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Difference-in-differences assessment of impacts on SMEs

Report to Energy Systems Catapult

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Executive Summary

Context and scope

1. Following the 2010 Hauser Review of innovation centres and their contribution to the UK's technological progress, the government established the UK Catapult Programme. The network has since grown to nine Catapults operating across more than 65 locations nationwide. The Catapults were set up as independent not-for-profit organisations, with the shared aim of closing the gap between promising technological concepts and their route to commercialisation.

2. Energy Systems Catapult (the Catapult) launched in Birmingham in 2015, reflecting the growing importance of the Net Zero agenda. It now employs more than 220 specialists across technical, engineering, commercial and policy disciplines, supported by sector-leading test facilities and modelling tools. The Catapult's mission is to accelerate Net Zero transition, by helping the companies it supports to become global leaders in energy innovation. It pursues this goal by:

   - helping innovators test, trial and scale new products and services using state-of-the-art test and demonstration environments, and
   - offering the firms the necessary expertise to identify the best way to grow their business: clarify their route to market and their position within the value chain, secure customers, attract investment.

3. The Catapult takes an evidence-driven approach to its work and in 2026 commissioned SQW to undertake the second wave of quasi-experimental assessment of its impacts on supported companies. Similar to the first iteration of the analysis (which was published in 2025)[1] this study covered Small and Medium Enterprises (SMEs) that the Catapult engaged with through its Energy Launchpad Platform (including Incubation, Acceleration, Innovator Challenge Calls, and Investor Readiness Support), collaborative R&D projects using the Catapult's Living Lab (a community of over 5,000 connected smart homes spread across the UK), and other activities that help SMEs to commercialise energy system innovations.

4. The key outcomes of interest for the analysis included employment, turnover, assets, and whether the support helped supported SMEs attract further external finance (e.g. grants or equity) or increase their valuation. The work also included modelling the impacts of the Catapult's support in terms of additional Gross Value Added (GVA) generated by supported SMEs, and a programme of qualitative interviews to aid the interpretation of results and inform assumptions for the GVA modelling.

[1] SQW, 2025. *Difference-in-differences Analysis of SME Impacts*. Energy Systems Catapult

5. Wider anticipated impacts of the Catapult's work (such as generating well-being and distributional benefits for the population, driving innovation and decarbonisation in adjacent sectors, facilitating R&D knowledge transfer, and contributing to the development of the Net Zero economy) were out of scope, since they are inherently difficult to identify using quasi-experimental designs.

Approach and methods

6. Our core analysis focused on estimating the impact of the Catapult's support using a difference-in-differences (DiD) design, i.e. by comparing the trajectories of supported SMEs against comparator companies over time. The primary comparison group was selected from the wider UK business population using statistical matching techniques, to enable a comparison against unsupported companies with similar profiles, including on metrics of their innovation activity and involvement in the development of particular types of technologies. The complementary comparison group included unsuccessful applicants and recipients of light-touch support, who provided a strong comparison on otherwise unobservable characteristics such as growth aspirations and propensity to seek support from the Catapult.

7. We implemented the DiD analysis using Bayesian econometric methods. The Bayesian approach allowed us to incorporate prior evaluation and academic evidence into the analysis, helping us extract a signal about the relationship between the Catapult's support and business outcomes from relatively small samples. This approach also provided us with additional tools to test the robustness of our conclusions and allowed us to characterise the uncertainty in the estimates more fully, avoiding an overreliance on the concept of statistical significance, where nearly identical results could be interpreted differently depending on which side of the significance threshold they would fall on.

8. The main data sources underpinning the analysis included: monitoring data provided to us by the Catapult, Beauhurst and Data City datasets, and the Business Structure Database (BSD), a research version of the Inter-Departmental Business Register which we accessed through the ONS's Secure Research Service (SRS).

9. Informed by the results of the DiD analysis, we developed a bespoke Monte Carlo simulation model that translated the econometric estimates of net employment impacts into Gross Value Added (GVA) generated by supported SMEs. We followed a simulation approach to systematically capture the uncertainty in the econometric estimates as well as in the scale of impacts across supported firms, reflecting that some supported SMEs inevitably performed better than others.

10. Although a formal cost-benefit analysis and wider Value for Money assessment remained outside the scope of this assignment, we compared the resulting GVA estimates against the

value of the Catapult's core grant funding to provide an indicative benefit-to-cost ratio (BCR), based on a conservative and partial view of the benefits.

11. The quantitative analysis was supplemented by seven interviews with supported SMEs, deliberately including both the most successful companies and those with more modest outcomes. These discussions explored how the consultees used the Catapult's support and how it interacted with other factors relevant to their outcomes, informing several of the assumptions underpinning the GVA model.

Findings

Overall assessment

12. Overall, based on our quantitative and qualitative evidence, the Catapult's support was strongly associated with the growth of supported SMEs, particularly during the earlier stages of their commercialisation journey. Employment among supported SMEs was found to be, on average, approximately 17% higher than the counterfactual trajectory, with the effects persisting for up to three years after support. Supported SMEs were also more likely to secure external finance, and the finance they secured was substantially larger in scale than would be expected under the counterfactual, which was also reflected in a considerably larger asset base than that of similar unsupported companies. We were not, however, able to statistically identify any impacts on either turnover growth or valuations of supported companies.

13. Based on our impact analysis and simulation modelling, we estimated that the Catapult's support generated approximately £210m in additional GVA across the SMEs it has supported since 2018, of which the majority had already been realised. The corresponding estimate for the subsample of SMEs supported since the start of the current core grant period in 2023/24 was £72m. These figures are expressed in 2025 prices (as of end of year).

14. Comparing these estimates against the Catapult's core grant funding (£101.4m since 2018; £37.7m since the start of the current grant period, in 2025 prices) indicated that every £1 of public investment generated approximately £2 of additional GVA. This is an indicative and deliberately conservative comparison rather than a formal benefit-to-cost ratio, because the core grant funding covers activities beyond the SME support included in the benefits estimate.

15. These findings pointed towards good value for money, particularly since the analysis captured only direct benefits to supported SMEs, while excluding wider indirect effects such as additional activity generated through the supported SMEs' supply chains. In addition, the estimate did not cover any potential GVA benefits to the UK from the Catapult's wider work driving innovation in the clean energy sector, for example potential system-level savings from the Catapult's impact in accelerating the development of a lower-cost, flexible future energy system.

Econometric results

16. Table 1 summarises the estimated effects across the outcome measures, based on our preferred model specification for each.

Table 1: Summary of estimated effects

Outcome	Central estimate
Employment	+16.8%
Probability of securing external finance (grants, equity, loans)	+10 p.p.
Cumulative value of external finance secured (grants, equity, loans)[2]	+735%
Total assets	+72.5%
Current assets	+73.4%
Turnover	No reliable effect identified
Company valuations	No reliable effect identified

Source: SQW

17. Employment among supported SMEs was estimated to be, on average, 16.8% higher than the counterfactual trajectory. This finding proved to be highly robust to the choice of model specifications (including prior expectations about the scale of effects based on the existing literature) and comparison groups: the central estimates from the well-performing specifications remained positive and within the uncertainty interval of our preferred estimate.[3] The effects persisted for up to three years after support, before weakening in the fourth year, possibly reflecting a reduced number of observations available that far out rather than a genuine decline in impact.

