

**IMPACT OF INNOVATION SUPPORT DELIVERED THROUGH
THE NATIONAL MEASUREMENT PROGRAMME ON BUSINESS
OUTCOMES: SUMMARY**

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Impact of Innovation Support Delivered through the National Measurement Programme on Business Outcomes- Summary.

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ABSTRACT

This study examines the effect of National Measurement System (NMS) and National Physical Laboratory (NPL) on the performance of supported businesses, focusing on employment growth, earnings, fixed assets expansion, R&D investment and business survival. The study utilises data from the Office for National Statistics Secure Research Service and other external sources spanning 2012 to 2021. It applies various statistical techniques, including Propensity Score Matching, Panel Data analysis, Bootstrapped Quantile Regression, and Kaplan-Meier Survival Estimates. The findings show that NPL's support led to a 3.0% increase in employment growth and a 5.1% rise in real fixed assets growth among the regularly supported firms compared to a matched control group of untreated businesses. Workers moving to one of NPL's regularly supported firms benefit from a wage premium of 7.1%, while R&D investment grew by 5.8% for a particular segment of regularly supported firms with average R&D investment growth. The closure rate, between 2012 and 2021, was 14.8% among the unsupported matched control-group while closures were observed among the regularly supported firms. The results indicate that NPL support boosts workers' earnings and business survival, fosters employment and fixed assets growth, and increases R&D spending in firms with moderate R&D growth.

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Executive Summary

This study presents new evidence on the impact of National Measurement System (NMS)/ National Physical Laboratory (NPL) innovation interventions on private businesses, with a particular focus on employment growth, earnings, fixed assets expansion, private R&D investment growth and business survival. A quasi-experimental approach is utilised to explore cause-and-effect relationships between an intervention and its outcomes, without random assignment of participants to groups. This involves utilisation of methods such as Propensity Score Matching (PSM) and Difference-in-Difference (D-i-D) to ensure fair comparisons between groups. Additionally, techniques like Bootstrapped Quantile Regression (BQR) are applied to address outliers in growth of private R&D spending, panel data analysis is used to track changes in wages over time, and Kaplan-Meier Survival Estimates are employed to examine the duration of firms' survival. The data, covering the period from 2012 to 2021, was primarily sourced from the Office for National Statistics Secure Research Service (ONS SRS) and supplemented with data from databases such as FAME (Financial Analysis Made Easy) and Beahurst. The monetary variables were adjusted to real terms using 2021 as the base year.

The findings indicate that:

- NPL interventions had a significant effect on employment and fixed assets growth. PSM analysis revealed average treatment effects of approximately **3.0%** for employment growth and **5.1%** for real fixed assets growth.
- Panel data analysis of earnings showed that workers who switched from non-treated to treated firms experienced a wage premium of approximately **7.1%**, equating to an additional **£60** per week.
- BQR analysis indicated that the median R&D investment growth among treated firms increased by about **5.8%**.
- The survival analysis shows that all treated firms survived between 2012 and 2021. This was not the case with non-treated matched control group where all but **14.8%** survived until 2021.

The results suggest that the difference in survival rates could explain the differences in the business outcomes. The wage premium for workers switching to NPL-supported firms implies an underlying improvement in their labour productivity, as wages tend to reflect the value of worker's output. The impact on employment growth suggests that NPL's support enables treated firms to adopt new technologies and expand their operations, necessitating the recruitment of additional employees. Meanwhile, the impact on fixed assets growth implies that NPL's support enables treated firms to acquire new equipment and facilities to implement new technologies. Additionally, NPL innovation support enables firms to increase their real R&D investment, particularly among those experiencing moderate R&D growth. However, for firms already exhibiting high growth in their real R&D investment, the findings reveal that NPL's support may result in a "crowding-out" effect, where these firms reduce their own R&D expenditure, potentially leveraging public support to offset private investment.

1. Introduction

To achieve the goal of economic growth and prosperity, a country needs a world-leading and cutting-edge science and innovation at the heart of its development process. This is because innovation is a key driver of business growth through its impact on enhancing production processes and the creation of new products and services which are crucial to competitiveness, business survival, employment creation and improved wages.

Public support is crucial in achieving high-performing science and innovation because of the associated market failures. Firstly, innovation activities create positive externalities (or spillover impacts) for firms which did not invest directly into innovation activities. Hence, the private investment required to generate the desired innovation activities would always be below the socially optimal threshold. Secondly, the fixed costs associated with the uptake of innovation activities could be so high that they exceed the private gains. This creates a disincentive for a private firm to invest in such innovation alone, despite the total social benefit outweighing the cost. To achieve the optimal level of R&D investment, government policy needs to bring private incentives in line with the social rate of return (Griffith, 2000). However, there is a need for high quality evidence to understand and assess whether public innovation support is having its intended effects.

Research and Development (R&D) has been central to the overall UK economic policy. There is a well-established theoretical link between R&D investment and economic growth. That is, R&D investments of firms affect the overall economic output through an expansion of the firms' knowledge stock that aids competitiveness, improves productivity, and leads to output growth. Studies such as Griffith (2000), Hall and Mairesse (1995) and Griliches and Lichtenberg (1984) have established the importance of R&D investment as an enabler of productivity growth.

The UK maintains a National Measurement System (NMS) through funding from the NMS programme. This system is centred around a national infrastructure of specialist laboratories who use their world leading measurement science to deliver traceable and accurate measurement standards to end-users across many sectors of the economy (UK National Measurement System, 2023). Moreover, the NMS programme fits into the UK's overall innovation strategy, to improve the UK's prosperity, productivity, and growth. The private sector is critical and central to achieving these objectives through its role in the provision of goods and services that meet people's needs and improve their lives, job creation, better living conditions through higher earnings, and the generation of tax revenue to fund public services.

Existing studies (Belmana, 2019 and BEIS, 2017) with scope covering 2008-2012 and 2010-2015, respectively, have established that public innovation support, delivered through the NMS programme, contributed positively to business success in the UK. Specifically, the latest report (Belmana, 2019) showed that businesses which sought regular support from NMS experienced an increase of 5.5% in economic activity (measured by employment growth) compared to unsupported businesses in the matched control-group. Furthermore, the regularly supported firms paid an average wage premium of £50 a week to new joiners when these workers switch from jobs at unsupported businesses. This is in addition to an enhanced survival rate, where only 4% of the NMS regularly supported businesses closed compared to 12% of similar firms in a matched control-group.

The primary motivation for this study was the need to provide up-to-date evidence on the impact of NMS support on private businesses. Specifically, the study aims to contribute evidence for the Spending Review 2024 (SR24) by generating objective analysis to inform the allocation of public funds. This econometric study is crucial for ensuring accountability and

enabling future public funding to be allocated based on proven outcomes. With such evidence, the rationale for continued public investment in measurement services would be significantly strengthened.

The main objective of this study is to estimate the impact of NMS innovation support on business outcomes using the most recent data. There are three specific objectives including:

- i. Assessing the impact of NMS support on the wage rates and employment of supported firms.
- ii. Quantifying the impact of NMS support on investments (fixed assets and R&D) of the supported firms.
- iii. Estimating the survival effect of NMS support on the supported firms.

It is important to note the following:

- In this study, the treated firms are those that have received NPL's support through collaborations and paid measurement services. The control group is comprised of firms with similar attributes to the treated firms, but which did not receive such support. These firms are selected from those that had interactions with NPL in the distant past but have since ceased doing so, as well as those that have weakly engaged with NPL in other ways besides collaborations and paid measurement services. In addition to providing a suitable control group (due to their previous support or ongoing engagement), the inclusion of fixed assets as an additional outcome variable—data not housed by the ONS SRS—necessitates this approach.
- The business outcome variables, such as employment, fixed assets, earnings, and private R&D investment, represent the average annual growth in these variables in the years following treatment, where the length of the post-treatment period varies depending on the cohort year.
 - The full post-treatment period is the six-year period that proceeds the designated cohort-year. The first five cohorts (2012 to 2016) have the full six-year post-treatment period during which the impacts occur.
 - Data limitations mean that earlier cohorts have less than six years for their post-treatment period. So, this results in a shorter post-treatment impact period for the most recent cohort year, meaning that for some cohorts there isn't an extensive post-treatment period in which to observe changes in assets, employment or wages.
- To obtain a suitable sample, the estimates are based on pooling treated firms across cohort years. The control-group for a regularly supported firms is composed of unsupported businesses that - based on their observable characteristics - had the same probability of receiving NPL support but ultimately went unsupported. The proportion of treated businesses that are matched to untreated businesses with the closest propensity scores is approximately 61%.

The following sections focus the background to the study outlining the trends in levels of treatment and key variables, provide a summary of the methodology employed, discuss the treatment impacts, and offer inferences and conclusions.

2. Background to the Study

2.1. Trend and Levels of Treatment

A total of 9,006 firms, along with their Company Registration Numbers (CRNs)—including current NPL customers (those supported by NPL between 2007 and 2022) and those no longer supported by NPL after 2006—were submitted to the ONS for matching. It is important to highlight that, for the purposes of this study, NPL's support is defined primarily as formal

collaboration involving a written agreement to collaborate (referred to as *collaborations*) or through paid contract research or the use of measurement services (referred to as *paid services*). Other types of interaction, such as, classroom training, e-learning, or event attendance, are considered low-intensity forms of engagement and are not classified as support in this study.

Summary of Firms Classification:

- **Supported firms** fall into three categories based on the intensity of support: *treated*, *close-to-treated*, and *pathway-to-treated*. These firms constitute approximately 15.6% of the firms submitted to the ONS SRS for matching.
- **Unsupported firms** include those that have not received NPL's support since 2006 or have only engaged with NPL through low-intensity interactions such as e-learning, classroom training, or events. These firms represent approximately 84.4% of those submitted to the ONS SRS. The control group used for matching with treated firms was drawn from this category.

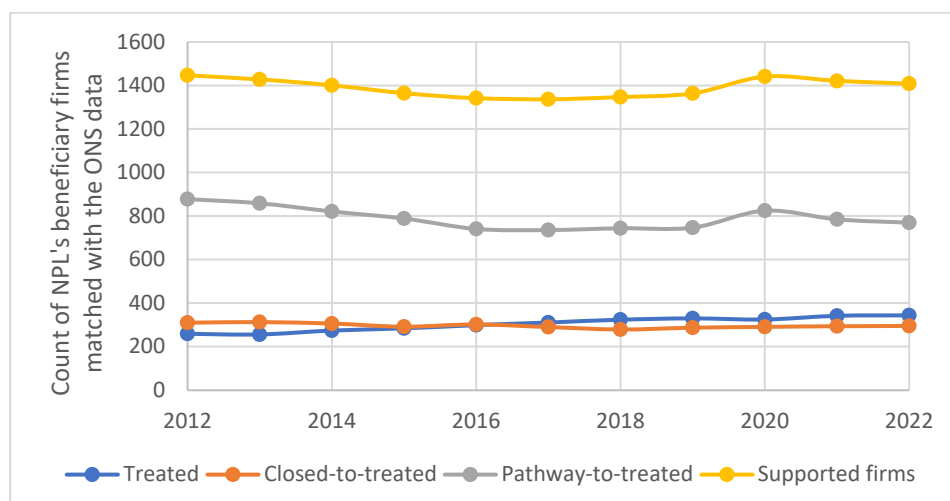
Of the 9,006 firms submitted to the ONS SRS, 93.53% were successfully matched with the ONS database using its unique Enterprise Reference Number (Entref), while the remaining 6.47% could not be located in the ONS records. Figure 1 provides a summary of the matched sample of firms across different treatment types.

Further, private businesses receiving support are categorised based on the level/intensity of support they have received from NPL during the intervention period. The categories are as follows:

- **Treated:** Firms that accessed NPL's support through collaborations or paid services in 5 or 6 years out of a given 6-year intervention period.
- **Close-to-treated:** Firms that accessed NPL's support through collaborations or paid services in 3 or 4 years out of the 6-year intervention period.
- **Pathway-to-treated:** Firms that accessed NPL's support through collaborations or paid services in 1 or 2 years out of the 6-year intervention period.

Treatment levels for firms are assigned by reviewing the preceding six years for each year of analysis in a dynamic manner, ensuring that the treatment is completed before evaluating the benefits gained. A 6-year intervention period is used to reflect the typical time required for a firm to transform an innovation into new revenue streams and transition from one form of innovation support to another. Additionally, the benefits of innovation are assumed to last approximately six years, based on a depreciation rate of 15% per annum, which aligns with the period most businesses use to write off the cost of their assets, including R&D assets. Section 3.1 provides further details on the treatment design.

