (Athey et al., 2018, Sun and Abraham, 2021). For the intensive margin, we estimate a continuous two-way fixed-effects model (CTWFE).[2] Furthermore, we investigate the mechanism

[1] Further information about Transition 4.0 investments under the Italian NRRP is available at the following link: `https://www.italiadomani.gov.it/en/Interventi/investimenti/transizione-4-0.html`.

[2] A staggered difference-in-differences approach is used when different units receive a policy or treatment at different

through which Transition 4.0 funds may stimulate tfp and employment growth. In particular, we verify whether larger gains are experienced by firms investing in employee training and upskilling activities. Finally, we assess the heterogeneity of our results across firms.

Our core results suggest that firms benefiting from Transition 4.0 NRRP funding experienced an average increase in tfp ranging from 16.9% to 17.8%, alongside an approximate 15.2–15.8% rise in employment. Likewise, the intensive margin analysis demonstrates that a 1% increase in Transition 4.0 funding per unit of asset is associated with a 1.1%–1.2% improvement in tfp and a 0.6% expansion in employment. We also show that firms investing in training and competence enhancement exhibit a stronger growth in tfp and employment.

These results remain consistent across a comprehensive set of robustness checks, including alternative model specifications, and the introduction of various control variables. The validity of these findings is further reinforced by a falsification and a placebo tests. The falsification test examines the effect of other NRRP funds, not targeted to the Transition 4.0, on tfp and employment. The placebo test verifies that there is no spurious positive relationship between our dependent variables and randomly assigned placebo treatments, supporting the validity of our treatment and control group identification. Moreover, we highlight that ICT and Wholesale Trade firms experience the strongest gains in tfp and employment, whereas the Professional Activities sector does not experience significant improvements.

Overall, our findings contribute to the ongoing debate on sustainable digitalization and offer actionable recommendations for policymakers and practitioners seeking to balance technological innovation with human-centric development. First, to the best of our knowledge, it provides the first empirical evaluations of the Italian NRRP's Transition 4.0 programme—a timely and highly relevant policy initiative aimed at supporting digital transformation and recovery in the post-pandemic context. Second, the analysis employs a robust causal inference framework, leveraging a detailed linkage between funded projects, recipient firms, and expected outcomes to ensure a credible identification strategy. Third, it sheds light on the mechanisms driving the observed effects. Finally, unlike much of the existing literature that examines productivity and employment in isolation, this study jointly analyses total factor productivity and employment, offering a more comprehensive assessment of the programme's impact on firm dynamics.

The rest of the paper is organized as follows. Section 2 reviews the related literature, states our research hypotheses, and describe the regulatory framework under which the NRRP funds devoted to the Transition 4.0 are allocated to Italian firms. Section 3 describes the data used in the analysis, while Section 4 outlines the

points in time. Through this method, we compare how outcomes evolve across units that are treated at different times, using those never treated as a comparison group. This approach helps isolate the effect of the policy from other time trends or differences between units. We also implement a continuous two-way fixed effects model, which control for both time-invariant differences across units and common shocks over time, while allowing treatment to vary continuously rather than as a binary on/off variable.

methodology. Section 5 presents our main findings alongside an extensive set of robustness checks. Finally, Section 6 concludes by discussing the main implications of this paper.

2 Theoretical Background

2.1 Research Hypotheses

The transformative potential of Transition 4.0 technologies to enhance productivity is well-documented in theoretical studies. Early research emphasized efficiency gains from automation, real-time data analytics, and interconnected cyber-physical systems (Rüßmann et al., 2015, Delke et al., 2023). For instance, case studies from Germany demonstrate productivity improvements of 5–25% across manufacturing sectors, driven by smart logistics and predictive maintenance (Rüßmann et al., 2015).

Beyond these initial findings, a growing body of literature has clarified the multiple channels through which Transition 4.0 technologies drive productivity increases at both the firm and sectoral levels. The integration of advanced technologies such as robotics and artificial intelligence with digital capabilities not only automates repetitive tasks but also enables more sophisticated forms of process optimization, including adaptive scheduling and quality control, which reduce waste and downtime (Delke et al., 2023, Abeliansky et al., 2024). Moreover, the widespread deployment of IoT devices facilitates real-time monitoring and data-driven decision-making, allowing firms to rapidly respond to supply chain disruptions, meet evolving market demands, and face external shocks.

A deeper theoretical understanding of why the Transition 4.0 should enhance total factor productivity emerges when considering the concept of digital transformation as a general-purpose technological shift (Van Meeteren et al., 2022, Benitez et al., 2023). Indeed, the true impact of the Transition 4.0 extends beyond isolated efficiency gains to encompass broad-based changes in production paradigms, organizational routines, and innovation ecosystems. The implementation of interconnected digital solutions, such as advanced robotics, artificial intelligence, cloud platforms, and real-time data analytics, enables firms to unlock synergies across multiple business functions. This integration fosters not only process innovation but also the rapid development and scaling of new products and services (Delke et al., 2023, Robinson and Mazzucato, 2019).

Moreover, the cumulative and self-reinforcing nature of digital adoption means that early investments in the Transition 4.0 can generate positive feedback loops, where initial productivity improvements facilitate further technological upgrades and organizational learning. This dynamic is particularly evident in firms that successfully integrate digital tools with complementary changes in management practices, workforce skills, and inter-firm collaboration (Robinson and Mazzucato, 2019).

Recent firm-level analyses in emerging economies corroborate these findings, showing that Transition 4.0 adoption boosts tfp through technological innovation and resource optimization (Guo, 2025). However, the magnitude of tfp gains appears heavily contingent on organizational factors. Emerging economy studies reveal stark disparities: privately-owned manufacturers in competitive markets report 14.7% tfp growth post-Transition 4.0 adoption, whereas state-owned enterprises in regulated sectors exhibit negligible improvements (Guo, 2025). Critics further caution against technological gains, noting that 37% of firms fail to achieve projected productivity gains due to misaligned implementation strategies (Khanna and Sharma, 2024). Thus, while the directional relationship between the Transition 4.0 and tfp remains positive, its economic significance hinges on complementary investments in organizational agility. In particular, Transition 4.0 investments—centered on the adoption of advanced digital technologies—have the potential to significantly boost firm productivity, but their effectiveness depends heavily on the capabilities of the workforce (Black and Lynch, 1996, Edeh and Acedo, 2021, Wang et al., 2021). When employees receive targeted training and upskilling, they are better equipped to operate, adapt to, and innovate with new technologies such as automation, data analytics, and smart manufacturing systems. Competence enhancement ensures that technological tools are not just adopted, but are fully integrated into business processes in a way that maximizes efficiency, reduces errors, and fosters continuous improvement. In this sense, workforce training is a critical enabler that translates Transition 4.0 investments into tangible productivity gains.

Overall, the theoretical and empirical literature converges on the notion that the Transition 4.0 is a powerful lever for enhancing total factor productivity, provided that its adoption is accompanied by strategic organizational change, investment in human capital, and active participation in digital ecosystems. These insights reinforce the rationale for policy initiatives and firm-level strategies that prioritize not only technological upgrades but also the broader transformation of business models and capabilities.

Building on this theoretical foundation (see also Figure 1), we propose our first research hypothesis (RH):

RH1: The Transition 4.0 adoption exerts a positive net effect on tfp, with heterogeneous effects across sectors. In particular, investments in workforce training and competence enhancement represent the main mechanism behind tfp growth.

While productivity gains dominate discourse, the Transition 4.0's impact on employment remains contentious. Indeed, the employment implications of Transition 4.0 technologies constitute one of the most polarized debates in contemporary labor economics. On one side of the spectrum, displacement theorists cite robust evidence of automation-induced job losses, particularly in routine-intensive manufacturing roles. Longitudinal data from OECD countries indicates that a 1% increase in industrial robot density correlates with an 18%–33%

decline in employment growth, with mid-skill occupations bearing the brunt of this contraction (Ayhan and Elal, 2023, Sharfaei and Bittner, 2024). These findings align with skill-biased technological change models, which predict labor market polarization as machines substitute for human intermediation in codifiable tasks. Furthermore, empirical evidence from occupational health research identifies risks such as work intensification, mental health strains, and erosion of labor rights in digitized workplaces (Min et al., 2019, Abeliansky et al., 2024).

Contrasting this perspective, creation theorists emphasize demand elasticity and occupational transformation effects. Case studies from consumer goods industries reveal that automation-driven price reductions can stimulate market expansion, ultimately increasing employment by 0.8% for every 1% productivity gain (Bettiol et al., 2024). Furthermore, the emergence of new job categories—such as AI trainers and digital twin engineers—offsets 62% of displaced roles in technologically advanced firms (Margherita and Braccini, 2021). This schism in empirical outcomes suggests that employment impacts are not inherent to the technologies themselves but mediated by workforce adaptability strategies. Firms implementing concurrent reskilling programs demonstrate 68% higher employment retention rates post-automation, highlighting human capital investment as a critical moderating variable (Rikala et al., 2024). Cross-country panel analyses reveal that automation reduces low-skilled jobs but creates demand for technical roles, necessitating workforce reskilling (Ayhan and Elal, 2023, Sharfaei and Bittner, 2024). Systematic reviews highlight a persistent "techno-centric" bias in implementation, where social dimensions like job quality and skill gaps are secondary concerns (Cunha et al., 2022, Peerally et al., 2022). For example, studies on Operator 4.0 frameworks often portray workers as gender-neutral, hyper-skilled entities compensating for technological limitations (Cunha et al., 2022).

Through our paper, we examine this tension between technological advancement and sustainable labor practices, contributing to the debate on the need to balance automation with human-centric policies like upskilling programs and participatory workplace design (Margherita and Braccini, 2021). In particular, building on this theoretical foundation, we propose our second RH (see also Figure 1):

RH2: The Transition 4.0 generates net employment growth, with heterogeneous effects across sectors. In particular, investments in workforce training and competence enhancement represent the main mechanism behind employment growth.

