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The impact of R&D and exporting on advanced technology adoption among UK SMEs

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ABSTRACT

This paper examines the impact of simultaneous engagement in research and development (R&D) and exporting—termed dual engagement—on the adoption of advanced and emerging technologies (AET) among UK small and medium-sized enterprises (SMEs). Using 7,336 observations from the Department for Business and Trade's Longitudinal Small Business Survey (2018–2022), we apply propensity score weighting and a control function approach to address selection bias and endogeneity. We further extend the analysis with machine learning methods to generate a synthetic dataset, enabling panel estimations as a robustness check. Our results show that dual engagement significantly increases the likelihood of AET adoption, raising adoption rates by around 11 percentage points compared to non-engaged firms. However, the effect is not synergistic: R&D engagement is the primary driver, while exporting contributes modestly. The impact intensifies in 2022, coinciding with the rapid diffusion of generative AI. These findings highlight the critical role of absorptive capacity in shaping SME technology adoption and suggest that policies to accelerate AET uptake should prioritise strengthening SME R&D activity, complemented by internationalisation support.

Keywords: R&D, Exporting, SMEs, Technology adoption, Artificial intelligence, Innovation policy

JEL: O32, O33, F14, L25, C21

CONTENTS

1. INTRODUCTION

As globalisation continues and technology rapidly advances, it is critical to understand how firms engage with international markets and participate in innovation. A substantial body of research has examined the relationship between exporting and R&D, finding them to be mutually reinforcing. Firms that export are more likely to invest in R&D, and R&D-active firms are more likely to export, creating a virtuous cycle of innovation and internationalisation (Aw, Roberts, & Winston, 2005; Esteve-Pérez & Rodríguez, 2013; Cassiman & Golovko, 2007). Similarly, there is extensive evidence that firms which export and/or invest heavily in R&D achieve gains in technological adoption, innovation outcomes, and productivity growth (Bernard & Jensen, 1999; Camisón & Villar-López, 2014; Gkypali, Love, & Roper, 2021; Zaman & Tanewski, 2024).

Less understood is the impact that R&D and exporting – performed together – have on firm outcomes. Given the increasingly significant role which these activities play in the global economy, this paper seeks to better understand their conjunctive impact. While research has shown complementarities between these activities in terms of productivity (Aw, Roberts, & Xu, 2011), their combined role in shaping the adoption of new technologies remains largely unexplored. This gap is particularly salient in the context of advanced and emerging technologies (AET), including artificial intelligence (AI), automation, robotics, and virtual/augmented reality. Adoption of these technologies has become a central concern for policymakers worldwide due to their transformative implications for competitiveness, labour markets, and economic growth (Anzoategui et al., 2019; OECD, 2021). In the UK, the Industrial Strategy and subsequent policy frameworks have highlighted AI and automation as strategic priorities, emphasising both the opportunities for productivity and the challenges for skills and employment.

This paper addresses three interrelated research questions. First, are firms that are dually engaged in R&D and exporting more likely to adopt AET than those engaged in neither? Second, between R&D and exporting, which activity contributes more strongly to AET adoption? Third, does dual engagement have a *synergistic* effect—greater than the sum of its parts—or are its benefits primarily additive? We also examine how these effects vary over time and across firm characteristics such as size, sector, and growth orientation.

To answer these questions, we draw on 7,336 firm-year observations from the UK Department for Business and Trade's Longitudinal Small Business Survey (LSBS). Given limited longitudinal coverage, we treat the data as repeated cross-sections. Our empirical strategy combines propensity score weighting to address selection bias with a control function approach to mitigate endogeneity and reverse causality. To extend robustness, we further employ machine learning methods to generate a synthetic dataset, enabling us to explore panel estimations and validate our results across a larger sample.

Our findings show that dual engagement has a distinct and meaningful impact on AET adoption. However, R&D activity is the primary driver of this relationship, with exporting contributing more modestly. We do not find evidence of a synergistic effect beyond the additive contributions of each activity. The effect strengthens over time, reaching its peak in 2022, when the diffusion of generative AI technologies such as ChatGPT brought AET adoption into mainstream business practice.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on the links between R&D, exporting, and technology adoption, highlighting the gaps this study seeks to address. This section also develops the theoretical framework underpinning our hypotheses. Section 3 describes the data, variables, and summary statistics, while Section 4 outlines the empirical methodology, including the propensity score weighting and control function approaches. Section 5 presents the main results, robustness checks, and mechanism analysis. Section 6 explores heterogeneity across firm characteristics and extends the analysis using machine learning methods to generate a synthetic dataset for panel estimation. Finally, Section 7 concludes by discussing the implications of our findings for theory and for policy aimed at accelerating advanced technology adoption among UK SMEs.

2. LITERATURE REVIEW

2.1 Empirical Framework

Prior research has explored questions related to the relationship between R&D, exporting, productivity, and (to a lesser extent) technology adoption. Literature finds that R&D involvement makes a firm more likely to adopt new technologies (Camisón & Villar-López, 2014; Esteve-Pérez & Rodríguez, 2013; Gómez & Vargas, 2012). It also suggests that exporting firms become more productive, in part because of technological adoption (Aw et al., 2005; Gómez & Vargas, 2012). Evidence of this relationship, though, is weaker. Studies consistently show that more productive and technologically intensive firms self-select to export – so called, “learning to export” (Bernard & Bradford Jensen, 1999; Gkypali et al., 2021; Melitz, 2003; Zaman & Tanewski, 2024). The alternative is “learning by exporting,” in which firms become more productive and technologically advanced because of their exporting due to new knowledge from international markets and increased competition. Other research finds diverse experiences across firms. Some firms are productive and subsequently learn to export; others learn by exporting; and others still do both (Aw et al., 2005; Gkypali et al., 2021; Gómez & Vargas, 2012; Jibril & Roper, 2022; Zaman & Tanewski, 2024).

Therefore, it would follow that firms which are dually engaged in both R&D and exporting are likelier to adopt technology than those which do neither. For instance, in their study of Taiwanese electronics firms, Aw et al. (2005) find that firms which export see higher future productivity than those which did not export. Additionally, they find that firms which export *and* perform R&D see greater productivity gains than those which only exported because they had a greater absorptive capacity for new technologies.

Gaps in the research remain, however. There is little analysis into how R&D and exporting impacts the adoption of modern technologies, including AI. Additionally, few studies examine the *dual* impact of R&D and exporting on technology adoption, instead looking at each individually. One study (Aw et al., 2011) finds that R&D and exporting have an additive but not synergistic impact on productivity. Here, we turn that question to technology adoption specifically. Nor has research considered the mechanism which connects exporting and/or R&D to technology adoption. Some research has found that R&D is more important than exporting in subsequent productivity gains from exporting (Aw et al., 2005, 2011; Camisón & Villar-López, 2014; Cassiman & Golovko, 2007; Gómez & Vargas, 2012). However, the importance of each factor for technology adoption remains unknown.

2.2 Theoretical framework

2.2.1 R&D and technology

Does R&D cause firms to adopt technology, or vice-versa? The literature suggests that the relationship is bidirectional. Romer (1990) finds that technological adoption is endogenous to firm decisions. Firms – ever profit-seeking – which invest in R&D are more likely to create and adopt new technologies. This in turn makes the firm more productive leading to more investment in R&D, leading further to greater technology creation and adoption – a virtuous cycle.

Cohen and Levinthal (1990) complement this theory. In their model of absorptive capacity, firms which have more preexisting knowledge are better suited to adopt and integrate new ideas (like technology). R&D can help facilitate this process. Specifically, a firm's R&D investment *first* creates new knowledge, *and second* provides the firm with greater preexisting knowledge, increasing their absorptive capacity and ability to integrate new knowledge. In other words, R&D investment equips firms with the capability to integrate new technologies more effectively. By contrast, firms without R&D activity often lack the absorptive capacity to realise the full benefits of cutting-edge technologies, leaving them at a disadvantage in adoption and diffusion.

2.2.2 Exporting and technology

Does exporting cause firms to adopt technology, or is exporting primarily the outcome of prior technological advancement? The balance of evidence suggests that the causal direction runs more strongly from technology adoption to exporting. Seminal work by Bernard and Bradford Jensen (1999) and Melitz (2003) suggest that only the most productive firms—often those already using advanced technologies—are able to overcome the fixed costs of entering international markets. This process is typically described as *learning to export*.

The alternative hypothesis, *learning by exporting*, posits that firms become more productive and technologically advanced as a result of exposure to international competition, knowledge spillovers, and interactions with foreign customers and suppliers. While some evidence supports this mechanism, it is generally weaker and more context-dependent (Aw, Roberts, & Winston, 2005; Gkypali, Love, & Roper, 2021). For many firms, productivity and technology adoption precede exporting, rather than the reverse.

In sum, exporting is more consistently a consequence of prior technological capabilities than a direct driver of technology adoption. Nevertheless, exporting may play an indirect role by exposing firms to new knowledge and practices, thereby reinforcing absorptive capacity and creating opportunities for subsequent adoption. Thus, while exporting alone is unlikely to initiate adoption of advanced and emerging technologies, it may accelerate diffusion once firms already possess a technological base.

2.2.3 R&D and exporting and technology

When considered together, R&D and exporting create a reinforcing sequence that enhances technology adoption. Building on Romer (1990) and Cohen and Levinthal (1990), firms first make intentional, profit-seeking investments in R&D. These investments generate new technologies and expand absorptive capacity, equipping firms to integrate external innovations more effectively. Increased productivity then follows, which, according to Bernard and Bradford Jensen (1999) and Melitz (2003), is a prerequisite for successful entry into export markets.

