MASTER
ECONOMICS OF BUSINESS AND STRATEGY

Digital Transition and Firm Productivity: The Impact of RRP Support on Total Factor Productivity in Portuguese Manufacturing Firms

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2026

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Dissertation

Master's in Economics of Business and Strategy

Supervised by

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Acknowledgments

This dissertation marks the closing of a very important chapter in my life and the completion of a long-awaited academic journey. This achievement would not have been possible without the support of many people, to whom I would like to express my sincere gratitude.

First and foremost, I would like to extend my deepest thanks to Professor José Manuel Peres Jorge, Director of the Master's programme I am now completing and my dissertation supervisor. His time, knowledge and guidance were invaluable throughout the programme and, in particular, during the development of this dissertation.

I would also like to thank my family for being by my side throughout this journey, each in their own way. To my parents, thank you for instilling in me the importance of education from an early age, for standing by me through both the best and the most difficult moments, and for giving me the opportunity and the foundations that enabled me to reach this stage of my education. To my cousins and uncles, thank you for your companionship and for the moments of joy and encouragement that gave me hope, even during the times when anxiety felt overwhelming.

To Margarida, thank you for your constant presence throughout this academic journey and for your enduring friendship.

A kind word to Maria Francisca for all the support, encouragement and reassurance she gave me throughout this Master's degree. Your presence and everything you have done for me are deeply appreciated and mean more than words can express.

To all of you, my heartfelt thank you.

Abstract

Productivity is widely recognised as a key determinant of firm competitiveness and long-run economic growth. In Portugal, persistent productivity challenges and relatively low levels of advanced digital adoption have motivated public policies aimed at accelerating firms' digital transformation. One of the most important initiatives in this context is Component 16 - Businesses 4.0 of Portugal's Recovery and Resilience Plan (RRP), which provides support for digital-transition projects.

This dissertation examines the short-run effects of RRP Component 16 support on the Total Factor Productivity (TFP) of Portuguese manufacturing firms. Using firm-level accounting data from the SABI database and beneficiary information from the *Mais Transparência* portal, Cobb-Douglas production functions are estimated using Ordinary Least Squares (OLS) and Fixed Effects (FE) estimators, from which firm-level TFP measures are derived. The effects of the programme on TFP are then evaluated through a matched Difference-in-Differences framework comparing supported firms with comparable non-supported firms over the period 2021-2024.

The results do not provide statistically significant evidence that RRP Component 16 support increased TFP among treated firms during the first two years after treatment.

This dissertation provides one of the first firm-level evaluations of the effects of RRP Component 16 support on TFP in Portuguese manufacturing firms. More broadly, it contributes to the literature on digitalisation, productivity and public policy evaluation by examining whether public support for digital transformation translates into measurable improvements in productive efficiency.

Keywords: Total Factor Productivity; Digitalisation; Recovery and Resilience Plan; Component 16; Manufacturing Firms; Difference-in-Differences; Portugal.

Resumo

A produtividade é amplamente reconhecida como um determinante fundamental da competitividade das empresas e do crescimento económico de longo prazo. Em Portugal, os persistentes desafios de produtividade e os níveis relativamente baixos de adoção de tecnologias digitais avançadas têm motivado políticas públicas destinadas a acelerar a transformação digital das empresas. Uma das iniciativas mais relevantes neste contexto é a Componente 16 - Empresas 4.0 do Plano de Recuperação e Resiliência (PRR), que apoia projetos de transição digital.

Esta dissertação analisa os efeitos de curto prazo do apoio da Componente 16 do PRR na Produtividade Total dos Fatores (PTF) das empresas portuguesas da indústria transformadora. Utilizando dados contabilísticos ao nível da empresa provenientes da base de dados SABI e informação sobre beneficiários obtida através do portal Mais Transparência, são estimadas funções de produção Cobb-Douglas recorrendo aos estimadores de Mínimos Quadrados Ordinários (OLS) e Efeitos Fixos (FE), a partir das quais é estimada a PTF ao nível da empresa. Os efeitos do programa são depois avaliados através de uma abordagem de Difference-in-Differences com matching, comparando empresas apoiadas com empresas não apoiadas, mas comparáveis, no período de 2021 a 2024.

Os resultados não fornecem evidência estatisticamente significativa de que o apoio da Componente 16 do PRR tenha aumentado a PTF das empresas tratadas durante os dois primeiros anos após o tratamento.

Esta dissertação constitui uma das primeiras avaliações ao nível da empresa dos efeitos do apoio da Componente 16 do PRR na PTF das empresas portuguesas da indústria transformadora. Adicionalmente, contribui para a literatura sobre digitalização, produtividade e avaliação de políticas públicas ao analisar se o apoio público à transição digital se traduz em melhorias mensuráveis da eficiência produtiva.

Palavras-chave: Produtividade Total dos Fatores; PTF; Digitalização; Plano de Recuperação e Resiliência; Componente 16; Indústria Transformadora; Difference-in-Differences; Portugal.

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1. Introduction

Productivity is a fundamental determinant of firm competitiveness, profitability, and long-run economic growth. At the firm level, productivity differences help explain why some firms survive, expand, and compete internationally while others remain small or exit the market (Syverson, 2011). For Portugal, these dynamics carry particular significance. Despite decades of European integration, the country's productivity performance has remained persistently below the European Union average. Amador and dos Santos (2020) find that Total Factor Productivity (TFP) contributions to Portuguese GDP growth were systematically below the EU average over the period 1990-2017, highlighting the importance of identifying the firm-level mechanisms and policies that may support productivity growth.

Digitalisation has emerged as one of the main channels through which firms may improve productive efficiency. Digital technologies can reduce information-processing costs, improve internal coordination, and automate routine tasks (Gal et al., 2019). Evidence from European firms suggests that more intensive users of digital technologies tend to be more productive, pay higher wages, and exhibit stronger export performance (Amador & Silva, 2023). In Portugal, however, the diffusion of advanced digital technologies remains relatively limited, particularly in traditional manufacturing sectors. The European Investment Bank (2019) identifies several barriers to adoption, including limited managerial awareness, insufficient technical capabilities, and difficulties financing intangible investments. These challenges provide the policy rationale for the digital-transition component of Portugal's Recovery and Resilience Plan (RRP). Approved in 2021 as part of the Next Generation EU framework, the RRP allocates substantial resources to accelerating the digital transformation of Portuguese firms. Component 16 (C16) - Businesses 4.0 is one of its flagship measures, providing support for the adoption of digital technologies and business-process modernisation (República Portuguesa, 2023).

Despite the growing literature on digitalisation and public support, limited evidence exists at the intersection of these two strands. Studies of ICT adoption and digitalisation have examined their relationship with firm performance and productivity, whereas evaluations of public support programmes have more often focused on broader outcomes such as employment, investment, turnover and exports (Gal et al., 2019; Amador and Silva, 2023; Cabral and Campos, 2023; Dvouletý et al., 2021). Consequently, it remains unclear whether public support specifically targeted at firms' digital transition generates improvements in productive efficiency, as measured by Total Factor Productivity.

This dissertation addresses that gap in the context of Portugal's RRP Component 16. Its main research question is: **Does RRP Component 16 support generate short-run improvements in the Total Factor Productivity of Portuguese manufacturing firms?** Two related questions are also examined: **Do European public supports have a measurable impact in Portuguese firms' TFP?** and **Are the conclusions robust to alternative approaches to estimating firm-level TFP?**

To answer these questions, the analysis links firm-level accounting data from SABI (Sistema de Análise de Balanços Ibéricos) with beneficiary information from the *Mais Transparência* portal for the period 2021-2024. Firm-level TFP is estimated using gross-output Cobb-Douglas production functions. A matched Difference-in-Differences (DiD) framework then compares the evolution of TFP among firms that received C16 support with that of comparable non-beneficiary firms.

The results do not provide statistically robust evidence that C16 support increased TFP among treated firms during the first two post-treatment years. In the preferred fixed-effects specification, supported firms did not experience a significantly different TFP trajectory from their matched counterparts. The robustness test using the OLS specification confirm these results. This pattern is consistent with, but does not establish, the possibility that productivity gains from digital investments require time to materialise through implementation, organisational adjustment and workforce adaptation.

The remainder of the dissertation is organised as follows. Chapter 2 reviews the literature on productivity and TFP measurement, firm-level productivity heterogeneity, digitalisation, public support programmes and impact evaluation. Chapter 3 describes the data sources, sample construction and data-treatment procedures. Chapter 4 presents the empirical strategy, including the estimation of firm-level TFP, propensity score matching and the Difference-in-Differences design. Chapter 5 reports and discusses the empirical results, including robustness analyses. Finally, Chapter 6 concludes by summarising the main findings, discussing the study's limitations and outlining avenues for future research.

2. Literature Review

This chapter reviews the theoretical and empirical literature that motivates the present study. It first discusses the concept of productivity and Total Factor Productivity, before examining the main approaches to firm-level TFP estimation and their limitations. It then reviews evidence on productivity heterogeneity, digitalisation and ICT adoption, and the role of public support programmes in shaping firm performance. Finally, the chapter identifies the research gap addressed by this dissertation and outlines its main contribution.

2.1 Productivity and Total Factor Productivity

The study of productivity has a long history in economic research and is relevant across several fields of economics. In simple terms, productivity is the measure of how efficiently inputs are transformed into output (Syverson, 2011). A firm is more productive when it can produce more output with the same quantity of inputs, or the same output using fewer resources (Van Biesebroeck, 2007) and the same logic is easily applied to the case of a country. For this reason, productivity is closely associated with competitiveness, profitability, firm survival, and long-run economic growth (Syverson, 2011).

Productivity measures can be distinguished between single-factor indicators and multifactor indicators (OECD, 2001). Single-factor indicators relate output to a single input (OECD, 2001). The typical example of this type is labour productivity (Syverson, 2011), it is usually defined as output per worker, output per hour worked, or quality-adjusted hours worked (Bartelsman & Doms, 2000) and is valued for its intuitive interpretation and ease of computation (OECD, 2001). However, single-factor measures have a fundamental limitation: they capture the effects of excluded inputs (Syverson, 2011) and can therefore misinterpret increases in capital intensity as underlying efficiency differences, masking the true sources of output growth (OECD, 2001). Simply put, a firm may display higher labour productivity not because it uses workers more efficiently, but because it employs more capital per worker (Syverson, 2011). A multifactor productivity measure, commonly referred to as total factor productivity (TFP), addresses this limitation by relating output to an aggregate of the observable inputs included in the production specification, typically labour and capital and, in gross-output specifications, intermediate inputs (OECD, 2001; Syverson, 2011).

The modern empirical treatment of TFP has its origins in aggregate growth accounting (Hulten, 2001), particularly through the seminal contribution of Solow (1957), who introduced a framework in which aggregate output is decomposed into the contribution of observable inputs and a residual component associated with shifts in the production function over time. Under Hicks-neutral technical change, output is represented as shown in Equation (2.1):

$$Q_t = A_t f(K_t, L_t) \tag{2.1}$$

where Q_t is output, K_t is capital, L_t is labour, and A_t captures the efficiency with which inputs are transformed into output. The growth of A_t, later known as the Solow residual, became a central empirical measure of TFP (Hulten, 2001). In Solow's (1957) application to US data for 1909-1949, output per man-hour approximately doubled. Solow concluded that roughly one-eighth of this increase could be attributed to higher capital intensity, while the remaining seven-eighths could be attributed to the growth of the A_t factor, which the author named broadly as "technical change", illustrating the empirical importance of productivity beyond factor accumulation.

As Syverson (2011) notes, TFP is most easily understood by examining a production function directly. Starting with a simple Cobb-Douglas specification with two inputs, labour and capital, presented in Equation (2.2):

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \tag{2.2}$$

where Y_t is output, K_t is capital L_t is labour, and A_t is simply a neutral factor that changes over time. The portion of output that cannot be accounted for by the quantities of capital and labour inputs is captured by A_t. This residual component (A_t) is TFP. It is important, however, to interpret TFP carefully. Hulten (2001) stresses that TFP is a residual concept, since it may capture genuine technological and organisational innovation, but also measurement error, omitted variables, aggregation bias, model misspecification and unadjusted variation in capacity utilisation. Abramovitz (1956) famously described the residual as a "measure of our ignorance", acknowledging its composite nature. In this dissertation, TFP is interpreted as a measure of firm-level productive efficiency as revealed by accounting data.

2.2 Firm-Level TFP Estimation

At the firm level, the growth-accounting logic is adapted by estimating a production function in which firm output is explained by observable inputs, with productivity recovered as the residual component (Bournakis & Mallick, 2018; Van Beveren, 2012). Establishment-level productivity studies typically assume output, usually measured as deflated sales or value added, to be a function of the inputs employed by the firm and its productivity (Van Beveren, 2012).