Overall, our research framework presents several novel elements. First, it provides combined evidence on tfp and employment effects, offering a more integrated understanding of firm-level responses to the Transition 4.0 programme, rather than examining these dimensions in isolation. Second, it adopts a rigorous causal empirical framework that not only identifies the impact of the policy but also explores the mechanisms behind the results—particularly the role of workforce training. Finally, it delivers timely and original evidence on a key, yet underexplored, component of Italy's NRRP, contributing to the broader evaluation of digital transformation policies in the EU recovery agenda.

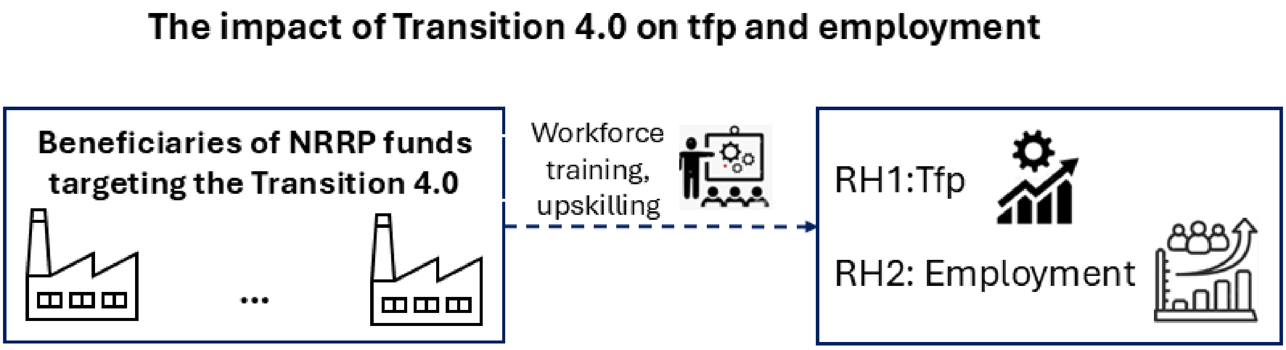


Figure 1: Research hypotheses.

2.2 The regulatory Framework

As part of Italy's response to the COVID-19 pandemic, the National Recovery and Resilience Plan (NRRP) was launched to support economic recovery, strengthen resilience, and accelerate digital and green transitions. Funded through the European Union's NextGenerationEU initiative, the plan includes several targeted investments and reforms across six missions.[3]

In this paper, we analyse the impact of Mission 1 – Digitalization, Innovation, Competitiveness, and Culture, Component 2 – Transition 4.0, since it plays a central role in modernizing the productive structure of the country.

The Transition 4.0 is designed to boost the digital transformation and competitiveness of Italian firms, especially small and medium-sized enterprises (SMEs). It has a total allocation of €13.38 billion from the NRRP, supplemented by €5.08 billion from a complementary national fund. The core aim is to incentivize private investment in digital technologies and innovation by offering tax credits for eligible expenditures.

These credits cover (i) Tangible 4.0 assets (e.g., advanced machinery and equipment), (ii) Intangible 4.0 assets (e.g., software, AI tools, cloud systems), (iii) research, development, and innovation activities, as well as (iv) training programs to enhance digital and technical skills. Firms can access the benefits through their tax returns. Eligible investments must be made between January 1, 2021, and December 31, 2023.

[3]Italy has received approximately €194.4 billion under the NRRP (€71.8 billion in grants and € 122.6 billion in loans). The Italian NRRP is allocated across six missions, representing key areas of sustainable development, as follows: "Green Revolution and Ecological Transition" (€ 55.5 billion), "Digitization, Innovation, Competitiveness, and Culture" (€ 41.3 billion), "Education and Research" (€ 30.1 billion), "Infrastructure for "Sustainable Mobility" (€23.7 billion), 'Inclusion and Cohesion' (€ 16.9 billion), and 'Healthcare' (€ 15.6 billion). Further details about the Italian NRRP is available at the following link: `https://commission.europa.eu/business-economy-euro/economic-recovery/recovery-and-resilience-facility/country-pages/italys-recovery-and-resilience-plan_en`

The allocation of resources under the NRRP is based on the following multi-level disbursement process. Financial transfers from the European Commission to the Italian government are conditional on the fulfillment of performance milestones and reforms set out in the NRRP. Once received, these funds are distributed to relevant ministries and implementing bodies. In the case of the Transition 4.0, the Ministry of Enterprises and Made in Italy (MIMIT) represents the implementing body entrusted with the operational management of this specific measure. Its responsibilities include the execution of interventions, monitoring of progress, compliance with regulatory frameworks, and the achievement of predefined targets and milestones.

Conversely, the final beneficiaries refer to the end recipients of the support instruments—in this context, private firms that undertake eligible investments in digital technologies, innovation, and workforce training. These enterprises benefit indirectly from NRRP resources through a system of tax credits, rather than through direct grants or subsidies. The incentive structure is thus designed to stimulate private sector investment while ensuring alignment with the broader strategic objectives of digital transformation and technological upgrading. Firms autonomously apply the tax benefits by declaring qualifying expenditures in their tax returns, and subsequently offsetting them through standard fiscal channels (e.g., the F24 form). This model allows for streamlined administration while preserving fiscal oversight, thus ensuring transparency, conditionality, and coherence with EU governance principles.

Our analysis focuses on the impact of the NRRP funds targeting the Transition 4.0 at the level of the final beneficiaries in terms of growth of tfp and employment opportunities. The Transition 4.0 programme holds particular significance for Italy, given the dominant role of small and medium-sized enterprises in the national economy. SMEs constitute over 99% of Italian businesses and contribute approximately two-thirds of employment and more than 50% of the country's value added. These firms often face structural barriers to innovation, digitalisation, and workforce upskilling. Transition 4.0 aims to address these challenges by supporting technological adoption and human capital development through targeted tax incentives. The programme sets ambitious quantitative targets, including reaching at least 111,700 tax credits to firms under Transition 4.0.

3 Data

3.1 Dependent Variables

Our dependent variables are represented by the natural logarithm of the number of employees and tfp. In terms of employees, we rely on the number of full-time equivalents disclosed by ORBIS Bureau van Dijk.[4]

We estimate the tfp based on the approach proposed by Ackerberg et al. (2015). This is an appropriate

[4]The dataset is accessible at the following link: `https://login.bvdinfo.com/R1/Orbis`.

choice for estimating the tfp as it addresses the simultaneity and collinearity issues inherent in production function estimation. This method improves robustness by using a control function approach that corrects for the endogeneity of input choices, offering more reliable productivity estimates than earlier methods such as (Olley and Pakes, 1996, Levinsohn and Petrin, 2003). This approach has been widely employed in the literature analysing the drivers of the tfp (Siliverstovs et al., 2016, Ren et al., 2022, Braunerhjelm and Lappi, 2023).

In particular, consider a Cobb-Douglas production technology for firm i at time t, as follows:

$$y_{it} = \beta_l \ell_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \tag{1}$$

where y_{it} is the natural logarithm output, ℓ_{it} the natural logarithm labor input, k_{it} is the natural logarithm capital input, ω_{it} is the unobserved tfp parameter, and ϵ_{it} is a normally distributed idiosyncratic error term.

Estimating Equation 1 by an OLS model provides inconsistent estimates for the tfp due to simultaneity issues. Indeed, the technology of one enterprise can be recognized in advance to some extent, so the decision-maker can immediately adjust the inputs according to the new information, thus introducing correlation between ω_{it} and the other input factors.

To solve this issue, Ackerberg et al. (2015) argue that intermediate inputs m_{it} are a function of productivity, capital, and labor, as follows:

$$m_{it} = f_t(\omega_{it}, k_{it}, \ell_{it}) \tag{2}$$

If f_t is strictly increasing in ω_{it}, it is possible to compute it, based on the following Equation:

$$\omega_{it} = h_t(m_{it}, k_{it}, \ell_{it}) \tag{3}$$

Substituting Equation 3 into the production function (Equation 1), we obtain:

$$y_{it} = \beta_l \ell_{it} + \beta_k k_{it} + \beta_m m_{it} + h_t(m_{it}, k_{it}, \ell_{it}) + \varepsilon_{it} \tag{4}$$

Furthermore, ω_{it} evolves according to the following first-order Markov process:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it} \tag{5}$$

where ξ_{it} is assumed to be uncorrelated with input choices made at $t-1$, allowing valid instruments, and $g(\cdot)$ is approximated by a low-order polynomial. [5]

[5] In particular,

$$g(\omega_{it-1}) \approx \gamma_0 + \gamma_1 \omega_{it-1} + \gamma_2 \omega_{it-1}^2$$

According to this model, lagged inputs are uncorrelated with the productivity innovation:

$$\mathbb{E}[\xi_{it} \cdot Z_{it}] = 0 \tag{6}$$

where Z_{it} is a vector of instruments including lagged values of ℓ_{it}, k_{it}, and m_{it}.

By substituting Equation 5 into Equation 6, the following moment condition used for GMM is obtained:

$$\mathbb{E}\left[(y_{it} - \beta_l \ell_{it} - \beta_k k_{it} - \beta_m m_{it} - g(\omega_{it-1})) \cdot Z_{it}\right] = 0 \tag{7}$$

After estimating the coefficients, firm-level tfp is recovered as:

$$\hat{\omega}_{it} = y_{it} - \hat{\beta}_l \ell_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_m m_{it} \tag{8}$$

We use the `Prodest R` (v1.0.1) package to obtain tfp estimates (Rovigatti, 2017).

3.2 Explanatory Variables

Our primary explanatory variable captures the extent of financial support received by Italian firms under the National Recovery and Resilience Plan (NRRP) for the Transition 4.0 initiative.[6] To assess the extensive margin, we construct a binary indicator equal to one if a firm receives Transition 4.0 funds and zero otherwise. The intensive margin is instead operationalized as the total monetary amount of NRRP funds received by each firm in support of the Transition 4.0.