Figure 1. NPL's Beneficiary firms



Source: Computed using NPL's administrative data as matched in the ONS

Figure 1 shows that the number of treated firms grew somewhat from 2012 to 2022, unlike the other categories of treated firms. The rise in the number of Pathway-to-Treated firms in 2020 can be attributed to NPL's innovation support programmes, such as M4R. Some of these initiatives were introduced in response to the COVID-19 and focused on measurement and analysis to overcome technological obstacles, identify areas for improvement, and implement solutions for recovery, boosting resilience, competitiveness, and growth of firms in the UK.

2.2. Trend of Key Variables

Table 1 presents key employment metrics for different treatment categories, including treated, close-to-treated, pathway-to-treated, and untreated¹ firms using the BSD (Business Structure Database) of the ONS. This data provided detailed information on the population of the UK businesses over time. It is derived from the Inter-Departmental Business Register (IDBR), which records data on firms registered for VAT or PAYE. The BSD includes key variables such as business size, industry classification, geographical location, and turnover, making it a vital resource for analysing business demographics, entry and exit rates, and growth patterns. The average number of employees is highest in the treated group (869.81) and lowest in the pathway-to-treated group (426.21). The logarithmic transformation of employment data (which minimises the effect of outliers) also suggests similar trends (Figure 2). The percentage of large companies within each category varies, with the treated group having the largest proportion (31.26%) and the pathway-to-treated group the smallest proportion (22.34%).

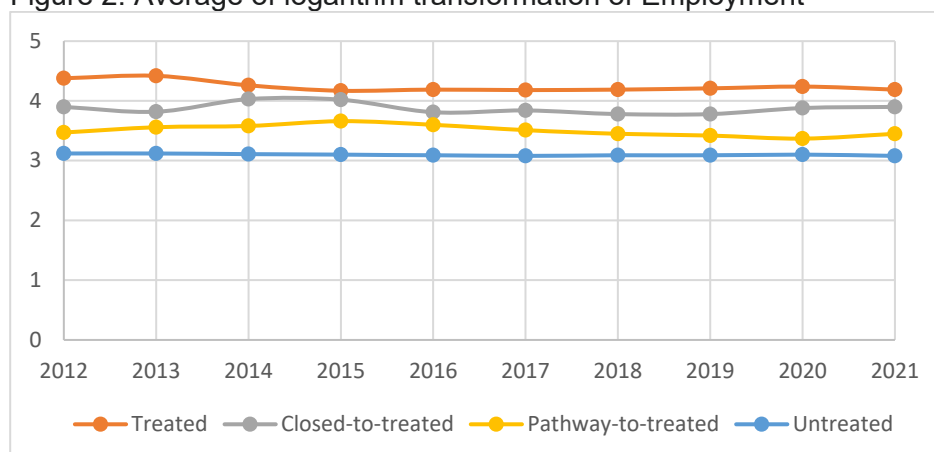
¹ These are firms that have not engaged with NPL through official collaboration involving a written agreement to collaborate (referred to as collaborations) or through paid contract research or measurement services (referred to as paid services) since 2007.

Table 1: Employment and Size of the Sampled Firms

	Treated	Close to treated	Pathway to treated	Untreated
Employment (mean)	869.81	634.68	426.21	519.78
Log employment (mean)	4.24	3.87	3.50	3.14
Size (large, % of the sample)	31.26	24.37	22.34	25.48
Average Count	288	284	749	5193

Source: Computed using Business Structure Database (BSD) of the ONS SRS

Figure 2: Average of logarithm transformation of Employment



Source: Computed using BSD of the ONS SRS

Table 2 reveals significant differences in median² values and proportions across various employee-related statistics among different categories of the sampled firms using ASHE (Annual Survey of Hours and Earnings) data. The ASHE is a comprehensive longitudinal panel dataset produced by the ONS in the UK. It provides detailed information on the levels, distribution, and composition of earnings and hours worked across different industries, occupations, and regions. The survey is based on a 1% sample of employee jobs, drawn from HM Revenue and Customs' Pay As You Earn (PAYE) records. It also relates to gross pay before tax, National Insurance or other deductions, and excludes payments in kind.

Treated firms offer significantly higher wages (Figure 3) and greater job stability, employ more full-time and high-skilled workers, and are more resilient during economic shocks like Covid-19. These firms tend to have older, more experienced workers and invest heavily in innovation-related activities. Close-to-treated and pathway-to-treated firms exhibit intermediate characteristics, with wages and employment conditions better than untreated firms but not as favourable as treated firms. This suggests that firms supported by NPL already demonstrate positive labour market outcomes. Employees in untreated firms lag behind treated firms in terms of wages, skill levels, and job stability, but they represent the bulk of the workforce.

² The focus is on median values because they are less influenced by outliers compared to mean values.

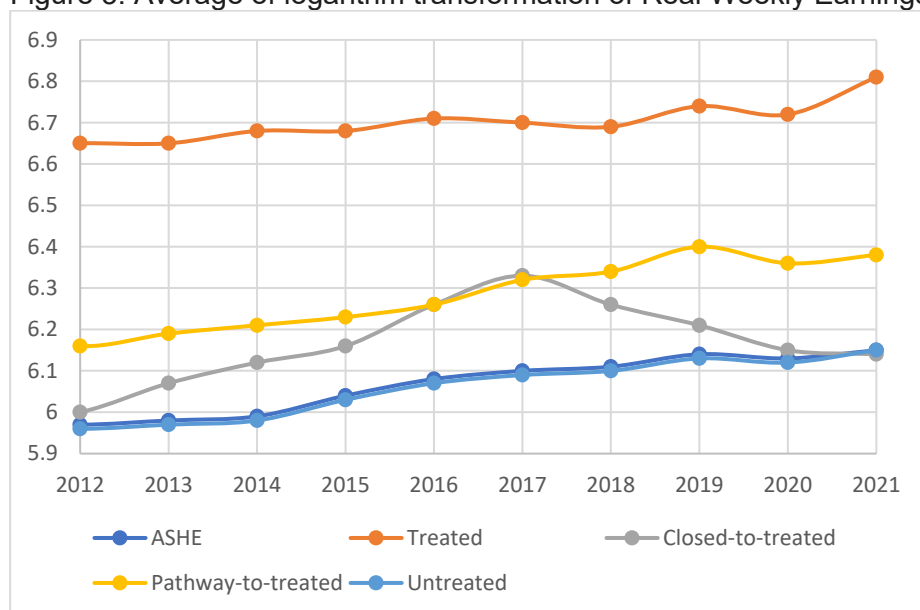
Table 2: Summary Statistics of Employees in the Sampled Firms

Variables	ASHE	Treated	Closed to treated	Pathway to treated	Untreated
Real Gross weekly pay (median)	465.9	817.7	486.9	568.5	462.2
Basic paid hours worked (median)	36.8	37.0	35.0	37.0	36.8
Total paid hours worked during the reference period (median)	37.0	37.0	35.0	37.4	37.0
Age (median)	36.0	37.0	35.0	37.0	36.0
Experience (job start year, median)	11.3	14.0	14.2	13.3	11.3
sex (female %)	52.6	27.5	44.1	42.1	53.0
Full/Part-time (full-time %)	72.2	95.7	70.0	81.2	71.9
Number of jobs (one job %)	97.8	99.5	98.5	98.9	97.8
High skilled (SOC 1-3) (%)	26.8	40.6	22.0	24.5	26.8
Medium skilled (SOC 4-8) (%)	56.5	50.1	66.3	65.3	56.3
Low skill (SOC 9) (%)	16.7	9.3	11.8	10.2	16.9
Furlough Status (not furloughed %)	80.6	91.8	88.2	87.0	80.4
Furlough Status (furloughed %)	16.1	6.2	3.7	11.3	16.4
Employment type (Permanent %)	93.2	97.0	98.2	96.5	93.0
Observations (National Insurance numbers)	1025762	9185	14650	11471	990456

Source: Computed using ASHE of the ONS SRS

Note: **Sex** distinguishes between male and female employees. **Full-Time/Part-Time Status** distinguishes between full-time and part-time employment. Full-time employees are defined as those working more than 30 paid hours per week, or for those in teaching professions, at least 25 paid hours per week. **Number of jobs** identifies individuals with only one job and multiple jobs. **Furlough status** indicates whether an employee was furloughed under the COVID-19 Job Retention Scheme (CJRS). There are three categories: employees not furloughed, those furloughed, and those with unknown status but assumed to be not furloughed. **Employment type** specifies whether a job is permanent or temporary.

Figure 3: Average of logarithm transformation of Real Weekly Earnings (2021=100)



Source: Computed using ASHE of the ONS SRS

Table 3 further provides a comparison of business characteristics across four groups of sampled firms: treated firms, firms close to being treated, firms on the pathway to treatment, and an untreated group using data from the BSD and BERD (Business Enterprise Research and Development) data. The BERD dataset is the key resource in the UK for understanding the research and development (R&D) activities undertaken by businesses. Compiled by the ONS, it provides detailed information on R&D expenditure, sources of funding, and employment in R&D by industry sector and region. The BERD data plays a crucial role in assessing the contribution of businesses to innovation and economic growth, tracking trends in investment, and evaluating the impact of R&D tax incentives and policies. It is important to note that variables relating to R&D activities, liquidity ratio, and real turnover in Table 3 are raw averages. To deal with the possible impact of outliers in the data, the key variables which are central to this study are log-transformed and presented in figures 2, 3, 5 and 5. However, some firms recorded zero R&D investment in some years. To deal with the "log of zero" issue (which is mathematically undefined) a small positive constant (that is, 1) was added to all R&D values greater or equal to zero before taking the logarithm. This helps to preserve the count of firms having zero R&D investment and also allows for the logarithmic transformation to be applied without errors.

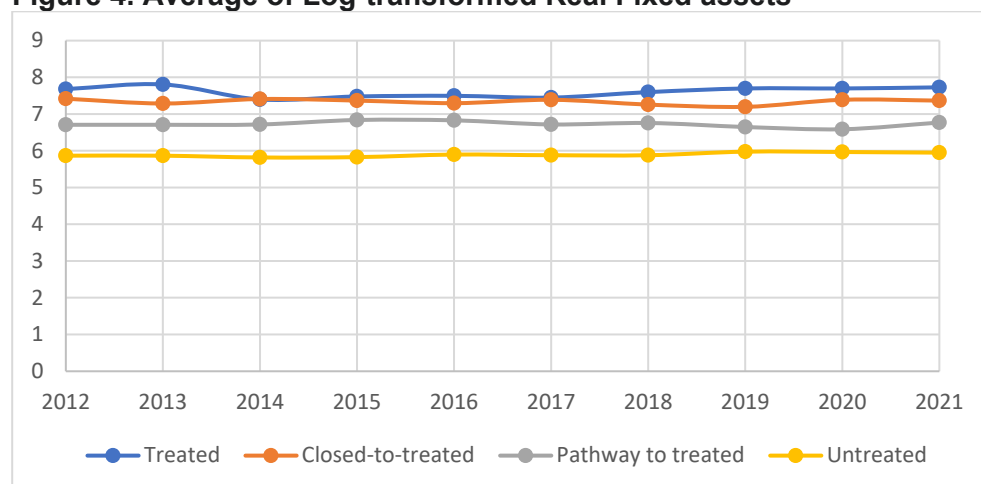
Table 3: Summary of other key variables and sampled firms' characteristics

	Treated	Close to treated	Pathway to treated	Untreated
Panel observations	3,348	3,259	8,695	953,274
Other measures of Business size				
Average real turnover (£ mill.)	466.6	390.2	209.2	207.5
Average real fixed assets (£ mill)	735.8	378.3	176.3	496.2
Industry classification (% of the tech manufacturing firms' sample)				
High-tech manufacturing	57.85	48.12	39.03	29.09
Innovation proxies				
Past IUK project (% of the sample)	49.88	51.55	40.60	36.03
Past NMS project (% of the sample)	100.00	100.00	100.00	43.24
Beauhurst Tracked (% of the sample)	43.74	45.18	37.85	24.04
Average real intramural/in-house expenditure total (£ 000's)	8810.91	7261.36	5229.55	3098.623
Average real in-house R&D expenditure funded by private businesses (£ 000's)	81.76	58.56	27.35	52.77
Average real in-house expenditure funded by own funds (£ 000's)	5312.02	5265.19	4395.07	2257.52
Average real in-house expenditure funded by central government (£ 000's)	1798.25	476.28	126.63	81.85
Average real in-house R&D expenditure on Basic research (£ 000's)	443.53	268.95	245.88	242.07
Average real in-house R&D expenditure on Applied research (£ 000's)	3512.9	2640.86	1835.55	994.99
Average real in-house R&D expenditure on Experimental Development (£ 000's)	4248.87	3915.58	2694.43	1674.85
Average number of scientists, researchers	35.54	26.85	16.46	2.14
Other characteristics				
Average Log of age	3.21	3.13	2.98	3.01
Furloughed (% of the sample)	15.38	6.62	13.00	13.39
Active (% of the sample)	99.38	98.73	98.54	95.93
Credit score (above 80, % of the sample)	64.25	62.02	56.80	49.72
Average liquidity ratio	2.58	2.89	2.97	2.90

Source: Computed using BSD and BERD of the ONS SRS

Firms receiving NMS support are typically larger, more established, and more innovation-driven, particularly in high-tech manufacturing. They invest significantly in R&D, especially in applied research and experimental development, and benefit from substantial government funding for innovation. Also, treated firms employ more researchers and maintain higher credit scores, indicating both innovation capacity and financial stability. The NMS treatment seems to support firms that are already innovation-intensive, helping them leverage government funding and increase their R&D efforts, although their liquidity may be slightly lower due to higher capital reinvestment.