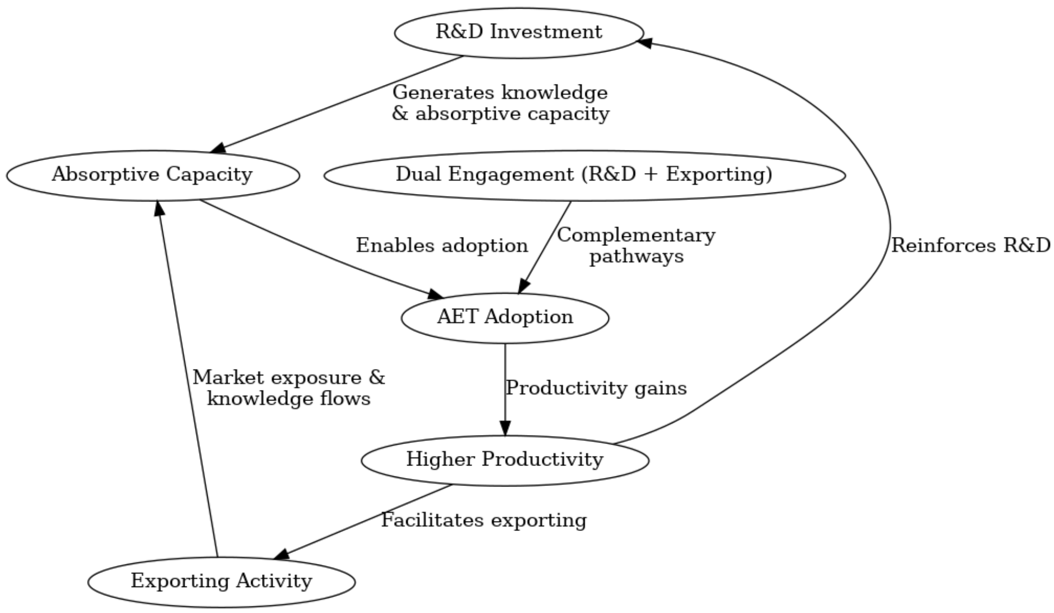
Once firms begin exporting, they are exposed to new customers, competitors, and knowledge flows across international markets. This exposure further strengthens their absorptive capacity, enabling them to recognise and adopt technologies more rapidly. In turn, higher productivity and competitiveness reinforce the incentive to continue both exporting and investing in R&D, sustaining a dynamic cycle of innovation and internationalisation (Aw, Roberts, & Xu, 2011).

In this framework, R&D provides the critical foundation for technology adoption, while exporting acts as a complementary channel that broadens the scope of knowledge and accelerates diffusion. Firms engaged in both activities simultaneously—*dual engagement*—are therefore theoretically positioned to be among the earliest adopters of advanced and emerging technologies.

2.2.4 Dual engagement and technology

Bringing these perspectives together, we return to the paper's central question: Does dual engagement lead to greater AET adoption? The theoretical framework suggests that it should. Firms that invest in R&D enhance their absorptive capacity, while exporters benefit from exposure to international knowledge flows and competitive pressures. When combined, these activities are likely to position firms as early adopters of cutting-edge technologies (**Figure 1**).

Figure 1. Conceptual framework: Dual engagement and AET adoption



Note: This framework illustrates the hypothesised pathways linking R&D, exporting, and advanced and emerging technology (AET) adoption. R&D investment enhances a firm's absorptive capacity by generating new knowledge and strengthening its ability to integrate external innovations. Exporting contributes by exposing firms to international markets, competitive pressures, and knowledge flows. Dual engagement combines these pathways, increasing the probability of AET adoption. Feedback loops suggest that AET adoption raises productivity, which in turn reinforces R&D activity and facilitates further exporting.

At the same time, important questions remain. First, which of the two activities—R&D or exporting—is the stronger driver of adoption? Second, does their joint effect exceed the sum of their individual contributions, indicating a synergistic relationship? Third, what is the direction of causality? It is possible that dual engagement prompts firms to adopt AET, but equally plausible that adopting AET enhances productivity and competitiveness, enabling firms to invest in R&D and expand into foreign markets. Moreover, the two components of dual engagement may not operate symmetrically: while R&D has a strong and direct link to technology adoption, exporting is more likely to exert an indirect influence, functioning through its interaction with R&D and productivity gains.

These questions underscore the need for empirical analysis. The remainder of the paper therefore examines whether dual engagement increases the likelihood of AET adoption, disentangles the relative contributions of R&D and exporting, and tests whether their effects are additive or synergistic.

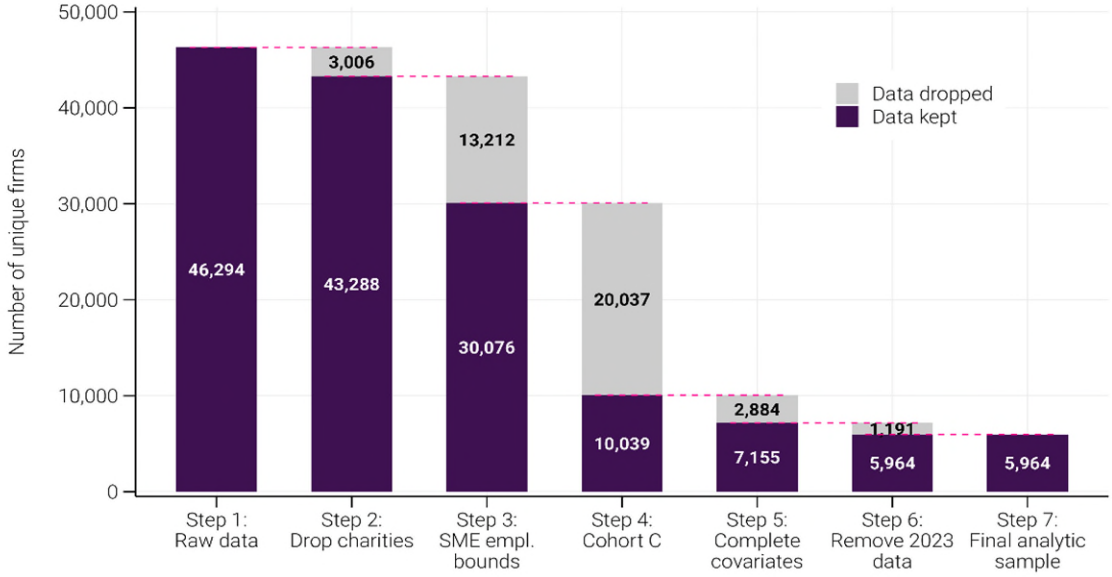
3. DATA

3.1 Sample

This study draws on the *Longitudinal Small Business Survey* (LSBS), conducted annually by the UK Department for Business and Trade (DBT) since 2015 (see **Annex A** for survey administration dates). The LSBS is the largest and most comprehensive survey of UK small and medium-sized enterprises (SMEs), defined here as firms with between 2 and 250 employees. It collects detailed information on firm demographics, performance, innovation activity, and management practices.

Our analysis begins with the full survey population of 46,294 unique firms. Several steps were taken to construct the analytic sample (see **Figure 2** for the sample design). First, we exclude 3,006 charities, focusing only on commercial enterprises. Second, we restrict the sample to firms reporting between 2 and 250 employees, removing 13,212 observations outside the SME threshold.

Figure 2: Data sample filtering diagram



A further reduction arises because questions on R&D engagement were introduced only in 2018 and asked of a random one-third of respondents (Cohort C). Retaining only Cohort C reduces the sample to 10,039 firms. We then require complete information on all covariates used in the econometric models, including firm region, size, R&D engagement, exporting status, age, sector, profitability, ownership characteristics, legal structure, growth expectations, and external advice received. This results in 7,155 firms.

Finally, because respondents were not asked about AET adoption in the 2023 wave, our analytic period ends in 2022. After applying all restrictions, the final sample consists of 5,964 unique firms, yielding 7,336 firm-year observations. **Annex B** provides details of the LSBS questions used to construct the R&D, exporting, and AET adoption variables.

3.2 Independent and dependent variables

The primary independent variable is a binary indicator of dual engagement, equal to one if a firm reports both undertaking R&D and exporting, and zero otherwise. This variable captures the combined effect of innovation and internationalisation activities.

The primary dependent variable is a binary measure of advanced and emerging technology (AET) adoption. This is constructed from two LSBS questions. The first asks whether the firm has adopted artificial intelligence (AI), robotics, or automation technologies. The second asks whether the firm has adopted virtual or augmented reality (VR/AR). Firms responding “yes” to either question are coded as AET adopters; firms responding “no” to both are coded as non-adopters.

We group these technologies under the category of AET for two reasons. First, all four represent general-purpose, digitally enabled technologies with broad potential applications across sectors, consistent with definitions used in the UK Industrial Strategy and OECD technology adoption frameworks (OECD, 2021). Second, LSBS asks about these technologies in a comparable format, allowing for a consistent binary measure of adoption across survey years.

Finally, dual engagement is treated as a binary variable rather than continuous because LSBS collects only activity indicators for R&D and exporting, not their intensity. While this limits the ability to explore variation in the scale of engagement, the binary construction ensures consistent measurement and aligns with prior studies of SME innovation and exporting behaviour (Esteve-Pérez & Rodríguez, 2013; Gkypali, Love, & Roper, 2021).

A detailed description of the survey questions and coding methodology for these variables is provided in Annex B.

3.3 Covariate description

In addition to the primary independent and dependent variables, we include a set of covariates to control for firm characteristics that may jointly influence R&D/exporting behaviour and AET adoption. Our selection follows Liu, Cowling, and Zhang (2025), the most recent work using LSBS data to study R&D decisions in the context of R&D tax credits. The covariates capture four broad dimensions: firm demographics, owner characteristics, organisational capabilities, and entrepreneurial orientation.

- **Firm demographics.** We control for firm size (log of employees), sector, age, region, urban/rural location, legal form, and profitability. Larger firms generally have greater resources to invest in both R&D and technology adoption (Cohen & Klepper, 1996; Hall, Lotti, & Mairesse, 2009). Sectoral and regional groupings capture structural heterogeneity in technology intensity and market conditions (Mairesse & Mohnen, 2010). Firm age is relevant as younger firms may be more agile in adopting new technologies but may lack resources (Huergo & Jaumandreu, 2004). Profitability controls for financial slack that facilitates investment in innovation and adoption (Coad, 2007). We use employee count rather than turnover due to collinearity, and because employment is considered a more reliable and stable measure across firms (OECD, 2005).

- **Owner characteristics.** We include gender, ethnic minority status, and family ownership. Prior research suggests that ownership structure and managerial demographics shape innovation outcomes: female- and minority-owned firms may face additional barriers to finance and market access (Robb & Watson, 2012; Lee & Marvel, 2014), while family ownership can influence long-term orientation and risk-taking behaviour in R&D and adoption decisions (Block, 2012).

- **Firm capabilities.** As LSBS does not directly measure dynamic capabilities, we rely on proxies. An indicator for whether the firm received external advice on management training serves as a proxy for resource coordination and leadership development (Teece, 2007). A broader indicator for whether firms sought external advice on growth, technology, exporting, access to finance, innovation, relocation, or productivity (hereafter *advanced advice*) reflects intent to strengthen capabilities and absorptive capacity, which is strongly associated with innovation adoption (Zahra & George, 2002).