To mitigate potential biases from observable heterogeneity between treated and untreated units, we incorporate a comprehensive set of control variables. Specifically, we include *Total Assets* as a proxy for firm size, and *Production Value* as an indicator of the firm's capacity to generate economic output through its core activities (Tzouvanas et al., 2020). Additionally, we account for firms' financial structure by including the *Gearing*, expressed as the ratio of a company's debt to its equity, to capture financial risk. Moreover, we consider the long-term debt (*Total Debt*) as a measure of capital structure, since leverage can significantly influence both investment capacity and operational decisions, thereby affecting employment and productivity outcomes. Controlling for debt levels helps isolate the effect of financial constraints and ensures that our estimates are not confounded by differences in firms' access to external financing. (Hatakeda et al., 2012). The *Liquidity index*

[6] This variable is built based on information available in the OpenPNRR open data portal, managed by Openpolis. This dataset is accessible at the following link: `https://openpnrr.it/opendata/`. It provides structured datasets in CSV format detailing public investment projects under Italy's National Recovery and Resilience Plan (PNRR). These datasets include information such as project descriptions, associated missions and components, start and end dates, allocated funding amounts, and final beneficiaries identified by their fiscal codes. Additional data covers project locations, implementing organizations, payment records, and procurement notices.

is included to assess firms' cash positions (Segura et al., 2018, Fernandez-Cuesta et al., 2019), while return on equity (*ROE*) is employed to control for differences in economic performance across treated and control groups (Lewandowski, 2017). All firm-level financial data are sourced from the Orbis Bureau van Dijk database. Table 1 displays the descriptive statistics for our dependent and independent variables.

Table 1: Descriptive Statistics.

	Q1	Mean	Median	Q3	Sd
Dependent Variables:					
Total Factor Productivity	12.814	14.597	14.541	16.383	2.755
Employees	0.000	4.569	4.443	5.836	1.858
Explanatory Variables:					
NRRP Funds	0.000	2.062	0.000	9.068	4.940
Total Assets	12.510	16.011	14.738	16.217	5.174
Total Debt	9.128	12.959	9.863	13.012	4.453
ROE	-1.532	13.731	12.641	27.193	6.162
Gearing	0.064	0.248	0.198	0.357	0.134
Liquidity Index	0.000	0.121	0.113	0.181	0.371
Production Value	10.960	15.962	15.049	16.018	4.063

4 Methods

We estimate both the intensive and extensive margins of the impact of NRRP funds, aiming to support the Transition 4.0. In the case of the NRRP funds supporting the Transition 4.0, the extensive margin would involve assessing the different dynamics in tfp and employment between firms receiving and not receiving support under the initiative, essentially capturing the participation decision. On the other hand, the intensive margin focuses on analyzing how the amount of Transition 4.0 funds a firm receives affects its outcomes.

To estimate the extensive margin, we rely on the panel event study introduced by Callaway and Sant'Anna (2021), since it allows dealing with staggered treatment adoption and multiple time periods. Furthermore, this empirical approach solves some issues of a traditional Difference in Differences (DiD) linear regression, such as the "negative weight problem" and the parameters estimation that is particularly sensitive to the group size, treatment timing and overall number of analysed time periods (De Chaisemartin and d'Haultfoeuille, 2020, Goodman-Bacon, 2021).

In particular, defining G_i as the year in which unit i is treated for the first time ($G_i = year\ t : \tau_{i,t} = 1\ \&\ \tau_{i,t-1} = 0$) and $G_{i,g} = 1\{G_i = g\}$, we estimate the average treatment on treated (ATT) based on the following Equation:

$$ATT(g,t) = \mathbb{E}[\frac{G_g}{\mathbb{E}[G_g]} * (Y_t - Y_{g-1} - m_{g,t}(X))] \quad (9)$$

where $\tau_{i,t}$ is our treatment variable that is equal to 1 if unit i is treated in year t and 0 otherwise. Treated units are firms receiving NRRP funds under the Mission 1, Component 2 in favour of the Transition 4.0. We classify firms as treated from the year a project ends. Based on the OpenPNRR open data portal, we identify 2,271 firms receiving NRRP funds targeting the Transition 4.0 over the time frame 2021-2023 that represent our treated units.

The control group consists of firms that receive NRRP funds for purposes other than the Transition 4.0. Selecting firms with alternative NRRP funding objectives enhances comparability between treated and control units, as firms not receiving any NRRP funds may exhibit distinct characteristics. For instance, non-recipients might be less adept at navigating the bureaucracy required to obtain NRRP funds. Our objective is to compare firms that are otherwise similar, differing only in whether they receive NRRP funds for the Transition 4.0. Furthermore, Y_t is our dependent variable observed in year t, $m_{g,t}(X) = \mathbb{E}[Y_t - Y_{g-1}|X, C = 1]$ with C being a binary variable equal to 1 for never treated units, and X_t corresponds to a vector of control variables (see Section 3.2 for additional details).

We also estimate the following summary measures of the causal impact of the analysed policy, providing information on the average effect of participating in the treatment when firms are observed exactly e time periods away from the start of the treatment ($\theta_{dynamic}(e)$) and an aggregated average of the treatment effect across all groups and years ($\theta_{aggregate}$):

$$\theta_{dynamic}(e) = \sum_{g \in G} 1\{g + e \leq T\} * P(G = g|G + e \leq T) * ATT(g, g + e) \tag{10}$$

$$\theta_{aggregate} = \sum_{g \in G} \sum_{t=2}^{T} \omega(g, t) * ATT(g, t) \tag{11}$$

where $\omega(g, t)$ are weighting functions representing the size of each set of units observed in a specific year t and belonging to group g.

Although the estimator $\theta_{dynamic}(e)$ allows to test for the condition of pre-treatment parallel trends, before estimating Equation 9, we apply a Propensity Score Matching (PSM) procedure to restrict the analysis to a set of firms with comparable observable characteristics (Rubin, 1973, Imbens, 2000, Rosenbaum et al., 2010). We use the same set of variables contained in the vector of control variables X_t introduced in Equation 9 to identify comparable treated and not treated units. Furthermore, we impose an exact matching condition on NACE rev. 2 sector at the 2-digit level, meaning that the matched treated and not-treated units should be established in the same industry. Finally, we use nearest neighbor as a simple, intuitive, and interpretable matching method that enables transparent pairing of treated and control firms based on their propensity scores. The propensity score summarizes the influence of all covariates (X) on the probability of receiving the treatment, ensuring comparability between matched units. In line with Rosenbaum and Rubin (1983), we compute the propensity score as: $\pi_i(X_i) = P(\tau_i = 1|X_i)$.

Table 2 presents descriptive statistics for the full sample of untreated firms (column 1), control units after PSM (column 2), and treated units, representing firms receiving Transition 4.0 NRRP funds (column 3). The fourth column reports the difference in means between the two subsamples of treated and control units, which is statistically insignificant in all cases, thus providing evidence in favour of the internal validity of our analysis.

Table 2: Descriptive statistics

	Not getting Transition 4.0 NRRP funds	Control units	Treated units	Difference in the mean
	(1)	(2)	(3)	(4)
Dependent Variables:				
Total Factor Productivity	13.472 (2.959)	14.318 (2.538)	14.863 (2.607)	−0.545
Employees	4.271 (2.018)	4.469 (1.852)	4.608 (1.964)	−0.139
Explanatory Variables:				
NRRP Funds	9.638 (5.049)	10.038 (4.874)	10.531 (4.933)	−0.493
Total Assets	15.621 (5.368)	16.018 (4.995)	16.209 (5.388)	0.191
Total Debt	12.317 (4.791)	12.818 (4.318)	12.641 (4.520)	0.177
ROE	12.276 (7.301)	12.647 (6.220)	12.582 (6.318)	0.065
Gearing	0.271 (0.152)	0.263 (0.138)	0.257 (0.137)	0.006
Liquidity Index	0.113 (0.401)	0.116 (0.360)	0.136 (0.371)	0.020
Production Value	15.721 (4.439)	15.592 (3.981)	15.791 (4.129)	−0.199

Note: The table presents descriptive statistics, distinguishing among firms not receiving NRRP funds dedicated to the Transition 4.0, our control units obtained after PSM, and our treated units. The first three columns report the mean and standard deviation (in parentheses) for key variables of interest across the untreated firms, control and treated units, respectively. The last column shows whether the mean difference between treated and control units is statistically significant, based on a two-sample t-test. Significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.

As a second step, we aim to capture the extensive margin to disentangle the effect of the amount of funds received. Therefore, we employ a continuous two-way fixed effects (CTWFE) approach. Our baseline model is specified as follows:

$$\text{Y}_{it} = \theta_1 + \beta \text{ Transition 4.0 funds}_{it} + \left(X_{it-1}\gamma'\right) + \rho_i + \eta_t + \varepsilon_i \tag{12}$$

where Y_{it} is our dependent variable (e.g., tfp or employees), $Transition\ 4.0\ funds_{i,t}$ is our variable of interest representing the total amount of NRRP funds supporting the Transition 4.0 by firm i in year t and

X_{it-1} is the vector of control economic and financial variables described in Section 3.2. To limit endogeneity and reverse causality issues, as well as reduce simultaneity bias, all balance sheet variables are lagged by one year (see, e.g., Wagner 2010, Busch and Hoffmann 2011, Clarkson et al. 2011, Misani and Pogutz 2015, Lewandowski 2017, Pekovic et al. 2018, Makridou et al. 2019, Flori et al. 2024). In this way, we ensure that the explanatory financial data precede and potentially cause changes in employment and productivity, rather than being simultaneously determined.

To complement our causal inference framework, we implemented machine learning algorithms to assess the predictive power of NRRP funding variables on firm-level outcomes. Following Breiman (2001) and Chen and Guestrin (2016), we train Random Forest and XGBoost regression models using scikit-learn (v1.6.1) and XGBoost (v2.1) libraries in Python. We employ default hyperparameters (n_estimators=100, max_depth=3) to avoid overfitting, with an 80-20 train-test split stratified by treatment status. SHAP (SHapley Additive exPlanations, v0.47.2) values (Lundberg and Lee, 2017) further quantify variable contributions.

To analyze feature importance in our machine learning framework, we compute both model-specific importance metrics and SHAP values. For Random Forest and XGBoost implementations, we extract the native feature importance attribute, which calculates the mean decrease in impurity across all trees for each predictor variable (Breiman, 2001, Chen and Guestrin, 2016). The importance scores are stored for comparative analysis between treatment effects on total factor productivity and workforce size.