18. Supported SMEs were also more likely to secure external finance following their engagement with the Catapult, with the predicted probability of securing grants, loans or equity rising by 10 percentage points (from 59% to 69%), and by 13 percentage points for grant funding specifically (47% to 60%). The amounts raised were also substantially larger than implied by the counterfactual trajectory, with supported SMEs securing £791m in external finance after the start of support, of which, according to our modelling, approximately £300m was additional. Further analysis confirmed that the magnitude of the estimate was not driven by a

[2] This is a relative effect, to some degree driven by SMEs moving from no external finance to attracting it. See the discussion in Section 4 and the £791m / £300m figures below.

[3] Model performance was assessed using out-of-sample predictive power (leave-one-out cross-validation). Well-performing specifications were those with statistically indistinguishable predictive power from our best model.

small number of exceptionally large investments, but reflected a broader increase in the number of supported SMEs successfully securing funding.

19. The findings on the higher success in securing external finance were corroborated by the results for total and current assets, both estimated to be around 73% higher than their respective counterfactual trajectories. Since external funding is ultimately reflected on company balance sheets, this consistency between the finance and asset findings strengthened our confidence in both.

20. At this stage, we did not have enough evidence to suggest that the Catapult's support consistently affected turnover or company valuations during the observation period. Supported SMEs continued to grow their turnover, but at a rate broadly comparable to that observed among the comparison groups. In our Bayesian models, the estimates for the additional growth varied considerably from model to model depending on the assumptions, and specifically the expectations about the scale of potential effect informed by prior evidence. A more standard frequentist approach also did not identify any statistically significant effects. Taken together, these results indicated that the underlying data did not contain a sufficiently strong signal about the relationship between the Catapult's support and SMEs' turnover.

21. Likewise, although some supported SMEs experienced substantial increases in company valuations, the available evidence did not suggest a systematic effect across the population of firms supported by the Catapult. We note, however, that post-support data was available for only a limited number of supported SMEs and comparator companies, severely constraining our ability to detect an effect even if one were present.

22. One possible explanation for the lack of detectable impacts on turnover and valuations is that both reflect later-stage commercial outcomes. While our analysis found evidence that supported SMEs were securing additional resources and expanding their organisational capacity, it often takes time for these changes to translate into stronger commercial performance. This interpretation was corroborated by our qualitative evidence: several supported SMEs reported that, having received the Catapult's support largely at the technical product development stage, they now lacked the internal commercialisation and sales expertise needed to translate their progress into commercial success, identifying this as the main barrier to growth. Other consultees pointed to external market and regulatory conditions as a further factor slowing this transition.

Estimates of economic impact

23. Our economic impact model expressed the estimated impacts on employment of supported SMEs in GVA terms. In addition to the econometric results, the model relied on two key assumptions: displacement (set at 20%, reflecting the extent to which supported SMEs could displace economic activity elsewhere) and attribution of additional employment to the support rather than other contributing factors (set at 80% in the year of support, declining by 10 percentage points in each subsequent year). Both parameters were informed by qualitative

interviews and wider evaluation expertise. The findings were also subject to sensitivity testing.

24. Of the £210m in additional GVA estimated across the whole period, £154m had already been realised at the time of analysis, with the remaining £56m expected to materialise by 2029 as the effects of more recent support continued to come through.

25. Table 2 below summarises the estimated additional GVA generated by the Catapult's support, distinguishing between benefits already realised and those still expected in the future, for both the whole period since 2018 and the subsample of SMEs supported since the start of the current core grant period in 2023/24.

Table 2: GVA impacts from support

	Mean (expected) value	95% confidence interval
Full population of supported SMEs		
Additional GVA	£210m	£176m – £249m
Realised	£154m	£126m – £185m
Expected	£56m	£44m – £72m
Support since 2023/24 onwards		
Additional GVA	£72m	£54m – £94m
Realised	£26m	£19m – £35m
Expected	£46m	£34m – £63m

Source: SQW

26. The sensitivity testing reinforced our overall conclusion that the Catapult's support was likely to represent good value for money. Even in the most pessimistic scenario, the central estimate of benefits exceeded the core grant funding. For the full period since 2018, the entire 95% confidence interval (£105m-£150m) in that scenario was above the £101.4m invested. The lower limit of the confidence interval fell below the grant value only for the more recent subsample, where the estimate did not yet cover all SMEs expected to be supported by the end of the grant period. At the other extreme, in the most favourable scenario, even the lower limit of the confidence interval reached over 2.5 times the public investment for the full period since 2018 (£259m), and over double the investment for the current grant period (£79m).

1. Introduction

1.1 Following the 2010 Hauser Review of innovation centres and their contribution to the UK's technological progress, the government established the UK Catapult Programme.[4] The network has since grown to nine Catapults operating across more than 65 locations nationwide. Innovate UK set up the Catapults as independent not-for-profit organisations, with the shared aim of closing the gap between promising technological concepts and their route to commercialisation. In practice, they:

- provide companies with the expertise and facilities needed to bring new products, processes and services to market
- bring industry, research organisations and academia together to collaborate
- help derisk innovation activity, particularly for smaller firms
- support work that strengthens the UK's knowledge base and competitiveness.

1.2 Energy Systems Catapult (the Catapult) launched in Birmingham in 2015, reflecting the growing importance of the Net Zero agenda. It now employs more than 220 specialists across technical, engineering, commercial and policy disciplines, supported by sector-leading test facilities and modelling tools. As with others in the network, the Catapult receives core government grants from Innovate UK, which part funds its activity. Other sources of funding include competitive business-funded research and development (R&D) contracts, and collaborative R&D projects (funded jointly by the public and private sectors).

1.3 The Catapult's mission is to accelerate Net Zero innovation, with a strategic goal for UK companies it supports to become global leaders in energy innovation. It pursues this by helping innovators test, trial and scale new products and services; clarify their route to market and position within the value chain; secure customers; attract investment; and grow their businesses, drawing on the expertise of its staff as well as state-of-the-art test and demonstration environments.

Objectives and scope of this report

1.4 The Catapult takes an evidence-driven approach to its work. It has published annual impact reports and developed an Evaluation Framework for the 2023/24-2027/28 core grant funding period, which sets out the Catapult's Logic Model (see Annex A) and a detailed evaluation plan informed by the best-practice principles in the Magenta Book.[5] The Framework adopted a theory-based approach to evaluation, grounded in the principles of

[4] Hauser, H., 2010. The current and future role of technology and innovation centres in the UK.
[5] HMT Magenta Book: Central Government guidance on evaluation (2026)

contribution analysis, involving an iterative review of quantitative and qualitative evidence to build a narrative of how the Catapult generated impacts alongside other factors affecting the companies they support.[6] As part of its evaluation activity, and to supply quantitative evidence for that contribution narrative, the Catapult previously commissioned a scoping study to establish the feasibility of a difference-in-differences (DiD) approach, followed by a first wave of DiD analysis, published in 2025.[7]

1.5 This report presents the findings of the second wave of quasi-experimental analysis. Compared with the first wave, the scope of this study was wider: alongside the DiD analysis, we modelled the economic impacts of the Catapult's support in terms of additional Gross Value Added (GVA), and supplemented the quantitative findings with qualitative discussions with supported SMEs. These discussions aimed to fill gaps in the quantitative evidence, providing insight into how companies used the support and how it interacted with other factors in shaping their outcomes.