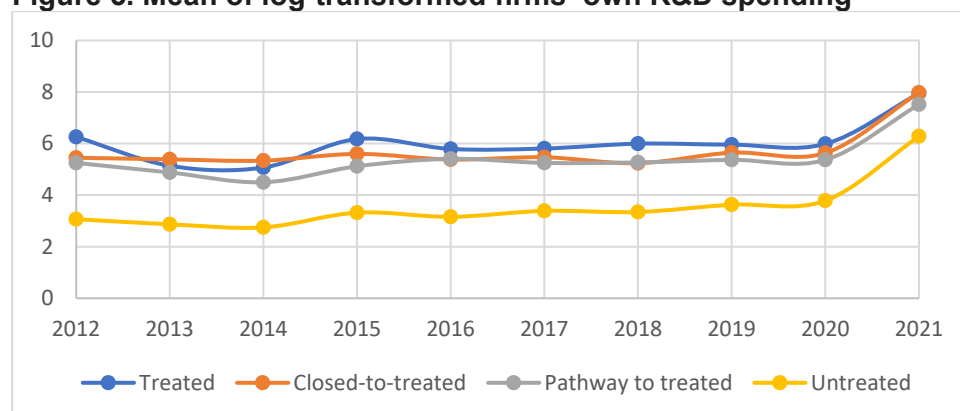
Figure 4. Average of Log-transformed Real Fixed assets



Source: Computed using BSD the ONS SRS

Over the period covered by this study, treated firms have significantly larger fixed assets (Table 3 and Figure 4) and invest more in in-house R&D that is funded through their own resources (Table 3 and Figure 5), highlighting their R&D intensity and innovation focus compared to other categories. It is important to note that a surge in in-house R&D expenditure in 2021 resulted from a change in the Office for National Statistics (ONS) methodology, which improved coverage of less R&D-intensive industries and small to medium-sized businesses. This change led to higher R&D spending estimates and a more accurate distribution of R&D across the economy, with small and medium-sized businesses' share of R&D adjusted from 74% in 2020 to 40.4% in 2022 (ONS, 2024)³.

Figure 5. Mean of log-transformed firms' own R&D spending



Source: Computed using BERD of the ONS SRS

³<https://www.ons.gov.uk/economy/governmentpublicsectorandtaxes/researchanddevelopmentexpenditure/bulletins/businessenterpriseanddevelopment/2022#:~:text=The%20improvements%20to%20methods%20to,1.7%25%20of%20business%20R&D%20expenditure.>

3. Methodology and Data

3.1. Treatment Design

This study adopts a dynamic treatment assignment method, which helps to structure supported firms into cohorts. It functions as a rolling window, where each year, we look back five years, including the current year, to determine how many times a firm has received support (through collaborations and /or paid services). The assumptions underlying this approach include: (i) the flow of economic benefits can only reasonably commence once a firm has completed its treatment. During the treatment period, the impact is assumed to be minimal; (ii) treatment status is only known upon completion of the treatment; (iii) firms may transition between treatment statuses across cohorts; (iv) each cohort can be analysed separately or in combination. Table 4 presents a hypothetical, rather than real, scenario of this treatment design.

Using this approach, the first cohort comprises firms supported between 2007 and 2012. The decision to begin in 2007 was based on when NPL started recording data on collaborations. Specifically, if a firm was supported in 83.3% or more of the years (i.e., at least five to six times) between 2007 and 2012, it is classified as a treated firm. If the level of support falls between 50% and 66.7% (i.e., three to four times) over this period, the firm is designated as close-to-treatment. Any firm supported fewer than three times within the six-year period from 2007 to 2012 is categorised as a pathway-to-treated firm. Firms considered for assignment during this period are referred to as the 2012 cohort, meaning they were supported between 2007 and 2012. The six-year post-treatment period for this cohort spans from 2013 to 2018.

The next cohort is the 2013 cohort, comprising firms supported between 2008 and 2013. The post-treatment period for this cohort extends from 2014 to 2019. This process continues until the 2022 cohort, which includes firms supported between 2017 and 2022. However, for this cohort, the post-treatment period is not yet available, meaning it is not yet mature for post-treatment evaluation. It is important to note that only the 2012 to 2016 cohorts have a complete six-year post-treatment period.

As previously mentioned, each cohort can be analysed independently. However, due to data limitations—particularly the need to conduct analyses based on the level of treatment a firm has received—this study organises firms based on the first year of treatment within each cohort. This is represented by t in Table 4, which outlines the construction of the hypothetical treatment assignment. While this approach maximises the use of data by combining firms (based on their level of treatment) from a previous cohort with subsequent cohorts, the estimates may be considered a lower bound, as the post-treatment/assignment impact is shorter for treated firms in cohorts after 2017. That is, some cohorts have not yet fully matured for post-treatment assessment.

Within this framework, t represents the year in which treatment is completed, also known as the assignment year, during which a firm's treatment status is determined. The subsequent post-treatment years are denoted as $t+1$, $t+2$, ..., $t+6$, while the treatment years leading up to the assignment year t are labelled $t-1$, $t-2$, ..., $t-5$, representing the period in which firms are receiving treatment.

The business outcome variables—employment, fixed assets, earnings, and private R&D investment—are analysed using PSM to measure their average annual growth following treatment, which varies by cohort year. For example, firms in the 2021 cohort in Table 4 have only one year of post-treatment data.

Table 4. Hypothetical Dynamic Cohort Formation

Year/ Cohort	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Treat ment status of an exemplar firm
2012	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6					close to treatment
2013		t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6				treated
2014			t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6			treated
2015				t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6		treated
2016					t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6	close to treatment
2017						t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	close to treatment
2018							t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	close to treatment
2019								t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	pathway to treatment
2020									t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	pathway to treatment
2021										t-5	t-4	t-3	t-2	t-1	t	t+1	pathway to treatment
2022											t-5	t-4	t-3	t-2	t-1	t	pathway to treatment

Keys

Instances of Support	Instances of no Support

3.2. Estimation Techniques

3.2.1. Propensity Score Matching and Difference-in-Difference

Two key methodologies—PSM and DiD— were employed to estimate the impact of NPL's support. These methods control for firms' characteristics and account for unobserved factors.

The PSM was used to estimate the causal effect of the NPL's treatment by accounting for potential confounding variables. The modelling structure is defined as follow:

Defining the Treatment Model

Let D_i be a binary support indicator:

$$D_i = \begin{cases} 1, & \text{if firm } i \text{ receives support} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Before estimating the propensity score model, it is useful to check whether the treatment variable D_i is correlated with the outcome Y_i . It is a diagnostic step that provides insights into the potential selection bias and treatment effect before proceeding with PSM. In observational studies, firms are not randomly assigned to treatment. Hence, differences in means may indicate that selection bias exists—i.e., the treated and untreated groups differ systematically before matching. If there is a large difference, it implies that covariates may need to be carefully controlled in the propensity score estimation.

This was implemented using a simple mean comparison test (t-test). The null hypothesis is that there is no difference in mean of an outcome between the treated and control groups.

Given the mean of an outcome for treated ($D_i = 1$) and control ($D_i = 0$) groups:

$$\bar{Y}_1 = \frac{1}{N_1} \sum_{i:D_i=1} Y_i \quad (2)$$

$$\bar{Y}_0 = \frac{1}{N_0} \sum_{i:D_i=0} Y_i \quad (3)$$

where:

- $\bar{Y}_1$ is the average outcome for the treated group.
- $\bar{Y}_0$ is the average outcome for the control group.
- N_1 and N_0 are the number of treated and control firms, respectively.

The difference in means is computed as:

$$\Delta = \bar{Y}_1 - \bar{Y}_0 \quad (4)$$

The t-statistic for testing the null hypothesis $H_0: \bar{Y}_1 - \bar{Y}_0$ is:

$$t = \frac{\bar{Y}_1 - \bar{Y}_0}{SE(\Delta)} \quad (5)$$

Where $SE(\Delta)$ is the standard error of the difference in means which is a function of the sample variances of the treated and control groups, respectively. If the t-statistic is significant (p-value < 0.05), the null hypothesis is rejected, indicating that the outcome is initially correlated with treatment, justifying the need for PMS to balance the groups. This step ensures that treatment selection bias is addressed systematically before implementing PSM.

Further, the probability of receiving treatment given a set of observable covariates X_i (the propensity score) is estimated using a logit model:

$$P(X_i) = \Pr(D_i = 1 | X_i) = \frac{\exp(X_i' \beta)}{1 + \exp(X_i' \beta)} \quad (6)$$

where:

$\Pr(D_i = 1 | X_i)$ is the probability of being in the treated group given a set of covariates.

X_i is a vector of covariates that could influence treatment.

β is a vector of coefficients.

The covariates such as firm size, industry, location, R&D intensity (measured by ratio of private R&D expenditure to turnover), COVID-19 (measured by furloughed scheme participation) and previous IUK's support were used in this study. Equation (6) is used to assess the relationship between treatment status and these covariates. For instance, if large and R&D intensive firms are more likely to be treated by NPL, then comparing employment outcomes directly between treated and untreated groups would be misleading. Hence, we need to assess whether these characteristics are imbalanced and correct for them using PSM.

Matching Procedure

Treated and control units are matched based on similar propensity scores using Nearest Neighbour Matching. For each treated firm i , the set of matched control units is denoted as $J(i)$, with weights w_{ij} assigned to each matched control j . This ensures that the matching of treated firms and control firms is based on their similar propensity scores rather than underlying disparities in baseline characteristics. This created balanced control groups that mitigate selection bias.

Estimation of Average Treatment Effect on the Treated (ATT)

ATT refers to the average effect of a treatment on the group of firms which received the treatment, meaning it only considers the outcome for treated firms, not the whole study population; it is a key concept in causal inference used to evaluate the impact of an intervention.

The treatment effect for firm i is defined as:

$$\tau_i = Y_{1i} - Y_{0i} \quad (7)$$

where:

- Y_{1i} is the potential outcome if treated.
- Y_{0i} is the potential outcome if untreated.

Since Y_{0i} for treated firms is unobserved, the Average Treatment Effect on the Treated (ATT) is estimated as:

$$ATT = E[Y_1 - Y_0 \mid D = 1] = E[Y_1 \mid D = 1] - E[Y_0 \mid D = 1] \quad (8)$$

Since $E[Y_0 \mid D = 1]$ is unobserved, it is estimated using the matched control firms:

$$ATT = \frac{1}{N_1} \sum_{i:D_i=1} \left(Y_i - \sum_{j:D_j=0} (Y_i - w_{ij} Y_j) \right) \quad (9)$$

Where:

N_1 is the number of treated units and w_{ij} are the matching weights for control firm j .

Covariate Balance and Robustness Checks

After matching, it is crucial to check whether the covariate distributions between treated and control groups are balanced. This ensures that selection bias is minimised. Hence, Covariate Balance Check was carried out using diagnostic statistics and graphical tools to verify the validity of the matching process.

To optimise matching precision, nearest-neighbour matching with multiple neighbours was used imposing a caliper value—the difference between the maximum and minimum propensity scores that removes outliers in the propensity scores. These enhancements balance the trade-off between variance reduction and potential bias due to less precise matches. The final output provided an unbiased estimate of the treatment effect, accounting for initial imbalances and minimising the influence of outliers or poorly matched observations. This rigorous approach ensures robust causal inference in non-experimental settings.

Moreover, one of the limitations of PSM is that some firms' characteristics such as management competency, and board composition which may be unobserved and may influence a firm-level economic outcome. To capture the possible importance of these factors, DiD methodology was used to account for fixed unobserved characteristics. The key assumption is that the outcome between the treated and control groups would follow the same growth pattern in the absence of support. This is called the parallel trend assumption. This is, however, difficult to verify (Oxford Economics, 2020). Studies such as Belmana (2019) index pre-treatment data at 100 to demonstrate that the trends are the same before the treatment takes place.