A common starting point in the applied literature is the Cobb-Douglas production function (Van Beveren, 2012; Syverson, 2011). In its gross-output form, it can be written as presented in Equation (2.3):

$$Y_{it} = A_{it}\ K_{it}^{\beta_k}\ L_{it}^{\beta_l}\ M_{it}^{\beta_m} \tag{2.3}$$

where Y_{it} denotes output, K_{it} capital, L_{it} labour, M_{it} intermediate inputs, and A_{it} firm-level productivity (Syverson, 2011). Taking logarithms yields the log-linear specification in Equation (2.4):

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it} \tag{2.4}$$

Estimated log TFP is obtained as the part of output not explained by the estimated contribution of observable inputs (Van Beveren, 2012), as represented in Equation (2.5), in an analogue manner of the Solow residual (Solow, 1957) in growth accounting:

$$\widehat{tfp_{it}} = \widehat{a_{it}} = y_{it} - \widehat{\beta_k} k_{it} - \widehat{\beta_l} l_{it} - \widehat{\beta_m} m_{it} = \widehat{\beta_0} + \widehat{\varepsilon_{it}} \tag{2.5}$$

The literature on firm-level TFP estimation is extensive, encompassing a variety of modelling approaches as well as different accounting proxies for output and inputs (Van Beveren, 2012). A first important distinction concerns the choice between a value-added and a gross-output specification. In a value-added specification, output is measured as sales net of intermediate consumption, and the production function is typically estimated with capital and labour only. This approach is parsimonious, but it relies on the assumption that intermediate inputs can be separated from the role of primary factors in the production technology (OECD, 2001).

In a gross-output specification such as that in Equation (2.3), by contrast, output is measured before subtracting intermediate inputs, and materials or other intermediate expenditures enter explicitly as an additional input. This specification is widely used in firm-level productivity studies. Van Beveren (2012) presents a Cobb-Douglas production function in which output depends on capital, labour, and materials, and obtains firm-level productivity as the residual from that relationship. Matos and Neves (2020), using Portuguese firm-level data, adopt the same specification and explicitly discuss the value-added alternative before dismissing it on the grounds of its implausibility under imperfect competition.

The choice between value added and gross output therefore depends both on theoretical considerations and on data availability. When information on intermediate inputs is unavailable or poorly measured, value added may be a practical solution (OECD, 2001; Gal, 2013). When reliable data on materials and external services are available, a gross-output specification allows the researcher to model more directly the transformation of capital, labour, and intermediate inputs into output (Levinsohn & Petrin, 2003). This is particularly relevant in manufacturing, where materials, machinery and labour are often jointly involved in the production process (Hulten, 2001).

TFP estimation at the firm level involves well-known econometric challenges that have generated a substantial methodological literature (Olley & Pakes, 1996; Ackerberg et al., 2015). The most extensively discussed challenge is endogeneity, which gives rise to two distinct problems: simultaneity bias and selection bias.

Simultaneity bias arises because firms may observe their own productivity when deciding how much labour, capital, or materials to use, while the econometrician does not directly observe this productivity. If more productive firms systematically choose higher input levels, observed inputs become correlated with the productivity component, violating the assumptions required for consistent OLS estimation (Van Beveren, 2012). Selection bias, in turn, arises from the non-random exit of firms from the sample: firms with low productivity are more likely to exit, so if the production function is estimated without modelling this exit process, the estimated input elasticities can be biased, particularly the coefficient on capital, and can distort inferred productivity measures (Olley & Pakes, 1996; Van Beveren, 2012). The simplest approach to estimate TFP is OLS. This estimator is transparent and easy to implement, but it does not control for unobserved productivity shocks that affect input choices (Gal, 2013). As a result, OLS estimates of input elasticities may be biased upwards for variable inputs (Van Beveren, 2012). A common alternative is the fixed-effects estimator, which removes time-invariant firm-specific heterogeneity. However, its validity requires that the relevant unobserved productivity component be time invariant and that inputs be strictly exogenous conditional on firm effects (Van Beveren, 2012).

The econometric literature has developed more advanced approaches to address the simultaneity and selection biases, such as Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015). However, these methods are not without limitations and require more demanding assumptions, as summarised in Table 1. In practice, the choice of estimator is often constrained by data availability, sample structure, research objectives and the assumptions the researcher is willing to make (Gal, 2013; Van Beveren, 2012; Syverson, 2011). Consequently, simpler approaches such as OLS and fixed effects remain common in applied productivity studies. In addition, Van Beveren (2012) shows empirically that different TFP estimators can generate highly correlated productivity measures and yield similar conclusions in a policy evaluation exercise, although the author also stresses that no single estimator fully resolves all methodological concerns.

Method	Main idea	Main limitation
OLS	Estimates production function parameters assuming inputs are exogenous.	Biased when firms adjust inputs in response to productivity shocks.
Fixed Effects (FE)	Removes time-invariant firm-specific heterogeneity.	Does not fully solve simultaneity between inputs and productivity.
Olley-Pakes (OP)	Uses investment decisions to proxy for unobserved productivity and corrects for firm exit.	Investment may be zero or irregular for many firms.
Levinsohn-Petrin (LP)	Uses intermediate inputs as a proxy for unobserved productivity.	Relies on monotonicity assumptions and may face identification concerns.
Ackerberg-Caves-Frazer (ACF)	Improves identification in proxy-variable approaches by modifying the timing assumptions.	More complex implementation and stronger data requirements.

Table 1: Main ideas and limitations of TFP estimators. Source: Author's elaboration, based on Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015), and Van Beveren (2012).

For the purposes of this dissertation, this literature has two implications. First, TFP should not be treated as a mechanically observed variable. It is a residual measure that depends on the specification of output, inputs, and the estimator used. Second, simpler estimators such as OLS and fixed effects can still be informative when the objective is to construct a transparent productivity measure for an applied policy evaluation, provided their limitations are explicitly recognised.

2.3 Firm-Level Productivity Heterogeneity and the Portuguese Manufacturing Context

The availability of longitudinal firm-level datasets since the 1980s has yielded one of the central findings of modern productivity research: firms exhibit very different productivity levels, even within the same narrowly defined industry, with ratios between the upper and lower portions of the productivity distribution typically on the order of two to one or more (Bartelsman & Doms, 2000; Syverson, 2011). Syverson (2011) provides a precise quantification: a plant at the ninetieth percentile of the productivity distribution is typically approximately twice as productive as one at the tenth percentile within the same four-digit industry.

Foster et al. (2008) further document that this dispersion reflects not only technical efficiency differences but also differences in demand and product appeal, and show that market selection operates to concentrate output in more productive firms over time. Critically, high-productivity firms tend to be larger, pay higher wages, export more, and exhibit lower exit rates, suggesting that productivity differences reflect genuine and durable efficiency advantages (Bartelsman & Doms, 2000; Syverson, 2011).

The Portuguese evidence is consistent with the international pattern of significant and persistent productivity dispersion among firms within the same industry (Simões & Pereira, 2019; Pereira & Nogueira, 2020). Simões and Pereira (2019) document that entry and exit dynamics contribute to aggregate productivity trends, with exiting firms being less productive than survivors on average. Pereira and Nogueira (2020) also note that firm-level performance in Portugal is highly skewed, characterized by a large mass of low-productivity firms and a small group of high-performing firms.

The sources of this heterogeneity have been extensively investigated. Syverson (2011) organises the determinants of TFP into internal and external categories. Internal drivers include managerial quality and practices, R&D intensity, human capital, learning-by-doing, and the adoption of information and communication technologies (ICT), while external factors include product market competition and trade openness.

This evidence is corroborated in the Portuguese case. Caliendo et al. (2016), show that firms' internal organisational structure is significantly related to measured productivity, Silva (2025) specifically highlights the importance of corporate digital integration and digital literacy to enhance productivity effects, a complementarity that digital investments may also affect (Amador & Silva, 2023; Amador & Silva, 2025), and Matos and Neves (2020) highlight that innovation, skilled labour, and international openness significantly boost TFP.

This evidence is highly relevant for Portugal, since productivity growth has been a persistent challenge for the Portuguese economy, and understanding its firm-level determinants is central to informing policies aimed at improving competitiveness and economic convergence with European partners (Amador & dos Santos, 2020; Simões & Pereira, 2019). Duarte and Restuccia (2007) show that aggregate TFP movements were the main driver of Portugal's convergence towards US income levels during the second half of the twentieth century, underscoring the central role of productivity in the country's economic development. More recently, this convergence process has stalled. Amador and dos Santos (2020), estimating a dynamic stochastic production frontier for EU economies over 1990-2017, find that TFP contributions to Portuguese GDP growth have been systematically below the EU average across all decades studied. Their decomposition shows that Portugal's weak TFP performance is largely driven by negative efficiency developments, meaning that Portuguese firms and sectors have been slow to close the gap with the international productivity frontier, rather than by technological regress per se (Amador & dos Santos, 2020). This persistent productivity underperformance provides the broader motivation for studying firm-level policies and mechanisms that may support productivity growth in Portugal.

2.4 Digitalisation, ICT Adoption and Firm Productivity

Digitalisation is one of the main channels through which firms may improve productivity, by reducing information processing costs, improving internal coordination, automating routine tasks and supporting management decisions (Amador & Silva, 2023; Silva, 2025; Gal et al., 2019). However, as the ICT productivity literature has long emphasised, digital investment does not automatically translate into immediate efficiency improvements. Returns to ICT tend to materialise gradually and depend on complementary investments in organisational restructuring and workforce skills (Amador & Silva, 2023; Gal et al., 2019; Syverson, 2011). At the firm level, the evidence on ICT and productivity has become increasingly robust (Amador & Silva, 2025). Gal et al. (2019) also find a positive and economically significant association between digital adoption and both labour productivity and TFP. Their results indicate that productivity gains from digitalisation are particularly pronounced in manufacturing and in sectors performing routine-intensive tasks, consistent with the view that digital technologies substitute for routine labour while complementing complex cognitive activities (Gal et al., 2019). However, causally establishing the link between ICT and TFP is methodologically challenging, as digitalisation and productivity are simultaneously determined: more productive firms may be better positioned to invest in and benefit from digital technologies (Gal et al., 2019).

In terms of ICT adoption patterns, Amador and Silva (2023) document that Portuguese firms have made progress in basic digital adoption, but that the diffusion of advanced technologies remains limited. The study finds strong heterogeneity in adoption rates across firm size, sector and geography. Crucially, firms using digital technologies more intensively are systematically more productive, pay higher wages and are more export-driven (Amador & Silva, 2023). These correlations reinforce the policy relevance of digital transition support for Portuguese manufacturing.

At the aggregate level, the European Investment Bank (2019) report on small and medium-sized enterprises (SME) digitalisation in Portugal documents that overall digital adoption by Portuguese firms is slightly below the EU average, particularly in traditional manufacturing sectors. The report identifies a set of structural barriers that limit adoption: limited awareness among managers, insufficient technical capabilities, difficulty integrating digital tools into existing processes, and constraints in financing intangible digital investments through conventional bank lending (European Investment Bank, 2019). These barriers provide the direct policy rationale for the digital transition component of Portugal's RRP (Cabral & Campos, 2023; European Investment Bank, 2019).

2.5 The RRP, Public Support and Impact Evaluation

Portugal's RRP, approved in 2021 as part of the Next Generation EU framework, was a plan conceived in the aftermath of the COVID-19 pandemic to address the economic and social consequences of the crisis, serving as a major instrument to implement the Portugal 2030 Strategy (República Portuguesa, 2023; Cortes et al., 2022).

The main purposes of the program are to reinforce Portugal's economic recovery and accelerate convergence with the European Union, address persistent structural bottlenecks, which is the case of low productivity, and to prepare the country for the challenges of the green and digital transitions (República Portuguesa, 2023; Cortes et al., 2022).

The RRP is structured around three main dimensions (República Portuguesa, 2023; Cortes et al., 2022):

- Resilience - Focused on social and economic robustness, including health, housing, and qualifications;
- Climate Transition - Dedicated to decarbonization, sustainable mobility, and energy

efficiency;

- Digital Transition - Aimed at modernizing the state and the business fabric, and the most relevant to the present dissertation.

The Digital Transition dimension of the RRP accounts for 22% of the plan's total initial funds and follows three main pillars: training/inclusion of people, digital transformation of businesses, and digitalisation of the state (Cortes et al., 2022). A critical part of the Digital Transition dimension is C16 - Businesses 4.0, centred on its high expected impact on the Portuguese economy. It is considered essential because it addresses the Portuguese business fabric, particularly SMEs, characterized by a low level of digitalisation. Also, it aims to boost competitiveness by digitalizing processes, production, and innovation. Finally, it addresses an important economic transformation, ensuring that businesses can adopt the most advanced practices and processes at the technological frontier (Cortes et al., 2022). C16 provides support in five fronts: Digital Transition Reform, *Indústria 4.0* (Industry 4.0), Digital Commercial Neighbourhoods, Digital Innovation Hubs, and Regional Support (República Portuguesa, 2023)

Since Section 2.4 documents positive links between digital adoption and productivity and since the RRP C16 introduces a policy context that is directly related to the mechanisms discussed above explicitly designed to support digital tools and technologies, there is theoretical motivation to expect TFP gains. However, the literature also warns that productivity effects may be weaker, delayed or heterogeneous across firms. Digital investments require complementary organisational changes, skills and implementation time before affecting measured productivity (Gal et al., 2019). With only two post-treatment years available, the empirical analysis represents an early assessment of short-run effects rather than a definitive long-run evaluation.