- **Entrepreneurial growth orientation.** We include expected short-term turnover growth expectations (12 months) and long-term sales growth intentions (3 years). Growth-oriented firms are more likely to pursue innovation and technology adoption as a means of scaling (McKelvie & Davidsson, 2009; Delmar, Davidsson, & Gartner, 2003).

To capture structural heterogeneity, we classify firms into broad technology groups based on two-digit SIC codes, following Office for National Statistics guidelines. The categories are: (1) high- and medium-tech manufacturing; (2) ICT, professional, and scientific activities; (3) low-tech manufacturing; (4) knowledge-intensive services; and (5) other services. A full list of sectoral classifications is provided in Annex C.

Similarly, firms are grouped into regional categories: (1) South East; (2) Midlands, South West, and East of England; (3) Northern England and Yorkshire and the Humber; (4) Scotland and Wales; (5) Northern Ireland; and (6) London. We treat Northern Ireland separately from the other devolved nations due to its distinctive exporting position linked to access to the EU via the Republic of Ireland.

A complete table of all covariates, their variable types, and coding methodology is provided in **Annex D**.

3.4 Summary statistics

We begin by presenting descriptive statistics for the core variables of interest: dual engagement (R&D and exporting), AET adoption, and their distribution over time.

Table 1 provides a cross-tabulation of R&D and exporting status. Of the 7,336 firms in our analytic sample, the majority (59%) are neither exporters nor R&D-active. Around 27% are singly engaged—either R&D-only (14%) or exporting-only (13%). A relatively small minority, 14% (1,017 firms), are dually engaged in both R&D and exporting. This distribution highlights that while dual engagement is uncommon among UK SMEs, it represents a distinct group of firms with potentially greater innovation capacity.

Table 1: Dual engagement crosstabs

	Not Exporter		Exporter	
Not R&D	4330	(59%)	977	(13%)
R&D	1012	(14%)	**1017**	**(14%)**

Note: Dually engaged firms are highlighted. Percentages are calculated by divided each value by the total of 7,336 firms in our analytic sample.

Table 2 shows the prevalence of dual engagement over time. The share of dually engaged firms remains relatively stable, fluctuating between 12% and 15% from 2018 to 2022. This suggests that dual engagement is not strongly cyclical or affected by short-term shocks but instead reflects more persistent firm strategies. Importantly, this stability provides a consistent treatment group for the analysis.

Table 2: Dual engagement over time

Dually engaged?	2018		2019		2020		2021		2022		All years	
No	1686	85%	1431	85%	875	87%	1282	88%	1045	86%	**6319**	**86%**
Yes	295	15%	250	15%	132	13%	171	12%	169	14%	**1017**	**14%**
Total	**1981**	**100%**	**1681**	**100%**	**1007**	**100%**	**1453**	**100%**	**1214**	**100%**	**7336**	**100%**

Table 3 reports AET adoption rates across years. Overall adoption is low: only 7% of firms report using AI, robotics, automation, or VR/AR technologies across the period. Adoption rates are particularly modest between 2018 and 2021, at 5–7%. In 2022, however, adoption nearly doubles to 12%. This sharp increase coincides with the rapid diffusion of generative AI and heightened policy and media attention to automation technologies, suggesting that external technological trends significantly shaped SME uptake.

Table 3: AET adoption over time

Adopted AET?	2018		2019		2020		2021		2022		All years	
No	1888	95%	1577	94%	952	95%	1352	93%	1071	88%	**6840**	**93%**
Yes	93	5%	104	6%	55	5%	101	7%	143	12%	**496**	**7%**
Total	**1981**	**100%**	**1681**	**100%**	**1007**	**100%**	**1453**	**100%**	**1214**	**100%**	**7336**	**100%**

Note: Firms are classified as an AET adopter if they say that have used either (1) AI, robotics, or automation, OR (2) virtual reality. These two technology groups are asked in separate questions in the survey (see Annex B).

Taken together, the descriptive statistics highlight two important patterns. First, dually engaged firms represent a small but stable share of the SME population, providing a useful lens to study complementarities between R&D and exporting. Second, AET adoption remains rare among SMEs overall, but shows signs of acceleration in the most recent survey wave. These patterns support our hypothesis that dual engagement may be an important driver of early adoption, particularly as transformative technologies like AI gain prominence.

Table 4 shows that dually engaged firms differ markedly from the broader SME population. They are concentrated in knowledge- and technology-intensive sectors: 64% of high-tech manufacturers and 27% of ICT/professional/scientific firms are dual, compared with just 6–10% in service-oriented sectors. Regionally, dual engagement is somewhat more prevalent in London (16%) and Northern Ireland (23%), but lower in Scotland, Wales, and Northern England (10–13%). These distributions indicate that dual engagement is embedded in industrial and geographic contexts that provide greater exposure to innovation and international markets.

Structural characteristics also distinguish dual firms. They are larger on average—employing 41 workers compared with 25 among non-dual SMEs—and are predominantly incorporated companies rather than partnerships or sole proprietorships. While slightly younger in log terms, they remain mature businesses with an average age of 24 years, suggesting they combine both accumulated experience and organisational capacity with continued dynamism.

Finally, dual firms exhibit stronger growth orientation and more active capability-building. They are more likely to expect turnover growth in both the short and long term, and nearly twice as likely to seek advanced external advice compared with other SMEs. At the same time, they are less likely to be family-owned (12% vs 74%) or female-owned (13% vs 48%), pointing to ownership and governance structures that prioritise external opportunities and professionalisation. Taken together, the descriptive statistics indicate that dual engagement is strongly associated with firm size, sectoral specialisation, and capability development—all of which are themselves important correlates of technology adoption.

Table 4: Covariates summary statistics

Value	Mean	Median	Min	Max	Mean-Dually engaged	Mean-Not Dually engaged	Diff	P-value
High-tech manufacturing	4%	0	0	1	64%	36%	0.28	0.00
ICT, professional & scientific	18%	0	0	1	27%	73%	-0.47	0.00
Low-tech manufacturing	10%	0	0	1	30%	70%	-0.41	0.00
Other KI Services	9%	0	0	1	4%	96%	-0.93	0.00
Other service and non-manufacturing sectors	60%	1	0	1	6%	94%	-0.88	0.00
London	11%	0	0	1	16%	84%	-0.68	0.00
South East	15%	0	0	1	15%	85%	-0.69	0.00
Midlands, SW, EE	38%	0	0	1	14%	86%	-0.72	0.00
Northern England	18%	0	0	1	13%	87%	-0.74	0.00
Scotland, Wales	15%	0	0	1	10%	90%	-0.80	0.00
NI	3%	0	0	1	23%	77%	-0.54	0.00
Company	86%	1	0	1	16%	84%	-0.69	0.00
Partnership	8%	0	0	1	4%	96%	-0.93	0.00
Sole proprietorship	6%	0	0	1	1%	99%	-0.97	0.00
Profit-earning	85%	1	0	1	14%	86%	-0.73	0.00
Urban	70%	1	0	1	14%	86%	-0.71	0.00
Age (log)	2.95	3.00	0.00	6.03	2.92	3.11	-0.19	0.00
Age (level)	24.48	19.00	0.00	413.00	24.13	26.64	-2.51	0.00
N. employ. (log)	2.54	2.40	0.69	5.52	2.46	3.05	-0.59	0.00
N. employ. (level)	26.93	11.00	2.00	250.00	24.69	40.84	-16.15	0.00
Expects short-term (12-month) growth	49%	0	0	1	18%	82%	-0.64	0.00
Expects long-term (3 years) growth	84%	1	0	1	16%	84%	-0.69	0.00
Received advanced advice	14%	0	0	1	27%	73%	-0.46	0.00
Received leadership development advice	1%	0	0	1	27%	73%	-0.46	0.00
Ethnic minority in ownership	6%	0	0	1	14%	86%	-0.71	0.00
Female in ownership	48%	0	0	1	13%	87%	-0.75	0.00
Family owned	74%	1	0	1	12%	88%	-0.76	0.00

4. METHODOLOGY

4.1 Theoretical model

The starting point for our analysis is the idea that firms' adoption of advanced and emerging technologies (AET) depends on their ability to generate, absorb, and apply knowledge. Two activities are especially relevant: investment in R&D, which builds internal knowledge and absorptive capacity, and exporting, which exposes firms to external knowledge flows and competitive pressures.

We can represent the probability of adopting AET, AET_i^*, as a latent function of these two activities and their interaction:

$$AET_i^* = f(RD_i, EXP_i, RD_i * EXP_i, Z_i) \quad [1]$$

where RD_i denotes R&D engagement, EXP_i denotes exporting activity, and Z_i is a vector of firm-level characteristics (e.g., size, age, sector, ownership). AET adoption is observed as a binary outcome:

$$AET_i = \begin{cases} 1 & if\ AET_i^* > 0 \\ 0 & otherwise. \end{cases} \quad [2]$$

The theoretical expectation is as follows:

- R&D effect (RD_i). R&D raises the likelihood of AET adoption directly by generating new knowledge and building absorptive capacity (Cohen & Levinthal, 1990). Firms with stronger knowledge bases are better positioned to evaluate, integrate, and exploit new technologies.

- Exporting effect (EXP_i). Exporting contributes indirectly by exposing firms to international markets, where they encounter new technologies, standards, and customer demands. This external exposure enhances absorptive capacity, though its effect on AET adoption is weaker than that of R&D (Bernard & Jensen, 1999; Melitz, 2003).

- Dual engagement effect ($RD_i * EXP_i$). When both activities are undertaken simultaneously, firms benefit from complementarities: R&D enhances the ability to process external knowledge, while exporting increases the variety and richness of that knowledge. In principle, this could generate a synergistic effect that is greater than the sum of its parts (Aw, Roberts & Xu, 2011).

The central hypothesis of this paper is therefore that dually engaged firms are more likely to adopt AET than those engaged in neither activity. Whether the effect is primarily additive (driven by R&D alone) or synergistic (driven by complementarities between R&D and exporting) is an open empirical question, which we investigate in the following sections.