This machine learning approach serves two complementary purposes: it validates the economic significance of our main covariates by assessing the model's predictive performance-demonstrating that the ability to generate accurate predictions reflects the true relevance of the variables under consideration-and simultaneously uncovers potential nonlinear relationships or complex interactions among factors that traditional parametric models, constrained by predefined functional forms, might overlook or underestimate.

5 Empirical Evidence

5.1 Main Results

Table 3 reports the main results of this paper. Columns 1–2 display results where the main explanatory variable is a dummy (indicating receipt of NRRP funds devoted to the Transition 4.0) and the Callaway and Sant'Anna (2021) estimator is used. Columns 3–4, by contrast, display results when the main explanatory variable represents the logarithm of the total amount of NRRP funds targeting the Transition 4.0 estimated with a CTWFE model. The columns differ in the number of time-varying controls included in each specification. Columns 1 and 3 include no additional controls; Columns 2 and 4 include all firm-level controls.

Across all specifications, the primary explanatory variable, NRRP Funds, is positively and significantly correlated with tfp and employees, suggesting that such funds effectively support firms' productivity and employment opportunities. In particular, receiving NRRP funds in favour of the Transition 4.0 increases tfp by 16.9%-17.8%, with respect to our counterfactual, strongly supporting our *RH1*. Interestingly, such results are in line with Bettiol et al. (2024) who estimate that the adoption of Transition 4.0 technologies increases productivity by 7.4% on micro, small, and medium enterprises specialized in manufacturing activities in the North of Italy. A stronger effect in magnitude is rather obtained by Hwang and Kim (2022) who find that SMEs adopting emerging technologies like "AI," "Big Data," and "Robotics" in the production process have remarkably higher productivity by more than 26%, compared to non-adopters.

Furthermore, we observe that a 1% increase in these funds is associated with a 1.1%-1.2% growth in firms's tfp, thus corroborating our *RH1*. Our findings confirm previous evidence obtained by Cirillo et al. (2023) who find that the impact of the Transition 4.0 on Italian firms' productivity fluctuates between 5% and 7%, with stronger effects for small and medium-size firms, with a more mature business.

We also obtain a positive impact of such funds on the number of employees, although with a smaller magnitude. Indeed, our treated firms experience a variation in their tfp which is 15.2%-15.8% larger than that observed in the control group. Moreover, a 1% increase in these funds determines a 0.6% increase in firms' employment, in line with our *RH2*. These findings corroborate previous results by Sharfaei and Bittner (2024) who highlight that a 1% increase in Transition 4.0 robots, leads to a 1.1% increase in employment, with stronger effects in advanced than developing countries. Similarly, Ayhan and Elal (2023) discuss how technological changes induced by research and development expenditures are positive on employment. These results suggest that firms should invest on training programmes to acquire digital competencies, maintain a higher level of knowledge, and increase their flexibility to adapt to technological change and update their skill sets for new forms of production (Margherita and Braccini, 2021, Delke et al., 2023). Indeed, the digital transformation, particularly in the Transition 4.0, demands specific skills that are not necessarily taught by educational institutes or developed in the labor market, and fostering a work environment in which employees can continuously develop their potential is vital to avoid labour destruction (Wallin et al., 2020, Rikala et al., 2024). Overall, our results are consistent with Acemoglu et al. (2020), who find positive effects of robots' adoption on French firms' total employment, besides tfp.

Figure 2 shows the result of an endogeneity assessment. We examine the parallel trends assumption, which is essential for the validity of our results using the Callaway and Sant'Anna (2021) estimator, based on Equation 10. Valid parallel trends ensure that treated and control units do not differ significantly in terms of tfp and employment trends before the intervention. Satisfying the parallel trends assumption also helps to address

Table 3: The impact of NRRP funds on tfp and employment. Results refer to the whole sample of firms. Coefficients are estimated based on Equation 11.

	CS		CTWFE	
	(1)	(2)	(3)	(4)
Total Factor Productivity				
NRRP Funds	0.178***	0.169***	0.012***	0.011***
	(0.054)	(0.052)	(0.002)	(0.002)
Employment				
NRRP Funds	0.158***	0.152***	0.006***	0.006***
	(0.032)	(0.030)	(0.001)	(0.001)
Observation	14,476	14,476	14,476	14,476
Firms' controls		✓		✓

Note: The table displays the relationship between tfp and NRRP funds. Columns 1–2 display results for Model 1, where the main explanatory variable is a dummy variable indicating receipt of NRRP funds. Columns 3–4, by contrast, present results for Model 1 with the main explanatory variable as the total amount of NRRP funds obtained by the firm.Significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.

concerns about self-selection into treatment due to the staggered adoption of NRRP projects.

Red segments represent the difference in the dynamics of tfp and employment between treated and control units before the disbursement of NRRP funds. Blue segments represent such difference after the intervention. The pre-treatment differences are not statistically significant, providing evidence in favour of the parallel trends assumption. Furthermore, the post-treatment effects tend to increase their magnitude over time. This finding is consistent with previous literature highlighting that innovation based investments may require time before producing tangible results (Courvisanos, 2009, Weber and Rohracher, 2012, Prettner and Werner, 2016). Conversely, these results contrast with Bettiol et al. (2024) who highlight that Transition 4.0 investment effects tend to vanish after one year from the completion of the project.

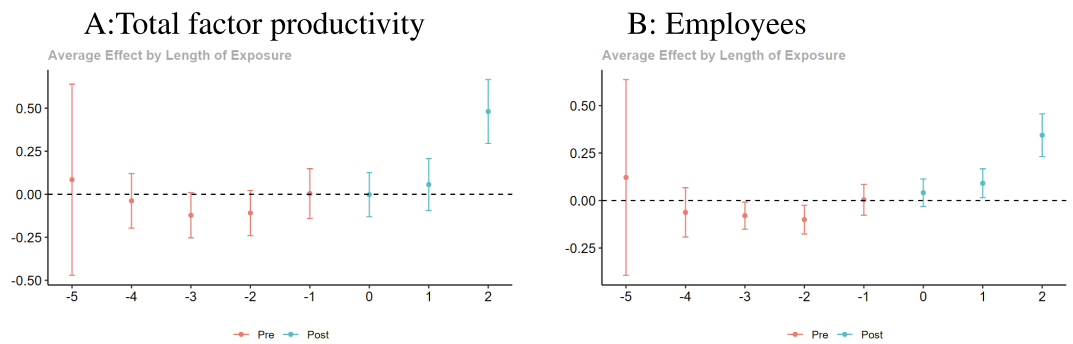


Figure 2: A: Dynamic impact of NRRP funds on tfp. B: Dynamic impact of NRRP funds on employees. Results refer to the whole sample of firms. Coefficients are estimated based on Equation 10.

We also try to corroborate our previous findings about the key role of NRRP funds supporting the Transition 4.0 in increasing tfp and employment. In particular, to highlight that the growth in our dependent variable is driven by such funds and not by other factors influencing the business of the analysed firms, we rank the relevance of our explanatory variables based on Shapley Values and Feature Importance obtained through Random

Forest and XGBoost models. Panels A, C, and E confirm that NRRP funds constitute the main determinant of tfp. We clearly observe that larger values of such funds are associated with higher tfp. Moreover, NRRP funds exhibit the strongest feature importance with values between 0.78 and 0.88. We also find that NRRP funds constitute a relevant driver of employment, with firms obtaining stronger financial support also displaying a higher number of employees. In this case the NRRP funds highlight a feature importance around 0.2 that is lower only with respect to the variable production value.

Figure 3: A: Shapley Values of economic and financial variables estimated through a random forest on tfp. B: Shapley Values of economic and financial variables estimated through a random forest on employees. C: Shapley Values of economic and financial variables estimated through an XG Boost on tfp. D: Shapley Values of economic and financial variables estimated through an XG Boost on employees. E: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on tfp. F: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on employees. All plots refer to the whole sample of firms.

5.2 The mechanism behind the impact of Transition 4.0 funds

In a second step, we investigate the mechanism through which Transition 4.0 funds may generate tfp and employment growth. In particular, we hypothesize that beneficiary firms may achieve significant improvements in tfp and employment through workforce training and upskilling. Consistently, we restrict our analysis to 348 treated firms receiving Transition 4.0 funds for projects aimed at employee training and skill development.[7]

Table 4 highlights that Transition 4.0 funds targeting the training and upskilling of employees have a positive and statistically significant impact on both tfp and employment in all our specifications. Moreover, in line with our *RH1* and *RH2*, the magnitude of such coefficients is larger than that observed when analysing the full sample of firms. Figure 4 shows the estimated coefficients with a 95% confidence interval based on models estimated in Tables 3 and 4. Moreover, Table 5 formally compares through a t-test whether such coefficients are statistically different.[8]

Results obtained suggest that, in all our models, the magnitude of such coefficients is statistically different at least at the 10% significance level, thus suggesting that investing in training and competence enhancement of the workforce allows firms to experience larger benefits in terms of tfp and employment growth. In particular, treated firms exhibit a tfp approximately 30% larger than that of the control group. Moreover, a 1% growth in Transition 4.0 funds fostering the training and upskilling of the workforce produces a 1.8-1.9% raise in tfp. Finally, in terms of employment, the extensive margin is approximately 28%, while the intensive margin corresponds to about 1.1%.

[7] We identify training-focused projects by merging our dataset with the OpenCUP database, which provides detailed information on public investments linked to Unique Project Codes (CUP), including project descriptions, funding sources, and links to broader programs like the NRRP. The merge with OpenPolis, based on the CUP, allows us to isolate projects aimed at employee training and upskilling through enriched project-level details.

[8] We compute the t-test based on the following statistic:

$$t - test = \frac{\beta_{training-upskilling} - \beta_{full\ sample}}{\sqrt{Variance(\beta_{training-upskilling}) + Variance(\beta_{full\ sample})}}$$

Table 4: The impact of NRRP funds on tfp and employment. Results refer to the sample of firms receiving funds targeting the training and upskilling of the workforce. Coefficients are estimated based on Equation 11.