1.6 Similar to the previous wave of analysis, this study covered Small and Medium Enterprises (SMEs) that the Catapult engaged with through its Energy Launchpad Platform (including Incubation, Acceleration, Innovator Challenge Calls, and Investor Readiness Support), collaborative R&D projects using the Catapult's Living Lab (a community of over 5,000 connected smart homes spread across the UK), and other in-depth engagements to commercialise energy system innovations. Through these channels, the Catapult provided SMEs with bespoke innovation needs assessments, in-depth consumer research and insights, testing and trialling of new products and services, technical and commercial expertise (including energy markets, regulation, and their implications for business models), mentoring and coaching, and facilitating partnerships and networks with potential customers and investors.

1.7 The key outcomes of interest included employment, turnover, total and current assets, and whether the support helped supported SMEs attract further external finance (e.g. grants or equity) or increase their valuation. Wider anticipated impacts of the Catapult's work (such as generating well-being and distributional benefits for the population, driving innovation and decarbonisation in adjacent sectors, facilitating R&D knowledge transfer, and contributing to the development of the Net Zero economy) were out of scope since they are inherently difficult to identify using quasi-experimental designs.

Approach and methods

1.8 Our core analysis focused on estimating the impact of the Catapult's support using a difference-in-differences (DiD) design, i.e. by comparing the trajectories of supported SMEs against comparator companies over time. The comparison group included unsuccessful

[6] Mayne, J., 2008. Contribution analysis: An approach to exploring cause and effect.
[7] SQW, 2025. *Difference-in-differences Analysis of SME Impacts*. Energy Systems Catapult.

applicants and recipients of light-touch support, who provided a strong comparison on otherwise unobservable characteristics such as growth aspirations and propensity to seek support from the Catapult, and unsupported companies selected from the wider business population.

1.9 To identify comparator companies from the wider business population, we primarily used Propensity Score Matching (PSM), which selected companies similar to supported SMEs across a mix of observable characteristics (such as age, location, and sector). We also investigated a machine learning technique, decision trees, as a possible way to complement PSM, but subsequent robustness testing led us to rely on PSM alone for the final comparison group (see Section 3 for further detail).

1.10 The main data sources underpinning the analysis included: monitoring data provided to us by the Catapult, Beauhurst and Data City datasets, and the Business Structure Database (BSD) – a research version of the Inter-Departmental Business Register which we accessed through the ONS's Secure Research Service (SRS).[8]

1.11 We implemented the DiD analysis using Bayesian econometric methods. The Bayesian approach allowed us to incorporate prior evaluation and academic evidence into the analysis, helping us extract a signal about the relationship between the Catapult's support and business outcomes from relatively small samples, and gave us the tools to test the robustness of our conclusions across a range of expectations about the outcomes.[9]

1.12 A further advantage of the Bayesian approach for this project was in how it characterised uncertainty, providing a full statistical distribution around the central estimates, derived from the data and our prior expectations about the result. This additional information gave us the grounds to reach a more thorough verdict on the nature of the support's effects, considering both the likelihood of a positive effect and the likelihood that the effect was large enough to matter, rather than collapsing the results into a binary significant/non-significant judgement (which sometimes can lead to almost identical results being treated as completely different findings depending on which side of the threshold they fall on).

1.13 Informed by the results of the DiD analysis, we developed a bespoke Monte Carlo simulation model to estimate the additional Gross Value Added (GVA) generated by the SMEs as a result of the Catapult's support. We followed a simulation approach to capture the uncertainty in the econometric estimates as well as the scale of impacts across supported firms in a systematic and transparent way, reflecting that some supported SMEs inevitably performed better than others over the medium term.

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[8] Office for National Statistics, released 18 May 2026, ONS SRS Metadata Catalogue, dataset, Business Structure Database - UK, https://doi.org/10.57906/7kh0-0910

[9] We further explain this point in Section 4 of the report, where we present the results of the econometric analysis.

1.14 The quantitative analysis was supplemented by seven interviews with supported SMEs. The sample deliberately included both the most successful companies and those with more modest outcomes. These discussions explored how the consultees used the Catapult's support and how it interacted with other factors relevant to their outcomes, helping to explain the differences in success observed across the supported population. They also provided additional evidence for the GVA model, in particular informing our assumptions about the extent to which observed outcomes could be attributed to the Catapult's support as opposed to other factors, internal or external to the businesses.

1.15 The rest of this report is organised as follows. Section 2 characterises the companies receiving the Catapult's support. Section 3 describes how we selected the comparison groups. Section 4 presents the results of our impact analysis. Section 5 summarises the findings from our qualitative discussions with supported SMEs. Section 6 presents the estimates of economic impact attributable to the Catapult's support, and Section 7 provides our reflections on the findings. The main body of the report is accompanied by four annexes. Annex A presents the Logic Model, Annex B provides supplementary statistical detail (such as outputs from robustness tests), Annex C describes our approach to sampling and recruitment for the qualitative discussions and Annex D presents the results of the economic impact estimations using an alternative methodology.

2. Supported SMEs

Key points

- Between April 2018 and January 2026 the Catapult provided in-depth support to 288 SMEs. The four financial years between 2020/21 and 2023/24 accounted for around 77% of all first-time interactions with supported SMEs.
- SMEs working with the Catapult are heavily concentrated in three sectors of the economy: professional, scientific and technical services; information and communication; and manufacturing. Together, these account for around three-quarters of the population and are all substantially overrepresented relative to the wider UK business base.
- Supported firms demonstrate high innovation and growth potential: most of the SMEs are linked to modern sector classifications (buzzwords or RTICs) centred on clean technology and net zero, and a majority have secured Innovate UK funding, R&D grants, or are formally tracked by Beauhurst as high-growth or high-potential businesses.
- Supported SMEs are concentrated in London and the South-East, alongside a notably strong presence in Scotland and the West Midlands, both of which are established hubs for low-carbon and net zero economic activity.
- Before engaging with the Catapult, supported SMEs were, on average, six years old and employed 15 people at the point of first support, though the median figures (four years old, five employees) show that many were at the smaller end of the spectrum with clear room to grow.