4.2 Econometric specification and identification

4.2.1 Core model

Our central objective is to estimate the effect of dual engagement in R&D and exporting on the likelihood of adopting advanced and emerging technologies (AET). In its simplest form, the relationship of interest can be written as:

$$AET_i = \alpha + \beta Dual_i + \gamma X_i + \varepsilon_i \quad [3]$$

where AET_i is a binary indicator equal to one if firm *i* reports adopting at least one AET (AI, robotics/automation, or VR/AR), and zero otherwise; $Dual_i$ is a binary variable equal to one if the firm is simultaneously engaged in R&D and exporting; and X_i is a vector of firm-level control variables (e.g., demographics, ownership, capabilities, growth orientation). The coefficient of interest, β, measures the average treatment effect of dual engagement on AET adoption.

In an ideal setting, identification would rely on a randomised experiment—assigning firms exogenously to dual engagement or non-engagement—or on panel data that would allow comparisons of firms before and after becoming dually engaged. However, the structure of the LSBS data (limited repeat participation across waves and partial coverage of R&D and AET questions) makes these designs infeasible.

Instead, we adopt a cross-sectional approach and use econometric strategies to approximate causal inference. Specifically, we combine propensity score weighting (to mitigate selection bias) with a control function approach (to account for endogeneity and reverse causality).

In the first stage, we estimate the probability that a firm is dually engaged using a probit model:

$$\begin{gathered}\Pr(dualEngaged)_i = \\ f[\ln(employees)_i, \ln(age)_i, profit_i, ownerFemale_i, ownerMinority_i, \\ familyOwned_i,\ urban_i, manageTrain_i, advancedAdvice_i, expGrowth1yr_i, \\ expGrowth3Yr_i, \text{legalForm}_i, \text{Sector}_i, \text{Region}_i, \text{Year}_i, Z_i, \varepsilon_i] \end{gathered} \quad [4]$$

where Z_i is an exclusion instrument: the proportion of dually engaged firms in firm *i*'s two-digit SIC sector. From this model, we obtain (1) **propensity scores** used to construct overlap weights (ω_i), and (2) **residuals** (ρ_i), which serve as the control function correction for unobserved factors affecting both dual engagement and AET adoption (Wooldridge, 2015).

In the second stage, we estimate the main model:

$$AET_i = \alpha + \beta_1 Dual_i + \gamma X_i + \omega_i + \rho_i + \varepsilon_i \quad [5]$$

Here, β_1 is our parameter of interest, representing the estimated difference in AET adoption probability between dual and non-engaged firms, conditional on observables and the control function adjustment. The treatment group consists of dually engaged firms, while the control group consists of firms engaged in neither exporting nor R&D. We exclude singly-engaged firms (R&D-only or exporting-only) from this stage but incorporate them in subsequent mechanism analysis (Section 4).

We estimate this specification using ordinary least squares (OLS) for interpretability of coefficients. Results are presented both for the pooled sample (2018–2022) and separately by year to assess heterogeneous effects over time. Each firm-year observation is treated as independent, given the limited panel dimension of the LSBS.

4.2.2 Propensity score weighting

To address selection bias, we employ propensity score weighting (PSW). First, we estimate each firm's probability of being dually engaged as a function of its observable characteristics (Equation 4). These probabilities are then converted into weights (ω_i) and applied in the main specification (Equation 5).

Ideally, lagged covariates would be used to reduce endogeneity. However, this would require firms to appear in multiple survey waves. Restricting the sample to multi-year respondents reduces coverage dramatically—from 5,964 firms to just 1,148 (19%). Moreover, most covariates are time-invariant or change little over time: only 37% of repeat firms show variation in two or more covariates, and just 13% in three or more. For this reason, we retain the full cross-sectional sample using contemporaneous covariates. We use the smaller "time-limited" sample with lagged variables as a robustness check.

We prefer weighting over matching, as it avoids arbitrary choices about neighbour counts and caliper widths. The conventional approach, inverse probability of treatment weighting (IPTW), assigns weights of:

$$IPTW_{treated} = \left(\frac{1}{PS}\right), \qquad IPTW_{untreated} = \frac{1}{(1-PS)}$$

Given that only 14% of firms are dually engaged, IPTW produces highly skewed weights, even after trimming (Chesnaye et al., 2022). To overcome this, we adopt **overlap weights (OW)**, widely used in recent applied research (Li et al., 2018; Thomas et al., 2020, 2023). Overlap weights are defined as:

$$OW_{treated} = 1 - PS\,, \qquad OW_{untreated} = PS$$

This approach upweights "surprising" cases—non-dual firms with a high propensity to dual, and dual firms with a low propensity. In doing so, OW improves balance between groups and reduces the influence of extreme observations, providing a more robust basis for estimating the treatment effect.

5. RESULTS

5.1 Core results

We estimate the average treatment effect of dual engagement on AET adoption using a Control Function approach. In the first stage, we model the probability of dual engagement on firm covariates and include an exogenous instrument (the sector-level dual engagement rate). From this, we derive predicted residuals, which enter the second-stage structural equation as an exclusion instrument. First-stage regression results are reported in **Annex E. Annex F** shows the distribution of all weighting possibilities, which are derived from first stage results. **Annex G** shows the covariate balance by weighting methodology. Our core model results – the second stage structural equation – are displayed in **Table 5** below.

Table 5 presents the core second-stage results. Model 1 estimates the effect of dual engagement on AET adoption controlling only for the first-stage residuals. Model 2 introduces firm-level covariates. Model 3 applies overlap weights, and Model 4 – our preferred specification – includes covariates, weights, and year indicators.

Across all specifications, dual engagement has a positive and statistically significant effect on AET adoption. In the preferred Model 4, being dually engaged increases the probability of adopting AET by 11 percentage points. This confirms dual engagement as a leading determinant of AET adoption among UK SMEs.

Table 5: Core model pooled estimates

	Dependent variable: **AET adoption**			
	(1)	(2)	(3)	(4)
Dual Engaged	0.221***	0.159***	0.108***	0.113***
	(0.013)	(0.026)	(0.030)	(0.030)
Constant	0.012***	0.092***	0.151***	0.133***
	(0.004)	(0.024)	(0.047)	(0.047)
Year indicators	No	No	No	Yes
Weights	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes
Residuals	Yes	Yes	Yes	Yes
Observations	5,347	5,347	5,347	5,347
R^2	0.070	0.083	0.061	0.069
Adjusted R^2	0.070	0.079	0.056	0.064
F Statistic	202.292***	20.200***	14.317***	14.125***

Note: *p**p***p<0.01. Reference groups are London (region), ICT/scientific/professional (sector technology group), sole proprietorship (legal form)

Table 6 reports the unpooled estimates, with our preferred pooled model (Model 1) included for comparison. While the pooled specification establishes a consistent positive and significant effect of dual engagement on AET adoption, the year-by-year results allow us to explore how this effect evolved over time. Each annual model controls for covariates and first-stage residuals and applies overlap weights.

The year-specific results reveal substantial variation. In 2018 and 2019, the treatment effect is statistically insignificant. The effect becomes weakly significant in 2020 and 2021, corresponding to an increase of 15 and 12 percentage points in adoption likelihood, respectively. By 2022, however, the impact strengthens dramatically: dually engaged firms were nearly 39 percentage points more likely to adopt AET.

This sharp rise coincides with a broader surge in AET uptake. As shown in **Table 3**, adoption rates remained stable at 5–7% between 2018 and 2021 but nearly doubled to 12% in 2022. The timing aligns with the release of ChatGPT in late 2022 and the rapid diffusion of generative AI technologies. These results suggest that the most innovative firms—those combining R&D and exporting—were among the earliest adopters of this new wave of technologies.

Table 6: Core model unpooled estimates

	Dependent variable:					
	AET adoption					
	All years	2018	2019	2020	2021	2022
	(1)	(2)	(3)	(4)	(5)	(6)
Dual Engaged	0.113***	0.006	-0.021	0.146*	0.124*	0.387***
	(0.030)	(0.050)	(0.059)	(0.080)	(0.068)	(0.096)
Constant	0.133***	0.141*	0.232***	-0.001	0.164	-0.041
	(0.047)	(0.083)	(0.081)	(0.122)	(0.237)	(0.130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes
Residuals	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,347	1,452	1,225	722	1,066	882
R^2	0.069	0.080	0.070	0.241	0.083	0.149
Adjusted R^2	0.064	0.064	0.052	0.216	0.063	0.125
F Statistic	14.125***	5.158***	3.775***	9.634***	4.108***	6.259***

Note: *p**p***p<0.01. Reference groups are London (region), ICT/scientific/professional (sector technology group), sole proprietorship (legal form). All models here have overlap weights applied.

5.2 Mechanism of impact

Having established that dual engagement significantly increases the likelihood of AET adoption, we now turn to the mechanisms driving this effect. Specifically, we ask two questions: (1) which component—R&D or exporting—matters more, and (2) does dual engagement generate a synergistic effect, i.e. an impact greater than the sum of its parts? To address this, we employ two complementary approaches: one emphasising interpretability and another designed for statistical robustness.

5.2.1 Approach 1: treatment–control comparisons

We divide the sample into five subsamples, each comparing different treatment and control groups:

1. Dual engagement vs. no engagement
2. Dual engagement vs. R&D only
3. Dual engagement vs. exporting only
4. R&D only vs. no engagement
5. Exporting only vs. no engagement

For each subsample, we re-estimate propensity scores (using the same covariates as before), construct overlap weights, and compute residuals. The weighted models are then estimated via OLS to recover the average treatment effect for each treatment–control comparison.

5.2.2 Approach 2: interaction model

To test for synergy more directly, we estimate a multinomial probit model predicting a firm's probability of belonging to one of four treatment states: dual engagement, R&D only, exporting only, or no engagement. These propensities are used to generate overlap weights and residuals, which are then included in a regression of AET adoption on R&D status, exporting status, and their interaction term. The coefficient on the interaction term (β_3) is of primary interest, as it captures whether the effect of dual engagement exceeds the additive effects of R&D and exporting individually.

5.2.3 Findings

Table 7 presents the results from the first approach. Dual engagement raises the likelihood of AET adoption by 11 percentage points compared with firms that do neither. However, when dual engagement is compared with R&D alone (Model 2) or exporting alone (Model 3), the effect is insignificant. R&D engagement by itself (Model 4) has the strongest effect: a 26.5-point increase relative to no engagement. Exporting alone (Model 5) has a modest but significant impact of 3.8 points. These results suggest that R&D is the primary driver of adoption, with exporting playing a secondary role, and that dual engagement does not generate a synergistic boost.