Evaluating the causal impact of public policy interventions requires addressing a fundamental identification problem: firms that receive support differ systematically from non-recipients in size, managerial quality, investment plans and growth expectations (Gertler et al., 2011). Simple comparisons between supported and unsupported firms therefore confound programme effects with pre-existing differences.

Evidence on public support programmes in Portugal and Europe establishes important expectations. Cabral and Campos (2023) evaluate the COMPETE structural funds programme on Portuguese firms and find positive effects on employment, turnover, capital intensity and exports, but smaller effects on labour productivity. Dvouletý et al. (2021), in a systematic review of EU public grants to SMEs, conclude that grants generate more consistent effects on survival, employment and investment than on labour productivity or TFP. This pattern suggests that public support expands firm scale more readily than it raises productive efficiency.

Overall, two competing expectations emerge. Digital-transition support may improve productivity if it helps firms overcome barriers to adopting efficiency-enhancing technologies. Yet, the broader evidence on public support suggests that productivity effects are often weaker and slower to materialise. This dissertation evaluates which pattern RRP C16 digital support follows by estimating firm-level TFP for Portuguese manufacturing firms and comparing early beneficiaries with comparable non-treated firms.

2.6 Research Gap and Contribution of this Dissertation

The literature reviewed above establishes several important points. First, productivity is widely recognised as a fundamental determinant of firm competitiveness and long-run economic growth, with Total Factor Productivity (TFP) providing a comprehensive measure of productive efficiency beyond the mere accumulation of capital and labour (Solow, 1957; Syverson, 2011). Second, firm-level productivity is characterised by substantial and persistent heterogeneity, making the identification of productivity-enhancing mechanisms a central concern for both researchers and policymakers (Bartelsman & Doms, 2000; Syverson, 2011). Third, a growing body of evidence indicates that ICT adoption and digitalisation can contribute positively to firm performance, although their effects depend on complementary organisational capabilities, workforce skills and firms' ability to integrate new technologies into production processes (Gal et al., 2019; Amador & Silva, 2023).

These issues are particularly relevant in Portugal, where productivity performance remains a structural concern and the adoption of more advanced digital technologies is uneven across firms and sectors (Amador & dos Santos, 2020; European Investment Bank, 2019; Amador & Silva, 2023). In response, the Recovery and Resilience Plan (RRP), particularly C16 - Businesses 4.0, was designed to accelerate the digital transformation of Portuguese firms through targeted public support.

Despite the growing literature on productivity, digitalisation and business support, an important empirical gap remains. Existing evidence has generally examined either the relationship between firms' adoption of ICT and digital technologies and their performance, or the effects of public support programmes on broader firm-level outcomes. However, these two strands of literature have remained largely separate. More specifically, there is limited evidence on whether public support targeted at firms' digital transition generates measurable improvements in productive efficiency, as captured by TFP. This study aims to address this gap by estimating the short-run effects of RRP Component 16 digital-transition support on the TFP of Portuguese manufacturing firms observed between 2021 and 2024. To do so, it applies a matched Difference-in-Differences framework.

The contribution of this dissertation is therefore threefold. First, it provides evidence on the effects of public support for digital transition on firm-level productivity. Second, it focuses on TFP rather than solely on broader performance indicators, thereby assessing whether support is associated with a more efficient use of firms' productive inputs. Third, it combines beneficiary information from the *Mais Transparência* portal with firm-level accounting data from SABI in a quasi-experimental framework, providing early evidence on the productivity effects of a recent and policy-relevant programme in Portugal.

3. Data and Sample Construction

This chapter describes the data sources and data-preparation procedures used to construct the analytical samples employed in the empirical analysis. Although the formal methodological specifications are presented in Chapter 4, the empirical design is briefly outlined here to clarify how the data are used throughout the study.

As summarised in Figure 1, the empirical analysis follows four sequential stages. First, accounting data from SABI is combined with beneficiary information from the *Mais Transparência* portal to construct a longitudinal sample of Portuguese manufacturing firms, identify firms receiving RRP Component 16 support and apply the required cleaning and sample restrictions. Second, gross-output Cobb-Douglas production functions are estimated using Ordinary Least Squares (OLS) and Fixed Effects (FE) estimators, from which firm-level Total Factor Productivity (TFP) measures are derived. Third, treated firms are matched with comparable non-beneficiary firms using pre-treatment characteristics. Finally, the resulting matched sample is used in a Difference-in-Differences framework to estimate the short-run effects of RRP Component 16 support on firm-level TFP.

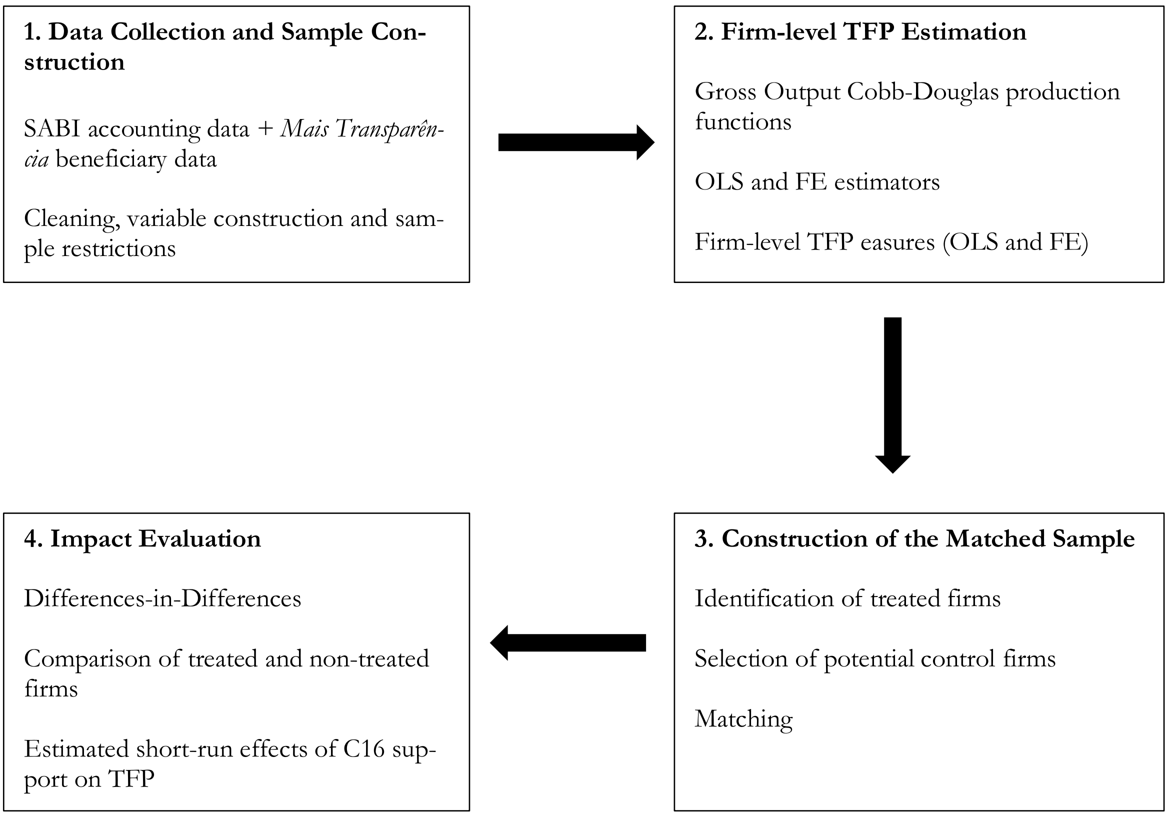

Figure 1: Stages of the empirical work. Source: Author's elaboration.

The implementation of this empirical design required the collection, cleaning and integration of information from different sources at successive stages. Section 3.1 introduces the accounting and beneficiary datasets. Section 3.2 describes the preparation of the data used to estimate firm-level TFP, including the construction of the SABI panel, the identification of the treatment cohort and the merge between the accounting and RRP datasets. Section 3.3 then explains the additional sample restrictions required to implement the matching procedure used in the analysis. Finally, Section 3.4 discusses the main data limitations.

3.1 Data Sources

The empirical analysis combines two complementary sources of firm-level information. The first source provides annual accounting data required to estimate firm-level TFP. The second identifies firms receiving RRP Component 16 support and provides information on the timing of supported projects.

Accounting information was obtained from SABI (Sistema de Análise de Balanços Ibéricos). For the purposes of this dissertation, annual data were extracted for the period from 2021 to 2024 for Portuguese firms classified under Section C of the Portuguese Classification of Economic Activities, Revision 3 (CAE Rev. 3), covering divisions 10 to 33, which correspond to manufacturing activities. The extracted variables are used to proxy output, capital, labour and intermediate inputs in the gross-output production function.

Information on RRP beneficiaries was obtained from the *Mais Transparência* portal, a Portuguese public platform reporting information on public resources and funded projects (Portal Mais Transparência, n.d.). Two datasets were used: one identifying the entities associated with each project and their respective roles, and another containing project-level information, including contracted amounts, payments and project start dates. Both datasets were accessed in the versions available in March 2026.

3.2 Data Preparation and Sample Construction

Before estimating firm-level TFP, the two data sources were prepared and combined in three stages. First, the SABI extract was cleaned and transformed into a firm-year panel containing the accounting variables required for the production-function estimation. Second, a temporally homogeneous cohort of RRP Component 16 beneficiaries was identified. Third, the accounting and beneficiary datasets were merged to construct the sample used to estimate the production-function coefficients and derive firm-level TFP. The analytical sample used for the matching procedure is constructed subsequently in Section 3.3.

3.2.1 Construction of the SABI Panel

The original extract from SABI was then subjected to several data-cleaning procedures. First, the dataset, originally structured in wide format with one row per firm and separate columns for each accounting variable and year, was reshaped into long format. This transformation was necessary because both the production-function estimation and the subsequent DiD analysis require a panel structure in which individual firms can be tracked over time.

The main variables required for the production-function estimation were then constructed. Turnover serves as the measure of gross output (Y_{it}). Tangible Fixed Assets (TFA) proxy for the capital input (K_{it}). The labour input (L_{it}) is measured by the average number of persons employed by the firm (*Pessoas ao serviço da empresa, remuneradas e não remuneradas: número médio de pessoas*), as reported in SABI. This labour variable captures both remunerated and non-remunerated workers and represents an annual average, which is preferable to a point-in-time headcount because employment levels may fluctuate within the year. Using an annual average therefore provides a more representative measure of the labour effectively deployed in the production process over each accounting period. Finally, Intermediate inputs (M_{it}) are constructed as the sum of Cost of Goods Sold (COGS) and External Supplies and Services (ESS) and act as a proxy for materials:

$$Y_{it} = Turnover_{it}, \quad K_{it} = TFA_{it}, \quad L_{it} = Emp_{it}, \quad M_{it} = COGS_{it} + ESS_{it}$$

This variable construction is consistent with applied studies on Portuguese firm-level TFP (Matos & Neves, 2020), who adopt similar proxies from the same type of accounting data. All monetary variables were deflated to constant 2021 prices (Banco de Portugal, n.d.; Direção-Geral das Atividades Económicas, 2026).

Because the production function is estimated in logarithmic form, the dataset was restricted to firm-year observations with strictly positive real values of turnover, intermediate inputs, tangible fixed assets, and employment. Observations with missing or non-positive values in these variables were excluded, as logarithmic transformations are undefined for zero or negative values. Then, an outlier filter was applied to exclude abnormal observations.

Finally, firms were retained only if they had at least three years with valid observations across all four production-function variables. This restriction serves a dual purpose: it ensures that each firm is observed in both the pre-treatment period (2021 or 2022) and the post-treatment period (2023 or 2024) for the DiD analysis, and it improves the reliability of TFP estimation by providing a minimum number of time-series observations per firm. This cleaning process led to an initial panel of 26,994 unique firms.

A more detailed description of the SABI extraction and cleaning process is provided in Annex A, the outlier-filtering procedure is described in greater detail in Annex B, and the deflators used for each monetary variable are detailed in Annex C.

3.2.2 Identification of Treated Firms

The next step was the definition of the treatment group, which consists of manufacturing firms whose first RRP project under C16 - Businesses 4.0 started between 1 January 2023 and 31 March 2023. All six sub-investments (C16-i01 through C16-i06) of the component were retained in the treatment definition, since they belong to the same broad policy framework of firm-level digital transition (República Portuguesa, 2023).

The treatment window, 1 January 2023 to 31 March 2023, was selected deliberately for two reasons. First, restricting the treatment group to firms whose projects started within a narrow time interval reduces treatment-timing heterogeneity and simplifies the subsequent DiD design. Second, this window allows for relatively balanced pre-treatment (2021-2022) and post-treatment (2023-2024) observation periods. Following this procedure, 2,079 unique treated firms were identified in the RRP data. Additional details on the treatment-data construction from the *Mais Transparência* portal are provided in Annex D.