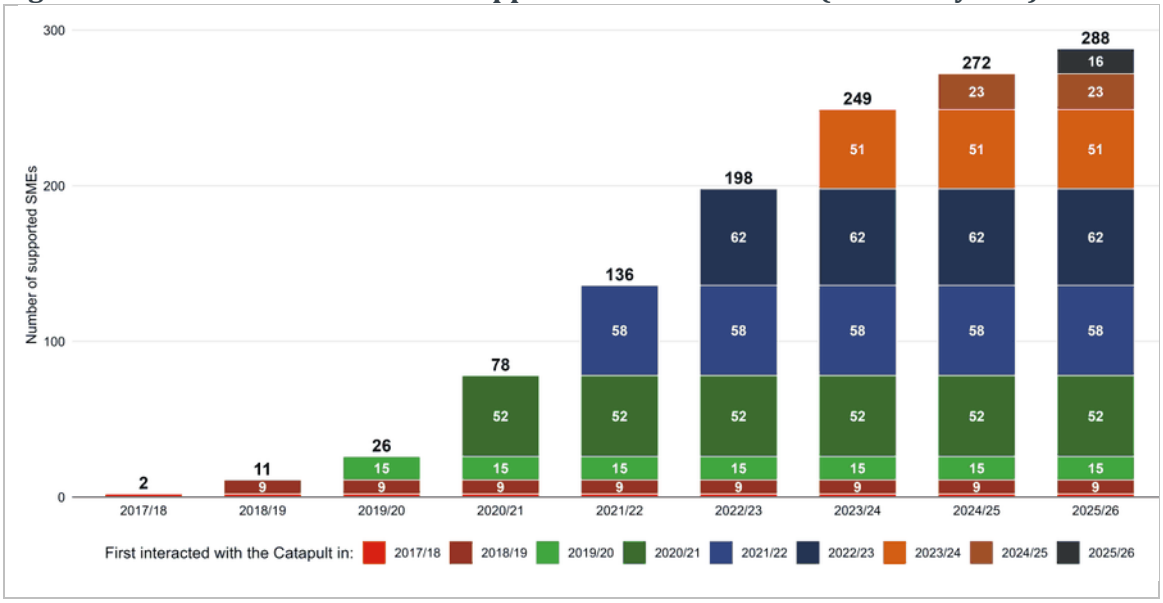
2.1 This section profiles the SMEs supported by the Catapult on key characteristics, including their age, size, geographical location, economic sector, innovation activity, and when they accessed the support. This descriptive analysis was based predominantly on the Catapult's monitoring data, Beauhurst, and the Data City. We were able to find all supported SMEs in those datasets. The data was also linked to the BSD (by the SRS team), with a match rate of approximately 90%.[10]

[10] Not all companies can be found in BSD due to failure to meet the criteria for inclusion (e.g. being registered for PAYE), or an incorrect or otherwise missing company registration number (CRN).

Time profile of the support

2.2 According to the monitoring data, to January 2026 the Catapult provided in-depth support to 288 SMEs. As shown in Figure 2-1, support started on a relatively small scale, with fewer than 30 companies supported across the first three financial years combined. From 2020/21 onwards, the scale of the programme increased substantially, peaking in 2022/23 when 62 new SMEs were supported in a single year. Four financial years, 2020/21 to 2023/24, account for around 77% of all supported companies.

Figure 2-1: Cumulative number of supported SMEs over time (financial years)



Source: SQW

2.3 Because the Catapult provides bespoke support to SMEs depending on their needs and plans, firms can engage with the Catapult in relation to multiple projects, meaning some SMEs interacted with the Catapult more than once. The monitoring data provided us with the dates of these interactions between the Catapult and each supported company.

2.4 Of the 288 supported SMEs, 86 (30%) engaged with the Catapult on more than one occasion. For repeat participants, for the purposes of the core analysis, we took the date of their first interaction as the start of their support period. Given that a substantial share of SMEs were first supported only in the past two to three financial years, our analysis is likely to reflect predominantly short- to medium-term effects of the Catapult's support. We also investigated the possibility of estimating the effects of repeat support. We discuss this further analysis in Section 4 of this report.

Characteristics of supported SMEs

Sector and innovation focus

2.5 Supported SMEs are highly concentrated in three sectors of the economy, according to their primary SIC 2007 code: professional, scientific and technical activities (section M); information and communication (section J); and manufacturing (section C). Together, these three sectors account for around three quarters of all supported SMEs. Each is substantially overrepresented compared with the UK's wider business population, by margins ranging from around 14 to 18 percentage points (Table 2-1).

Table 2-1: Top sectors of supported SMEs

Sector (SIC 2007)	Supported SMEs (#)	Supported SMEs (%)	Wider business population (%)
M – Professional, scientific and technical activities	84	29.2%	15.3%
J – Information and communication	73	25.3%	6.9%
C – Manufacturing	57	19.8%	4.8%
Other sectors	74	25.7%	73.0%

Source: SQW analysis of Beauhurst and UK Business counts[11]

2.6 Both Beauhurst and the Data City developed their own indicators of activity in modern and emerging sectors. Beauhurst links firms to 'buzzwords', whereas the Data City uses machine learning to assign Real-Time Industrial Classification codes (RTICs).[12] 227 of the supported SMEs (79%) are associated with at least one buzzword, most commonly 'CleanTech' (194 supported SMEs, 67%) and 'clean renewable energy' (171 supported SMEs, 59%). Similarly, 178 supported SMEs (62%) have an RTIC code, with 154 (53%) specifically assigned the 'Net Zero' RTIC. The classification of supported SMEs into modern sectors is similar across the two platforms and, crucially, is well aligned with the sectors and activities that the Catapult targets (Figure 2-2).

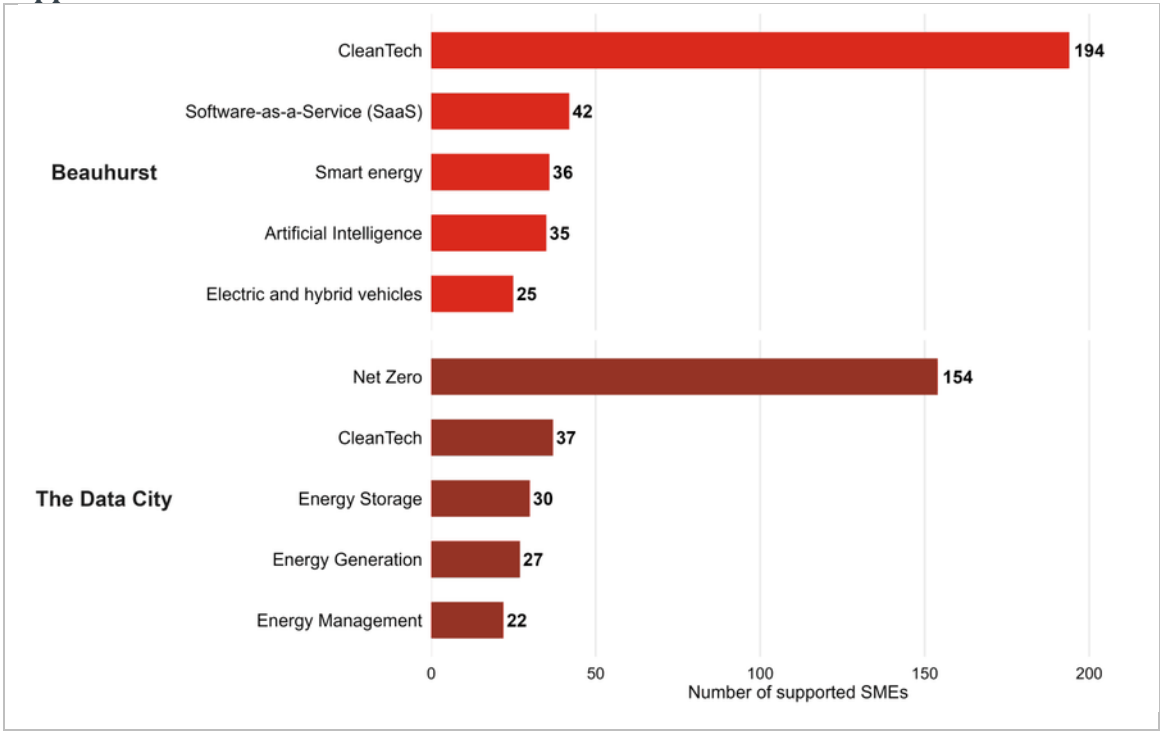
2.7 The fact that most supported SMEs are linked to either a buzzword or an RTIC also provides an indication of their high innovation activity, since these classifications tend to represent newer sectors reliant on cutting-edge technology. This pattern is reinforced by other