Implementing DiD leverage fixed effects and control for unobserved heterogeneity among the sampled firms. The fixed effects utilises within-firm variations (that is, changes within the same firm) over time to estimate the causal effect. This helps to isolate the impact of treatment from other unobserved factors that are constant over time. The specification of the model is as follow:

$$Y_{it} = \alpha_i + \partial_t + \beta(treated_i * post_t) + \epsilon_{it} \quad (10)$$

Where Y_{it} is the outcome variable (such as growth in employment) at time t , α_i are the unit fixed effects (capturing time-invariant characteristics of each firm), ∂_t are time fixed effects (capturing common shocks to all firms at a given time), $treated_i$ is a dummy variable indicating whether a firm is in the treatment group, $post_t$ is the DiD interaction term, capturing the differential effect of the treatment, and ϵ_{it} is the error term. The coefficient β on the interactive term is of primary interest, as it represents average treatment effect.

As previously noted, the DiD method relies on the assumption of parallel trends, meaning that the control and treatment groups would have exhibited similar trajectories in the absence of treatment. This parallel trend assumption was tested using Mora and Reggio (2015). This approach involved estimating treatment effect by defining the treatment and post-treatment periods, focusing on the time frame when the intervention's impact is expected to manifest. This approach ensures that the analysis does not attribute outcomes to the treatment during its implementation phase. Variables representing treatment status, time, and other controls are included to capture the causal effects. By structuring the analysis around clear pre-treatment and post-treatment periods, the framework enables precise identification of intervention impacts, accounting for any deviations from parallel trends and offering robust insights into treatment outcomes.

3.2.2. Wage Equation

To determine the impact of NMS on earnings, a multivariate estimation of an hourly wage equation was estimated using panel data at the individual worker level within the sampled companies. This approach was preferred to estimating aggregate annual wage bills divided by the number of employees, as the latter assumes uniform wages across all worker categories within a company, which is rarely accurate. Also, the aggregate method fails to capture the earnings effects on workers who move between NMS-supported and non-supported businesses. The analysis included four dummy variables to account for the impact of such moves, allowing for a deeper understanding of wage effect in the context of NPL's support. The estimated equation is as follow:

$$dw_{it} = \alpha + \beta l x_{i,t} + \gamma f x_{i,t} + \partial jobswitches_{it} + \epsilon_{it} \quad (11)$$

Where,

dw_{it} = change in log transformed real hourly wages of an individual worker (i) working in a sample firm in time t .

α = captures the average growth in hourly wages that is not explained by the independent variables in the model. However, it does not provide detailed insights into the individual-specific or time-specific variations; these are typically modelled through the fixed or random effects.

β = vector of time-variant and time-invariant workers' characteristics such as years of work experience of a worker with an employer, skills level of an individual worker (based on SOC 2010), dummy of nature of work (1 if full time and 0 if part time; 0 if temporary and 1 if permanent), dummy of impact of COVID-19 on earnings (0 if not furloughed; 1 if furloughed; 2

if furloughed status is unknown)⁴, dummy of sex (0 if female 0 and 1 if male), and dummy of keeping multiple jobs (0 if one job and 1 if multiple jobs).

γ = firms' characteristics such as technology level of the company an individual works. This was based on SIC (Standard Industrial Classification of Economic Activities) sector classification.

∂ = is vector of possible job switches. The descriptions of these dummies are given as follow:

- switch1= dummy capturing if a worker switch from NPL supported business to non-NPL supported businesses (1, if a worker switch to a non-NPL supported business between time t and t+1, and 0 if they remained with an NPL supported firms within same period).
- switch2: dummy capturing if a worker switch from non-NPL supported business to NPL supported businesses (1, if a worker switch to NPL supported business between time t and t+1, and 0 if they remained with a non-NPL supported firm within same period).
- Switch3: dummy capturing if a worker switch between NPL supported businesses (1, if a worker switch to another NPL supported business between time t and t+1, and 0 if they remained with an NPL supported firms within same period).
- Switch4: dummy capturing if a worker switch between non-NPL supported businesses (1, if a worker switch to another non-NPL supported business between time t and t+1, and 0 if they remained with an NPL supported firms within same period).

ε_{it} = the error term which represents the unexplained variability in hourly wage and accounts for unobserved or omitted factors. Its structure and interpretation depend on the specific panel model being used (pooled, fixed effects, or random effects). In the pooled regression, it represents the deviation of the dependent variable from the predicted value for individual i at time t, assuming all entities share the same intercept and slope. In fixed effect mode, it captures the individual-specific effects (unobserved heterogeneity), and the idiosyncratic error (random noise at the individual-time level). Hence, the error term in fixed effect model represents factors that are not observed but vary across both entities and time. In the random effect model, the error term is decomposed into random individual effects (assumed to be uncorrelated with the independent variables), and the idiosyncratic error (random noise).

Estimating equation (11) started by estimating a pooled least squares regression, which ignores individual or time-specific effects and serves as a baseline. Next, fixed effects model was estimated, which accounts for unobserved heterogeneity by allowing each entity to have its unique intercept, typically by demeaning or including dummy variables. Then, the random effects model was estimated, which assumes individual effects are random and uncorrelated with the regressors, incorporating these effects via an error component structure. After estimating fixed effect model, an F-test was performed to compare the pooled least square and fixed effect models, testing whether individual effects are significant. If the F-test rejects the null hypothesis, the fixed effect model is preferred. To decide between the fixed effect and random effect models, the Hausman test was utilised, which examines whether the random model's assumptions hold. If the Hausman test rejects the null hypothesis, fixed effect model is favoured; otherwise, the random effect model is appropriate.

3.2.3. Research and Development (R&D) Equation

⁴ 'Not furloughed' was the baseline category.

The Bootstrapped Quantile Regression (BQR), which combines two statistical methods: quantile regression and the bootstrap resampling technique, was used to estimate the impact of NPL support at various levels of in-house private R&D expenditure growth. The use of this method to estimate R&D equation is based on the characteristics of R&D data where some firms show extreme values. The structure of the BQR is presented below.

Consider a quantile regression model with the conditional quantile function:

$$Q_{\tau}(Y | X) = X'\beta_{\tau} \quad (12)$$

Where Y is the dependent variable (that is, private R&D investment growth), X is a vector of covariates (factors determining private R&D investment growth including dummies of treatment types), β_{τ} is the vector of quantile-specific coefficients, and $\tau \in (0,1)$ denotes the quantile of interest ($\tau=0.5$ for the median).

This method has the advantage of being robust to heteroskedasticity and non-normality. Furthermore, this method provides a comprehensive view of conditional distributions beyond the mean and improves inference reliability, especially in small samples. It also focuses on estimating conditional quantiles instead of means which makes it less sensitive to extreme values in the data. It also enabled the examination of conditional heterogeneity in R&D expenditure growth among the sampled firms receiving varying levels of treatment and captured how the treatment influences R&D investments in firms experiencing different rates of R&D investment growth. This has a theoretical basis and could be used to check the crowd-in or -out effect of a public R&D intervention. For instance, reinforcing the existing private R&D, when it is already adequate, reduces the efficiency of public R&D support as it could lead to the crowding out of private R&D spending.

However, the main drawbacks of BQR include computational intensity and challenges in inference and interpretation. To minimise these challenges, Paired Bootstrap was used to improve the reliability and efficiency of BQR.

3.2.4. Survival Estimate

This study also estimates survival impact of treatment incorporating Kaplan-Meier survival curves, Cox proportional hazards estimation, and the test of the proportional hazards assumption.

Given the previous matching procedures, survival analysis begins with the Kaplan-Meier estimator, which provides a non-parametric estimate of the survival function:

$$\hat{S}(t) = \prod_{t_i \leq t} \left(1 - \frac{d_i}{n_i}\right) \quad (13)$$

where d_i represents the number of failures at time t_i and n_i is the number of firms at risk just before t .

In terms of sequencing, the first step was to identify the firms whose death years have been determined. To obtain time to event (death) and censoring variables, failure was defined as the year in which a firm remained inactive in the event of death, and event as number of years since death occurred starting from 2012.

The Kaplan-Meier analysis was then stratified by treatment. This step establishes a baseline understanding of survival probabilities over time, allowing visualisation of differences across groups

Building on the survival estimates, the Cox Proportional Hazards Model introduces covariates to explain variations in survival:

$$h(t | X) = h_0(t) \exp(X\beta) \quad (14)$$

where:

- $h(t | X)$ is the hazard function given covariates X ,
- $h_0(t)$ is the baseline hazard function,
- β represents the effect of covariates.

In the context of survival analysis, the hazard is the instantaneous failure rate at a given time, conditional on survival up to that time. Formally, it is defined as:

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t} \quad (15)$$

where:

- T is the time to event (that is death of a firm)
- $h(t)$ represents the rate at which events occur at time t , given that the firm has survived up to t .

It is important to note that, unlike a survival probability, the hazard function can exceed 1 because it is a rate. Hazard function does not measure the probability of failure at time t , but rather the risk of failure at that exact moment, conditional on survival up to that point. A higher hazard at t suggests a higher likelihood of failure occurring immediately after t .

To ensure the validity of the Cox model, the assumption that hazard ratios remain constant over time was tested with Schoenfeld residuals. This test checks for hazard ratios correlation with time. Zero correlation implies proportional hazards.

3.3. Data sources and Variables Measurement

The data for this study spans the period from 2009 to 2021, focusing on business outcomes and other moderating variables. The data was sourced from the NPL's administrative systems detailing the support provided and matched to the ONS Secure Research Service. This includes business data on employment, wages, turnover, assets, and results from ONS surveys on productivity, R&D, and innovation, such as the ONS Business Expenditure on Research and Development (BERD), the ONS Business Structure Database, the Annual Survey of Hours and Earnings (ASHE) and external datasets from FAME. The survival analysis was based on Beahurst data. The monetary variables were adjusted to real terms using 2021 as the base year.

NPL's administrative data containing levels and types of treatment, assets, and Companies House company registration numbers (CRN) were matched with ONS datasets using their unique Enterprise Reference Number (Entref). ONS datasets are available annually; therefore, Stata syntaxes were used to reshape and construct one-to-one merging to create panel datasets for the analysis.

In terms of labour productivity, two broad measures of labour productivity at firm level are growth in value added per employees (that is, real turnover growth divided by employment growth) and wages. The major shortcoming of the former is its inability to capture improvements as less resources are used in producing the same level of sales. For example, turnover-based measure will miss where innovation reduces the use of inputs such as materials or energy used in production (Belmana, 2019). Besides, an increase in turnover-based measure may not necessarily imply improvement associated with innovation but a mere

reduction in employment growth relative to real turnover growth. Hence, wages as a measure of productivity overcome this challenge. This is based on the argument that labour is paid the value of its marginal productivity. Hence, disparities in wage premium received when labour moves between treated and matched untreated firms is an indication of productive differences. Other firm-level variables such as assets and R&D expenditure were measured in real terms.

4. Treatment Impacts

4.1. Employment and Real Fixed assets Growth Impacts

In analysing employment and real fixed assets growth as business outcomes, PSM methodology was employed to ensure comparability between treatment and control groups. Firstly, as previously explained, a binary indicator was created to distinguish between these groups, and covariates/cofounding variables such as firm size, industry, turnover, location, age, R&D intensity, a COVID-19 dummy, and prior innovation support were obtained.

The sample for this study is limited to the list of beneficiary and past-beneficiary firms, including their information on treatment types and intensity, as well as data on fixed assets and previous participation in IUK funding. This data was taken to the ONS SRS for matching. It is important to note that the BSD dataset does not contain information on fixed assets. Therefore, the matching process, used to obtain other required data on the treated and control groups, was conducted solely among the firms included in NPL's administrative data that were matched to the ONS dataset.

Secondly, to check if firms were randomly assigned to treatment or control, although in observational studies this could introduce bias, a simple t-test was used to compare the mean employment and fixed assets growth in each group independent of confounding variables. The results indicate that employment and fixed assets growth were higher in the treated groups compared to the untreated firms. This necessitated the need to proceed to estimating the PSM.