Table 7: Mechanism results – pooled estimates by different treatment/control groupings

	Dependent variable:				
	AET adoption				
	Dual v. Nothing	Dual v. R&D only	Dual v. Exporting only	R&D only v. Nothing	Exporting only v. Nothing
	(1)	(2)	(3)	(4)	(5)
Treatment	0.113***	-0.038	0.068	0.265***	0.038*
	(0.030)	(0.064)	(0.071)	(0.041)	(0.021)
Constant	0.133***	0.197*	0.071	-0.007	-0.039
	(0.047)	(0.102)	(0.092)	(0.033)	(0.026)
Controls	Yes	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes
Residuals	Yes	Yes	Yes	Yes	Yes
Observations	5,347	2,029	1,994	5,342	5,307
Adjusted R^2	0.064	0.063	0.062	0.056	0.028
F Statistic	14.125***	5.898***	5.712***	12.240***	6.526***

Note: *p**p***p<0.01. This table compares different treatments with different control groups. For each model, we estimate propensity scores across only firms which are in either that model's treatment or control group. Treatment estimates are then showing the average treatment effect of either dual engagement, R&D only, or exporting only compared to firms involved in nothing, only R&D, or only exporting. Reference groups are London (region), ICT/scientific/professional (sector technology group), sole proprietorship (legal form)

Table 8 confirms this conclusion using the interaction model. Across all years, the R&D × Exporting interaction term is statistically insignificant, reinforcing the absence of synergy. By contrast, R&D consistently exerts a strong and positive effect (5–18 points across years), while exporting has a smaller but still positive effect (5–8 points, significant in three years).

Table 8: Unpooled interaction model results

	Dependent variable:					
	AET adoption					
	All years	2018	2019	2020	2021	2022
	(1)	(2)	(3)	(4)	(5)	(6)
R&D × Exporter	-0.018	0.020	-0.015	0.011	-0.060	-0.073
	(0.017)	(0.026)	(0.032)	(0.043)	(0.042)	(0.052)
R&D Active	0.090***	0.050***	0.063***	0.086***	0.104***	0.177***
	(0.012)	(0.018)	(0.023)	(0.029)	(0.028)	(0.036)
Exporter	0.041***	0.028	0.014	0.062**	0.054*	0.083**
	(0.012)	(0.017)	(0.022)	(0.030)	(0.029)	(0.037)
Constant	0.093***	0.116**	0.092	0.123	0.072	0.116
	(0.031)	(0.047)	(0.059)	(0.084)	(0.072)	(0.098)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes
Residuals	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,336	1,981	1,681	1,007	1,453	1,214
Adjusted R^2	0.053	0.052	0.048	0.091	0.043	0.081
F Statistic	16.707***	5.156***	4.292***	5.043***	3.611***	5.133***

Note: *p**p***p<0.01 Reference groups are London (region), ICT/scientific/professional (sector technology group), sole proprietorship (legal form)

These results carry two important implications. First, R&D capability is the central channel through which firms acquire the absorptive capacity needed to integrate advanced technologies, whereas exporting alone provides only incremental benefits. Second, policies that encourage dual engagement may be most effective if they prioritise strengthening firms' R&D capacity, rather than assuming that exporting will amplify its impact. For firms themselves, the lesson is clear: international exposure helps, but without a strong R&D base, the adoption of cutting-edge technologies is unlikely to follow.

5.3 Robustness checks

To test the robustness of our core findings, we re-estimate the preferred specification (Table 5, Model 4) using alternative weighting schemes and a restricted sample. Specifically, we compare results from inverse probability of treatment weighting (IPTW) to our preferred overlap weights (Models 1–2 in **Table 9**). We also re-estimate the model on a time-limited sample that includes only firms observed in two or more years, allowing us to use lagged covariates (Models 3–4 in Table 9; see Section 4.2.2 for details).

Overall, the findings are broadly consistent with our main results. Using IPTW on the full sample produces an almost identical treatment effect to the overlap-weighted model (12 vs. 11 percentage points). On the restricted sample, the IPTW model suggests an even larger effect of 31.4 points, while the overlap-weighted model produces an insignificant estimate.

While these differences reflect the sensitivity of results to weighting choice and sample size, the consistency of the main full-sample estimates supports the robustness of our conclusions. The variation in effect sizes across the restricted models highlights the value of further research with richer longitudinal data to obtain more precise magnitude estimates. Importantly, these robustness checks also set the stage for our next analysis, which examines how the impact of dual engagement varies across different types of firms.

Table 9: Robustness check - full sample results with alternate weights

	Dependent variable: AET adoption			
	Overlap wts.	IPTW wts.	Overlap wts.	IPTW wts.
	(1)	(2)	(3)	(4)
Dual Engaged	0.113***	0.120***	0.025	0.314***
	(0.030)	(0.027)	(0.109)	(0.101)
Constant	0.133***	0.101***	-0.162	-0.081
	(0.047)	(0.029)	(0.117)	(0.077)
Sample	Full	Full	Time lmtd.	Time lmtd.
Controls	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
Residuals	Yes	Yes	Yes	Yes
Observations	5,347	5,347	860	860
Adjusted R^2	0.064	0.080	0.107	0.151
F Statistic	14.125***	17.693***	4.821***	6.643***

Note: *p**p***p<0.01. Reference groups are London (region), ICT/scientific/professional (sector technology group), sole proprietorship (legal form)

5.4 Heterogeneous effects

We next examine whether the impact of dual engagement on AET adoption varies across key firm characteristics: growth expectations, sector, firm size, and access to advice (Figure 2).

Gazelles. We begin with high-growth firms. A “gazelle” is typically defined as a firm experiencing three consecutive years of at least 20% growth. As we cannot observe past growth trajectories in our data, we use LSBS forecasts of turnover growth over the next 12 months. Firms expecting growth above 20% are classified as gazelles; those forecasting lower growth as non-gazelles. We find that dual engagement has a larger effect on AET adoption among gazelles (14 percentage points) compared to non-gazelles (7 points). However, these estimates are only weakly significant (90% confidence level).

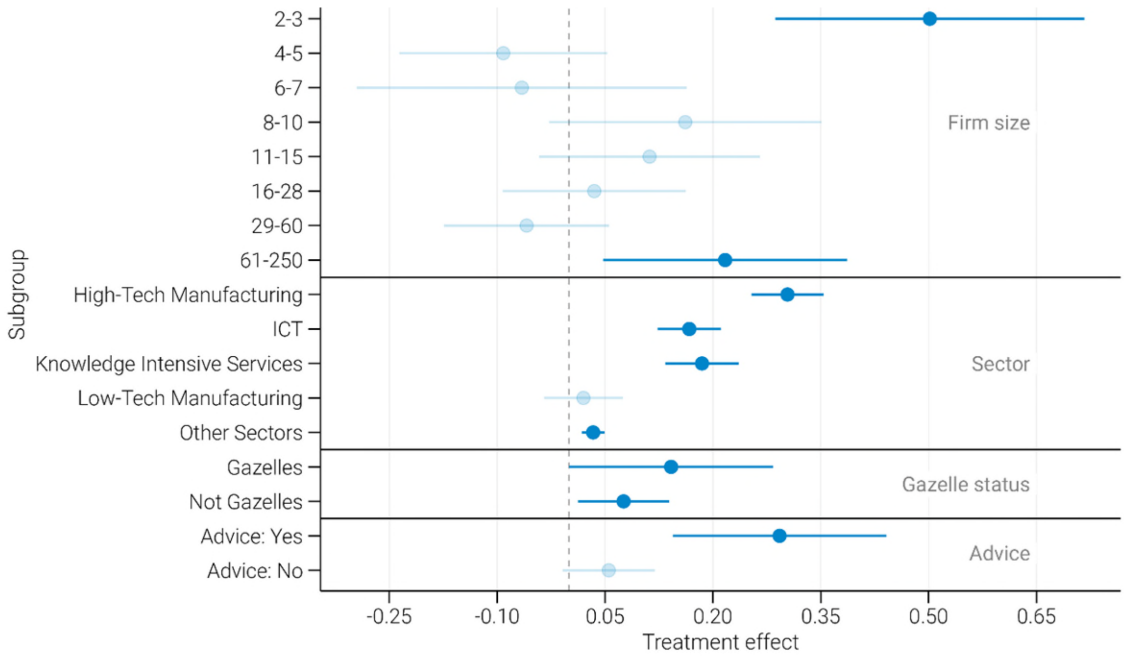
Sector. The treatment effect is strongest in technologically intensive industries. Dual engagement increases AET adoption by 30 points among high-tech manufacturers, 17 points among ICT firms, and 18.5 points among knowledge-intensive service providers. By contrast, the effect is insignificant for low-tech manufacturers and very small (3 points) in other service sectors.

Firm size. Splitting firms into eight quantile-based size groups, we find significant effects only at the extremes. Among the smallest firms (2–3 employees), dual engagement raises AET adoption by 50 points. Among the largest SMEs (60–249 employees), the effect is 22 points. For firms in the middle of the size distribution, the impact is not statistically significant.

Advice. Firms receiving advanced external advice show a much stronger effect of dual engagement than those without such support (29 vs. 5.5 points). This suggests that complementary managerial or strategic capabilities enhance the benefits of R&D and exporting for technology adoption.

Taken together, these results suggest that the benefits of dual engagement are far from uniform. They are concentrated among high-growth firms, technologically intensive sectors, the smallest and largest SMEs, and firms that supplement engagement with external advice. This points to important heterogeneity in how absorptive capacity and external linkages condition the effectiveness of dual engagement strategies.

Figure 1: Heterogeneity estimates, full results



While these subgroup results provide valuable insight into where dual engagement matters most, they are limited by the cross-sectional nature of the data. To further validate these findings and overcome sample constraints, we next extend our analysis by generating a synthetic panel using machine learning methods, enabling us to test the robustness of our conclusions with richer and larger data.

6. EXTENSION: CREATING A SYNTHETIC DATASET FOR PANEL ESTIMATIONS

6.1 Motivation and background

A central limitation of our analysis is data availability. Only a subset of LSBS respondents were asked about R&D and AET adoption, leaving us with a relatively small sample and making panel techniques infeasible. To address this constraint, we extend our study by generating a synthetic dataset using machine learning (ML). Our approach uses ML to predict which firms (a) engaged in R&D and (b) adopted AET, based on observable firm characteristics. These predictions enable the construction of a larger synthetic panel that can support further econometric modelling.