	CS		CTWFE	
	(1)	(2)	(3)	(4)
Total Factor Productivity				
NRRP Funds	0.311***	0.307***	0.019***	0.018***
	(0.058)	(0.062)	(0.003)	(0.003)
Employment				
NRRP Funds	0.279***	0.276***	0.011***	0.011***
	(0.054)	(0.051)	(0.002)	(0.002)
Observation	2,664	2,664	2,664	2,664
Firms' controls		✓		✓

Note: The table displays the relationship between tfp and NRRP funds. Columns 1–2 display results for Model 1, where the main explanatory variable is a dummy variable indicating receipt of NRRP funds. Columns 3–4, by contrast, present results for Model 1 with the main explanatory variable as the total amount of NRRP funds obtained by the firm.Significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.

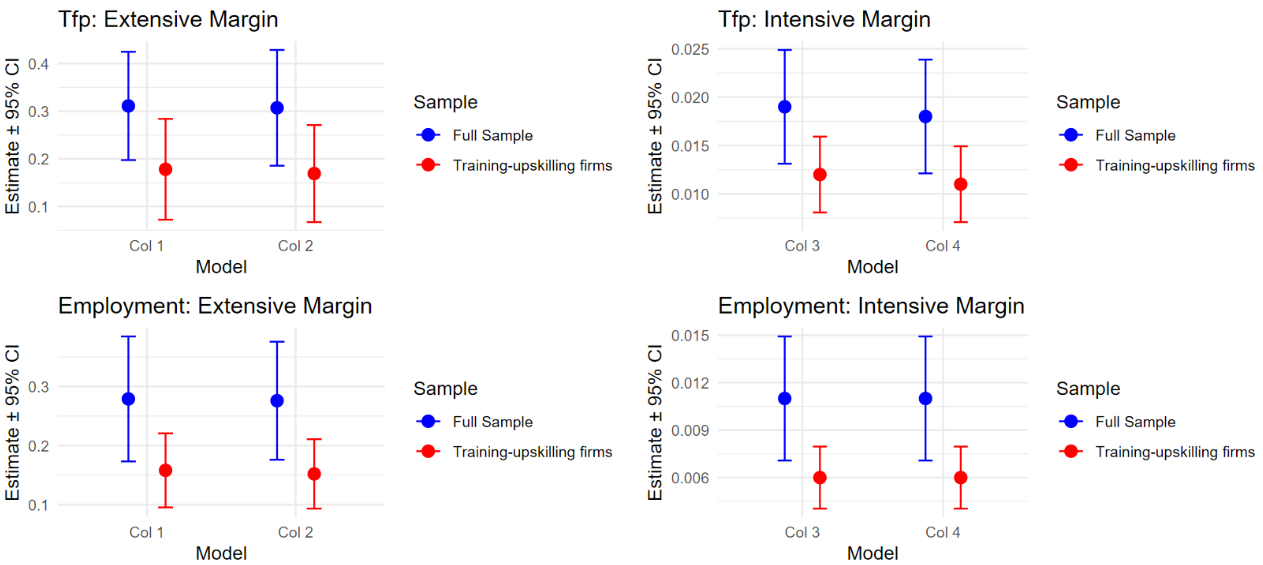


Figure 4: We show the Confidence Intervals (CI) of the coefficients of the variable NRRP funds shown in Tables 3 and 4.

Table 5: T-test statistics and p-values where we compare whether the coefficient of the variable "NRRP funds" is statistically different across samples in Tables 3 and 4.

Model Comparison	**t-statistic**	**p-value**
TFP (Column 1)	1.678	0.0932
TFP (Column 2)	1.705	0.0882
TFP (Column 3)	1.941	0.0522
TFP (Column 4)	1.941	0.0522
Employment (Column 1)	1.928	0.0540
Employment (Column 2)	2.096	0.0361
Employment (Column 3)	2.236	0.0253
Employment (Column 4)	2.236	0.0253

5.3 Robustness checks

We also perform two additional empirical exercises to validate the construction of our treatment and control units. The first is a falsification test that examines the relationship between other than NRRP funds devoted to the Transition 4.0 and firms' tfp and employment. If our treatment and control units are correctly defined, these NRRP funds other than those devoted to Transition 4.0 should not influence our dependent variables.

Table 6 shows the results of this exercise. As before, columns 1–2 present estimates using the Callaway and Sant'Anna (2021) estimator, with the main explanatory variable as a dummy set to one if the firm initiates at least one NRRP project not focused on the Transition 4.0, and zero otherwise. Columns 3–4, by contrast, report results where the main explanatory variable represents the total amount of NRRP funds other than those devoted to Transition 4.0 invested in the firm. These other NRRP funds are not significantly associated with both tfp and employment.

The second empirical exercise is a placebo test. We randomly assign placebo treatment status and start dates to firms in the control group, repeating this 500 times to assess whether spurious treatment effects arise. We estimate our Callaway and Sant'Anna (2021) estimator using a bivariate treatment variable. If our data were significantly affected by an underestimation of NRRP projects dedicated to the Transition 4.0, we would expect a consistent number of significant and positive point estimates. Figure 5 presents the results of this exercise: the x-axis shows each replication, while the y-axis displays the point estimates with their confidence intervals.

Table 6: The impact of NRRP funds on tfp and employment. Results refer to the whole sample of firms. Coefficients are estimated based on Equation 11.

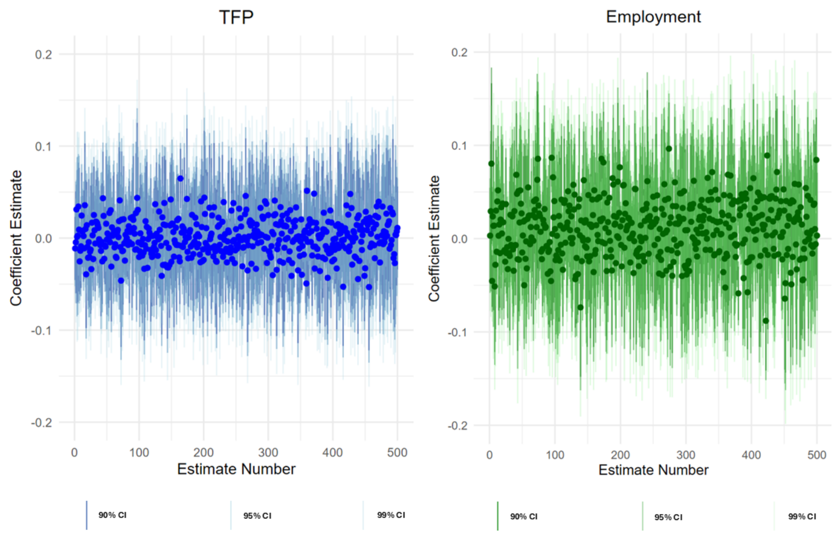
	CS		CTWFE	
	(1)	(2)	(3)	(4)
Total Factor Productivity				
Other NRRP Funds	0.013	0.009	0.002	0.003
	(0.081)	(0.079)	(0.102)	(0.098)
Employment				
Other NRRP Funds	-0.008	-0.006	0.003	0.004
	(0.061)	(0.058)	(0.096)	(0.095)
Observation	14,476	14,476	14,476	14,476
Firms' controls		✓		✓

The table displays the results of a placebo test which assess the relation between the other NRRP funds and firms' tfp and employment. Columns 1–2 present estimates using the Callaway and Sant'Anna (2021) estimator, with the main explanatory variable as a dummy set to one if the firm initiates at least one NRRP not focused on the Transition 4.0, and zero otherwise. Columns 3–4, by contrast, report results where the main explanatory variable represents the total amount of other NRRP funds invested in the firm. Significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.

In most cases, the confidence intervals intersect zero. This indicates no systematic effect, supporting the validity of our treatment assignment.

Together, these two exercises provide strong evidence supporting the validity of our research design, the robustness of our causal estimates through an appropriate identification of treatment and control units.

Figure 5: Placebo analysis.



Note: The figure displays the point estimates and their confidence interval of randomly selected treatment units on tfp and employment. In most cases, the confidence intervals intersect zero, indicating an absence of statistical significance.

5.4 The impact across sectors

As a final step, we investigate the heterogeneity in the impact of NRRP funds supporting the Transition 4.0 across sectors. In particular, we analyse the effect on the Manufacturing, Wholesale Trade, ICT and Professional Services sectors, which represent the four industries accounting for at least 250 treated firms.

Table 7 highlights significant and positive impacts of NRRP funds on tfp and employment for firms in the Manufacturing sector, although both the extensive (θ_{tfp} = 0.09 and $\theta_{employment}$ = 0.09) and intensive (β_{tfp} = 0.01 $\beta_{employment}$ = 0.003) margins display a lower magnitude with respect to results shown in Section 5.1, where we analyse the whole sample of firms.

Interestingly, we observe a stronger impact for firms operating in the Wholesale Trade sector (see Table 8). In particular, treated firms experience a tfp and employment which are about 23% and 19% larger than the counterfactual, respectively. Similarly, a 1% growth in NRRP funds is associated with a 1.6%-1.7% growth in tfp and a 0.06%-0.07% increase in employment.

Table 9 suggests that the highest impact of NRRP funds related to the Transition 4.0 is generated in firms operating in the ICT sector both for the extensive (θ_{tfp} = 0.48 and $\theta_{employment}$ = 0.46) and intensive (β_{tfp} = 0.02 $\beta_{employment}$ = 0.01) margins. Rather, we do not find a statistically significant effect on firms in the

Professional Services industry (see Table 10).