Thirdly, to identify the confounding variables that could influence the outcomes, selection equations were estimated to check the correlation between treatment and covariates, as treatment effects may be biased if they are correlated, and effort is not made to balance these covariates between the treated and control group. Focusing on the treated firms, the selection equation/estimation in Table A1 generated by *psmatch2*, along with the post-estimation covariate balancing test, is presented in Annex 1. It is also important to highlight that there is no need to calculate a propensity score in advance when using *psmatch2*. The *psmatch2* command generates: (1) *_treated*, a binary indicator identifying whether an observation belongs to the treatment or control group after matching. This is different from the initial binary treatment binary indicator created to distinguish between these groups; (2) *_weight*, which adjusts for any discrepancies in the number of treated and control units in the matching process; and (3) *_nn*, which identifies matched neighbours. The result in Table A1 show that the key factors influencing selection into treatment among the treated firms include size, prior participation in Innovate UK funding, COVID-19 furlough scheme participation and level of technology. Large sized, high tech manufacturing firms and firms not involved in COVID-19 furlough scheme participation are more likely to be treated.

Fourthly, PSM was implemented using STATA (a statistical package) to match treated firms with control firms based on propensity scores, ensuring balanced observable characteristics and calculating treatment effects. Also, post-estimation diagnostics were performed to evaluate the covariate balance after matching, with adjustments made as needed. To minimise bias, the nearest neighbour matching method was extended to multiple matches to reduce standard errors, though this could increase bias. To minimise the bias, a caliper value was applied to limit matches to those with small differences in propensity scores, reducing variance and minimising outliers' impact on the results.

The average treatment effects in Table 4 and 5, using the “teffects psmatch” method, matches treated firms with control group firms based on propensity scores, ensuring a balance in observable characteristics. The employment and fixed assets growth reported by this approach reflects the average treatment effects after adjusting for imbalances in the distribution of baseline characteristics between the treated and untreated groups. The results revealed average treatment effects of approximately 3% for employment growth and 5.1% for fixed assets growth over the 2012-2021⁵ period. The results indicate that about 3% and 5.1% employment and fixed assets growth respectively would have been experienced had the entire population been treated. That is, the average difference in employment and fixed assets growth between the treated firms and the matched control group is approximately 3% and 5.1%, respectively.

Table 4: Employment Growth Impact

Categories of treatment	Treatment-Effects Estimation	Coef.	Robust standard error	z	p> z	Raw	Matched/Obs	Control	Min. matching
Treated	Treated vs Untreated	0.03	0.00735	3.77***	0.000	171	1071	900	1
Closed-to-treated	Treated vs Untreated	0.04	0.02558	1.41	0.159	139	1089	960	1
Pathway-to-treated	Treated vs Untreated	0.02	0.00767	2.32**	0.020	280	1089	809	1
Estimator	Propensity score matching								
Outcome model	Matching								
Treatment Model	Logit								

Source: Computed using ONS SRS

It is important to note that the information on raw, matched, and control groups is derived from post-estimation covariate balance summary tables. The raw figure represents the count of unique treated firms that can be randomly matched, while the control group consists of a pool of similar untreated firms from which matches can be drawn. The matched group comprises both the matched unique treated firms and their corresponding control firms.

The post-estimation covariate balancing test for treated firms, as shown in Table A2, rejects the hypothesis of no covariate balancing as the proportion of bias between treated and control group in the covariates is insignificant, indicating that the differences observed between treated and control firms are attributable to the treatment. This finding is further illustrated in the covariate balance box in Figures A1 and A2, which focus on employment and fixed assets analysis for the treated firms. The analysis retains only those covariates that balance between treated and control firms, thereby eliminating the risk of erroneously attributing impact to pre-existing differences between the two groups. This is because the selection equation is not an end in itself but a means to achieving balance between the treated and control groups.

Table 5: Real Fixed assets Growth Impact

⁵ Average growth in log of employment and fixed assets were obtained for treated and control group within these periods before implementing the 'teffects psmatch' as this method is not suitable for panel data.

Categories of treatment	Treatment-Effects Estimation	Coef.	Robust standard error	z	p> z	Raw	Matched	Control	Min. matching
Treated	Treated vs Untreated	0.051	0.0157	3.26***	0.001	181	1081	900	5
Closed-to-treated	Treated vs Untreated	0.023	0.0171	1.35	0.159	132	1168	1036	5
Pathway-to-treated	Treated vs Untreated	0.036	0.0168	2.15**	0.032	289	1168	879	10
Estimator	Propensity score matching								
Outcome model	Matching								
Treatment Model	Logit								

Source: Computed using ONS SRS

Further, the employment and real fixed assets growth was 2% and 3.6% had the entire population been pathway-to-treated firms (Table 4 and 5). That is, the average difference in employment and fixed assets growth between pathway-to-treated firms and a matched control group is approximately 2% and 3.6%, respectively. However, the treatment effect was not significant for the closed-to-treated firms. The employment and fixed assets growth effects on the pathway-to-treated firms may be due to NPL's innovation programmes such as M4R which was introduced in 2020 to help firms cope with the impact of the COVID-19 pandemic.

The minimum matching shown in Tables 4 and 5 indicates that the matching process was based on both one-to-one and one-to-five matching—that is, for each treated firm, one or five similar untreated firms were matched. In the employment analysis, multiple matching does not enhance the treatment impact and does not affect the standard error. However, in the fixed assets analysis, as previously noted, multiple matching was applied to maximise the treatment effect while controlling for bias associated with multiple matching. To achieve this, the caliper values were set to restrict matches to those with minimal differences in propensity scores. This approach reduces variance and minimises the influence of outliers' propensity scores on the results.

As previously explained, PSM has imitations such as its inability to capture the impact of firms' unobservable characteristics such as management quality, company culture, employee morale, and market reputation. Hence, this study complements PSM with D-i-D methodology to account for the unobserved characteristics and time effects the business outcomes of interest. That is, D-i-D is used to compare the average change over time in outcome variables for the treated and the untreated control group. The key assumption is that the outcome between the treated and control groups would follow the same growth pattern in the absence of support. That is, prior to the treatment assignment, control and treatment firms followed a parallel path. However, the assumption of parallel trends was evaluated using a parallel-trends test. The outcome of the tests showed that the null hypothesis of parallel trends between treated and control firms in the pre-treatment assignment cannot be rejected⁶ (Table A3 and A4). That is, there's no difference in growth trend before treatment between treated

⁶ It is important to note that the test for common pre-dynamics requires at least three pretreatment periods. Since a firm's status was unknown until 2012, the pre-treatment period was set between 2012 and 2014, while the treatment period spanned from 2015 to 2021. The confirmed hypothesis is that there was no significant difference in employment and fixed assets growth between the treated and matched control groups during the 2012–2014 period.

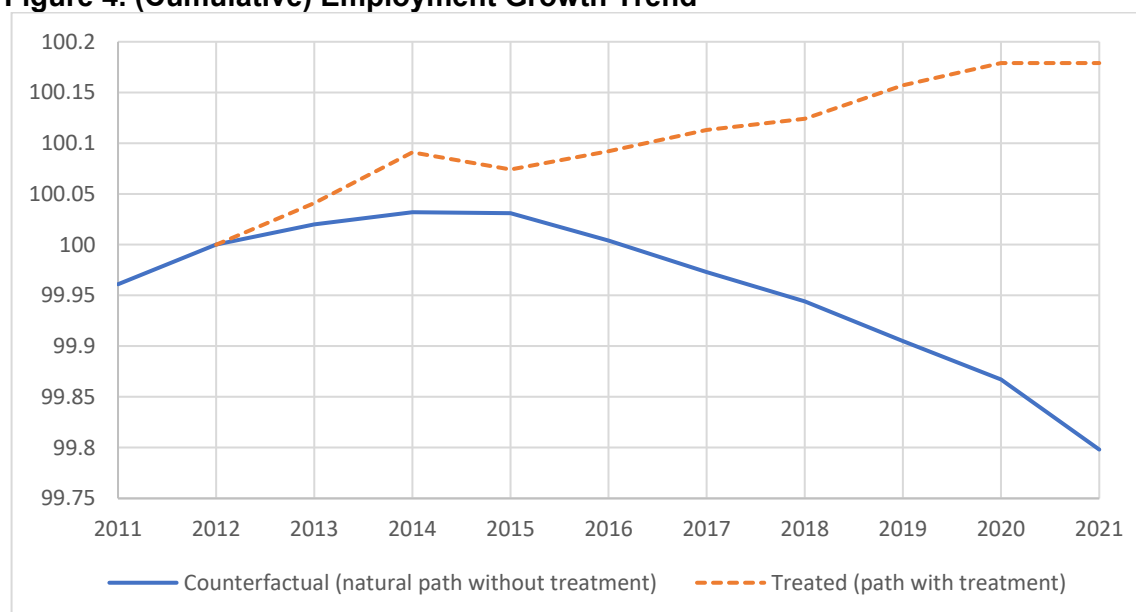
and control group. Hence, the fixed effect was estimated for each category of the supported firms to control for the unobserved factors that are constant over time but vary with individual firms. This approach also utilises its within-firm variations to estimate the causal effect of treatment.

For employment and fixed assets, the cumulative growth trend (from fixed effect estimates) of the treated firms is indexed to a base value of 100 at the year of treatment assignment (See figures 4 and 5.) . The difference in employment and fixed assets growth is approximately 3.0% and 4.0% between the treated and control groups, while the average employment and fixed assets growth is 1.4% and 7.3% among the treated firms respectively. This gives additionality of 214.3% and 54.8% in employment and fixed assets respectively.

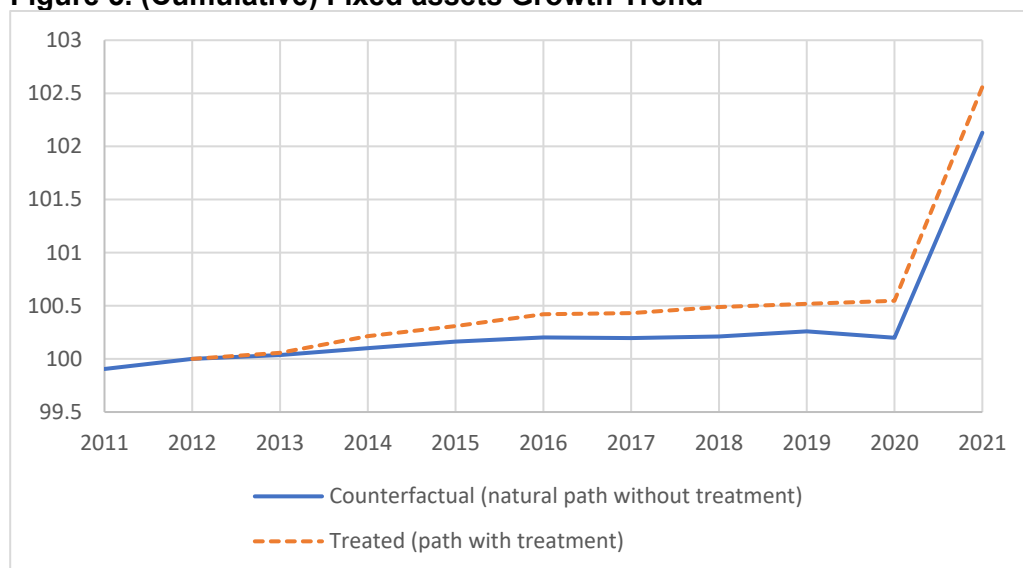
Further, a significant fixed assets growth was noticed among treated and control group during COVID-19 (Figure 5). This can be attributed to several factors, including:

- Investment in digital infrastructure due to remote working and the expansion of online business. Businesses may have increased spending on IT and e-commerce platforms.
- Financial aid (e.g., Bounce Back Loans) might have encouraged asset purchases.
- To address labour shortages during COVID-19, businesses may have invested in machinery and automation.
- Some sectors such as healthcare, logistics, and e-commerce companies expanded production facilities and warehouses during COVID-19.

Figure 4. (Cumulative) Employment Growth Trend



Source: Computed using ONS SRS

Figure 5. (Cumulative) Fixed assets Growth Trend

Source: Computed using ONS SRS

4.2. Earnings Impacts

There are several approaches by which the impact of an intervention on earnings can be analysed using firm-level data. This is well acknowledged in Belmana (2019). Firstly, the average wages per employee of a firm can be calculated. The wages before and after the intervention can subsequently be compared against the control group using PSM and D-i-D. One of the shortcomings of this approach is that workforce changes may cause changes in wages. Hence, wage changes may not necessarily be due to the intervention. Secondly, the wages of employees who remain with a firm throughout the period before and after support can be compared for treated and control firms, allowing for the measurement of innovation support's impact on individual productivity. However, individual characteristics such as wage growth from experience, skills, and seniority may render such a comparison between treated and control firms less adequate. Thirdly, individual worker-level effects on earnings from switching jobs between treated and untreated firms can be examined. D'Costa and Overman (2014) and Belmana (2019) used this approach. Treatment effects can be identified from job switchers, those joining treated firms around the treatment time. Higher wage growth for switchers to treated firms compared to non-treated firms suggests a positive treatment effect on earnings, even when accounting for targeted hiring due to support.