The objective of this section is not to derive new causal estimates. Rather, we are motivated by the following factors. First, it allows us to conduct more comprehensive analyses on an expanded sample. Second, the resulting estimates serve as a robustness check on our main findings. Third, the richness of LSBS—covering a wide range of firm-level characteristics—makes ML a natural methodological fit, particularly given its strength in handling high-dimensional data and non-linear relationships. Fourth, ML is now widely used in economics for prediction and classification tasks (*AMLEDS*, n.d.; Athey, 2019; Çağlayan Akay et al., 2022; Desai, 2023; Guerzoni et al., 2021; Heller et al., 2022; Shen & Xiu, 2025). Finally, this extension provides an opportunity to test novel, experimental methods on a policy-relevant question.

We emphasise that this exercise is exploratory. The ML analysis is not intended to be definitive or causal but rather to provide complementary evidence and stimulate further debate on the use of innovative methods in the study of technology adoption. In this way, it builds directly on our robustness checks and heterogeneity analysis, offering a further test of whether the patterns observed in the core sample hold in a larger, simulated dataset.

6.1.1 Predicting R&D engagement

Data preparation

The first step was data cleaning and preprocessing. We selected survey variables that (1) had minimal missing values, (2) were asked of all respondents, (3) displayed sufficient variance, and (4) could plausibly be related to R&D engagement. These covered firm size, scope, innovativeness, and general sophistication. A full list of predictors is provided in **Annex I**.

The training dataset included 8,209 observations, partitioned into an 80/20 training–testing split. A key challenge was class imbalance: only 26% of firms reported R&D engagement. To address this, we tested three common strategies: Synthetic Minority Oversampling Technique (SMOTE), undersampling of the majority class, and class weighting.

Models

We compared four widely used ML algorithms of increasing complexity: logistic regression (LR), random forest (RF), XGBoost (XGB), and a neural network (NN). Combined with the three imbalance corrections, this yielded 12 candidate models. All were trained using 5-fold cross-validation and standard hyperparameter tuning.[1]

[1] Specifically, we tune mtry (RF); boosting rounds, tree depth, and learning rate (XGB); size and decay (NN)

Performance assessment.

We prioritised **sensitivity** (true-positive rate) over overall accuracy. High sensitivity ensures that R&D-active firms are correctly identified, reducing the risk of biasing subsequent econometric analysis toward only the "obvious" R&D performers. This necessarily involved some trade-off with **specificity** (true-negative rate), meaning that a small share of non-R&D firms may be misclassified as R&D-active.

Each model generated predicted probabilities of engagement, which we converted into binary classifications using multiple thresholds (default = 0.5). We ultimately identified three model–threshold combinations that maximised sensitivity while maintaining acceptable levels of specificity and overall accuracy. These models, varying in conservatism versus aggressiveness, are reported in Table 10 and used in subsequent econometric analysis.

Table 100. Model performance comparison, metrics for different strategies

Model	Strategy	Threshold	Sensitivity	Specificity	Precision	F1 Score	Accuracy	Level
XGBoost	Cons. SMOTE	0.38	0.60	0.83	0.58	0.59	0.72	Conservative
Logistic	Weighted	0.60	0.79	0.68	0.49	0.60	0.74	Moderate
Neural_Net	Weighted	0.56	0.81	0.64	0.46	0.59	0.72	Aggressive

6.1.2 Predicting technological adoption

Data preprocessing and models

The procedure mirrors that for R&D engagement. The dependent variable is whether a firm adopted AET, based on a sample of 8,443 observations. Here too, class imbalance was pronounced (91.4% non-adopters vs. 8.6% adopters). We applied the same balancing methods (SMOTE, undersampling, class weighting) and tested the same four model types (NN, XGB, RF, LR) using 5-fold cross-validation.

Results

In this case, the best-performing models were all logistic regressions combined with weighting strategies. Performance metrics for the leading models are presented in **Table 11**.

Table 11. Model performance comparison, evaluation metrics for different strategies

Model	Strategy	Threshold	Sensitivity	Specificity	F1 Score	Precision	Accuracy
Logistic	Weighted	0.39	0.73	0.77	0.24	0.14	0.75
Logistic	Weighted	0.37	0.73	0.75	0.23	0.14	0.74
Logistic	Weighted	0.35	0.74	0.73	0.22	0.13	0.74

6.2 Panel methods and results

To test the robustness of our pooled estimates, we employ the Callaway and Sant'Anna (2021) difference-in-differences (DiD) estimator with multiple time periods. This approach allows us to compare the adoption trajectories of SMEs that became dually engaged in R&D and exporting at different points in time against a control group of firms that were never engaged.

Table 12 reports difference-in-differences estimates of the impact of dual engagement on AET adoption. Results are presented under three specifications—conservative, moderate, and aggressive—that are built on alternative samples generated through machine learning predictions of firms' R&D status. These samples vary according to the tuning parameters applied in the ML models, which adjust the balance between sensitivity and specificity in classifying whether a firm is engaged in R&D. The conservative specification reflects a stricter classification with higher specificity, the moderate specification balances sensitivity and specificity, and the aggressive specification favours sensitivity, thereby expanding the sample to include more predicted R&D-active firms.

Across all three samples, the overall treatment effect of dual engagement on AET adoption remains positive and statistically significant, though magnitudes differ. The conservative model yields the largest effect—around a 14 percentage point increase in adoption—while the moderate and aggressive models show smaller gains of 6–7 percentage points. When examined by treatment cohort, the 2019 and 2021 groups consistently display strong positive and significant impacts, confirming earlier results that these early adopters benefited most from dual engagement. In contrast, effects for the 2020 cohort are small and imprecise, while later cohorts (2022 and 2023) yield negative or null results, with the aggressive sample indicating particularly large adverse effects. This divergence across specifications suggests that the estimated impact is sensitive both to the timing of engagement and to how the ML-predicted R&D status is defined.

Table 12. Difference-in-Differences: Overall and By Cohort (Callaway & Sant'Anna, IPW-LS)

	(1)	(2)	(3)
	Conservative	Moderate	Aggressive
Overall ATT	0.144***	0.066**	0.059**
	(0.037)	(0.033)	(0.030)
ATT by Treatment cohort			
Group Average	0.098***	0.038	0.020
	(0.038)	(0.034)	(0.029)
Cohort 2019	0.161***	0.091**	0.080**
	(0.052)	(0.041)	(0.035)
Cohort 2020	0.059	0.036	0.074
	(0.079)	(0.077)	(0.093)
Cohort 2021	0.310***	0.156	0.137*
	(0.085)	(0.122)	(0.074)
Cohort 2022	-0.208	-0.295*	-0.631***
	(0.245)	(0.156)	(0.206)
Cohort 2023	-0.121	-0.075	-0.121*
	(0.099)	(0.097)	(0.070)
ATT by calendar year			
2019	0.233***	0.139***	0.114***
	(0.057)	(0.046)	(0.041)
2020	0.178***	0.060	0.041
	(0.057)	(0.046)	(0.044)
2021	0.252***	0.123**	0.125**
	(0.057)	(0.057)	(0.049)
2022	0.053	-0.103	-0.018
	(0.134)	(0.156)	(0.116)
2023	-0.095*	-0.037	-0.054
	(0.054)	(0.048)	(0.048)

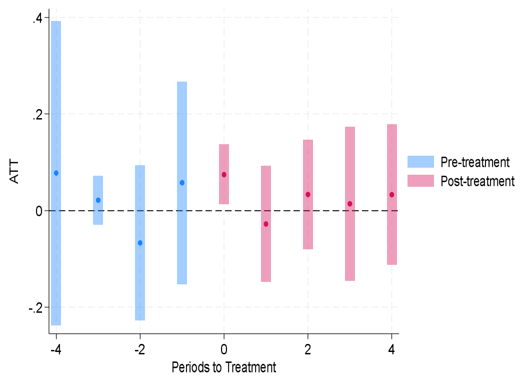
Notes: Conservative, moderate, and aggressive specifications are based on alternative samples derived from machine learning predictions of firms' R&D engagement. These samples vary by tuning parameters: the conservative specification prioritises specificity, the aggressive prioritises sensitivity, and the moderate balances the two. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Outcome model: least squares; Treatment model: inverse probability weighting; Control group: never treated.

Calendar-year estimates echo these findings. The years 2019–2021 show robust and significant increases in adoption across all specifications, while effects in 2022 and 2023 are weak or negative, regardless of sample. This reinforces the interpretation from previous pooled and unpooled models: dual engagement acts as a short-run catalyst for AET adoption, concentrated among early adopters, but it does not generate persistent effects for later cohorts. The reliance on ML-predicted R&D status underscores the importance of modelling assumptions—tuning parameters alter the sample composition and, in turn, the magnitude of the estimated effects. Nevertheless, the consistency of the positive impacts for early cohorts across all three approaches strengthens confidence in the conclusion that dual engagement provides an initial boost to technology adoption, though sustaining this momentum requires complementary capabilities and policy support.

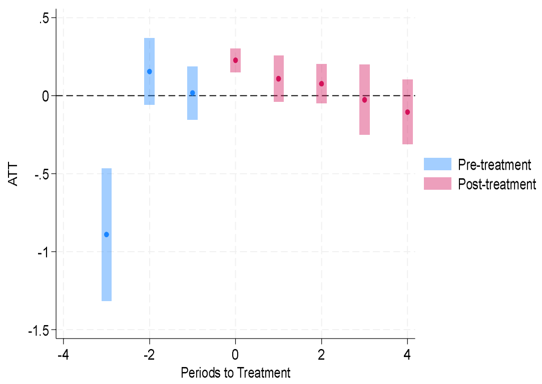
Figure 3 presents event-study estimates of the dynamic effects of dual engagement under the three alternative ML-based R&D prediction samples. Across all three panels, the results confirm the central pattern observed in **Table 12**: adoption effects emerge sharply at the point of treatment but fade quickly thereafter. In the conservative sample (Panel B), effects are tightly estimated with clear positive jumps at treatment and limited noise, reflecting the stricter classification of R&D-active firms. The moderate (Panel A) and aggressive (Panel C) samples, which include broader sets of predicted R&D-active firms, display greater variability, with wider confidence intervals and more fluctuation in post-treatment periods. Notably, all three panels show little evidence of strong pre-trends, reinforcing the validity of the identification strategy. Taken together, the findings show that while sample construction through ML tuning parameters influences the precision and size of estimates, the substantive conclusion holds consistently: dual engagement generates a short-run boost to AET adoption at the time of engagement but does not sustain continued increases in subsequent years.