[11] ONS, UK Business: Activity, Size and Location (2025)

[12] Examples of Beauhurst buzzwords include: CleanTech, FinTech, Internet of Things, Quantum, etc. RTICs are the Data City's proprietary form of industrial classification, based on web-scraped data and built using machine learning. RTICs are based on how companies describe themselves on their websites.

innovation signals recorded in Beauhurst: 122 supported SMEs (42%) had secured an R&D grant, 61 (21%) held a patent, and 22 (8%) were academic spinouts. The innovation focus of supported SMEs is also evident in the high proportion receiving Innovate UK funding (59%, 169 firms).

Figure 2-2: Beauhurst buzzwords and the Data City RTICs most common among supported SMEs



Source: SQW analysis of Beauhurst and the Data City data

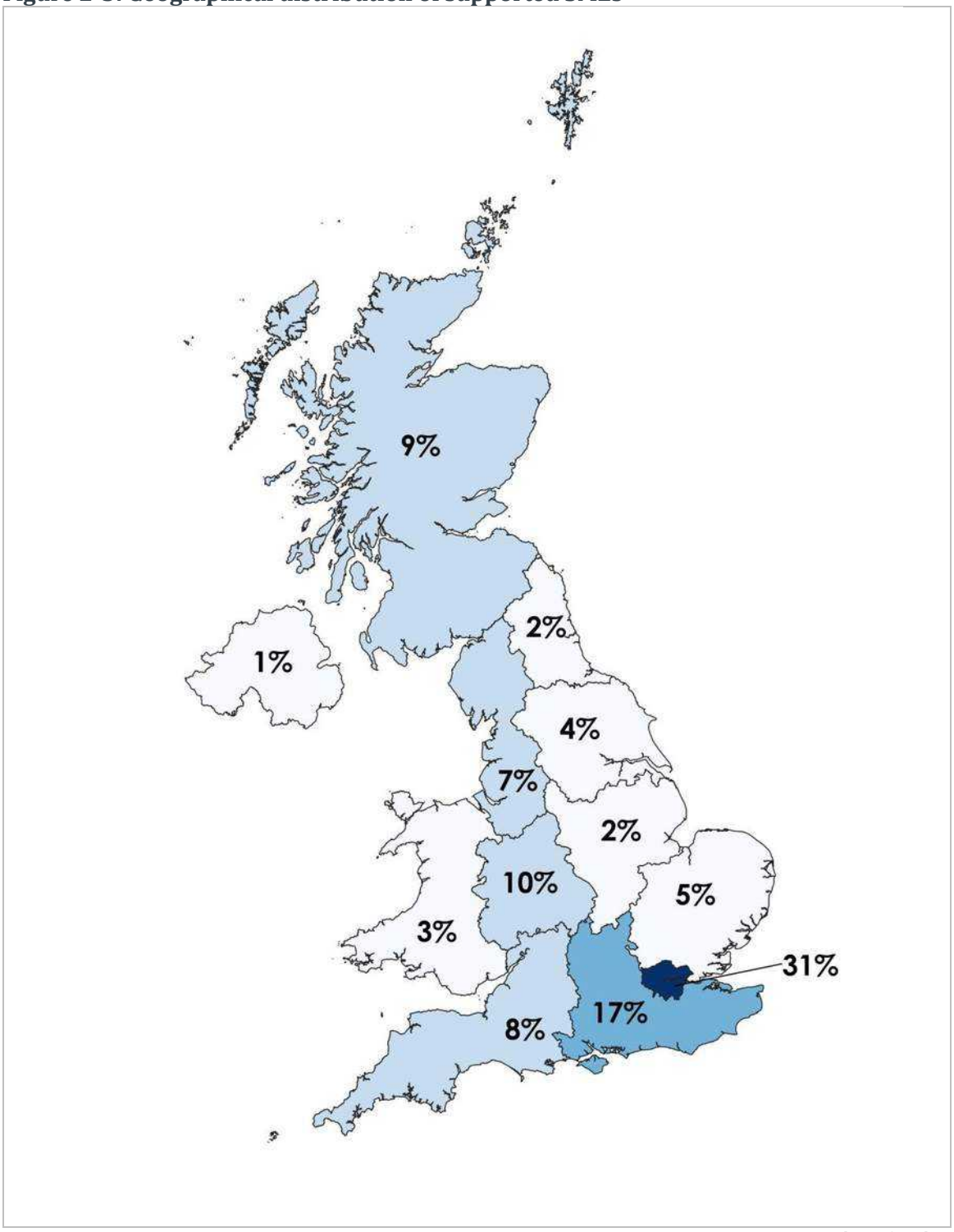
2.8 Furthermore, the population of supported SMEs contains a large proportion of high-potential companies. Of the 288 supported SMEs, 176 are currently 'tracked' by Beauhurst due to meeting a 'tracking trigger', with a further 13 having been tracked at some point but no longer meeting the criteria. In the wider business population, the proportion of businesses that are tracked is under 10%. Additionally, 44 supported SMEs (15%) are featured on Beauhurst's 'high-growth list', a list that further validates the ambition and growth prospects of featured companies. Some of this tracking activity may itself have been triggered by a company's engagement with the Catapult. The true proportion of supported SMEs that could be classed as high-potential prior to receiving support is therefore possibly somewhat lower than these figures suggest, but likely well above the business population baselines.

Geographical distribution

2.9 The Catapult supports SMEs across all regions of the UK; however, there is a substantial concentration in London (31%) and the South East (17%). Both of these regions are commonly considered to be the economic and innovation champions of the UK. As illustrated in Figure 2-3, the West Midlands and Scotland are the next two most represented regions, while Northern Ireland has the fewest supported SMEs. London stands out as by far the most

overrepresented region relative to the UK's overall business population, by around 12 percentage points, followed by Scotland and the South East, each overrepresented by around two to three percentage points. The largest underrepresentation is seen in the East of England and East Midlands, both around four to five percentage points below their respective shares of the wider business population.