The Belmana (2019) approach was adequate for controlling for individual worker-level effects of treatment on earnings from switching jobs between treated and untreated firms. However, the downside is that wage changes can be influenced by the individual worker's nature of work and their work pattern. For instance, it is difficult to attribute higher weekly wages of a worker in a supported firm, working full-time or more hours, to treatment if they moved from an unsupported firm where they were working part-time or fewer hours (see Table 3). Hence, comparing weekly wage changes as a worker switches jobs without accounting for these individual characteristics may bias such comparisons. Additionally, there is a need to establish a test of significance for earnings changes as workers switch jobs, beyond the use of descriptive statistics.

This study employed a similar approach to Belmana (2019) by generating switch dummies to obtain earnings as workers switch jobs. These switch dummies and other control variables were estimated based on the change in the log of real hourly earnings for the reference period, which was derived by dividing real gross weekly earnings by the total paid hours worked during the reference period. The use of real hourly earnings minimises the problem of overfitting, as

total paid hours appear to capture significant random fluctuations rather than the underlying pattern in earnings, making other variables appear less relevant in the estimates of change in the log of real gross weekly earnings. The results of real hourly earnings are subsequently used to generate wage premiums, as workers switch jobs between different categories of treated and untreated firms.

Table 6 presents the statistical distribution of change in log of hourly earnings among the workers in the sampled firms. The average change in hourly wage is about 2%. The hourly wage exhibits a considerable level of symmetry given the skewness value of -0.4.⁷ This means that the change in log of hourly wages, between 2012 and 2021, is evenly distributed around a central value and the left and right sides of its distribution mirror each other. The implication of this is that the spread around the mean is consistent, and parameter estimates of log of change in hourly wages, will be robust and less sensitive to small changes in the data. However, to better account for potential heterogeneity across individual workers, given the "tailedness" of the change in the log of hourly wages distribution, a panel data approach is employed to estimate the change in hourly earnings. (This "tailedness" issue was indicated by the kurtosis value.)

Table 6. Statistical distribution of change in log of real hourly pay among the sampled firms

	Percentiles	Smallest		
1%	-0.69375	-11.8327		
5%	-0.23173	-8.75349		
10%	-0.12038	-8.19871	Obs	698,280
25%	-0.02467	-6.67065	Sum of wgt.	698,280
50%	0.011766		Mean	0.024568
		Largest	Std. dev.	0.230326
75%	0.077417	6.576755		
90%	0.196815	6.62207	Variance	0.05305
95%	0.303026	6.768778	Skewness	-0.4069
99%	0.706051	6.880387	Kurtosis	62.55797

Source: Computed using ONS SRS

Table 7 presents the panel data analysis of changes in the logarithm of hourly earnings using pooled least squares (PLS). Both fixed and random effects were also estimated. However, the fixed effect was not significant, despite being preferred by the Hausman test. This implies that there is less heterogeneity in changes in hourly wages among workers in different treated firms. This is due to the symmetric nature of the change in log of hourly earnings previously presented. Additionally, the F-statistics across the estimates show that the estimates are significant and well-fitted.

There are four types of switches used in Table 6: the switch between NPL-supported businesses, the switch from NPL-supported businesses to non-NPL-supported businesses, the switch from non-NPL-supported businesses to NPL-supported businesses and the switch capturing if a worker switches between non-NPL-supported businesses.

The results show that a worker switching from non-NPL-supported to NPL-treated firms earns a wage premium of about 7%. This figure is approximately 6% if the switch is from a non-NPL-supported firm to a pathway-to-treated firm. However, switching from non-NPL-supported to

⁷ For skewness values between -0.5 and 0.5, the data exhibit approximate symmetry.

close-to-treated firms does not generate a significant wage premium. There is a wage decline of about 2% when moving between close-to-treated firms. This indicates premium that an employee might place on other factors such as work-life balance, reduced stress, and more desirable work environment. These non-monetary benefits can be more valuable to the individual than a higher wage.

Table 7: Panel Data Regression of Change in log of Real Hourly Earnings

	Baseline estimate (all supported firms)		Treated		Closed-to-treated		Pathway-to-treated	
	Coef.	T-stat	Coef.	T-stat	Coef.	T-stat	Coef.	T-stat
Change in hourly pay								
Labour Switches:								
Treated to treated	-	-	-0.013	-1.2	-0.024	-2.68***	-0.010	-1.16
Treated to non-treated	-	-	-0.044	-1.4	0.020	0.7	0.007	0.26
Non-treated to treated	-	-	0.071	1.99**	-0.015	-0.33	0.057	2.23**
Non-treated to non-treated	-	-	0.005	1.03	0.007	1.47	0.005	1.07
Experience	0.013	5.01***	0.013	5.02***	0.015	5.80***	0.014	5.58***
Full time	-0.030	-14.01***	-0.031	-14.00***	-0.031	-14.30***	-0.032	-14.61***
Double job	-0.003	-0.46	-0.005	-0.8	-0.004	-0.6	-0.004	-0.66
Medium Skilled jobs	0.009	3.58***	0.009	3.73***	0.010	3.97***	0.010	3.94***
High Skilled jobs	0.013	4.83***	0.013	4.72***	0.014	5.05***	0.014	5.13***
Furloughed	-0.062	-24.24***	-0.064	-25.00***	-0.063	-24.6***	-0.063	-24.69***
Furloughed of unknown status	-0.010	-1.86*	-0.008	-1.5	-0.011	-1.95*	-0.009	-1.55
Permanent	0.004	0.810	0.003	0.6	0.002	0.46	0.002	0.44
Sex	0.013	7.14***	0.014	7.21***	0.014	7.50***	0.014	7.58***
Tech-manufacturing	0.013	1.350	0.021	2.00**	0.006	0.58	0.011	1.03
_cons	0.031	6.38***	0.033	6.65***	0.033	6.63***	0.033	6.74***
R-squared (within)	0.31		0.32		0.315		0.316	
R-squared (between)	0.12		0.13		0.131		0.134	
R-squared (overall)	0.15		0.157		0.156		0.158	
F stat	74.05***		56.28***		57.05***		58.09**	
F-Test that all $u_i=0$ (from fixed effect)	0.68		0.68		0.68		0.67	
Hausman test: $\chi^2(11) = (b-B)'[(V_b-V_B)^{-1}](b-B)$	1006.01***		1003.14**		1013.16**		991.55***	
Observations	104,699		102,107		102,327		102,533	

Source: Computed using ONS SRS.

Note: Significance levels are 1% (***), 5% (**) and 10% (*). Low skilled jobs, workers with no furlough experience, female, part time, one job, temporary and workers in low tech-manufacturing are the baseline groups.

Experience on the job is a significant factor affecting changes in wages of workers across the treatment levels of firms they work. The change in wages associated with changes in years of experience is about 1.3%. Full-time workers experience less hourly wage growth of about 3% relative to part-time workers across firms' treatment levels. This can be interpreted to mean

that full-time workers can earn more hourly through overtime pay, bonuses, or benefits that are not reflected in the basic hourly rate. Besides, a higher basic hourly rate might be offered to part-time workers to attract those who prefer flexible hours or who work unsociable hours.

Skills are an important factor driving wage changes. Compared to low skills, wage changes increase with higher skill levels by about 1%. Covid-19 also affected wage growth. Workers furloughed during the pandemic experienced a wage growth decline of about 6% compared to those not furloughed. Workers' gender is another important factor driving earnings. Relative to females, male workers experienced about a 1% hourly wage change increase. Finally, workers in high-tech manufacturing, relative to those in low-tech manufacturing in the treated firms, experienced about a 2% wage increase.

The coefficients of the percentage changes in hourly earnings after job switches, as shown in Table 7, and the results of weekly earnings after job switches presented in Table 8 were combined to calculate the weekly earnings of an individual worker before the job switch, presented in Figure 8.

There are a few important points to note in Table 7 and Figure 8. Firstly, only the switch from non-NPL-supported firms to NPL-treated firms is significant; other forms of movement are not. Secondly, the earnings of job switchers to NPL-regularly supported firms are higher than the average pay of workers in those firms. This implies that higher wages are used to attract skilled workers from non-supported firms. Thirdly, the earnings before the switch among the workers moving from non-treated firms to NPL-treated firms are higher than the average earnings of workers in non-treated firms. This indicates that highly skilled and productive workers are attracted to NPL-treated firms by offering higher pay. Fourthly, the count of job switches between treated and untreated firms is lower than the count of job switches within treated and non-treated. Additionally, the count of switches from treated to non-treated firms is higher than the count of switches from non-treated firms to treated firms. These trends suggest that the skills gap is an important factor determining workers' ability to switch jobs. The weekly wage premium equivalent of 7% among the treated firms is approximately £60 (Figure 8). This outcome aligns with Belmana (2019) which found weekly wage premium of £50 when a worker moved from a non-NPL supported firms to a supported firm.

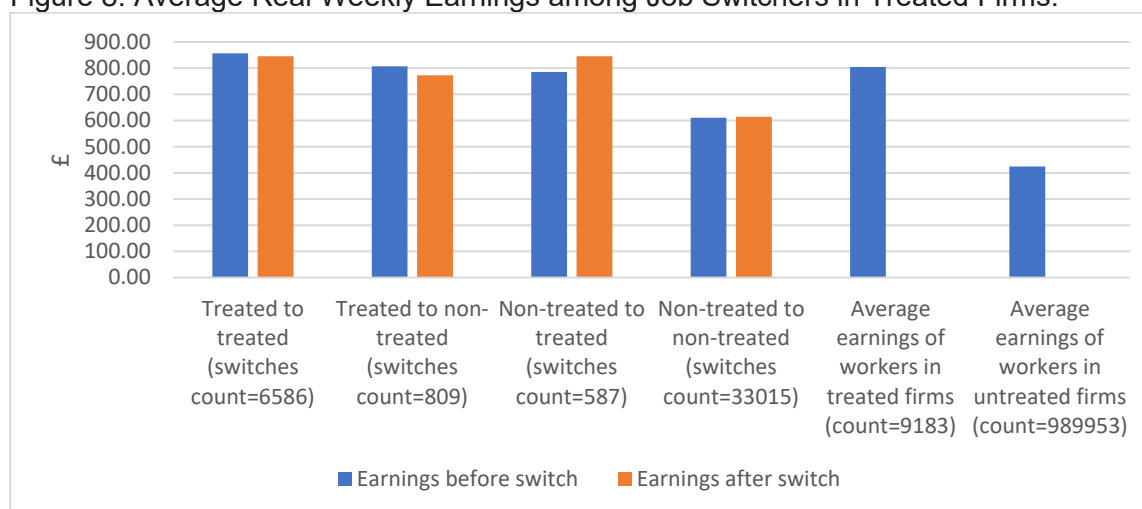
Table 8. Real Weekly Earnings after Job Switching among workers in the Treated firms.

	Treated to treated	Treated to non-treated	Non-treated to treated	Non-treated to non-treated
Log of real weekly pay (mean)	6.74	6.65	6.74	6.42
Average real weekly pay (£)	845.56	772.78	845.56	614.00
Log of weekly pay (median)	6.75	6.64	6.74	6.49
Median real weekly pay (£)	854.06	765.09	845.56	658.52
Count of switches	6586	809	587	33015

Source: Computed using ONS SRS

Note: Pounds equivalent of log of mean and median real weekly pay are also presented in table 1. The log transformation is used to reduce skewness of real weekly pay.

Figure 8. Average Real Weekly Earnings among Job Switchers in Treated Firms.



Source: Computed using ONS SRS

4.3. Firms' Own Real R&D Investment Growth Impacts

The analysis of the impact of NPL treatment on firms' own R&D investment with BQR, combining the benefits quantile regression and bootstrapping. The coefficient BQR represents the estimated change in a specific quantile of the firms' own R&D spending with respect to each independent variable. The key point is that coefficients are interpreted based on the chosen quantile level (e.g., 0.25 for the 25th percentile). This allows analysis of how different parts of growth in firms' own R&D spending's distribution are affected by the independent variables.

In terms of sequencing, firstly the statistical distribution of change in log of firms' own R&D investment growth was examined (Table A5 in the annex). The average growth in firms' own R&D investment is about 11%. The skewness of about 0.55 indicates that the data is moderately positively skewed. Also, a kurtosis of 14.1 indicates that a distribution is more peaked than a normal distribution (with heavier tails). This justifies the use BQR to deal with outliers, non-normal errors and conditional heterogeneity.