3.2.3 Merge Between SABI and RRP Data

The final step in the data-treatment process for TFP estimation consisted of merging the cleaned SABI panel with the treated-firms dataset. This merging process aimed to construct a unified firm-level panel containing both accounting information and RRP treatment status. The merge was performed at the firm level using the fiscal identification number (NIF). Table 2 reports the resulting outcome.

Merge status	Firms
SABI only / not treated (potential controls)	26,910
RRP treated, not found in SABI (excluded)	1,995
Matched SABI-RRP (treatment group)	84

Table 2: Merge coverage - SABI × RRP. Source: Author's elaboration.

Of the 2,079 firms identified as treated in Section 3.2.2, only 84, or 4.0%, were found in the cleaned SABI panel. The remaining 1,995 treated firms are absent from the final sample. This substantial difference does not reflect an error in the merging procedure. Instead, it is a direct consequence of the research design. RRP C16 - Businesses 4.0 targets firms across all sectors of the Portuguese economy, whereas the SABI extraction was restricted to manufacturing firms classified under Section C of CAE Rev. 3, divisions 10-33. Many C16 beneficiaries therefore operate in non-manufacturing sectors and were never included in the SABI panel. In addition, some manufacturing firms may fail to satisfy the data-quality requirements imposed in Section 3.2.1.

The 84 linked treated firms therefore represent the subset of C16 beneficiaries that operate in manufacturing and satisfy the accounting-data requirements of this study. This sample restriction should be borne in mind when interpreting the results: the estimated treatment effects pertain to manufacturing firms with adequate financial reporting and cannot be generalised to the full population of C16 beneficiaries.

At this stage, the firms not matched to the Jan-March 2023 treated list are best interpreted as potential controls. In the later matching stage, firms that received their first C16 support outside the January-March 2023 treatment window are excluded from the donor pool, so that treated firms are compared with clean non-recipients of C16 support during the relevant period.

For the estimation of the production function, an additional sectoral restriction is applied. Only CAE-2 sectors containing at least one treated firm are retained. The purpose of this restriction is to estimate input elasticities using firms operating in the same broad sectoral environment as the treated firms, while still preserving a large sample. The details regarding sectoral distribution of treated and potential control firms after the merge can be found in Annex E.

Table 3 reports the firm-year observations used for TFP estimation after applying this treated-sector restriction.

Year	Treated	Potential Controls	Total
2021	81	23,265	23,346
2022	84	24,159	24,243
2023	84	24,080	24,164
2024	82	22,757	22,839
Total	331	94,261	94,592

Table 3: Firm-Year observations used for TFP estimation. Source: Author's elaboration.

The resulting TFP estimation sample contains 84 different treated firms, 24,620 different potential control firms, resulting in a panel with 94,592 firm-year observations This is the sample used to estimate the production-function coefficients from which TFP is recovered, not the final matched sample used in the DiD regressions. The number of treated observations varies slightly across years because the underlying SABI panel is unbalanced: 79 of the 84 treated firms are observed in all four years, while the remaining 5 are observed in three years. This panel is therefore nearly balanced for the treatment group. It should be noted that there is a broad sectoral coverage of treated firms, which suggests that C16 digital-transition support among manufacturing beneficiaries was not concentrated in a single industry. Descriptive statistics for treated firms and potential controls in the TFP estimation sample, based on pre-treatment averages for 2021 and 2022, are reported in Annex F.

3.3 Construction of the Analytical Sample for Matching

After the estimation of firm-level TFP, an additional data-preparation stage was required to construct the analytical sample used in the matching procedure. While the production-function estimation benefits from retaining as many relevant firm-year observations as possible, the matching procedure requires complete pre-treatment information to ensure that treated firms can be compared with observationally similar untreated firms.

Firms were therefore required to have valid observations in both 2021 and 2022 for all variables used in the construction of the matching covariates, including production inputs, pre-treatment TFP and the pre-treatment TFP trend. Of the 84 treated firms included in the TFP estimation sample, three did not satisfy this requirement and were excluded from the analytical sample. The same completeness requirement was applied to potential control firms.

In addition, firms whose first RRP Component 16 support started outside the January-March 2023 treatment window were excluded from the pool of potential controls. This restriction ensures that the comparison group is composed of firms that did not receive Component 16 support during the relevant period, thereby reducing the risk of contamination from differently timed beneficiaries.

Following these restrictions, the analytical sample comprised 81 treated firms and 21,882 potential control firms. This sample constitutes the input to the propensity score matching procedure described in Section 4.2. Table 4 summarises the analytical sample eligible for matching.

Treated eligible for matching	Potential controls eligible for matching
81	21,882

Table 4: Analytical sample eligible for matching. Source: Author's elaboration.

The matching procedure subsequently determines the final group of treated and control firms included in the Difference-in-Differences estimations, comprising 80 treated firms and 80 control firms. One treated firm is excluded because no suitable control observation is available within the relevant region of common support.

3.4 Data Limitations

Some limitations of the dataset must be acknowledged. First, SABI data are based on accounting information, rather than physical quantities of output and inputs. Turnover, tangible fixed assets and intermediate inputs are monetary proxies, so the estimated TFP measure should be interpreted as revenue-based productivity rather than pure technical efficiency (Caliendo et al., 2016; Foster et al., 2008).

Second, the deflation procedure relies on aggregate or sector-level price indices rather than firm-level prices. This means that firm-specific price variation, product mix and pricing power cannot be fully separated from measured productivity.

Third, the RRP data identify the official start date of the supported project, but not the exact moment at which the digital investment became operational inside the firm. Some projects may require implementation, training and organisational adaptation, while some firms may have anticipated the project before the official start date. The post-treatment years 2023 and

2024 should therefore be interpreted as an early observation window.

Fourth, only a small subset of C16 beneficiaries is observed in the cleaned manufacturing SABI panel. This is mainly because the dissertation focuses on manufacturing firms with valid accounting information for the variables required to estimate TFP. Consequently, the results should not be interpreted as representative of all C16 beneficiaries.

Finally, the empirical analysis applies successive sample restrictions and covers only four years, from 2021 to 2024. These restrictions improve the internal consistency of the empirical design but reduce the effective sample and limit the ability to analyse long-run productivity effects.

4. Methodology

This chapter presents the empirical methodology used in the present work. It first describes the production-function specification used to construct the TFP measures, followed by the propensity score matching procedure used to improve the comparability between treated and untreated firms. The chapter then presents the Difference-in-Differences specification used to evaluate the short-run effects of RRP Component 16 support on firm-level productivity and concludes by discussing the main methodological limitations of the empirical design.

4.1 Production Function Specification

Following the empirical firm-level productivity literature, this dissertation adopts the log-linear Cobb-Douglas gross-output production function presented in Equation (4.1) (Van Beveren, 2012):

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it} \tag{4.1}$$

In this equation, y_{it}, k_{it}, l_{it}, and m_{it} denote the natural logarithms of real output, capital, labour and intermediate inputs for firm i in year t, respectively. Output is measured by real turnover, capital by real tangible fixed assets, labour by the number of employees, and intermediate inputs by the sum of cost of goods sold and external supplies and services, as explained in Section 3.2.1.

The gross output specification was chosen instead of a value-added specification where intermediate inputs are subtracted from output and excluded from the production function. Accordingly, Matos and Neves (2020), using Portuguese firm-level data, adopt turnover as the output measure and include intermediate inputs explicitly in the production function, arguing that the value-added alternative yields biased estimates when perfect competition cannot be assumed. Van Beveren (2012) similarly presents a gross-output Cobb-Douglas production function in which output depends on capital, labour and materials.

The production function is estimated on the treated-sector manufacturing sample, defined as the set of CAE-2 manufacturing sectors in which at least one treated firm is observed. Rather than estimating separate production functions for each sector (Bournakis & Mallick, 2018; Levinsohn & Petrin, 2003), a common production function is estimated for the manufacturing sample. This approach was adopted primarily for practical reasons. Given the relatively small number of firms in several sectors, estimating sector-specific production functions could lead to imprecise coefficient estimates and less reliable firm-level productivity measures.

Firm-level log TFP is then recovered using Equation (4.2), as output net of the estimated contribution of observable production inputs, both for OLS and FE specifications:

$$\widehat{tfp_{it}^{j}} = y_{it} - \widehat{\beta_K^{j}} k_{it} - \widehat{\beta_L^{j}} l_{it} - \widehat{\beta_M^{j}} m_{it}, \qquad j \in \{OLS, FE\} \tag{4.2}$$

where j denotes the estimator used to obtain the input elasticities. The labels OLS-based and FE-based TFP therefore refer to the method used to estimate $\widehat{\beta_K^{j}}$, $\widehat{\beta_L^{j}}$, and $\widehat{\beta_M^{j}}$. In both cases, TFP is recovered using the same coefficient-based expression.

Two estimators are used to obtain these input elasticities: Ordinary Least Squares (OLS) and fixed effects (FE). The OLS estimator provides a standard benchmark in the firm-level productivity literature (Van Beveren, 2012; Bournakis & Mallick, 2018). Since the data have a panel structure, with the same firm observed over time, standard errors are clustered at the firm level to allow for heteroskedasticity and arbitrary serial correlation within firms.

In the OLS case, the estimated production function is:

$$y_{it} = \widehat{\beta_0} + \widehat{\beta_K^{OLS}} k_{it} + \widehat{\beta_L^{OLS}} l_{it} + \widehat{\beta_M^{OLS}} m_{it} + \widehat{\varepsilon_{it}} \tag{4.3}$$

Therefore:

$$\widehat{tfp_{it}^{OLS}} = y_{it} - \widehat{\beta_K^{OLS}} k_{it} - \widehat{\beta_L^{OLS}} l_{it} - \widehat{\beta_M^{OLS}} m_{it} = \widehat{\beta_0} + \widehat{\varepsilon_{it}} \tag{4.4}$$

The fixed-effects estimator addresses the component of endogeneity that arises from time-invariant firm-specific heterogeneity. In the fixed-effects case, the production function is:

$$y_{it} = \widehat{\alpha_i} + \widehat{\beta_K^{FE}} k_{it} + \widehat{\beta_L^{FE}} l_{it} + \widehat{\beta_M^{FE}} m_{it} + \widehat{u_{it}} \tag{4.5}$$

Therefore:

$$\widehat{tfp_{it}^{FE}} = y_{it} - \widehat{\beta_K^{FE}} k_{it} - \widehat{\beta_L^{FE}} l_{it} - \widehat{\beta_M^{FE}} m_{it} = \widehat{\alpha_i} + \widehat{u_{it}} \tag{4.6}$$

By exploiting within-firm variation over time, it removes the component of simultaneity bias that is driven by persistent, firm-specific productivity differences (Van Beveren, 2012), such as long-standing managerial quality, location advantages or durable technological capabilities.

However, it does not fully solve simultaneity bias when productivity shocks vary over time and affect input choices. As Van Beveren (2012) formalises, the FE estimator corrects for both the simultaneity bias and also the selection bias arising from endogenous firm exit, provided that exit decisions are determined by the time-invariant component of productivity rather than by transitory shocks. Relative to OLS, these are meaningful theoretical advantages that directly address the most common criticism of production-function estimates.

The use of semi-parametric estimators was considered. However, although these methods are theoretically superior in addressing time-varying endogeneity, they were not adopted because of their stronger identifying assumptions and the limitations of the available data. In particular, the relatively short panel covering only two pre-treatment years (2021-2022) and two post-treatment years (2023-2024) could reduce the advantages typically associated with more complex productivity estimators.

More importantly, the current estimators allow for the construction of a consistent and transparent firm-level productivity measure for a treatment evaluation exercise. In addition, Van Beveren (2012) shows that different TFP estimators often generate highly correlated productivity measures and may lead to similar conclusions in evaluation settings. This does not eliminate the limitations of OLS or FE, but it supports the use of transparent coefficient-based TFP measures when the main empirical object is the relative evolution of productivity between treated and comparable control firms.

Therefore, the FE estimator is the preferred method for constructing the main TFP measure. OLS-based TFP is retained both as a descriptive benchmark in Section 5.1 and as a robustness outcome in the DiD analysis, allowing the dissertation to assess whether the conclusions are sensitive to the TFP construction method.

4.2 Propensity Score Matching

Since RRP C16 support was not randomly assigned, treated firms may differ systematically from non-treated firms even before the beginning of the supported project. For example, firms applying for and receiving digital-transition support may already be larger, more capital-intensive, more productive, or more oriented towards organizational change. A simple comparison between treated and untreated firms could therefore confound the effect of the programme with pre-existing differences (Stuart, 2010).

To address this concern, the present dissertation uses propensity score matching as a design-stage adjustment to construct a more comparable group of untreated firms from the pool of potential controls before estimating the DiD model. This combined approach has been applied in the related literature on public subsidies to firms (Dvouletý & Blažková, 2019; Srhoj et al., 2019), and Dvouletý et al. (2021) identify it as consistent with established practice in the evaluation literature for providing reliable information about the outcomes of public interventions.