Such results fuel the debate about the heterogeneity of the effects of the Transition 4.0 across sectors (Song et al., 2022, Bettiol et al., 2024, Khanna and Sharma, 2024, Guimarães et al., 2025, Guo, 2025). For instance, Guo (2025) highlight that Transition 4.0 investments generate larger gains in sectors characterized by higher competition across firms and strong manufacturing innovation. Moreover, Khanna and Sharma (2024) explain how sectors with a higher level of IT penetration may experience stronger benefits from the Transition 4.0. Indeed, these sectors are better positioned to integrate and leverage digital technologies, thereby amplifying the returns on investment in innovation and automation. Consistently, we find the highest impact of NRRP funds devoted to the Transition 4.0 in the ICT sector (48% tfp, 46% employment), also validating Fragapane et al. (2022) empirical findings on the usage of IT technologies for smart intralogistics solutions.

Finally, the null effect in Professional Services suggests that training implementation gaps may still exist in knowledge-intensive sectors. This heterogeneity mirrors skill-gap analyses performed by Rikala et al. (2024), suggesting the NRRP manufacturing focus inadvertently created sectoral path dependencies.

Overall, our results are confirmed by a set of robustness checks, including the assessment of the parallel trend assumption and the application of Random Forest and XG Boost machine learning methods to assess the relevance of NRRP funds devoted to the Transition 4.0 in driving our results (see Appendix A for futher details).

Table 7: The impact of NRRP funds on tfp and employment. Results refer firms operating in the Manufacturing sector. Coefficients are estimated based on Equation 11.

	CS		CTWFE	
	(1)	(2)	(3)	(4)
Total Factor Productivity				
NRRP Funds	0.092*	0.090***	0.010***	0.010***
	(0.053)	(0.048)	(0.002)	(0.002)
Employment				
NRRP Funds	0.089**	0.086**	0.003**	0.003**
	(0.037)	(0.036)	(0.002)	(0.002)
Observation	4,345	4,345	4,345	4,345
Firms' controls		✓		✓

Note: The table displays the relationship between tfp and NRRP funds. Columns 1–2 display results for Model 1, where the main explanatory variable is a dummy variable indicating receipt of NRRP funds. Columns 3–4, by contrast, present results for Model 1 with the main explanatory variable as the total amount of NRRP funds obtained by the firm. Significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.

Table 8: The impact of NRRP funds on tfp and employment. Results refer firms operating in the Wholesale trade sector. Coefficients are estimated based on Equation 11.

	CS		CTWFE	
	(1)	(2)	(3)	(4)
Total Factor Productivity				
NRRP Funds	0.237**	0.233***	0.017***	0.016***
	(0.112)	(0.109)	(0.003)	(0.003)
Employment				
NRRP Funds	0.191**	0.188**	0.007***	0.006***
	(0.077)	(0.075)	(0.002)	(0.002)
Observation	2,976	2,976	2,976	2,976
Firms' controls		✓		✓

Note: The table displays the relationship between tfp and NRRP funds. Columns 1–2 display results for Model 1, where the main explanatory variable is a dummy variable indicating receipt of NRRP funds. Columns 3–4, by contrast, present results for Model 1 with the main explanatory variable as the total amount of NRRP funds obtained by the firm. Significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.

Table 9: The impact of NRRP funds on tfp and employment. Results refer to firms operating in the ICT sector. Coefficients are estimated based on Equation 11.

	CS		CTWFE	
	(1)	(2)	(3)	(4)
Total Factor Productivity				
NRRP Funds	0.484**	0.476**	0.015**	0.015**
	(0.020)	(0.019)	(0.008)	(0.007)
Employment				
NRRP Funds	0.461***	0.455***	0.011***	0.010***
	(0.013)	(0.012)	(0.004)	(0.003)
Observation	1,221	1,221	1,221	1,221
Firms' controls		✓		✓

Note: The table displays the relationship between tfp and NRRP funds. Columns 1–2 display results for Model 1, where the main explanatory variable is a dummy variable indicating receipt of NRRP funds. Columns 3–4, by contrast, present results for Model 1 with the main explanatory variable as the total amount of NRRP funds obtained by the firm. Significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.

Table 10: The impact of NRRP funds on tfp and employment. Results refer to firms operating in the Professional services sector. Coefficients are estimated based on Equation 11.

	CS		CTWFE	
	(1)	(2)	(3)	(4)
Total Factor Productivity				
NRRP Funds	0.163	0.160	0.013	0.011
	(0.239)	(0.235)	(0.009)	(0.008)
Employment				
NRRP Funds	0.169	0.166	0.010	0.009
	(0.155)	(0.153)	(0.006)	(0.006)
Observation	1,027	1,027	1,027	1,027
Firms' controls		✓		✓

Note: The table displays the relationship between tfp and NRRP funds. Columns 1–2 display results for Model 1, where the main explanatory variable is a dummy variable indicating receipt of NRRP funds. Columns 3–4, by contrast, present results for Model 1 with the main explanatory variable as the total amount of NRRP funds obtained by the firm. Significance levels are indicated as ***p<0.01, **p<0.05, *p<0.1.

6 Conclusions

This paper contributes to the growing literature on the effectiveness of industrial policy by providing novel evidence on the impact of the Italian NRRP Transition 4.0 programme—a timely and policy-relevant intervention—on firm-level total factor productivity and employment. By jointly examining these two key dimensions of firm performance within a robust causal inference framework, and exploring the underlying mechanisms, the study offers a comprehensive assessment of the programme's effectiveness in fostering both technological upgrading and job creation. Using an econometric framework combining a panel event study approach with a continuous treatment model, the study finds that public support for digital transformation through tax incentives significantly enhances both tfp and workforce expansion. These findings contradict the zero-sum perspective often portrayed in debates on automation, whereby productivity gains come at the cost of labor displacement.

Firms benefiting from Transition 4.0 funds record tfp increases of approximately 17% compared to their non-treated counterparts. Employment effects are also positive and statistically significant, with a 15% increase observed among treated firms. Similarly, the intensive margin analysis reveals a 1.1%–1.2% increase in tfp and 0.6% growth in employment for every 1% rise in Transition 4.0 funding. We also provide evidence that investments in employee training and upskilling may serve as a key mechanism through which Transition 4.0 funds contribute to increases in tfp and employment. Our findings remain robust across multiple specifications, including placebo and falsification tests, and are further substantiated through advanced machine learning techniques. These results underscore the capacity of digital investments—particularly in advanced manufacturing technologies, AI, and data cloud—to improve operational efficiency. Employment impacts, while slightly more modest in magnitude, suggest that concerns about widespread job losses may be overstated when complemented by workforce development strategies.

Importantly, the effects are not uniform across sectors: the ICT and Wholesale Trade industries show the strongest responses, while manufacturing displays moderate gains, and the Professional Services sector exhibits no statistically significant effects. These disparities suggest that the impact of the Transition 4.0 is shaped by sector-specific technological readiness, absorptive capacity, and the alignment between digital tools and existing labor structures.

These findings carry relevant policy and managerial implications. First, managers should consider integrated investment strategies that combine technological investments with human capital development. Firms that complement digital transformation with targeted employee training reap the greatest gains in productivity and employment, suggesting that the full potential of technology deployment can only be realized when accompanied by parallel human capital measures, such as reskilling programs. Second, our study provides policymakers with data-driven evidence that a well-calibrated digital transition strategy—rooted in public-private collaboration and combining technological upgrades with human capital development—can effectively foster sustainable and inclusive industrial transformation in line with EU recovery objectives. Third, the heterogeneous effects across sectors suggest that a one-size-fits-all approach may limit policy effectiveness. Future programmes should therefore incorporate differentiated support instruments, tailoring incentives to the specific needs and digital maturity of each industry.

Future extensions of this work may aim to cover additional countries at the EU level with similar data repositories for their RRPs. Moreover, in the next years, it might be interesting to expand our analysis examining a longer time frame to assess long-term benefits of NRRP funds targeting the Transition 4.0. Finally, future research may try to further disentangle the mechanism behind tfp and employment gains or analyse a wider set of sectors.

Declarations

- **Competing interests:** The authors declare no conflict of interest.

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A Additional results on sectors

Figures A1, A3, A5, and A7 present the results of the endogeneity assessment when analysing samples restricted to firms operating in the Manufacturing, Wholesale Trade, ICT, and Professional Services sectors, respectively. Specifically, we test the parallel trends assumption using the estimator proposed by Callaway and Sant'Anna (2021), as specified in Equation 10. The validity of the parallel trends assumption implies that, prior to the intervention, treated and control units exhibit no significant differences in tfp and employment trends.

Moreover, Figures A2, A4, A6, and A8 highlight Shapley values and Feature Importance computed on tfp and employment based on Random Forest and XG Boost models. Results refer to firms operating in the Manufacturing, Wholesale Trade, ICT, and Professional Services sectors, respectively.

Manufacturing

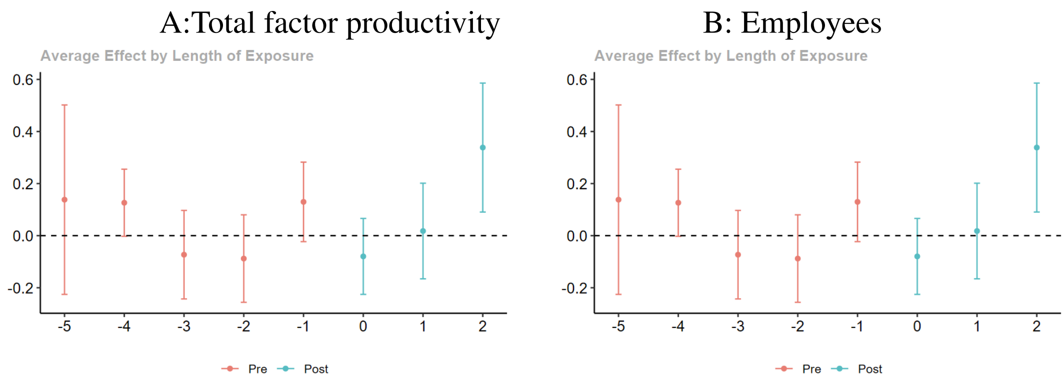

Figure A1: A: Dynamic impact of NRRP funds on tfp B: Dynamic impact of NRRP funds on employees. Results refer to firms operating in the Manufacturing sector