Figure 2-3: Geographical distribution of supported SMEs



Source: SQW analysis of MI data

2.10 The relatively strong representation of Scotland and the West Midlands among the companies working with the Catapult is consistent with each region's established profile in energy and low-carbon activity. According to ONS figures, Scotland's turnover in the low carbon and renewable energy economy grew faster between 2015 and 2024 than in any other UK nation, rising from £5.5 billion to £13.3 billion over the period.[13] Separately, analysis by CBI Economics for the Energy and Climate Intelligence Unit identified the Scottish Central Belt and the West Midlands (specifically, the Birmingham-Coventry Corridor) as two of the UK's leading net zero economic hotspots measured by direct Gross Value Added (GVA).[14] The West Midlands' prominence also links to the region's established strength in automotive manufacturing and its growing role in vehicle electrification: it produces around a fifth of all British-made cars and hosts significant battery and electric vehicle manufacturing capability, including the UK Battery Industrialisation Centre and the Advanced Propulsion Centre.[15] This regional strength is consistent with 'electric and hybrid vehicles' being among the most common buzzwords associated with supported SMEs.

Age and size

2.11 On average, supported SMEs were six years old when they first engaged with the Catapult, though the median age of four years indicates that the distribution was somewhat skewed by a smaller number of older companies, with the oldest having operated nearly seven decades at the time of support (Table 2-2).[16]

Table 2-2: Age of supported SMEs at the time of support

Mean age	Median age	St. Dev.	Max
6 years	4 years	7.4 years	68

Source: SQW analysis of Beauhurst data

2.12 Table 2-3 summarises available information about the pre-support size of the SMEs. The data on total assets comes from Beauhurst and is based on financial statements filed by firms at Companies House. Turnover figures are based on information from the BSD.[17] Employment data was available both in Beauhurst (self-reported by the firms to the Companies House) and

[13] ONS, Low carbon and renewable energy economy, UK: 2024 (published 25 February 2026)
[14] CBI Economics, 2026. *The Race for Net Zero: The UK Net Zero Economy and the Transition to a Competitive Future*. London: CBI Economics, for the Energy and Climate Intelligence Unit.
[15] Invest West Midlands, n.d. *Automotive*. [online]
[16] Age at the time of support was calculated as the difference between a business's year of support and its year of incorporation. A small number of supported SMEs restructured shortly after receiving support (likely following external investment), meaning their newly incorporated entity has a recorded incorporation date later than their first engagement with the Catapult.
[17] Only companies with turnover exceeding £10m are obliged to disclose it to Companies House. As a result, there are only 21 pre-support turnover observations in Beauhurst with a much higher mean of £59.3m and median of £11.4m.

BSD (based on a combination of information from Pay As You Earn tax records and business surveys, including the Annual Business Survey). For reasons explained in more detail in Section 4, we relied on Beauhurst as our primary source of information on employment.

Table 2-3: Average pre-support size of supported SMEs

	Mean	Median	St. Dev.	N[18]
Employees (Beauhurst)	15.2	5.0	34.5	193
Employees (BSD)	12.7	4.0	28.8	197
Turnover (BSD)	£1.5m	£183k	£4.5m	197
Total assets (Beauhurst)	£11.4m	£0.3m	£95.5m	206
Current assets (Beauhurst)	£5.4m	£0.2m	£42.8m	206

Note: some of the ONS data was suppressed. Source: SQW analysis of Beauhurst, The Data City, and BSD data.

2.13 As expected, the pre-support size of supported SMEs varied considerably, with the mean figures across all measures pulled above the median by a small number of larger companies. For the purposes of an impact assessment, employment is arguably the most informative of these measures, since many of the supported SMEs are at an early stage of their development, where the number of people involved in product or service development is a key driver of future growth.[19] On average, before starting their work with the Catapult, supported SMEs had 15 employees, with the median firm having five. In other words, supported SMEs tended not to be one- or two-person startups, but were somewhat more established businesses with considerable room to grow.

[18] Not all companies had pre-support information on record (i.e. the data from the year before they started their project with the Catapult).

[19] Beauhurst had current data on the stage of evolution for 189 of the supported firms. 66 of them were at the seed stage, which together with the age statistics corroborates the point that many of these companies are in their early stages of development.

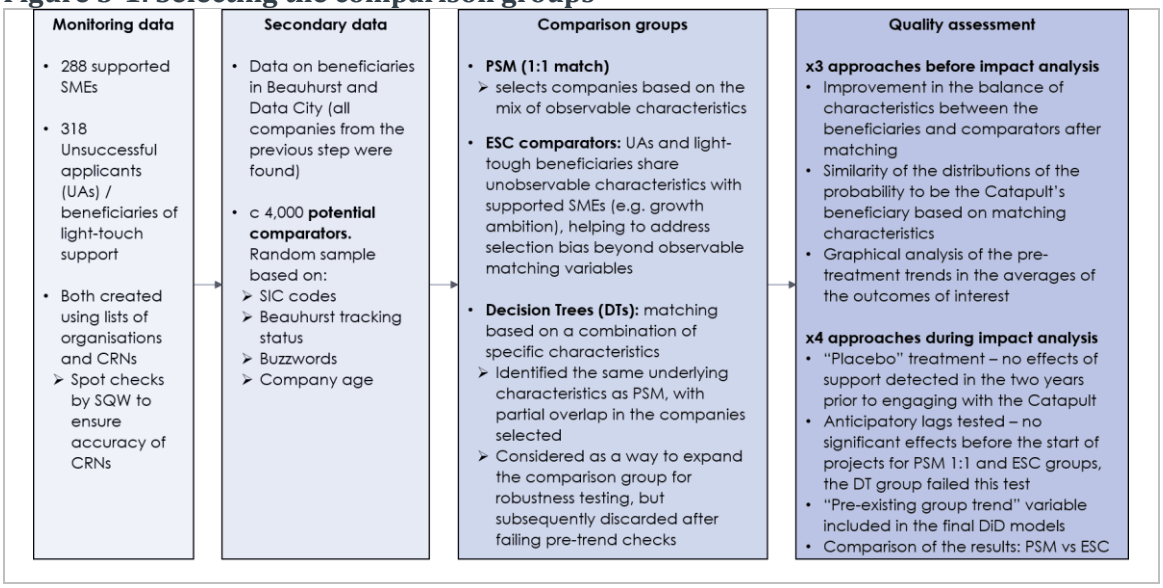
3. Comparison groups

Key points

- We built two comparison groups: a matched comparison group of 272 companies selected using Propensity Score Matching (PSM), and an ESC comparison group of 318 unsuccessful applicants and light-touch support recipients.
- Before carrying out any impact analysis we decided to treat the PSM matched group as our primary comparator and use the ESC group as a supplementary group for robustness checks.
- Both comparison groups closely mirrored the population of supported SMEs on sector, innovation activity, age and size, although the ESC group showed somewhat weaker innovation signals and a smaller average asset base.
- Balance diagnostics, graphical analysis, and formal statistical tests of pre-support trends confirmed that both the PSM matched and ESC comparison groups were appropriate and of good quality, providing a solid foundation for the difference-in-differences analysis.
- We also investigated the use of decision trees as an alternative method for selecting comparator firms. Although it identified similar firm characteristics as predictors of the Catapult's support as PSM, the resulting comparison group did not perform as well on pre-trend testing and was not used in the final analysis.