Matching is performed separately for the FE-based and OLS-based TFP samples. This is necessary because the pre-treatment TFP covariates differ depending on the estimator used to construct productivity. The FE-based matching sample is used for the main analysis, while the OLS-based matching sample is used for the robustness specification.

The matching procedure is implemented using one-to-one nearest-neighbour propensity score matching without replacement (i.e., each control firm is matched to at most one treated firm, ensuring that the matched control group consists of distinct firms and avoiding repeated use of the same control unit across multiple treated firms) (Stuart, 2010).

Propensity scores are estimated using pre-treatment information from 2021 and 2022 only. The covariates include the pre-treatment averages of log output, log capital, log labour and log intermediate inputs, together with mean pre-treatment log TFP and the change in log TFP between 2021 and 2022. These variables capture firms' initial production scale, input structure and productivity conditions.

Matching is conducted within two-digit CAE manufacturing sectors, ensuring that treated firms are compared only with potential controls operating in the same broad manufacturing industry. A common-support condition is imposed within each sector, so that treated firms without comparable control firms in the relevant propensity-score range are excluded.

The procedure yields a final FE-based TFP sample of 80 treated firms and 80 distinct matched control firms. The resulting covariate balance is summarised in Table 5, revealing that the mean absolute standardised bias falls from 16.8% before matching to 6.5% after matching, while the maximum absolute bias falls from 32.6% to 10.0%. The matching procedure therefore substantially improved the sample balance. Detailed information on the matching procedure is reported in Annex G, while covariate-balance diagnostics for the FE-based and OLS-based samples are reported in Annex H.

TFP	Mean abs. bias before (%)	Mean abs. bias after (%)	Max abs. bias before (%)	Max abs. bias after (%)	Reduction (%)
FE	16.8%	6.5%	32.6%	10.0%	61.1%

Table 5: FE model matching sample. Source: Author's elaboration.

4.3 Difference-in-Differences Specifications

After constructing the matched samples, the final stage of the empirical strategy evaluates whether manufacturing firms that received their first RRP C16 support in the treatment window experienced a different TFP trajectory from comparable firms that did not receive this support. Since the counterfactual productivity path of treated firms in the absence of support is not directly observable, the analysis relies on a DiD strategy. The basic intuition follows the standard before-and-after comparison between a treated group and an untreated comparison group (Card & Krueger, 1994): the change in the treated group is compared with the change in the control group over the same period. This logic is also applied in firm-level Portuguese policy evaluation by Cabral and Campos (2023), who employ a Difference-in-Differences framework to evaluate the effects of COMPETE funding on Portuguese firms.

The pre-treatment period is defined as 2021-2022, while the post-treatment period is defined as 2023-2024. This narrow treatment window creates an approximately homogeneous treatment cohort and reduces complications associated with staggered treatment timing (Callaway & Sant'Anna, 2021).

The baseline specification is the two-way fixed effects panel DiD model presented in Equation (4.7):

$$\widehat{tfp_{it}^{j}} = \alpha_i + \lambda_t + \delta^j \ (Treated_i \times Post_t) + \varepsilon_{it}^{j}, \qquad j \in \{FE, OLS\} \tag{4.7}$$

In Equation (4.7), $\widehat{tfp_{it}^{j}}$ denotes the estimated log TFP of firm i in year t, where j indicates whether TFP was constructed using FE-based or OLS-based production-function coefficients. Treated$_i$ equals one for firms whose first RRP C16 project started between January and March 2023, and Post$_t$ equals one in 2023 and 2024. The main specification uses FE-based log TFP as the outcome, while OLS-based log TFP is used as a robustness specification.

Firm fixed effects, α_i, absorb all time-invariant firm characteristics such as persistent managerial quality, location, organisational structure, or long-standing technological differences. Year fixed effects, λ_t, absorb shocks common to all firms in a given year, such as macroeconomic conditions, inflation, energy costs, or aggregate demand changes. Including year fixed effects is particularly important because the period 2021-2024 was marked by substantial aggregate disturbances including post-pandemic adjustment and energy-price shocks. The two-way fixed effects structure is standard in panel Difference-in-Differences applications and controls for both permanent firm-level heterogeneity and common time shocks (de Chaisemartin & D'Haultfoeuille, 2022). Under the parallel trends assumption, the coefficient δ^j identifies the average treatment effect on the treated (ATT), that is, the coefficient captures the differential change in log TFP experienced by treated firms relative to matched control firms after the introduction of RRP support, net of common time shocks and time-invariant firm characteristics. Since the dependent variable is log TFP, the coefficient can be interpreted approximately as the percentage difference in TFP growth between treated and control firms. More precisely, the percentage effect is given by $100 \times \left(e^{\delta^j} - 1\right)$.

The interpretation of δ^j as a treatment effect relies mainly on the parallel trends assumption (Callaway & Sant'Anna, 2021). In this setting, this means that, in the absence of RRP C16 support, treated and matched control firms would have experienced similar changes in TFP over the post-treatment period. This assumption cannot be directly tested, because the untreated productivity path of treated firms is unobservable. The empirical strategy attempts to make it more plausible in two ways. First, propensity score matching is used to construct a comparison group similar to the treated group in terms of pre-treatment production scale, input structure, sector, pre-treatment TFP level and pre-treatment TFP trend. Matching on pre-treatment TFP growth is particularly important because firms that were already following different productivity trajectories before treatment would be less credible counterfactuals (Stuart, 2010). Second, the DiD regressions include firm and year fixed effects, so the treatment effect is identified from the differential evolution of treated firms relative to matched controls after accounting for permanent firm differences and common shocks.

Other identifying conditions should also be acknowledged. The design assumes that firms did not adjust productivity-relevant behaviour before the official project start date in anticipation of treatment. It also assumes that control firms were not directly affected by the support received by treated firms and that remaining differences between treated and control firms after matching are not driven by unobserved time-varying factors correlated with both treatment selection and future productivity. These assumptions cannot be fully verified. The narrow treatment window, the matching procedure and the use of firm and year fixed effects were set to reduce these concerns, but they do not eliminate them. The estimates should therefore be interpreted as conditional short-run DiD estimates for the matched manufacturing sample, rather than as definitive evidence of the full long-run effect of RRP C16 support. Descriptive TFP trends for treated firms and matched controls are presented in Annex I.

5. Results and Discussion

This chapter presents and discusses the empirical results of the analysis. It first reports the estimated production-function coefficients and describes the evolution of the resulting TFP measures over time. It then presents the results of the Difference-in-Differences estimate for the effect of RRP Component 16 support, discusses its interpretation in light of the literature and the study's approach, and finally assesses whether the conclusions remain robust when TFP is constructed using alternative production-function estimates.

5.1 Production Function Estimates and TFP Evolution

Starting with the estimated production functions and respective input elasticities used to construct the OLS-based and FE-based firm-level TFP measures, Table 6 presents the pooled OLS estimates resulting from the econometric specification of Equation (4.3), while Table 7 reports the firm fixed-effects estimates resulting from the econometric specification of Equation (4.5). In both specifications, standard errors are clustered at the firm level. All estimated input elasticities are positive and statistically significant at the 1% level. Also, in both specifications, intermediate inputs account for the largest estimated share of output variation, followed by labour, while the estimated elasticity of capital is comparatively small.

	Log real turnover
Log capital	0.0166***
	(0.0012)
Log labour	0.3244***
	(0.0031)
Log intermediate inputs	0.7013***
	(0.0025)
R-squared	0.970
Observations	94,592

Table 6: Pooled OLS production-function estimates. Source: Author's elaboration.

Notes: The dependent variable is log real turnover. Robust standard errors clustered at the firm level are reported in parentheses. Returns to scale are calculated as the sum of the estimated input elasticities. *** $p < 0.001$. Source: Author's elaboration.

	Log real turnover
Log capital	0.0100***
	(0.0014)
Log labour	0.2113***
	(0.0055)
Log intermediate inputs	0.7400***
	(0.0050)
Within R-squared	0.715
Observations	94,592

Table 7: Firm fixed-effects production-function estimates. Source: Author's elaboration.

Notes: The dependent variable is log real turnover. Firm fixed effects are included. Robust standard errors clustered at the firm level are reported in parentheses. Returns to scale are calculated as the sum of the estimated input elasticities. *** $p < 0.001$. Source: Author's calculations using SABI data.

The estimated production function coefficients obtained using OLS and Fixed Effects (FE) are broadly consistent with the methodological literature on firm-level productivity estimation and reflect several of the well-known challenges associated with estimating production functions from accounting data.

A first notable result concerns the elasticity of capital. The estimated capital coefficient is relatively small in both specifications, amounting to 0.0166 under OLS and 0.0100 under FE. Such low capital elasticities are not uncommon in firm-level studies based on accounting data. Van Beveren (2012) and Ackerberg et al. (2015) note that OLS and FE estimators frequently generate comparatively small capital coefficients, particularly when capital varies little within firms over time. Similar evidence is reported by Matos and Neves (2020) for Portuguese firms, who obtain capital elasticities of 0.0332 under OLS and 0.0201 under FE. The relatively small contribution of capital may reflect both the limited within-firm variation in capital stocks and the dominant role played by intermediate inputs in manufacturing production processes.

The labour coefficient decreases substantially from 0.3244 in the OLS specification to 0.2113 in the FE specification, representing a reduction of approximately 35%. This pattern is consistent with the simultaneity problem highlighted by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Van Beveren (2012): more productive firms tend to employ more labour, causing labour inputs to be positively correlated with unobserved productivity shocks. Because OLS does not control for this unobserved heterogeneity, part of the productivity effect may be incorrectly attributed to labour, resulting in an upward-biased estimate. The lower labour elasticity obtained under FE suggests that controlling for time-invariant firm characteristics removes part of this bias.

In contrast, the elasticity of materials increases slightly from 0.7013 under OLS to 0.7400 under FE, an increase of approximately 5.5%. This result may reflect the fact that the fixed-effects estimator relies on within-firm variation, after removing persistent differences across firms. Since intermediate inputs are typically more flexible than capital and labour, year-to-year changes in materials are likely to be closely associated with year-to-year changes in output, particularly in a gross-output specification for manufacturing firms. The increase may also reflect the removal of permanent firm-level differences in production organisation, such as different degrees of vertical integration or reliance on external suppliers. However, the difference between the two estimates is modest, so the result should not be overinterpreted. The main implication is that materials remain the dominant input in both specifications, following the pattern of former empirical studies (Levinsohn & Petrin, 2003; Van Beveren, 2012).

Importantly, the reported elasticities are consistent with the data reported in Van Beveren (2012) where capital elasticities range from 0.025 to 0.048 across OLS, FE, GMM, OP and LP estimators, labour from 0.15 to 0.21, and materials from 0.65 to 0.79. The capital coefficients obtained in the present study sit at the lower end of this range but are not anomalous.

The estimated returns to scale also exhibit the expected pattern. Under OLS, the sum of input elasticities equals 1.042, suggesting mildly increasing returns to scale. Under FE, the sum falls to 0.961, indicating mildly decreasing returns to scale. Although the difference between the two specifications amounts to approximately 8 percentage points, both estimates remain close to unity and are therefore broadly consistent with constant returns to scale, a common assumption in empirical productivity studies (Syverson, 2011; Van Beveren, 2012). The decline in estimated returns to scale after controlling for firm fixed effects is also consistent with findings in the productivity literature, where FE estimators frequently produce lower scale elasticities due to the removal of persistent firm-level heterogeneity.

The goodness-of-fit measures further illustrate the differences between the two estimation approaches. The OLS specification achieves an R^2 of 0.970, indicating that observable inputs explain a very large proportion of output variation across firms and over time. By comparison, the FE model yields a within-R^2 of 0.715. This reduction is expected because the FE estimator relies exclusively on variation within firms over time and removes all time-invariant differences between firms. Consequently, a lower explanatory power relative to OLS does not necessarily indicate a poorer model but rather reflects the more demanding identification strategy.

Overall, the results are consistent with the methodological arguments advanced by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015), who emphasise that both OLS and FE estimators remain vulnerable to productivity-related endogeneity. Nevertheless, the estimated coefficients are economically plausible, display patterns observed in the empirical literature, and provide a transparent basis for constructing firm-level TFP measures for the subsequent policy evaluation.

Regarding log TFP evolution along the 4 years, Figure 2 plots the year-by-year evolution of mean log TFP for both measures over the full sample.

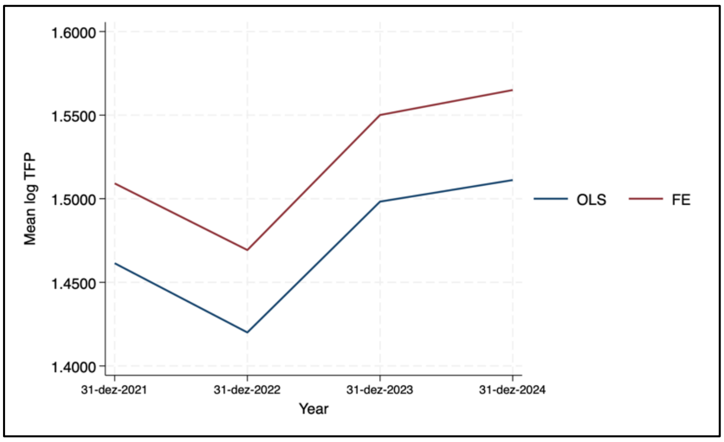

Figure 2: Mean coefficient-based log TFP by year. Source: Author's elaboration.