Manufacturing

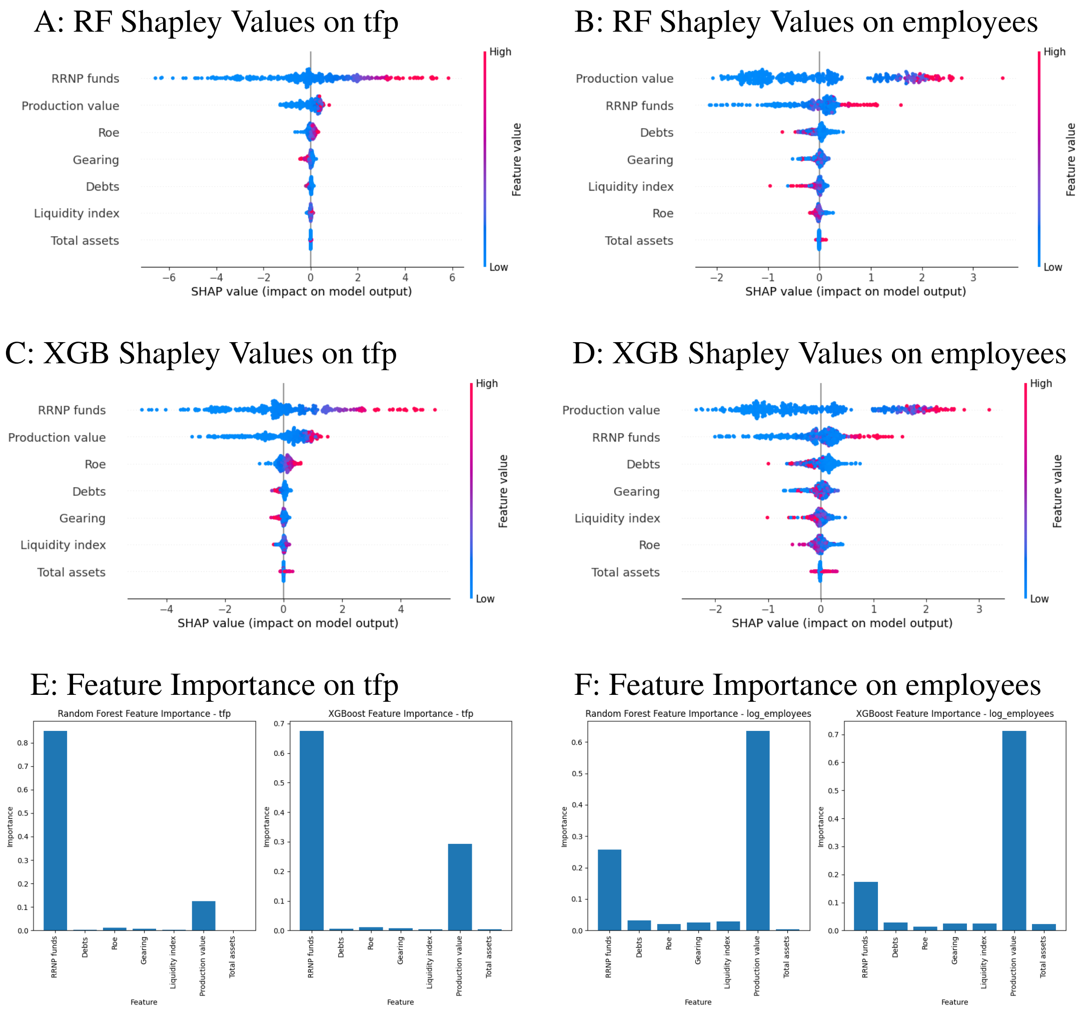

Figure A2: A: Shapley Values of economic and financial variables estimated through a random forest on tfp. B: Shapley Values of economic and financial variables estimated through a random forest on employees. C: Shapley Values of economic and financial variables estimated through an XG Boost on tfp. D: Shapley Values of economic and financial variables estimated through an XG Boost on employees. E: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on tfp. F: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on employees. All plots refer to firms operating in the Manufacturing sector.

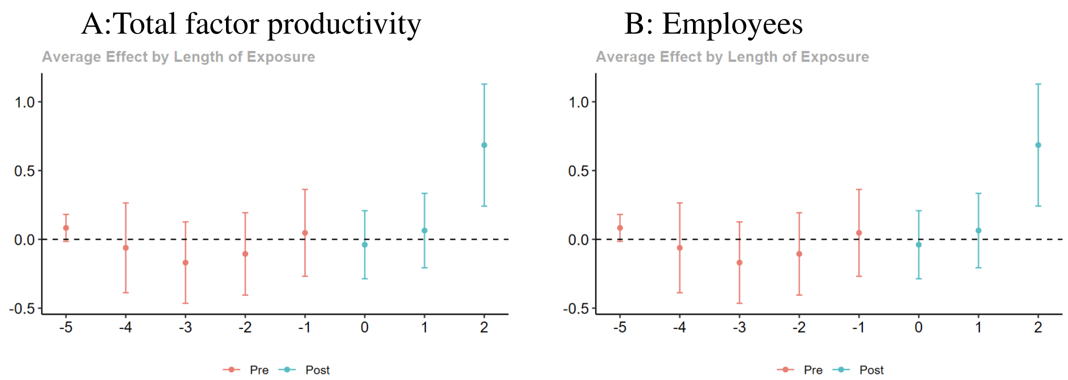

Figure A3: A: Dynamic impact of NRRP funds on tfp. B: Dynamic impact of NRRP funds on employees. Results refer to the firms operating in the Wholesale trade sector.

Wholesale Trade

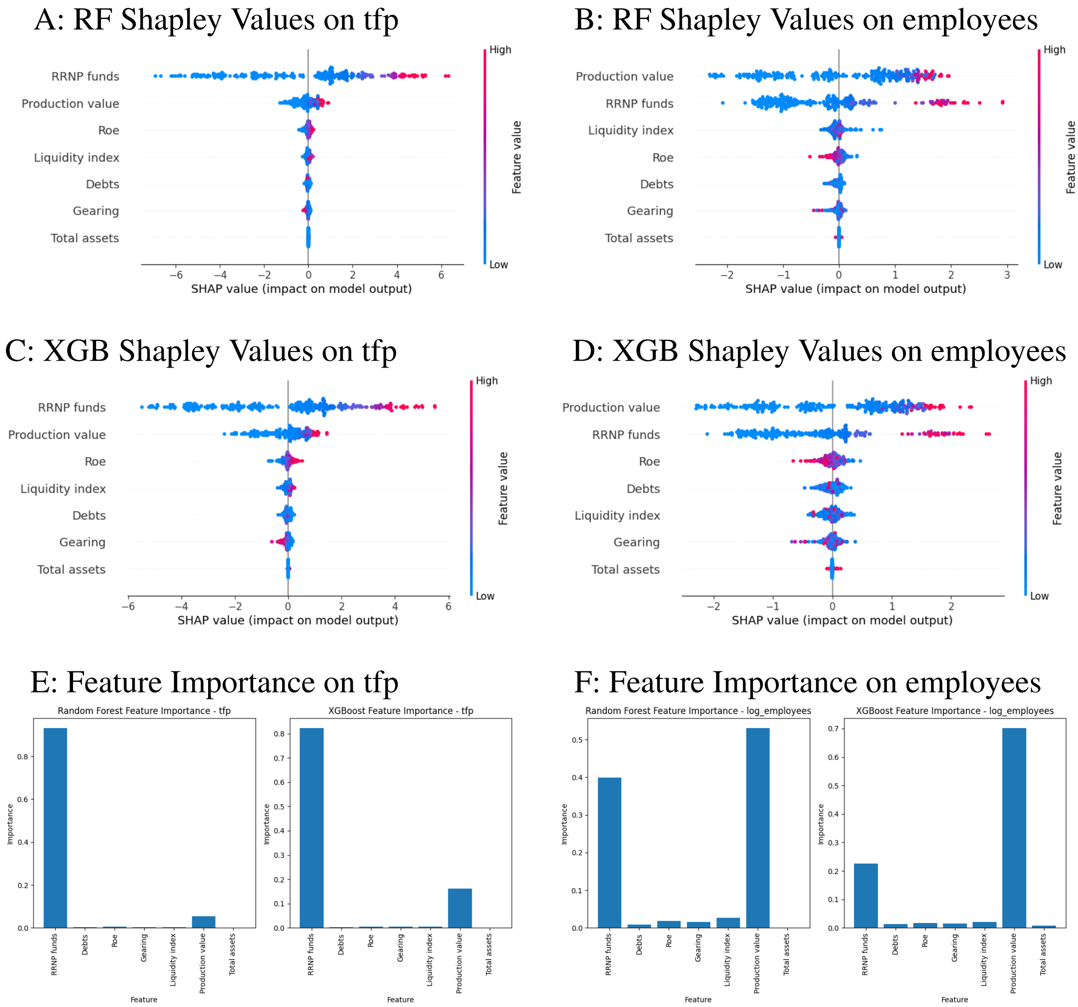

Figure A4: A: Shapley Values of economic and financial variables estimated through a random forest on tfp. B: Shapley Values of economic and financial variables estimated through a random forest on employees. C: Shapley Values of economic and financial variables estimated through an XG Boost on tfp. D: Shapley Values of economic and financial variables estimated through an XG Boost on employees. E: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on tfp. F: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on employees. All plots refer to firms operating in the Wholesale Trade sector.