The Table 9 presents a BQR on the determinants of firms' own R&D growth across different growth quantiles—specifically, the 25th (lowest), 50th (median), and 75th (highest) quantiles. The results offer insights into how treatment effects, firm characteristics, and other factors influence R&D growth differently across quantiles, allowing a more understanding of the drivers of innovation investment among sampled firms.

Treatment Effects on R&D Growth

Three treatment indicators were used to examine the impact of firm treatment pathways on R&D investment growth, relative to a baseline group of untreated firms. The estimates reveal notable heterogeneity in treatment impacts across growth quantiles.

Being pathway-to-treated is significantly and positively associated with R&D growth only at the median quantile⁸ (0.5) with about 5.5%. This suggests being pathway treated may provide an effective boost in R&D for firms within a moderate growth range, potentially due to

⁸In quantile regression, the median quantile refers to the 50th percentile of the data distribution, essentially meaning it represents the middle point where half of the data falls below and half falls above, just like a standard median calculation.

the incremental benefits of access to resources and support services associated with the treatment. However, the effect is insignificant in the lowest quantile and turns negative in the highest quantile, suggesting that pathway treatment is not as impactful for firms at either extreme of the R&D growth distribution.

Close-to-treated firms experienced a significant negative effect of 9.0% in the highest quantile, while treated firms also exhibit a positive effect of approximately 5.8% at the median quantile and a significant negative effect of about 8.5% in the highest quantile. These results indicate that treatment may have positive effects on R&D growth primarily for moderately R&D growing firms, aligning with theories suggesting that targeted support benefits firms best positioned to leverage these resources effectively (Aghion et al., 2005). However, treated firms already experiencing high R&D growth may experience diminishing returns from treatment, possibly due to existing saturation in their R&D capacities or the relative inefficiency of additional support at high growth levels. This outcome could also imply that public R&D support crowd-out⁹ private R&D spending for high R&D investment performance firms.

Table 9: BQR of Firms' Own R&D investment growth

	Lowest quantile (0.25)			Median quantile (0.5)			Highest quantile (0.75)		
Real R&D growth	Coef.	Std. err.	t	Coef.	Std. err.	t	Coef.	Std. err.	t
Pathway-to-treated	0.005	0.014	0.33	0.055	0.024	2.23**	-0.053	0.024	-2.19**
Close-to-treated	-0.002	0.016	-0.12	0.032	0.036	0.89	-0.090	0.030	-3.0***
Treated	-0.013	0.015	-0.88	0.058	0.027	2.16**	-0.085	0.030	-2.8***
Real fixed assets growth	0.020	0.010	1.91*	0.021	0.017	1.27	0.069	0.022	3.22***
Employment growth	0.071	0.030	2.4**	0.079	0.044	1.8*	0.146	0.047	3.09***
Real turnover growth	0.000	0.009	-0.05	0.020	0.014	1.41	-0.020	0.015	-1.33
Liquidity ratio growth	0.014	0.010	1.32	0.003	0.018	0.17	0.041	0.016	2.5***
Past Innovate UK grants	-0.009	0.020	-0.46	-0.024	0.032	-0.75	0.025	0.030	0.85
Medium size firms	-0.020	0.014	-1.35	-0.076	0.027	-2.85***	0.045	0.032	1.43
Large size firms	-0.076	0.015	-5.18***	-0.040	0.027	-1.5	-0.100	0.030	-3.39***
Beauhurst	0.017	0.019	0.89	0.041	0.029	1.42	-0.009	0.031	-0.29
Low tech-manufacturing	-0.065	0.025	-2.62***	-0.148	0.043	-3.48***	0.109	0.048	2.25**
High tech-manufacturing	-0.097	0.012	-7.96***	-0.154	0.025	-6.1***	0.040	0.022	1.81*
_cons	0.151	0.014	10.46***	-0.260	0.026	-10.2***	0.499	0.024	21.0***
Raw sum of deviations	5049.811 (about .056144)			4481.463 (about -.34291363)			4697.295 (about .50516152)		
Min sum of deviations	5033			5079.76			4678.755		
Pseudo R2	0.3			0.5			0.4		
Observations	9,627			9,627			9,627		

Source: Computed using ONS SRS

Note: *, **, *** implies significant at 10%, 5% and 1%, respectively.

⁹ Crowding-out effect is an economic theory that suggests that increased government spending reduces private sector spending.

Firm Size and R&D Growth

The dummy variables medium and large firms, with small firms as the reference category, were used to assess size effects. The results for the relative size effect are presented as follow:

The medium-sized firms in the median quantile exhibit a significant negative effect of about 7.6% on R&D growth, implying a disadvantage in R&D expansion compared to smaller firms. Also, large firms show a pronounced negative effect on R&D growth in both the lowest (-7.6%, $p < 0.01$) and highest (-10.0%, $p < 0.01$) growth quantiles. This finding aligns with empirical literature that highlights how large firms tend to engage in incremental rather than radical innovation, leading to slower R&D growth trajectories (Cohen and Klepper, 1996). This is particularly evident in firms with both low and high baseline R&D growth, where size may impose rigidity, diminishing the impact of additional R&D investments.

Sector-Specific Effects: Low-Tech and High-Tech Manufacturing

Industry-specific characteristics, captured by low-tech manufacturing and high-tech manufacturing with non-manufacturing as the base category, indicate the differentiated impact of R&D growth based on technological intensity.

Low-tech manufacturing firms have a significantly negative effect on R&D growth in both the lowest (-7.6%, $p < 0.01$) and median (-14.8%, $p < 0.01$) quantiles, suggesting structural limitations in R&D spending in lower-growth and moderately growing low-tech firms. However, a positive and significant effect appears at the highest quantile (10.9%, $p < 0.05$), suggesting that some high-growth low-tech firms are capable of achieving substantial R&D growth, potentially by integrating public support. Similarly, high-tech manufacturing firms show a negative impact on R&D growth in the lower and median quantiles but demonstrate a small positive impact at the highest quantile (4.0%, $p < 0.10$). This aligns with Hall and Lerner (2010) which suggests that new innovative firms experience high costs of capital while the evidence for high costs of R&D capital for large firms is mixed.

Growth in Fixed assets, Employment, and Liquidity Ratio Impact

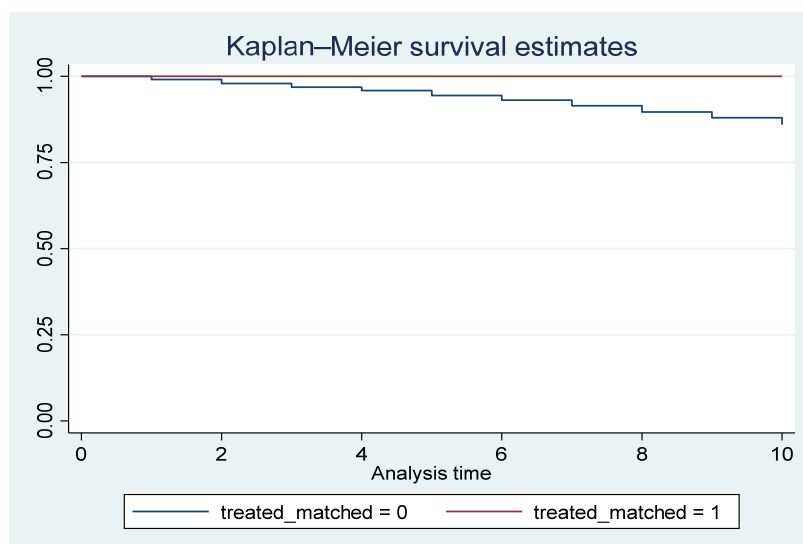
Real Fixed assets Growth: The positive impact of fixed assets growth on R&D increases with the growth quantile, most prominently at the highest quantile (6.9%, $p < 0.01$). This result suggests that high-growth firms leverage physical asset investments effectively to support R&D expansion, possibly due to complementary infrastructure needs for R&D activities in high-R&D growth firms.

Employment Growth: Employment growth has a positive effect across all quantiles, with the effect largest in the highest quantile (14.6%, $p < 0.01$). This indicates that workforce expansion supports R&D growth, likely by increasing human capital dedicated to innovation activities. This outcome aligns with Coad and Rao (2010) which found increase firms' total R&D expenditure following growth in sales and employment and Olakojo and King (2023) which revealed that employment growth is an important factor driving private R&D investment among firms supported by NPL. Also, employment-driven R&D growth aligns with the human capital theory of innovation, which posits that skilled labour is critical for effective R&D (Romer, 1990).

Liquidity and Real Turnover Growth: The growth in liquidity ratio and real turnover are largely insignificant across quantiles, suggesting that these variables play a minimal direct role in R&D growth within this dataset. This could imply that firms rely on more stable or external sources of R&D funding and that revenue fluctuations are less critical for R&D investments than other firm-specific resources.

4.4. Business Survival Impacts

The survival estimates with Kaplan-Meier shows that all treated firms survived from the start of treatment assignment in 2012 up until 2021. The reason is traceable to the nature of treatment design where a firm is required to have been exposed to treatment for six years before it can be assigned treatment status. That is, only active firms are qualified to be in the treatment group. However, survival of non-treated firms gradually reduces from about 100% in the year following treatment assignment in 2012 to about 86% in 2021. This implies that the closure incidents among the non-treated firms matched control firms (using PSM) was about 14%.



Source: Computed based on Beahurst data.

The Cox regression estimate with Breslow method (Table A6 in the annex) shows a significant hazard ratio of less than 1 indicating that treatment is associated with improved survival among the treated firms. The result also shows, as expected, that employment growth increases survival among treated firms. Additionally, the test of proportional hazard assumption (Table A7 in the annex), to establish whether the hazard ratio, or the ratio of the hazard function to the baseline hazard is constant over time, is insignificant. Hence, there is no evidence that the proportional-hazards assumption has been violated.

5. Inferences from the Results

The following conclusions can be reached based on the evidence on earnings and employment growth effect of the treatment:

- Firstly, the most important factors determining selection into treatment, which also passed covariate balancing test between treated and non-treated firms, are firms' size, level of manufacturing technology, participation in COVID-19 furlough scheme, and previous IUK funding participation.
- Secondly, treated firms experienced about 3.0% and 5.1% employment and fixed assets growth. This growth was not found among the similar untreated matched control group.
- Thirdly, the earnings effect of innovation support was about 7.1%. This means that when a worker switch from non-NPL treated firms to treated firms, wages grow by about 7.1%. This translates to wage premium of about £60 per week for workers switching from non-NPL treated to firms to treated firms.

- Fourthly, R&D support targeted at medium R&D investment-growth firms may yield higher returns on their R&D growth compared to high R&D investment growth firms, where diminishing returns are observed. Meanwhile, smaller firms appear more responsive in terms of R&D growth, supporting targeted policies for smaller entities that encourage early-stage innovation. For large firms, the observed negative growth effects suggest that alternative, structural support might be required to stimulate substantial R&D investment. Also, high-tech firms show greater responsiveness to R&D investments at high R&D investment-growth levels, reinforcing the economic importance of sectoral targeting in innovation policy. However, high R&D investment-growth low-tech firms may benefit from innovation support that address specific barriers to R&D scalability.
- Finally, business survival is associated with treatment.

The main applications of these findings are as follow. Firstly, business survival is dependent on innovation support from NPL. Secondly, it possible to improve welfare of workers (through enhanced earnings) and create job opportunities in the UK by supporting firms to overcome their innovation challenges through NMS. Thirdly, public innovation support via NPL makes firms to be more productive and offer higher wages that help to attract skilled workers from other firms, leading to employment and assets growth among them. Finally, innovation support tailored according to R&D investment growth stage of firms could maximise innovation investment efficiency.

6. Conclusion

This study examines the effects NPL's support on private businesses, focusing on employment growth, earnings, fixed assets expansion, R&D investment and business survival. The findings show that NPL interventions led to about 3.0% increase in employment growth and about 5.1% rise in real fixed assets. Workers moving to NPL-supported firms experienced a 7.1% wage premium, while R&D investment grew by 5.8% for firms with moderate R&D investment growth. The closure rate of about 14.8% among the non-treated firms was not found among the treated firms. These findings align with previous studies such as Olakojo and King (2023), Belmana (2019), Aghion et al. (2005) and Cohen and Klepper (1996).

While this study has been able to establish the impact of innovation support provided by NPL on private businesses, there are a few caveats. Firstly, earlier cohorts have less than six years for their post-treatment period, meaning that for some cohorts there is not an extensive post-treatment period in which to observe changes in assets, employment or wages. Hence, the results could be regarded as the average impact on firms in cohorts that are fully matured for impact assessment and those that are not yet fully matured, making it the lower bound estimate. With greater data availability, future studies could focus on cohort-level analysis, enabling comparisons and tracking of economic performance across each cohort over time and identifying factors that may contribute to variations in outcomes.