Both series display the same broad trajectory: a decline between 2021 and 2022 consistent with the macroeconomic pressure from rising energy and input costs during that period, followed by a recovery in 2023 and a modest further increase in 2024. The year-on-year changes are closely aligned across the two measures: -0.041 and -0.040 log points in 2022, +0.079 and +0.081 in 2023, and +0.013 and +0.015 in 2024 for OLS-based and FE-based TFP respectively, confirming that both estimators capture the same underlying productivity dynamics at the aggregate level.

5.2 DiD Results on TFP

Table 8 reports the baseline Difference-in-Differences estimates of the effect of RRP Component 16 support on FE-based log TFP resulting from the econometric specification of Equation (4.7). The specification includes firm and year fixed effects and is estimated on the matched sample using matching weights, with standard errors clustered at the firm level.

	FE-based log TFP
Treated × Post	**-0.0079**
	(0.0316)
Year 2022	0.0192
	(0.0192)
Year 2023	0.1055***
	(0.0301)
Year 2024	0.1149***
	(0.0321)
Observations	630
Within R-squared	0.100

Table 8: DiD results: effect of RRP C16 on Coefficient-Based log TFP FE. Source: Author's elaboration.

Notes: The dependent variable is FE-based log total factor productivity. The coefficient on Treated × Post is the Difference-in-Differences estimate and captures the differential change in log TFP for treated firms in 2023-2024 relative to matched control firms. Robust standard errors clustered at the firm level are reported in parentheses. The omitted year is 2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's calculations using

SABI and *Mais Transparência* data.

The estimated coefficient on the Treated × Post interaction, δ^j, is -0.0079, with a clustered standard error of 0.0316 and a p-value of 0.804. This estimate indicates that, on average across the 2023-2024 post-treatment period, the treated firms of the sample experienced a relative change in log TFP that was statistically indistinguishable from that of their matched control firms.

The estimated magnitude is also economically small. Expressed as a percentage effect, the coefficient corresponds to an approximately 0.8% lower relative TFP change among treated firms when compared to the control group. With these results therefore one cannot reject the null possibility that there wasn't a greater average short-run effect of RRP Component 16 digital-transition support on treated firms TFP when compared to the control group.

This result should not be interpreted as evidence that digital-transition support is inherently ineffective. Rather, it indicates that, among the treated manufacturing firms observed in the SABI panel and matched to comparable untreated firms, no statistically detectable average TFP effect is observed during the first two accounting years following the January-March 2023 project-start window.

The results are closely mirrored by Srhoj et al. (2019), who evaluate SME development grants in Croatia and obtain a TFP coefficient that is negative, small, and statistically indistinguishable from zero, while the same programme generates positive and significant effects on value added, capital, and intermediate inputs. This is consistent with a broader pattern in the firm-level policy evaluation literature, in which public support programmes more readily affect firm scale than productive efficiency. As reviewed in Cabral and Campos (2023), this pattern recurs across several European settings: Cerqua and Pellegrini (2014) find a negligible productivity effect in Italy despite positive effects on employment and investment, Criscuolo et al. (2019) find no TFP effect in the United Kingdom despite a positive employment effect, and Banai et al. (2020) find no effect on labour productivity in Hungary despite gains in employment and sales. Cabral and Campos (2023) themselves find a statistically significant but economically small and short-lived effect on labour productivity among Portuguese firms. Similarly, Dvouletý et al. (2021) conclude that SME grants in the European Union tend to produce more consistent effects on survival, employment and investment than on productivity.

The result is also consistent with the idea that productivity is a demanding outcome to affect in the short run. Digital-transition support may first affect investment, organisation, digital adoption or production capacity before generating measurable improvements in TFP. The negative-to-positive movement between 2023 and 2024 is compatible with this interpretation, but the available evidence is not strong enough to establish it as a causal pattern.

5.3 Robustness Test

As a robustness check, the DiD analysis is repeated using OLS-based log TFP instead of FE-based log TFP, resulting from the econometric specification of Equation (4.7). The purpose of this exercise is to assess whether the conclusions depend on the method used to construct the productivity measure. As discussed in Section 2.2, different production-function estimators address endogeneity concerns differently and may therefore generate different TFP measures. Table 10 reports the OLS-based robustness results.

	OLS-based log TFP
Treated × Post	**0.0252**
	(0.0266)
Year 2022	−0.0119
	(0.0179)
Year 2023	0.0432*
	(0.0236)
Year 2024	0.0550**
	(0.0250)
Observations	626
Within R-squared	0.066

Table 9: Difference-in-Differences robustness estimates: Effect of RRP C16 support on OLS-based log TFP. Source: Author's elaboration.

Notes: The dependent variable is OLS-based log total factor productivity. The coefficient on Treated × Post measures the average differential change in log TFP for treated firms relative to matched control firms during

2023-2024. The specification includes firm and year fixed effects and is estimated on the matched sample using matching weights. Robust standard errors clustered at the firm level are reported in parentheses. The omitted year is 2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's calculations using SABI and *Mais Transparência* data.

The OLS-based estimates show that the Treated × Post coefficient turns positive, inverting the signal of the same coefficient in the FE-based estimate. This difference may partly reflect the fact that OLS and FE generate TFP measures using different estimated production-function coefficients. Unlike FE, OLS does not remove time-invariant firm-specific heterogeneity when estimating the production function. Consequently, persistent differences across firms, such as managerial quality, organisational capabilities or technological advantages, may remain partly embedded in the OLS-based TFP measure. In addition, OLS exploits both between-firm and within-firm variation, whereas the FE estimator relies only on changes within firms over time. These differences in TFP construction may contribute to the more favourable OLS-based DiD estimates. However, the OLS post-treatment estimate remains statistically insignificant and should therefore be interpreted as suggestive rather than conclusive.

Overall, the robustness analysis supports the central conclusion of the dissertation. The evidence does not provide statistically robust support for a positive average effect of RRP C16 support on TFP during the first two post-treatment years.

5.4 Limitations of the Empirical Study

The empirical strategy provides a transparent and feasible short-run evaluation of RRP C16 support using firm-level TFP as the outcome. Nevertheless, as in every empirical study, it is not without limitations, which should be acknowledged.

First, TFP is estimated rather than directly observed. It is recovered from a production function and therefore depends on the accounting proxies, deflators, functional form and estimator used. As Hulten (2001) notes, the TFP residual is a composite measure that may capture not only technical change or productive efficiency, but also measurement error, omitted variables, price variation and model misspecification. These factors may introduce noise into the estimated productivity measure and reduce the precision with which treatment effects on true productive efficiency can be identified (Van Beveren, 2012).

Second, the production function is estimated using OLS and fixed-effects methods. These estimators are transparent and appropriate for the scope of this dissertation, but they do not fully resolve the endogeneity and simultaneity problems associated with production-function estimation. In particular, they may not fully address endogeneity arising from the correlation between input choices and unobserved time-varying productivity shocks. More sophisticated proxy-variable estimators have been proposed to address this issue, but they require stronger assumptions and more demanding implementation choices, which can be useful for further investigations.

Third, the production function is estimated as a common Cobb-Douglas technology across the treated-sector manufacturing sample. This preserves sample size and avoids unstable sector-specific estimates, but it imposes common input elasticities across heterogeneous manufacturing industries. If the true production technology differs substantially across industries within the Portuguese manufacturing sector, this may introduce misspecification into the estimated TFP measures.

Fourth, the treatment variable is binary. Firms are classified as treated if their first C16 project started in the selected treatment window, regardless of the amount received, number of projects or type of digital investment. This simplifies the evaluation design and allows a clear comparison between treated and matched control firms, but it may mask heterogeneous treatment effects associated with different levels of investment intensity or different types of digital-transition projects. If productivity gains are concentrated among firms receiving larger or more transformative support, the average treatment effect may understate those heterogeneous responses.

Finally, the matched DiD sample is small and the post-treatment window is short. The limited number of treated firms reduces statistical power, making moderate or heterogeneous productivity effects difficult to detect precisely. In addition, the 2023-2024 period captures only the early years after project start. Since digital-transition projects may require time to become operational, be integrated into production routines and generate measurable efficiency gains, the results should be interpreted as conditional short-run estimates rather than as a full long-run evaluation of RRP C16 support. In addition, the causal interpretation of the estimated treatment effects ultimately depends on the parallel trends assumption. Although matching on pre-treatment productivity levels and productivity growth helps improve its plausibility, the assumption cannot be directly verified and may be violated if treated and control firms are affected differently by unobserved time-varying factors during the study period.

6. Conclusion

This dissertation examined whether Portuguese manufacturing firms receiving support under Component 16 - Businesses 4.0 of Portugal's Recovery and Resilience Plan experienced higher Total Factor Productivity growth than comparable non-supported firms. Using firm-level data from SABI combined with beneficiary information from the *Mais Transparência* portal and a matched Difference-in-Differences framework, the study provided an early evaluation of the productivity effects of RRP digital-transition support.

The central finding is an absence of statistically robust evidence that C16 digital-transition support improved TFP among treated manufacturing firms during the first two post-treatment years. In the preferred fixed-effects specification, treated firms did not experience a meaningfully different productivity trajectory from their matched counterparts. The OLS-based robustness specification yields a coefficient of the opposite sign and larger magnitude, but this estimate remains statistically insignificant, and the FE-based measure is preferred for causal interpretation since it accounts for time-invariant firm heterogeneity. Taken together, the two specifications point in the same qualitative direction: an absence of detectable average short-run effects, rather than a definitive absence of productivity benefits.

These results are broadly consistent with two bodies of evidence. First, they align with the pattern documented for public support programmes more generally: grants and subsidies tend to generate clearer effects on firm scale than on productivity, and effects on productive efficiency, when present, are slower to materialise (Cabral & Campos, 2023; Dvouletý et al., 2021). Second, they are consistent with the ICT productivity literature's emphasis on complementarity and time: productivity returns to digital investment depend on organisational restructuring and workforce adaptation and may not be detectable within a short observation window (Gal et al., 2019). In this light, the early evaluation delivered here is not a refutation of the programme's potential, but rather an illustration of the difficulty of detecting productivity gains from digital-transition support over a two-year horizon and with a relatively small treated sample.

The findings carry implications for both researchers and policymakers. For the academic literature, the dissertation provides the first firm-level evidence on the productivity effects of RRP Component 16, contributing to an emerging body of work on the measurable impacts of Portugal's Recovery and Resilience Plan. It also demonstrates that TFP, rather than simpler indicators such as labour productivity, provides a more demanding and informative benchmark for evaluating whether digital investments translate into genuine efficiency gains. For policymakers and programme evaluators, the results suggest that assessing the productivity impact of digital-transition support requires a longer observation window than two post-treatment years. Evaluative frameworks that track beneficiaries for three to five years after project completion would be better placed to detect whether C16 support generates durable TFP effects.

Future research can further develop this study across several dimensions. The most important extension is temporal: as additional years of SABI data become available, the same framework can be applied to a longer post-treatment window, allowing a more definitive assessment of whether the positive pattern emerging in 2024 represents the beginning of a durable productivity improvement. Researchers may also explore heterogeneous treatment effects, examining whether the productivity response to C16 support differs by firm size, sector, investment intensity, or type of digital project. The availability of contracted amounts and project categories in the *Mais Transparência* data would allow a dose-response analysis that goes beyond the binary treatment design used here. Further work could also extend the outcome set to include employment, capital intensity, exports, and other firm outcomes alongside TFP, providing a more complete picture of the adjustment process following digital-transition support.

A related and methodologically distinct avenue concerns the dynamics of the treatment effect within the post-treatment period. A year-specific or event-study specification could, in principle, reveal whether the effect of C16 support strengthens, weakens or remains stable between the first and second post-treatment years, consistent with the possibility of an implementation lag whereby digital investments require time, organisational adjustment and workforce adaptation before affecting measured productivity.

Finally, future studies could also revisit the estimation of TFP itself. The relatively short panel available for this dissertation favoured the use of OLS and fixed-effects estimators due to their transparency and modest data requirements. As longer firm-level panels become available, researchers may be able to apply semi-parametric approaches such as Olley and Pakes (1996), Levinsohn and Petrin (2003), or Ackerberg et al. (2015). These methods were developed to address simultaneity and selection concerns that affect conventional production-function estimators and may provide more precise measures of firm-level productivity.

Consequently, future evaluations based on alternative TFP estimators may yield additional insights into the relationship between digital-transition support and productive efficiency.

In conclusion, despite its long-standing presence in economic research, productivity remains one of the most important topics in economics, with ongoing research continuing to open new avenues for investigation. This issue is particularly relevant in the Portuguese context, where sustained productivity improvements have the potential to generate substantial economic and social benefits, especially when supported by well-designed public policy interventions. It is hoped that this dissertation contributes to the growing body of evidence on the evaluation of public support programmes, helping to improve our understanding of their effects on firm performance and, in doing so, making a modest contribution to both the economics literature and to Portugal's long-term economic development.