Figure 3: Dynamic treatment effects from event-study specifications using alternative ML-based R&D samples

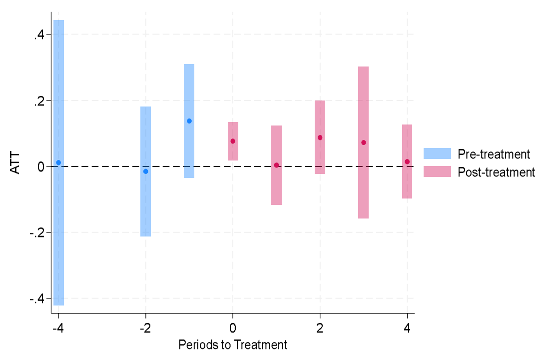
A) Moderate prediction on R&D



B) Conservative prediction on R&D



C) Aggressive prediction on R&D



Notes: Panels A–C report event-study estimates of the average treatment effect on the treated (ATT) for firms becoming dually engaged. Each panel corresponds to a different sample derived from machine learning predictions of firms' R&D status. The conservative specification (Panel B) prioritises specificity, the aggressive specification (Panel C) prioritises sensitivity, and the moderate specification (Panel A) balances the two.

7.CONCLUSION

This paper has examined the relationship between dual engagement—simultaneous participation in R&D and exporting—and the adoption of advanced and emerging technologies (AET) among UK SMEs. Using 7,336 firm-year observations from the Longitudinal Small Business Survey (LSBS), we applied propensity score weighting and a control function approach to address selection bias and endogeneity, and extended the analysis with machine learning methods to validate robustness.

Three key findings emerge. First, dual engagement significantly increases the probability of AET adoption: dually engaged firms are, on average, 11 percentage points more likely to adopt AET than those engaged in neither activity. Second, the effect is driven primarily by R&D engagement, with exporting playing a more modest role. R&D-active firms consistently show a higher probability of adoption, while exporting alone has only a small effect. Third, we find no evidence of a synergistic effect: dual engagement does not amplify adoption beyond the additive contributions of R&D and exporting. The results are particularly pronounced in 2022, when AET adoption rose sharply alongside the diffusion of generative AI, highlighting the role of dual firms as early adopters of transformative technologies.

These findings carry several implications. Theoretically, they reinforce the importance of absorptive capacity as a mechanism linking R&D to technology adoption, while suggesting that exporting is a complementary but secondary channel. Empirically, they highlight the persistent heterogeneity in SMEs: only a small share of firms combines innovation and internationalisation, but those that do are disproportionately likely to adopt frontier technologies. For policy, the results suggest that support for SME R&D is likely the most effective lever for accelerating AET adoption, with exporting support playing a supportive role. Policies that integrate innovation and internationalisation support—for example, linking R&D tax credits with export promotion schemes—may help build a larger pool of dually engaged, technology-ready firms.

At the same time, the analysis faces limitations. The LSBS data constrain us to a cross-sectional framework with limited coverage of R&D and AET questions, preventing a dynamic analysis of adoption pathways. The binary measures of engagement and adoption also obscure variation in intensity.

7.1 Areas for further research

Several avenues for future work emerge. First, richer longitudinal datasets would allow researchers to examine how firms transition into dual engagement over time, and whether technology adoption precedes or follows these activities. Second, distinguishing between types and intensities of R&D and exporting—for example, domestic versus international R&D collaborations, or export intensity by destination market—could reveal more nuanced effects. Third, disaggregating AET into specific technologies (AI, automation, robotics, VR/AR) would help identify whether dual engagement matters more for general-purpose technologies like AI than for niche applications. Fourth, future studies could investigate sectoral and regional ecosystems, testing how local clusters, supply chains, or export linkages shape the complementarity between R&D and exporting. Finally, exploring the role of policy interventions—such as export promotion programmes, or combined innovation–trade schemes—would offer direct evidence on how public policy can amplify or crowd-in private technology adoption.

In sum, dual engagement matters for SME adoption of advanced technologies, but the driving force is R&D. Strengthening SME innovation capacity remains essential if the UK is to accelerate adoption of transformative technologies and close gaps in productivity and competitiveness.

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ANNEX

Annex A: Survey administration dates

Survey year	Administration dates
2018	July 2018 - January 2019
2019	July 2019 -March 2020
2020	September 2020 - March 2021
2021	September 2021 - April 2022
2022	October 2022 - May 2023
2023	October 2023 - April 2024

Annex B: LSBS question descriptions and coding methodology

The core independent variable is a binary dual engagement indicator. The survey questions used to create this variable are:

J5: Has your business invested in R&D in the last three years?
C1_C2: Whether [the firm] export[s] goods or services?

The core dependent variable is a binary advanced and emerging technology adoption indicator. The survey questions used to create this variable are:

2018-2021

F11D: Which of the following do you use? Artificial intelligence, robotics, or automation. (Answer options are "AI, robotics, or automation" and "Not".)
F11E: Which of the following do you use? Virtual reality and augmented reality.

2022

1. **F11BA**: Which of the following production-enhancing technologies does your business use? Artificial intelligence (AI), robotics or automation. (Answer options are "AI, robotics, or automation" and "Not".)
2. **F11BF**: Which of the following production-enhancing technologies does your business use? Virtual reality (VR) and augmented reality (AR).

These dependent variable questions are child questions of a parent question, **F10**, which asks "Do you use any technologies or web-based software to sell to customers, or for use in the management of your business?" Firms which answer no to this question are not asked the child questions and therefore contain missing values for the subsequent child questions. Firms are coded as "YES – adopted AET technology" if they answered "yes" to either of the AET questions above in a given year. They are coded as "no" if they answered no to both or had missing values for both, as that indicates that they answered no to the parent question and do not use any technology.

The survey questionnaire for the latest year used in our analysis (2022) can be found at https://assets.publishing.service.gov.uk/media/650182ad5727800014251a4a/Small_Business_Survey_2022_-_Methodology.pdf

Annex C: Technology sector groups

The table below includes only sectors which are present in our analytic sample; for brevity, the table excludes "other service" sectors.

2 dig. SIC	Broad tech. group	SIC description
20	High-tech manufacturing	Manufacture Of Wood And Wood Products, Except Furniture
21	High-tech manufacturing	Manufacture Of Pulp, Paper And Paper Products
26	High-tech manufacturing	Manufacture Of Other Non-Metallic Mineral Products
27	High-tech manufacturing	Manufacture Of Basic Metals
28	High-tech manufacturing	Manufacture Of Fabricated Metal Products, Except Machinery And Equipment
29	High-tech manufacturing	Manufacture Of Machinery And Equipment Not Elsewhere Classified
30	High-tech manufacturing	Manufacture And Assembly Of Office Machinery And Computers
61	ICT, professional & scientific	Water Transport
62	ICT, professional & scientific	Air Transport
63	ICT, professional & scientific	Supporting And Auxiliary Transport Activities; Activities Of Travel Agencies
70	ICT, professional & scientific	Property Development
71	ICT, professional & scientific	Renting Of Machinery And Equipment Without Operator And Of Personal And Household Goods
72	ICT, professional & scientific	Computer And Related Activities
73	ICT, professional & scientific	Research And Development Activities
74	ICT, professional & scientific	Other Business Activities
75	ICT, professional & scientific	Public Administration And Defence; Social Security
10	Low-tech manufacturing	Mining Of Coal And Coal Extraction
11	Low-tech manufacturing	Extraction Of Crude Petroleum And Natural Gas; Service Activities Incidental To Oil And Gas Extraction
13	Low-tech manufacturing	Mining Of Metal Ores
14	Low-tech manufacturing	Other Mining And Quarrying
15	Low-tech manufacturing	Manufacturing Of Food Products And Beverages
16	Low-tech manufacturing	Manufacture Of Tobacco Products
17	Low-tech manufacturing	Manufacture Of Textiles
18	Low-tech manufacturing	Manufacture Of Wearing Apparel
22	Low-tech manufacturing	Publishing, Printing And Reproduction Of Recorded Media
23	Low-tech manufacturing	Manufacture Of Coke, Refined Petroleum Products And Nuclear Fuel
24	Low-tech manufacturing	Manufacture Of Chemicals And Chemical Products
25	Low-tech manufacturing	Manufacture Of Rubber And Plastic Products
31	Low-tech manufacturing	Manufacture Of Electrical Machinery And Apparatus Not Elsewhere Classified
32	Low-tech manufacturing	Manufacture Of Radio, Television And Communication Equipment And Apparatus
33	Low-tech manufacturing	Manufacture Of Medical, Precision And Optical Instruments, Watches And Clocks
65	Other KI Services	Financial Activities, Except Insurance And Pension Funding
66	Other KI Services	Insurance And Pension Funding, Except Social Security
80	Other KI Services	Education
85	Other KI Services	Health And Social Work
91	Other KI Services	Activities Of Membership Organisations Not Elsewhere Classified
92	Other KI Services	Recreational, Cultural And Sporting Activities
93	Other KI Services	Other Service Activities