Secondly, firms that have been previously treated or are engaged in ongoing interactions with NPL, which are in the BSD of the ONS, are used as the control group rather than selecting from the broader BSD population. This was due to the need to analyse the impact of NPL on fixed assets growth (a data point not housed in the ONS SRS) and to ensure consistency across the considered business outcomes regarding the control group selection. While these firms represent a reasonable control group, future impact assessments could explore the use of a control group drawn from the wider BSD population.

Lastly, future studies could employ alternative techniques, beyond those used in this study, to provide further evidence of the impact of NPL on private businesses.

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Annex1

Table A1: Selection equation for treated firms from psmatch2

treated	Coefficient	Std. err.	z	P>z
_lpastIUK_1	0.231	0.027	8.46	0.000
_lsize_nn_2	-0.076	0.023	-3.31	0.001
_lsize_nn_3	0.051	0.021	2.43	0.015
_lbeauhurst_1	0.040	0.028	1.45	0.146
_lfurlough_1	0.163	0.128	1.27	0.203
_lfurlough_2	-0.406	0.050	-8.18	0.000
_ltech_nont_1	-0.198	0.036	-5.54	0.000
_ltech_nont_2	0.115	0.021	5.56	0.000
_cons	-1.210	0.052	-23.24	0.000
obs	46,956			
Chi-2	424.45			0.000
Pseudo R2	0.0179			

Note: There's no need calculating a propensity score in advance when using psmatch2. The psmatch2 generates (1) *_treated*, a binary indicator identifying whether an observation belongs to the treatment or control group after matching. This is different from the initial binary treatment binary indicator created to distinguish between these groups; (2) *_weight*, which adjusts for any discrepancies in the number of treated and control units in the matching process; and (3) *_nn*, which identifies matched neighbours.

Table A2: Covariate balancing test for treated firms

Variable	Mean			t-test		V(T)/ V(C)
	Treated	Control	%bias	t	p> t	
_lpastIUK_1	.6015	.60902	-1.5	-0.12	0.901	.
_lsize_nn_2	.40602	.41353	-1.5	-0.12	0.901	.
_lsize_nn_3	.45113	.45113	0.0	-0.00	1.000	.
_lbeauhurst_1	.52632	.52632	0.0	0.00	1.000	.
_lfurlough_1	.06767	.06767	0.0	0.00	1.000	.
_lfurlough_2	.03008	.03008	0.0	-0.00	1.000	.
_ltech_nont_1	.09023	.09023	0.0	0.00	1.000	.
_ltech_nont_2	.28571	.29323	-1.6	-0.13	0.893	.

* if variance ratio outside [0.71; 1.41]

Ps	R2	LR	chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.000	0.08	1.000	0.6	0.0	3.5	1.01	.		

* if B>25%, R outside [0.5; 2]

Post-Estimation Balance boxes for treated firms

Figure A1: Employment growth post-estimation covariate balance box

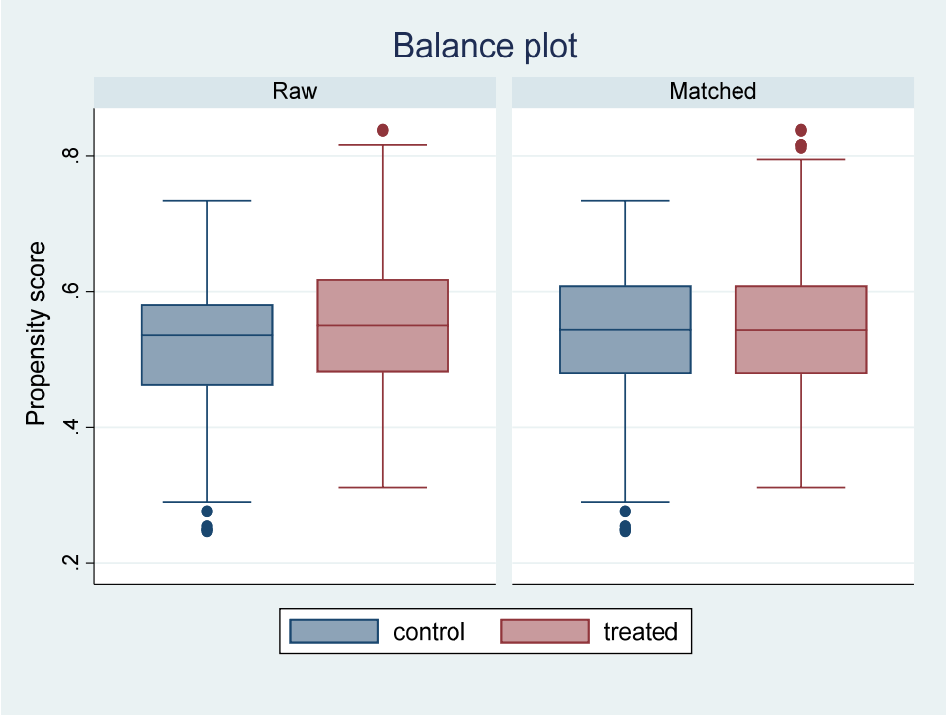


Figure A2: Fixed assets growth post-estimation covariate balance box

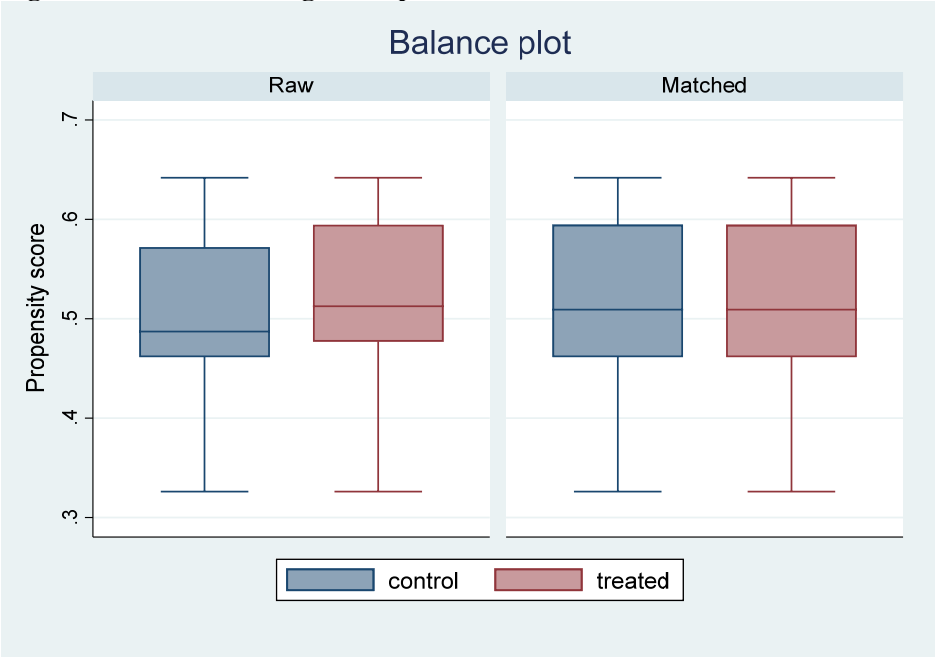


Table A4: Parallel-trend assumption test for Employment growth.

didq Dlogemployee, treated(treated) time(year) begin(2015) end(2021) standard

Unconditional Standard Model

Output: Dlogemployees

Number of obs = 38309

Sample Period: 2012:2021

H0: Common Pre-dynamics = 1.4

Treatment Period: 2015:2021

p-value = .4965

	All s	H0: s=s-1
-----+-----		
All q	.0041245	1.110731
	(0.0146)	[0.9531]

Robust Standard Errors in parenthesis

p-values in brackets

Table A5: Parallel-trend assumption test for Employment growth.

didq Dlogfixed_assets, treated(treated) time(year) begin(2015) end(2021) standard

Unconditional Standard Model

Output: Dlogrtotal_fixed_assets

Number of obs = 49167

Sample Period: 2012:2021

H0: Common Pre-dynamics = .6861

Treatment Period: 2015:2021

p-value = .7096

	All s	H0: s=s-1
-----+-----		
All q	.044793	.3856856
	(0.0341)	[0.9957]

Robust Standard Errors in parenthesis

p-values in brackets

Table A5. Distribution of change in log of own R&D spending

	Percentiles	Smallest		
1%	-4.02366	-13.3107		
5%	-1.54016	-11.843		
10%	-1.0287	-11.5485	Obs	192,802
25%	-0.28044	-10.784	Sum of wgt.	192,802
50%	0.12039		Mean	0.109842
		Largest	Std. dev.	1.29091
75%	0.468156	11.0358		
90%	1.160909	11.04552	Variance	1.66645
95%	1.768263	11.39799	Skewness	0.554533
99%	4.98184	11.48761	Kurtosis	14.19025

Table A6. Cox estimate

Cox regression with Breslow method for ties

No. of subjects = 3,527

Number of obs = 19,614

No. of failures = 4

Time at risk = 19,614

Wald chi2(2) = 5773.51

Log pseudolikelihood = -29.80357

Prob > chi2 = 0.0000

(Std. err. adjusted for 3,527 clusters in crn)

_t	Haz. ratio	Robust std. err.	z	P> z	[95% conf. interval]	
treated_matched	2.31e-17	1.18e-17	-74.93	0.000	8.50e-18	6.30e-17
Dlogemployees	.4811707	.0927178	-3.80	0.000	.3298218	.7019706

Table A7. Test of proportional hazard assumption

Test of proportional-hazards assumption

Time function: Analysis time

	rho	chi2	df	Prob>chi2
treated_ma~d	0.41331	0.00	1	0.9603
Dlogemploy~s	-0.41331	0.18	1	0.6688
Global test		0.18	2	0.9125

Note: Robust variance-covariance matrix used.

Annex2: GVA equation

Under the assumption of constant returns to scale and perfect competition (no super-normal profit), The GVA can be expressed directly in terms of primary inputs (labour and capital) as:

$$GVA = rK + wL \quad (1)$$

Total differentiation of equation (1) can be expressed as its growth rate:

$$d(GVA) = r dK + K dr + w dL + L dw \quad (2)$$

$$\frac{d(GVA)}{GVA} = \frac{rK}{GVA} \cdot \frac{dK}{K} + \frac{K dr}{GVA} + \frac{wL}{GVA} \cdot \frac{dL}{L} + \frac{L dw}{GVA} \quad (3)$$

Define $\alpha = \frac{rK}{GVA}$ and $(1 - \alpha) = \frac{wL}{GVA}$ share of capital and labour growth in GVA growth respectively. $\frac{K dr}{GVA}$ and $\frac{L dw}{GVA}$ is contribution from change in factor prices (interest rate and wages) to GVA growth. $\frac{dK}{K}$ is growth in capital stock and $\frac{dL}{L}$ is growth in employment. Therefore,

$$\frac{d(GVA)}{GVA} = 0.4(0.051) + 0.6(0.03) + 0.04 + 0.071 = 0.149$$

Where 0.4(40%) is the share of capital in GVA, 0.6 (60%) is the share of labour in GVA, 0.051 (5.1%) and 0.03 (3%) is the growth in capital stock and employment attributable to NPL support respectively among the treated firms. Additionally, 0.04 (4%) is the calculated growth of rental rate while and 0.071 (7.1%) is the estimated wage premium growth when a worker moves from unsupported business to NPL-supported business. This implies that GVA growth traceable to treatment among the treated firms is about 14.9%.

The observed GVA value among the treated firms is obtained using $GVA = rK + wL$ is:

$$GVA_{treated} = (0.47 * £2,018,278 + 41825.68 * 70) * 288 = £1.1 \text{ billion}$$

Where 0.47 is the calculated rental rate on capital stock using average saving ratio of 8.3% in the UK between 2012 and 2021, 7% depreciation rate (capital assets are assumed to last for about 15 years), 3% employment growth and 1.2% total factor productivity growth. The average of the exponential values of log of employment, weekly earnings, and fixed assets among the treated firms for the period is 70 (workers) per firm, £41825.68 (804.34*52 weeks), and £2,018,278 respectively.

$$GVA_{additional} = \Delta GVA_{treatment} * GVA_{treated} = 0.149 * 1.1 \text{ billion} = £163.9 \text{ million}$$

Hence, an average of about **£163.9 million** GVA is additional GVA among the treated firms due to NPL's support.

The monetary data used in the computation of the GVA are before tax. Since the tax-to-GDP ratio is 33% (King and Olakojo, 2023), the increase in taxes can be calculated as $0.33 * 163.9 =$ **£54.1 million**.

It is important to note that an addendum is in progress, explicitly detailing the processes used to calculate the GVA and presenting the net social benefits of NPL's impact.