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Annex A - SABI Data Treatment

Annex A provides additional detail on the preparation of the SABI accounting data used in the empirical analysis. It summarises the main cleaning steps applied to construct the firm-year panel, including the restructuring of the original extract, the treatment of missing observations and the restrictions imposed on the production-function variables.

The SABI data used in the present dissertation was retrieved using the following procedure: From the Financial Data → Portugal Detailed Format → SNC Accounts option: (i) under the Income Statement: turnover, cost of goods sold and consumed (COGS), and external supplies and services (ESS); (ii) under the Balance Sheet: tangible fixed assets (TFA). Employee data were retrieved from the Employee Segmentation → Portugal option, specifically the item Pessoas ao serviço da empresa, remuneradas e não remuneradas: número médio de pessoas (average number of remunerated and non-remunerated persons employed by the firm). In addition, the following identification variables were extracted for each firm: name, tax identification number (NIF), city, main CAE code, and date of establishment. This extraction yielded an initial sample of 46,753 firms before reshaping and cleaning.

Table A1 documents the sample attrition resulting from each cleaning step. The initial sample of 46,753 firms yields 187,012 firm-year observations after reshaping to long format. The most substantial reduction occurs at the positivity filter, which removes 12,060 firms (from 46,753 to 34,693). A further 565 firm-years are excluded by the outlier filter. The requirement for at least three years of valid observations produces another substantial reduction, leading to a panel with 103,367 firm-year observations corresponding to 26,994 unique firms.

Cleaning Step	N.º of Firms	N.º of Observations
After dropping year 2020 and NIF cleaning	46,753	46,753
After reshaping to long panel (4 obs. per firm)	46,753	187,012
After filtering for positive turnover, materials, capital and labour	34,693	116,503
After applying the outlier filter (p1-p99 GVA/Turnover, by year)	34,128	114,177
Resulting SABI panel: firms with ≥ 3 valid TFP years	26,994	103,367

Table A1: SABI cleaning process. Source: Author's elaboration.

Annex B - Outlier Filter

Annex B describes the outlier-filtering procedure applied to the accounting variables used in the production-function estimation.

The outlier filter was used to exclude implausible observations from the production-function estimation sample. Before applying the outlier filter, real gross value added (GVA) was computed for each firm-year observation as the difference between real turnover and real intermediate inputs:

$$GVA_{it} = Y_{it} - M_{it}$$

The filtering variable was then defined as the ratio between real GVA and real turnover:

$$GVA_{it}/Y_{it}$$

Observations falling below the 1st percentile or above the 99th percentile of this ratio within each year were removed. This procedure was applied separately by year in order to avoid treating cross-year price or macroeconomic variation as firm-level outliers, following the approach of Matos and Neves (2020). The filter is intended to remove extreme observations that may reflect reporting errors, abnormal accounting values, or implausible combinations of output and intermediate inputs.

Annex C - Variable Deflation

Annex C presents the deflation procedure used to convert monetary accounting variables into constant 2021 euros.

Turnover was deflated using the manufacturing-sector output price index ("Índice de preços de produção → volume de negócios", base year 2021 = 100), sourced from the Gabinete de Estratégia e Estudos (GEE) of the Portuguese Ministry of Economy (Direção-Geral das Atividades Económicas, 2026). The values applied were 100.000 for 2021, 122.000 for 2022, 117.700 for 2023, and 117.500 for 2024.

Materials were deflated using the annual industrial producer price index ("Índice de Preços da Produção Industrial, IPPI, base year 2021 = 100"), also retrieved from the GEE. The values applied were 100.000 for 2021, 119.900 for 2022, 122.500 for 2023, and 121.700 for 2024.

Tangible fixed assets were deflated using the annual price index for the net fixed capital stock (Deflator do stock de capital fixo líquido, base year 2021 = 100). The values applied were 100.000 for 2021, 110.166 for 2022, 116.507 for 2023, and 123.105 for 2024 (Banco de Portugal, n.d.). This deflator was selected because no price index specific to total fixed assets in the Portuguese manufacturing sector is available. A similar pragmatic choice is documented in Gal (2013), who uses investment deflators from the OECD STAN database at the two-digit industry level when asset-specific deflators are not available.

Using separate deflators for output, capital and intermediate inputs is preferable to applying a single common deflator, since these variables may be affected by different price dynamics. This choice follows the recommendation in the productivity literature to use variable- and sector-specific price indices whenever possible. (Van Beveren, 2012; Gal, 2013). Because firm-level prices are not observed, the resulting productivity measure should be interpreted as revenue-based TFP rather than pure quantity-based technical efficiency.

Annex D - *Mais Transparência* Portal Data Treatment

Annex D describes the preparation of the beneficiary data obtained from the *Mais Transparência* portal.

The identification of treated firms proceeded in two steps. First, the RRP entities file was imported and restricted to entities classified as "Beneficiário Final" (final beneficiary). This restriction is important because the same RRP project may involve different types of entities (e.g., intermediary bodies, managing authorities), but the relevant unit for this dissertation is the firm that actually implements the supported project. Public entities, individual taxpayers, and observations with missing or invalid identifiers were excluded from the treatment list.

Second, since a firm may be associated with more than one C16 project, firms were retained in the treatment group only if their **first** C16 project started between 1 January 2023 and 31 March 2023. This ensures that treatment timing is defined by the firm's initial exposure to C16 support, rather than by subsequent projects that may have begun later. Firms with additional C16 projects starting after the treatment window remain in the treated group, provided that their first C16 project started between January and March 2023.

For descriptive purposes, the total contracted value across the 2,079 firms identified in the RRP treatment dataset amounts to approximately €67.5 million, with a median contracted value per firm of €2,000 and a mean of approximately €32,488, reflecting a highly right-skewed distribution. These monetary values are not used as variables in the econometric analysis but provide context on the scale and heterogeneity of the policy intervention. The resulting dataset contains one observation per treated firm and is later merged with the cleaned SABI panel in order to construct the final treatment-and-control sample used in the empirical analysis.

Indicator	Value
Total treated firms identified (first C16 in Jan-Mar 2023)	2079
Firms with payment already disbursed	698
Total contracted value - all firms (EUR)	67542509.590
Mean contracted value per firm (EUR)	32487.980
Median contracted value per firm (EUR)	2000.000
Min contracted value (EUR)	500.000

Max contracted value (EUR)	4121074.250
Mean number of C16 projects per firm	1.504

Table A2: RRP treated firms descriptive statistics. Source: Author's elaboration.

Annex E - Sectoral Distribution After Merge

Annex E reports the sectoral distribution of treated firms and potential control firms after merging the SABI and RRP datasets.

The sectoral distribution of treated and potential control firms is shown in table A3. It shows that treated firms are present in 16 of the 24 manufacturing divisions. The largest concentrations are found in CAE 10 (food products), CAE 28 (machinery and equipment), CAE 25 (fabricated metal products) and CAE 31 (furniture). Eight divisions do not contain any treated firms: CAE 12, 15, 17, 19, 21, 24, 29, and 30. Since these sectors do not contribute any treated firm to the policy evaluation, they are excluded from the production-function estimation sample used to construct TFP.

The share of treated firms within each sector is generally small, typically below 1%, with the exception of CAE 26, computer and electronics, and CAE 28, machinery and equipment. The broad sectoral coverage of treated firms suggests that C16 digital-transition support among manufacturing beneficiaries was not concentrated in a single industry, although the small number of treated firms in most sectors limits the scope for sector-specific treatment-effect analysis.

For the estimation of the production function, an additional sectoral restriction is applied. Only CAE-2 sectors containing at least one treated firm are retained. This excludes CAE 12, 15, 17, 19, 21, 24, 29, and 30 from the TFP estimation sample.

CAE Division	Treated	Potential Controls	Total	% Treated
10 Food products	18	3,286	3,304	0.54
11 Beverages	4	693	697	0.57
12 Tobacco	0	4	4	0.00
13 Textiles	6	1,339	1,345	0.45
14 Wearing apparel	1	2,447	2,448	0.04
15 Leather and footwear	0	1,242	1,242	0.00
16 Wood products	3	1,761	1,764	0.17
17 Paper products	0	314	314	0.00
18 Printing and recording	2	1,072	1,074	0.19

19 Coke and refined petroleum	0	10	10	0.00
20 Chemicals	3	445	448	0.67
21 Pharmaceuticals	0	65	65	0.00
22 Rubber and plastic	4	725	729	0.55
23 Non-metallic minerals	4	1,651	1,655	0.24
24 Basic metals	0	172	172	0.00
25 Fabricated metal products	7	5,415	5,422	0.13
26 Computer and electronics	4	145	149	2.68
27 Electrical equipment	2	330	332	0.60
28 Machinery and equipment	10	869	879	1.14
29 Motor vehicles	0	357	357	0.00
30 Other transport equipment	0	126	126	0.00
31 Furniture	7	1,805	1,812	0.39
32 Other manufacturing	5	925	930	0.54
33 Repair and installation	4	1,712	1,716	0.23

Table A3: Sectoral distribution of treated and potential control firms. Source: Author's elaboration.

Annex F - Pre-Treatment Characteristics of the TFP Estimation Sample

Annex F presents pre-treatment descriptive statistics for treated firms and potential control firms in the TFP estimation sample.

Table A4 reports the pre-treatment characteristics of the TFP estimation sample. The pre-treatment period is defined as the average of the 2021 and 2022 variables for each firm.

Variable	Group	N	Mean	Median	Std. Dev.
Turnover, € thousands	Potential controls	24,620	2,633.918	322.510	17,141.514
Turnover, € thousands	Treated	84	1,931.540	377.534	8,285.760
Materials, € thousands	Potential controls	24,620	2,020.446	190.640	14,363.696
Materials, € thousands	Treated	84	1,286.980	252.118	5,208.503
Tangible fixed assets, € thousands	Potential controls	24,620	877.139	66.582	6,776.475
Tangible fixed assets, € thousands	Treated	84	952.565	154.860	3,637.624
Employees	Potential controls	24,620	20.705	7.000	63.968
Employees	Treated	84	22.571	7.000	79.390
Log turnover	Potential controls	24,620	5.966	5.763	1.676
Log turnover	Treated	84	6.101	5.908	1.454
Log materials	Potential controls	24,620	5.422	5.236	1.810
Log materials	Treated	84	5.686	5.469	1.507
Log capital	Potential controls	24,620	4.206	4.161	2.321
Log capital	Treated	84	4.535	5.040	2.813
Log labour	Potential controls	24,620	2.020	1.936	1.274
Log labour	Treated	84	2.074	1.946	1.197

Table A4: Pre-treatment descriptive statistics, 2021-2022 averages. Source: Author's elaboration.

Several patterns emerge from this comparison. In terms of mean levels, potential control firms display higher average turnover and materials than treated firms. Average turnover is €2.634 million for potential controls and €1.932 million for treated firms, while average materials are €2.020 million and €1.287 million, respectively. However, these differences are partly driven by the right-skewed distribution of the potential control group, as indicated by its substantially larger standard deviations.

The median values provide a more balanced picture. Treated firms exhibit slightly higher median turnover than potential controls, €377,534 versus €322,510, higher median materials, €252,118 versus €190,640, and substantially higher median tangible fixed assets, €154,860 versus €66,582. The median number of employees is identical at 7 for both groups. This suggests that treated firms are not larger on average in all dimensions, but they appear to have somewhat higher median capital intensity before treatment.

The log-transformed variables, which are the variables used in the production-function estimation, are broadly similar across groups. Treated firms display slightly higher average log turnover, log materials and log capital, while average log labour is very close across treated and potential control firms. These descriptive statistics suggest that the two groups are not radically different in the production variables used to estimate TFP. However, they refer to the potential control pool before matching and therefore do not guarantee comparability for causal inference. The formal matching procedure described later further restricts the donor pool and balances treated and control firms using pre-treatment covariates.

Annex G - Matching Procedure

Annex G provides additional technical detail on the propensity score matching procedure used to construct the comparison group for the Difference-in-Differences analysis.

For each TFP estimator, propensity scores were estimated using the default specification implemented by the psmatch2 command in Stata. Matching was conducted within each two-digit CAE sector. This means that each treated firm can only be matched to potential control firms operating in the same broad manufacturing industry. The matching algorithm runs separately for each CAE-2 sector, so sectors in which no treated firms or no control firms are present are automatically excluded from the matching procedure. Combining exact matching on sector with propensity score matching within sector helps improve the comparability of treated and control firms by ensuring that matched firms operate in similar industrial environments and are likely to face more similar production technologies, input requirements and market conditions (Stuart, 2010).