Annex D: Covariates descriptions

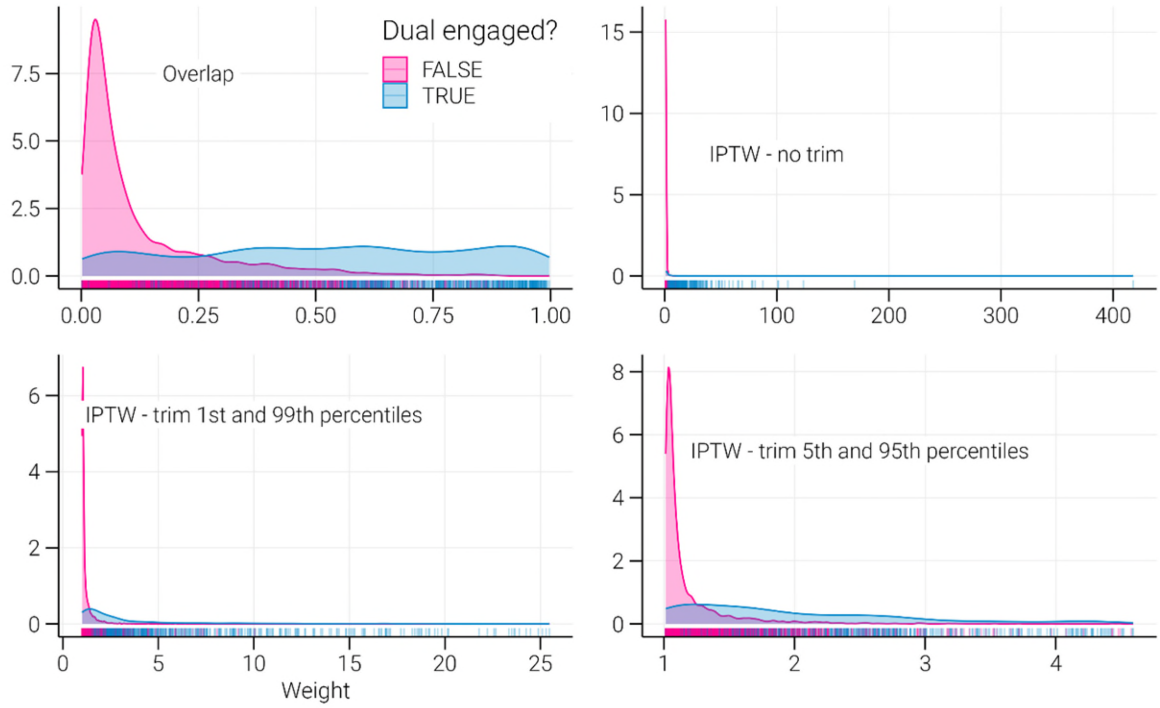
Firm demographics		
Urban or rural	Logical	Yes or no for if the firm is located in an urban or rural area
Legal form of organisation	Categorical	Firm's legal entity type - Company - Partnership - Sole proprietorship
Profitability	Logical	Yes or no for if the firm is profit-earning
Size	Continuous	Natural logarithm of the number of employees
Age	Continuous	Natural logarithm of firm age
Sector	Categorical	Technology sector group: - High and medium tech manufacturing - Low tech manufacturing - Knowledge intensive services - Other services - ICT, scientific, professional
Region	Categorical	Region group: - South East - Midlands, South West, East of England - Northern England - Scotland, Wales - Northern Ireland - London
Owner characteristics		
Family owned	Logical	Yes or no for if the firm is family-owned
Gender	Logical	Yes or no for if any of a firm's owners/directors/partners are female
Ethnic minority-status	Logical	Yes or no for if any of a firm's owners/directors/partners are ethnic minorities
Firm capabilities		
Management training	Logical	Yes or no for if a firm received external advice related to leadership/management training or development
Advanced advice	Logical	Yes or no for if a firm received external advice related to growth, technology, exporting, access to finance, innovation, relocation, and productivity
Entrepreneurial growth orientation		
Short-term growth expectations	Logical	Yes or no for if a firm expects to experience turnover growth in the next 12 months
Long-term growth expectations	Logical	Yes or no for if a firm expects to experience sales growth in the next 36 months

Annex E: Probability model results (Stage 1)

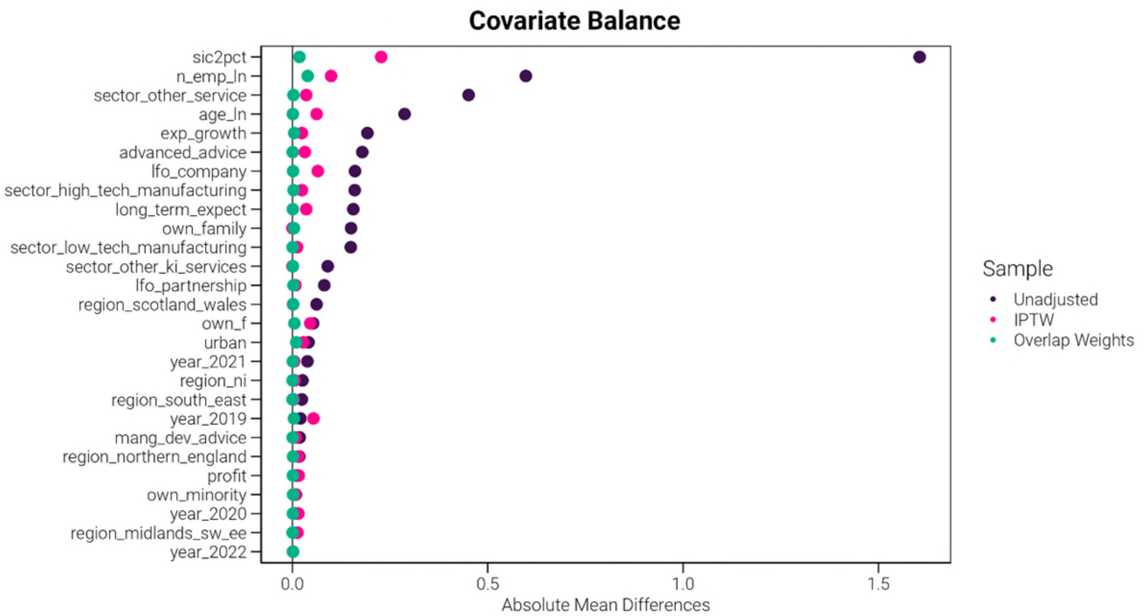
	OLS	Logit (ME)	Probit (ME)
(Intercept)	−0.106**		
	(0.033)		
profit	−0.005	0.003	0.002
	(0.011)	(0.011)	(0.011)
own_f	−0.002	−0.002	−0.003
	(0.008)	(0.008)	(0.008)
own_minority	−0.017	−0.015	−0.016
	(0.018)	(0.016)	(0.016)
own_family	−0.023*	−0.016+	−0.015+
	(0.010)	(0.009)	(0.009)
urban	−0.009	−0.011	−0.015
	(0.009)	(0.009)	(0.009)
mang_dev_advice	0.103**	0.072*	0.075*
	(0.039)	(0.033)	(0.036)
advanced_advice	0.135***	0.109***	0.112***
	(0.013)	(0.014)	(0.014)
exp_growth	0.046***	0.037***	0.036***
	(0.009)	(0.008)	(0.008)
long_term_expect	0.051***	0.078***	0.077***
	(0.011)	(0.012)	(0.011)
age_ln	0.017**	0.022***	0.022***
	(0.005)	(0.006)	(0.005)
n_emp_ln	0.044***	0.034***	0.032***
	(0.004)	(0.003)	(0.003)
year_2019	0.020+	0.019+	0.022*
	(0.012)	(0.011)	(0.011)
year_2020	−0.003	0.001	0.001
	(0.014)	(0.013)	(0.013)
year_2021	−0.020+	−0.017	−0.017
	(0.012)	(0.011)	(0.011)
year_2022	0.010	0.012	0.014
	(0.013)	(0.012)	(0.012)
sector_high_tech_manufacturing	−0.020	−0.049*	−0.043*
	(0.029)	(0.020)	(0.020)
sector_low_tech_manufacturing	−0.007	−0.007	−0.007
	(0.018)	(0.012)	(0.013)
sector_other_ki_services	−0.073***	−0.016	−0.007
	(0.020)	(0.021)	(0.020)
sector_other_service	−0.049**	0.003	0.006
	(0.015)	(0.013)	(0.013)
region_south_east	−0.028	−0.023	−0.025+
	(0.017)	(0.014)	(0.014)
region_midlands_sw_ee	−0.047**	−0.043***	−0.045***
	(0.015)	(0.013)	(0.013)
region_northern_england	−0.048**	−0.041**	−0.043**
	(0.016)	(0.013)	(0.013)
region_scotland_wales	−0.072***	−0.061***	−0.061***
	(0.017)	(0.013)	(0.013)
region_ni	0.075**	0.079*	0.078*
	(0.029)	(0.031)	(0.031)
lfo_company	0.016	0.090***	0.088***
	(0.017)	(0.026)	(0.023)
lfo_partnership	−0.035	0.014	0.022
	(0.021)	(0.043)	(0.040)
sic2pct	1.581***	1.096***	1.138***
	(0.058)	(0.049)	(0.050)
Num.Obs.	5347	5347	5347
R2 Adj.	0.429		
AIC	2202.9	2870.4	2863.1
BIC	2393.9	3054.8	3047.5
Log.Likelihood.	−1072.454	−1407.204	−1403.551
F	149.989	41.242	50.397
RMSE	0.30	0.28	0.28

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Annex F: Propensity score weight distributions



Annex G: Covariate balance



Var	Diff.Unadj	Diff.IPTW	Diff.OW
profit	0.03	0.04	0.00
own_f	0.11**	0.09***	0.01
own_minority	0.04	0.03	0.01
own_family	0.34***	0.00	0.01
urban	0.09*	0.06*	0.02
mang_dev_advice	0.14***	0.07**	0.01
advanced_advice	0.48***	0.09***	0.00
exp_growth	0.39***	0.05	0.01
long_term_expect	0.49***	0.11***	0.00
age_ln	0.29***	0.06*	0.00
n_emp_ln	0.60***	0.10***	0.04
year_2019	0.05	0.13	0.01
year_2020	0.02	0.05	0.00
year_2021	0.10**	0.01	0.00
year_2022	0.00	0.00	0.00
sector_high_tech_manufacturing	0.60***	0.09***	0.01
sector_low_tech_manufacturing	0.46***	0.04	0.00
sector_other_ki_services	0.36***	0.00	0.01
sector_other_service	1.01***	0.08**	0.01
region_south_east	0.07	0.01	0.00
region_midlands_sw_ee	0.00	0.03	0.00
region_northern_england	0.05	0.04	0.00
region_scotland_wales	0.18***	0.00	0.01
region_ni	0.14***	0.03	0.00
lfo_company	0.54***	0.22***	0.01
lfo_partnership	0.34***	0.03	0.01
sic2pct	1.61***	0.23***	0.02

* p < 0.05, ** p < 0.01, *** p < 0.001

Annex H: Firm size counts

Size category	Number of employees	N Firms
1	[2,3]	954
2	(3,5]	690
3	(5,7]	454
4	(7,10]	640
5	(10,15]	622
6	(15,28]	651
7	(28,60]	715
8	(60,249]	621

Annex I: Machine learning features

We use the following features to predict R&D activity:

- Log of number of employees
- Log of turnover
- Indicator for if a firm received *any* external advice
- Indicator for if a firm received *advanced* advice (related to business growth, e-commerce, exporting, sourcing finance, productivity, innovation, or relocation)
- Log of number of sites
- Log of number of contractor, agency, or self-employed staff
- Whether a firm has separate business premises
- If firm has a formal business plan (0 = no, 1 = yes, not kept updated, 2 = yes, kept updated)
- Indicator for if a firm receives the following types of finance: equity, government schemes
- Indicator if firm introduced new goods or services to market
- Region groups
- Sector technology group
- Legal status
- Year dummies

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