3.1 This section describes our approach to selecting the comparison groups and provides an overview of the companies selected for the analysis. To ensure the impact analysis was meaningful, we needed to identify unsupported companies that were as similar to the SMEs working with the Catapult as possible before the support took place. Selecting the comparison groups and testing their quality was a four-step process, summarised in Figure 3-1.

Figure 3-1: Selecting the comparison groups



Source: SQW

Unsuccessful applicants, light-touch support and a wide pool of potential comparators

3.2 Our review of the Catapult's monitoring data identified 318 companies that engaged with the Catapult but were either unsuccessful in their application or received only a 'very light' level of support through an SME Surgery, a brief, free-to-attend session offering energy innovators expert advice and a diagnosis of their business needs, without a guarantee of further direct support from the Catapult.[20] Unsuccessful applicants and SME Surgery attendees made up roughly equal shares of this group of companies.

3.3 Since these interactions were so brief that we would not be able to attribute any changes in their business performance to the Catapult, we used this group as one of our comparison groups, leveraging their likely similarities with supported SMEs on certain unobservable characteristics, such as propensity to seek support and business aspirations. However, at least half of these companies were unsuccessful applicants, who by definition differed from supported SMEs in ways that determined the outcome of their application, meaning we would not want to base our entire analysis on this group alone. We refer to this group as the Energy Systems Catapult (ESC) comparison group throughout the report.

3.4 To complement the ESC comparison group, we also sought to identify unsupported firms from the wider business population that matched the pre-support profile of supported companies.

[20] The initial list contained 344 records. We removed duplicates (companies that both attended an SME Surgery and made an application for further support) and a small number of companies that did not qualify as SMEs (had more than 250 employees).

Mirroring the innovation and sector profiles of these companies was particularly important when selecting our comparators.

3.5 We linked the monitoring data to information from Beauhurst and the Data City, and carried out descriptive analysis of both the populations of supported SMEs and wider businesses. This analysis identified around 4,000 potential comparator companies that met a set of filtering criteria based on the observed characteristics of companies working with the Catapult, including SIC codes, Beauhurst tracking status, and relevant 'buzzwords' – flags representing modern or emerging sectors and technologies (Table 3-1). We also assigned each of these potential comparator companies a quasi-treatment year, ensuring the distribution of these years matched the time profile across the population of supported SMEs (Figure 2-1).

Table 3-1: Criteria for potential comparator firms

Criteria	Restriction	Comment
Industry (primary SIC 2007 code)	35 5-digit SIC codes that were most common for supported SMEs	This range covers over 95% of supported SMEs
Date of incorporation	Jan 2005 – Dec 2024	This range covers over 95% of supported SMEs
Beauhurst Tracking status	60% of the sample were tracked (currently or at some point)	61% of supported SMEs were tracked by Beauhurst
Beauhurst Buzzwords	80% of the sample associated with at least one of the following buzzwords: • CleanTech – 62% of the sample were linked to this buzzword • Software-as-a-Service (SaaS) • Artificial Intelligence • Mobile apps • Electric and hybrid vehicles • Biomass and biofuels • Subscription • Smart energy • Internet of Things • FinTech	• 79% of supported SMEs are linked to a buzzword, 67% are associated with CleanTech specifically • The list of buzzwords on the left covers 89% of buzzwords tied to supported SMEs

Matched comparison group

3.6 We refined the wider pool of potential comparators using statistical matching and machine learning techniques, specifically PSM and decision trees, as described below.

Propensity Score Matching

3.7 We used PSM to identify the most 'like-for-like' comparator companies, taking into account a wider range of characteristics simultaneously. First, we estimated a statistical model that predicted the likelihood of a company being a supported SME, based on observable characteristics presented in Table 3-2. For each company, this model generated a 'propensity score' that blended all the matching characteristics into a single measure of similarity.[21]

Table 3-2: Observable characteristics used for statistical matching

Matching characteristics
SIC sector
UK Region (the geographical location of the registered office)
Being assigned to a Data City Real Time Industrial Classification (RTIC) code (a modern machine-learning based sector classification) – a proxy for innovation activity
Pre-support funding from Innovate UK
Being associated with innovation signals (Beauhurst)
Being associated with environmental signals, and in particular 'clean renewable energy' and 'Environmental Accolades' (Beauhurst)
Being an academic spinout
Being an ultimate parent within the corporate structure
Number of companies within the corporate structure
Being tagged with growth markers (Beauhurst)[22]

Source: SQW

3.8 For each supported firm, we selected the unsupported company with the closest propensity score, drawn from the pool of around 4,000 potential comparators, yielding a 1:1 matched comparison group. 12 supported SMEs were omitted from the sample due to missing data on

[21] There was a trade-off between the number of variables included in a matching model and the number of firms it can cover, since not all information was available for all the companies. We tested multiple matching specifications and compared the results, arriving at the list of variables presented in this section. Indicators of pre-treatment size (e.g. employment) are often viewed as important matching characteristics. However, including them lowered the sample of supported SMEs by over 30%, without any substantial improvement in the overall quality of the comparison group, including the similarity of pre-treatment trends.

[22] Growth markers could, in principle, be endogenous to the Catapult's support if they were assigned only after a company received it (the date of the marker is not recorded in the dataset). We included this variable because of our intention to capture companies on a broadly similar growth trajectory to that of supported SMEs, and our subsequent testing of pre-treatment trends did not identify any evidence that this introduced bias into the comparison group.

matching characteristics and four could not be matched (but were included in the impact analysis) resulting in 272 comparator companies picked with PSM.[23]

Decision trees

3.9 To keep the analysis consistent with previous waves, we retained PSM as our primary approach to selecting comparator companies. However, PSM does not guarantee that selected companies share specific combinations of characteristics that could be particularly relevant to the Catapult. To address this, we investigated the possibility of complementing PSM with decision trees, a machine learning technique that allowed us to target comparators more closely mirroring the distinct profile of the companies working with the Catapult. We trained the decision tree algorithm on a random sample drawn from the Beauhurst and Data City comparator pool.

3.10 The characteristics with the highest importance scores in identifying the final decision tree used for selecting comparators were: pre-support funding from Innovate UK; environmental accolades; innovation signals; being assigned a Data City RTIC code; environmental signals; and growth signals (see Annex B for further detail). These closely matched the statistically significant predictors in the PSM matching model, where the same characteristics were considered simultaneously rather than sequentially. Overall, the decision tree picked a larger comparison group of 528 companies, of which around half overlapped with the PSM 1:1 group.

Assessing the quality of the comparison groups

3.11 We assessed the quality of the comparison groups using several complementary checks: balance diagnostics comparing supported SMEs against the wider pool of unsupported comparators before and after matching; graphical analysis of pre-treatment trends in the key outcome measures across all comparison groups; and two formal tests of the parallel trends assumption underpinning the difference-in-differences approach, examining anticipatory effects and testing for placebo effects over the pre-treatment period.