The propensity score were estimated using only pre-treatment information from 2021 and 2022 and the covariates include the pre-treatment averages of log output, log capital, log labour and log materials:

$$\overline{ly}_{pre}, \quad \overline{lk}_{pre}, \quad \overline{ll}_{pre}, \quad \overline{lm}_{pre}$$

, as well as pre-treatment mean log TFP and the pre-treatment TFP trend:

$$\overline{\widehat{tfp}}_{pre}, \quad \Delta tfp_{\widehat{2022-2021}}$$

The first group of variables captures pre-treatment production scale and input structure. These variables are relevant because they may influence both the probability of receiving RRP support and future productivity dynamics. The second group of variables captures pre-treatment productivity, helping ensure that treated firms are compared with firms that were similarly productive before treatment. Including the pre-treatment TFP trend is particularly important for the DiD design because firms that were already following different productivity trajectories before treatment would provide less credible counterfactuals (Stuart, 2010). Matching on the 2021-2022 change in TFP therefore aims to reduce the risk that post-treatment differences simply reflect pre-existing productivity trends, thereby making the parallel trends assumption more plausible.

The donor pool is further restricted at this point to avoid contamination of the control group. Firms that received the first C16 support outside the January-March 2023 treatment window are excluded from the matching donor pool. This ensures that potential controls are clean non-recipients of C16 support rather than differently timed beneficiaries.

The common support condition is imposed within each CAE-2 sector, meaning that treated firms whose propensity scores lie outside the region of overlap with the available control firms in their sector are excluded from the matched sample. As Stuart (2010) notes, this condition ensures that treated units have comparable counterparts in the control pool, avoiding identification based on extrapolation beyond the region of common support. After matching, the quality of the matched sample is assessed by comparing the balance of pre-treatment covariates between treated and matched control firms.

Annex H - Matching Quality Diagnostics for FE-Based and OLS-Based TFP

Annex H reports detailed covariate-balance diagnostics for the FE-based and OLS-based matching procedures. It compares treated and control firms before and after matching and provides additional evidence on the extent to which matching reduced observable pre-treatment differences between the two groups.

Table A5 provides the detailed covariate-level matching diagnostics for the FE-based TFP.

TFP measure	Variable	Treated mean before	Control mean before	Treated mean after	Control mean after	Std. bias before (%)	Std. bias after (%)
FE	Log output	6.143	6.009	6.160	6.280	9.2%	-8.3%
FE	Log capital	4.563	4.251	4.764	4.696	10.9%	2.4%
FE	Log labour	2.115	2.052	2.133	2.247	5.3%	-9.6%
FE	Log materials	5.743	5.460	5.757	5.903	19.3%	-10.0%
FE	Mean TFP (pre)	1.400	1.492	1.401	1.390	-32.6%	4.0%
FE	TFP trend (pre)	0.014	-0.035	0.014	0.024	23.5%	-5.0%

Table A5: FE Model detailed matching quality. Source: Author's elaboration.

Three features of the balance results deserve attention. First, the largest pre-matching imbalance concerns pre-treatment TFP levels. In the FE-based sample, treated firms had lower average pre-treatment TFP than the unmatched control pool, with a standardised bias of -32.6%. After matching, this imbalance is strongly reduced to +4.0%. This improvement is important because productivity is the outcome of interest in the subsequent DiD analysis. After matching, treated and control firms are much more closely aligned in their initial productivity levels, reducing the risk that post-treatment differences simply reflect pre-existing productivity gaps.

Second, the pre-treatment TFP trend also improves substantially after matching, especially in the FE-based sample. Before matching, the standardised bias in the 2021-2022 FE-based

TFP change is +23.5%, indicating that treated and potential control firms were following different productivity trajectories before treatment. After matching, this falls to -5.0%. This imbalance reduction in pre-treatment productivity trends is particularly important for the credibility of the DiD design, since the parallel trends assumption requires treated and control firms to have similar counterfactual productivity trajectories in the absence of treatment (Stuart, 2010).

Third, the input structure variables also become more comparable after matching, although some moderate imbalances remain. In the FE-based sample, the standardised bias in log capital falls from +10.9% to +2.4%, while log output changes from +9.2% to -8.3% and log labour from +5.3% to -9.6%. Log materials, which had the largest input-related imbalance before matching, falls from +19.3% to -10.0%. Overall, matching substantially improves comparability in productivity, scale and factor intensity, although the remaining moderate imbalance in some covariates reinforces the importance of including firm and year fixed effects in the subsequent DiD estimation.

Table A6 reports the size of the OLS-based matched sample. Of the 81 treated firms eligible for matching, 80 are successfully matched to 80 unique control firms, while one treated firm is excluded because of the common support restriction. This means that the OLS robustness sample has the same treated sample size as the main FE-based matched sample, allowing a direct comparison between the main and robustness specifications.

TFP	Treated eligible for matching	Potential controls eligible for matching	Matched treated	Unique matched controls	Treated lost
OLS (robustness)	81	21,882	80	80	1

Table A6: Table : FE model detailed matching quality. Source: Author's elaboration.

Table A7 summarises the overall improvement in covariate balance after matching for the OLS-based TFP. The mean absolute standardised bias falls from 16.0% before matching to 8.1% after matching, while the maximum absolute bias falls from 33.0% to 11.7%. This corresponds to a reduction of 49.4% in the mean absolute bias. These results indicate that the matching procedure substantially improves the comparability of treated and control firms in the OLS-based robustness sample.

Table A8 provides the detailed covariate-level matching diagnostics for the OLS-based TFP. Before matching, the largest imbalance is observed in pre-treatment mean TFP, with a standardised bias of -33.0%, followed by log materials, with 19.3%, and the pre-treatment TFP trend, with 18.3%. This indicates that, before matching, treated and potential control firms differed especially in their initial productivity level and in some dimensions of production scale.

After matching, balance improves substantially for several key variables. The standardised bias in pre-treatment mean TFP falls from -33.0% to -1.0%, indicating that treated and matched control firms have almost identical OLS-based pre-treatment productivity levels after matching. The imbalance in log capital also falls from 10.9% to -3.1%, and the imbalance in log materials falls from 19.3% to -10.5%.

However, balance does not improve uniformly across all variables. The standardised bias for log output changes from 9.2% before matching to -10.8% after matching, while the absolute bias for log labour increases from 5.3% to 11.7%. The pre-treatment TFP trend also remains somewhat imbalanced after matching, with a standardised bias of 11.4%. These values are not excessively large, but they indicate that the OLS-based matched sample is not perfectly balanced across all covariates.

TFP	Mean abs. bias before (%)	Mean abs. bias after (%)	Max abs. bias before (%)	Max abs. bias after (%)	Reduction (%)
OLS (robustness)	16.0%	8.1%	33.0%	11.7%	49.4%

Table A7: OLS model matching quality. Source: Author's elaboration.

TFP measure	Variable	Treated mean before	Control mean before	Treated mean after	Control mean after	Std. bias before (%)	Std. bias after (%)
OLS	Log output	6,143	6,009	6,160	6,317	9,2%	-10,8%
OLS	Log capital	4,563	4,251	4,764	4,853	10,9%	-3,1%
OLS	Log labour	2,115	2,052	2,133	2,272	5,3%	-11,7%

OLS	Log materials	5,743	5,460	5,757	5,911	19,3%	-10,5%
OLS	Mean TFP (pre)	1,353	1,443	1,351	1,354	-33,0%	-1,0%
OLS	TFP trend (pre)	0,000	-0,039	0,000	-0,024	18,3%	11,4%

Table A8: OLS model detailed matching quality. Source: Author's elaboration.

Annex I - Descriptive TFP Trends

Annex I reports the descriptive evolution of OLS-based log TFP and FE-based log TFP for treated and matched control firms. This annex complements the FE-based descriptive trends presented in the main text by examining whether the productivity patterns are similar when TFP is constructed using OLS production-function coefficients.

The central identification assumption of the DiD approach is that, in the absence of RRP C16 support, treated and matched control firms would have followed similar TFP trajectories after the pre-treatment period. This parallel trends assumption is not directly testable because the counterfactual path of treated firms under no treatment is unobservable. With only two pre-treatment years available, the scope for formal pre-trend testing is limited. Nevertheless, the within-sample evolution of TFP between 2021 and 2022 for the matched groups provides useful indicative evidence.

Figure A1 and Table A9 present the year-by-year evolution of mean FE-based log TFP for the treated and matched control groups across the 2021-2024 window. In 2021, treated firms display a mean log TFP of 1.394, slightly above the control group mean of 1.377, corresponding to a gap of +0.016 log points. In 2022, both groups experience an increase: treated firms rise to 1.408 and controls to 1.402, narrowing the gap to +0.006 log points. The pre-treatment evolution is therefore broadly similar, with a small and declining difference between the two groups, which provides mild supportive evidence for the parallel trends assumption. However, given the availability of only two pre-treatment years, formal testing of parallel trends is not feasible, therefore the evidence presented should be interpreted as descriptive rather than as a formal validation of the assumption.

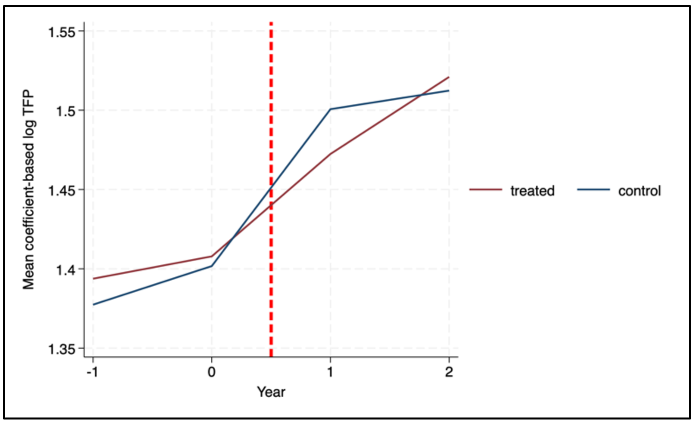

Figure A1: Matched mean coefficient-based log TFP - FE model. Source: Author's elaboration.

Year	Treated	Control	Difference
2021	1.394	1.377	+0.016
2022	1.408	1.402	+0.006
2023	1.472	1.501	-0.028
2024	1.521	1.512	+0.009

Table A9: Matched mean log TFP by year and group (FE). Source: Author's elaboration.

Table A10 presents the mean OLS-based log TFP of treated and matched control firms by year. In the pre-treatment period, differences between the two groups are small. In 2021, treated firms have slightly lower mean OLS-based log TFP than control firms, with a difference of -0.015 log points. In 2022, the difference becomes slightly positive, at 0.009 log points. This suggests that the two groups are relatively close in pre-treatment productivity levels, although the treated group displays a slightly more favourable evolution between 2021 and 2022.

In the post-treatment period, the descriptive pattern is mixed. In 2023, treated firms again display slightly lower mean OLS-based log TFP than matched controls, with a difference of -0.016 log points. This does not suggest an immediate positive productivity gap in the first post-treatment year. By contrast, in 2024, treated firms display higher mean OLS-based log TFP than matched controls, with a difference of 0.043 log points. This pattern is consistent with the possibility that any productivity gains associated with digital-transition support may take time to emerge.

Figure A2 provides a visual representation of the same year-by-year evolution reported in Table A10. The figure helps illustrate that treated and control firms remain close before treatment, show no clear treated advantage in 2023, and display a more favourable relative position for treated firms in 2024.

Overall, Table A10 and Figure A2 suggest that the OLS-based descriptive evidence does not point to an immediate improvement in 2023, but shows a more favourable relative position for treated firms in 2024. Nevertheless, these values are descriptive group means and should not be interpreted as causal estimates. The causal interpretation relies on the DiD regressions, which control for firm fixed effects, year fixed effects and statistical uncertainty.

Year	Treated	Control	Difference
2021	1.351	1.366	-0.015
2022	1.351	1.342	0.009
2023	1.410	1.426	-0.016
2024	1.457	1.414	0.043

Table A10: Matched mean log TFP by year and group (OLS). Source: Author's elaboration.

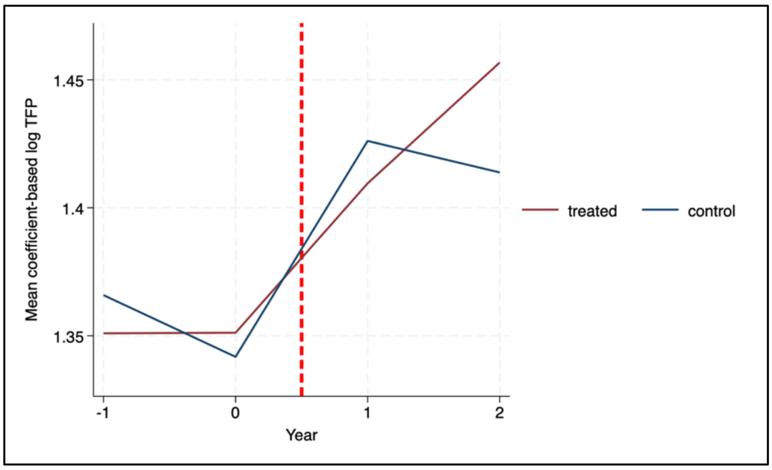

Figure A2: Matched mean coefficient-based log TFP - OLS model. Source: Author's elaboration.