ICT

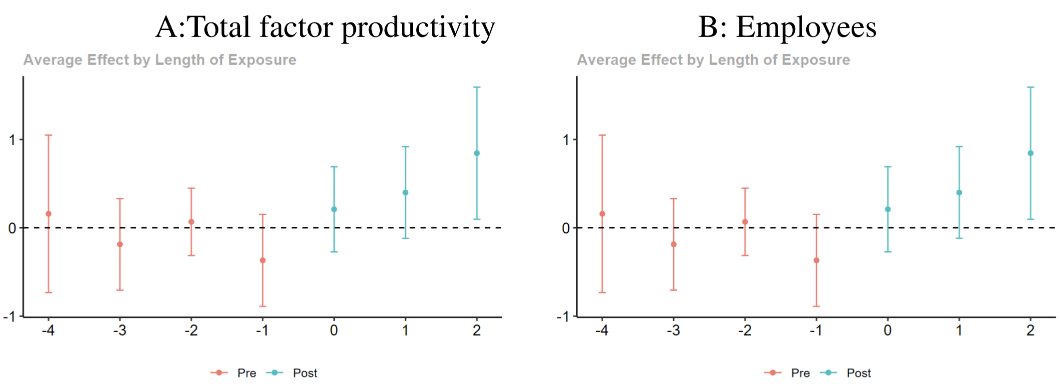

Figure A5: A: Dynamic impact of NRRP funds on tfp. B: Dynamic impact of NRRP funds on employees. Results refer to firms operating in the ICT sector.

ICT

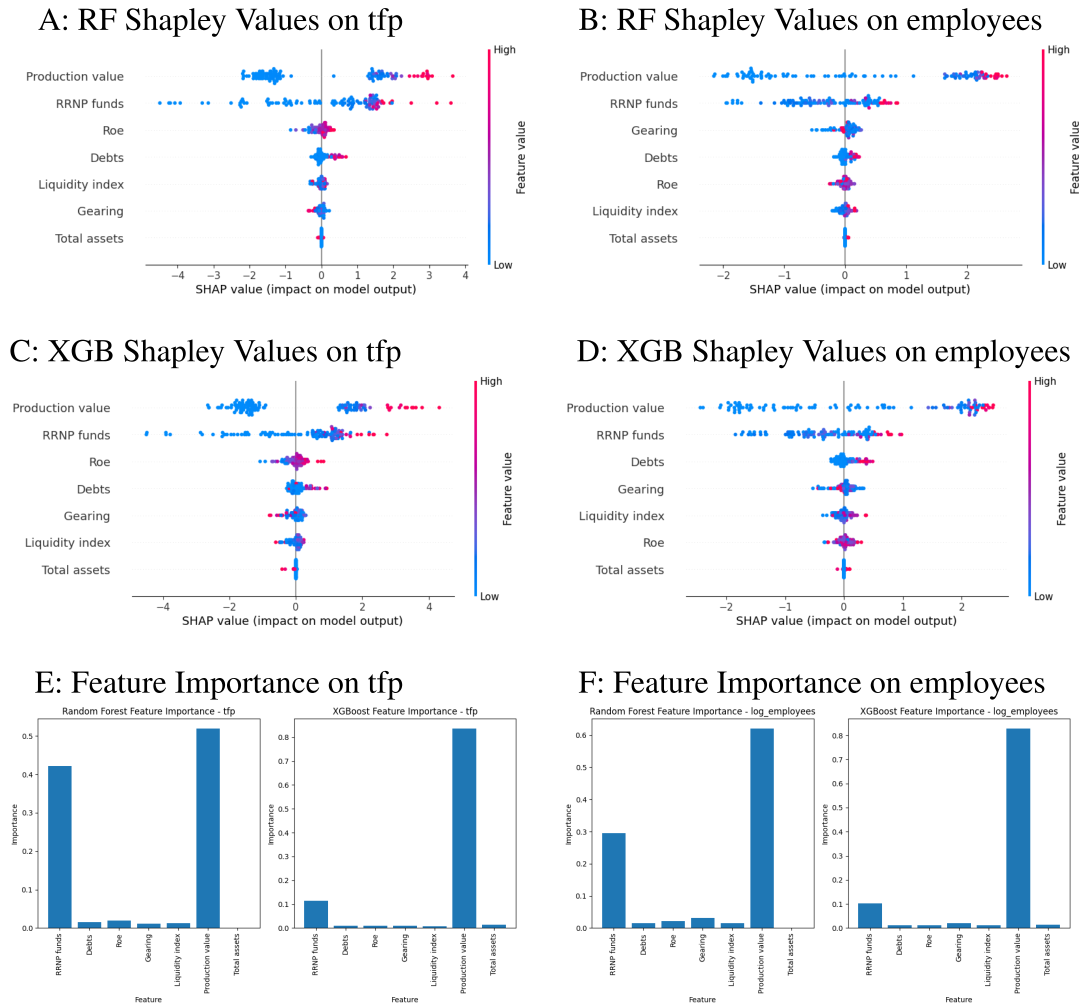

Figure A6: A: Shapley Values of economic and financial variables estimated through a random forest on tfp. B: Shapley Values of economic and financial variables estimated through a random forest on employees. C: Shapley Values of economic and financial variables estimated through an XG Boost on tfp. D: Shapley Values of economic and financial variables estimated through an XG Boost on employees. E: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on tfp. F: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on employees. All plots refer to firms operating in the ICT sector.

Professional Services

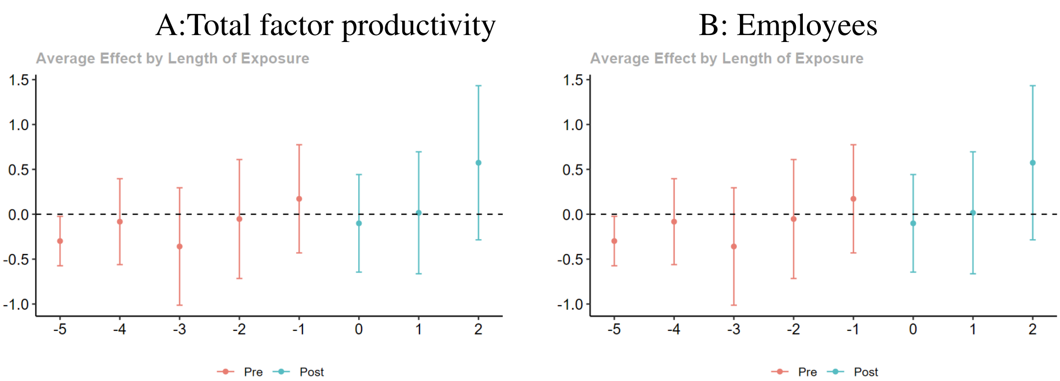

Figure A7: A: Dynamic impact of NRRP funds on tfp. B: Dynamic impact of NRRP funds on employees. Results refer to firms operating in the Professional services sector.

Professional Services

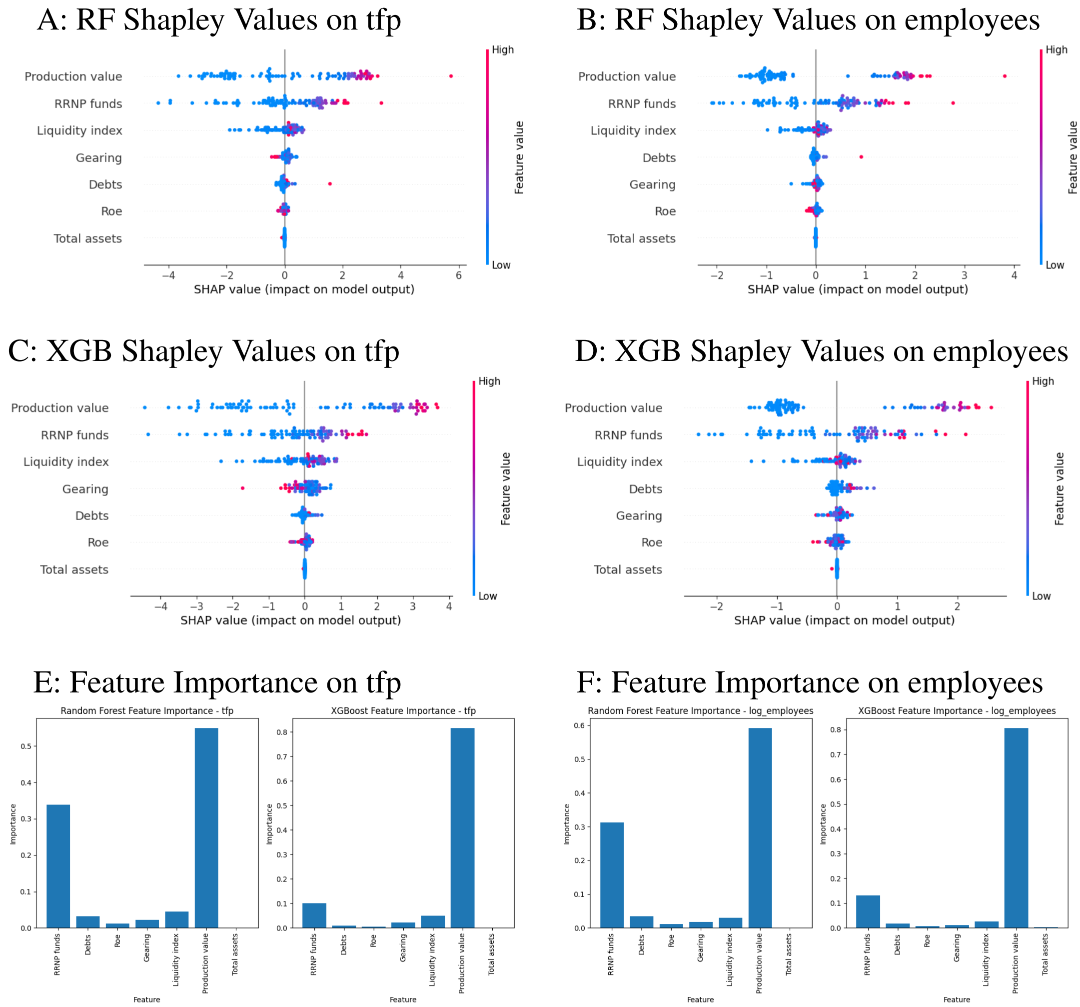

Figure A8: A: Shapley Values of economic and financial variables estimated through a random forest on tfp. B: Shapley Values of economic and financial variables estimated through a random forest on employees. C: Shapley Values of economic and financial variables estimated through an XG Boost on tfp. D: Shapley Values of economic and financial variables estimated through an XG Boost on employees. E: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on tfp. F: Feature Importance of economic and financial variables estimated through a random forest and XG Boost on employees. All plots refer to firms operating in the Professional Services sector.