3.12 The results of these checks are presented in Annex B. The PSM-matched and ESC comparison groups performed well across all checks, and we concluded that both were appropriate and of good quality. We therefore decided, prior to running any impact analysis, that the matched group would be our primary comparison group, with the ESC group used mainly to test robustness, and any substantial differences between the two groups' results pointing us towards patterns for further investigation.

[23] Four SMEs supported by the Catapult could not be appropriately matched to a comparator firm (there were no comparators within a 0.2 st. dev. caliper), but they were 'manually' included in the DiD sample for impact analysis. To ensure they did not skew the results, we performed estimations without them in the sample as well.

3.13 However, we had concerns that the parallel trends assumption did not hold for the decision tree-selected companies, possibly as a result of this method's tendency to draw in a wider set of companies. In other words, we could not be confident this group accurately represented what would have happened to supported SMEs without the Catapult. We therefore did not use this group to draw conclusions about impacts. As a precautionary measure, we also introduced an additional variable into all the impact models we used, aimed at capturing potential differences in pre-existing trends that should not be attributed to the Catapult's projects.

Key characteristics of the comparison groups

3.14 This subsection compares the headline characteristics of the two comparison groups used in our analysis, the matched PSM 1:1 comparison group and the ESC comparison group, against the population of supported SMEs described in Section 2. Table 3-3 sets out the number of companies in each group.

Table 3-3: Number of companies in each comparison group

Group 1: 1 to 1 PSM	Group 2: ESC
272	318

Source: SQW

Sector and location

3.15 The sector composition of both comparison groups broadly mirrors that of supported SMEs. In the matched comparison group, 78% of companies belong to the same three sectors as supported SMEs: professional, scientific and technical activities (section M); information and communication (section J); and manufacturing (section C). The equivalent share in the ESC comparison group is somewhat lower, at 73%, though these three sectors are still the most dominant by a large margin.

3.16 The geographical profile of the matched comparison group closely mirrors that of supported SMEs, with around 45% of matched comparators based in London or the South East, similar to the equivalent share among supported SMEs (48%), and Scotland and the West Midlands being the next most represented regions (Table 3-4).

Table 3-4: Regional profile of comparison groups vs supported SMEs

Region	Supported SMEs (%)	PSM 1:1 group (%)	ESC group (%)
London	31%	29%	30%
South East	17%	16%	5%
West Midlands	10%	10%	16%
Scotland	9%	13%	9%

Region	Supported SMEs (%)	PSM 1:1 group (%)	ESC group (%)
South West	8%	7%	6%
North West	7%	4%	9%
East of England	5%	6%	8%
Yorkshire and The Humber	4%	6%	3%
Wales	3%	4%	3%
East Midlands	2%	3%	6%
North East	2%	2%	1%
Northern Ireland	1%	1%	4%

Source: SQW

3.17 The regional profile of the ESC comparison group is notably different, consistent with the patterns we uncovered during the previous wave of the analysis. A much smaller share of this group is based in the South East (5% vs 17% among supported SMEs), while more of them are from the West Midlands (16% vs 10%). We attribute these differences to the proximity to the Catapult's Birmingham headquarters, which may increase awareness of the Catapult and lower the cost of engaging with it (for example, through reduced travel), making companies more likely to approach the Catapult for light-touch support even where they did not require more intensive engagement or if their proposal was underdeveloped.

Innovation activity and growth signals

3.18 Both comparison groups show signs of innovation activity, though to differing degrees. In the matched comparison group, 257 companies (95%) are linked to at least one buzzword and 160 (59%) have an RTIC code. These levels are a strong match to supported SMEs, if anything slightly exceeding their equivalent shares (79% and 62% respectively). In the ESC comparison group, 117 companies (37%) are linked to a buzzword and 71 (22%) have an RTIC code. These numbers are unsurprisingly lower than among supported SMEs, given the nature of this group, but still indicate a meaningful degree of innovation activity. As with supported SMEs, CleanTech, Software-as-a-Service (SaaS) and Artificial Intelligence were among the most common buzzwords linked to the comparator companies across both groups.

3.19 A similar pattern is evident in other markers of growth potential and innovation activity. In the matched comparison group, 222 companies (82%) have been tracked by Beauhurst at some point, exceeding the equivalent share among supported SMEs (66%), and 170 (63%) secured Innovate UK funding, close to the supported SME benchmark of 59%. In the ESC comparison group, 105 companies (33%) have been tracked at some point and 42 (13%) secured Innovate UK funding, both considerably lower than among supported SMEs, though

these proportions are substantially higher than would be expected in a sample from the general business population and nine companies (3%) also feature on Beauhurst's high-growth list.

Age and size

3.20 The age profile of both comparison groups is broadly consistent with that of supported SMEs (mean 6 years, median 4 years; see Table 2-2). The matched comparison group has a very similar mean age of 7 years, with a median of 6 years, though a narrower spread (standard deviation of 5.5 years, against 7.4 years for supported SMEs). The ESC comparison group consisted of younger companies: mean age of 5 years and an even lower median of two years.

Table 3-5: Age of companies in the comparison groups

Group	Mean age	Median age	St. Dev.	Max
PSM 1:1	7 years	6 years	5.5 years	21
ESC	5 years	2 years	6.5 years	33

Source: SQW analysis of Beauhurst data

3.21 Table 3-6 summarises the pre-support size of companies in the comparison groups, in terms of employment, turnover and total assets. For the ESC comparison group, the data was based on information from the year before they engaged with the Catapult. For the matched comparison group, it was based on data from the year prior to the 'quasi-treatment' year that we assigned to each company.

3.22 Relative to supported SMEs (mean employment 15.2; mean total assets £11.4m; see Table 2-3), the matched comparison group is very similar in size (mean and median employment, and median assets), despite our decision not to include pre-treatment employment as a matching characteristic, to preserve the sample size available for matching. The ESC comparison group, unsurprisingly, consisted of somewhat smaller companies, particularly in terms of their asset base.

Table 3-6: Average size of firms in the comparison groups

	Mean	Median	St. Dev.	N[24]
PSM 1:1				
Employees (Beauhurst)	13.4	5.0	22.5	157
Employees (BSD)	10.6	4.0	17.7	184

[24] Not all companies had pre-support information on record (i.e. the data from the year before they started their project with the Catapult).

	Mean	Median	St. Dev.	N[24]
Turnover (BSD)[25]	£1.5m	£185k	£2.2m	184
Total assets (Beauhurst)	£5.5m	£400k	£17.8m	199
Current assets (Beauhurst)	£2.7m	£300k	£8.8m	199
ESC comparison				
Employees (Beauhurst)	12.5	2.0	52.8	149
Employees (BSD)	7.8	2.0	25.0	138
Turnover (BSD)	£1.5m	£119k	£5.6m	138
Total assets (Beauhurst)	£1.4m	£50k	£6.7m	180
Current assets (Beauhurst)	£1.2m	£30k	£5.6m	180

Source: SQW analysis of Beauhurst, The Data City, and BSD data

3.23 As we highlighted above, for a difference-in-differences approach to work properly, it is more important to identify companies with similar ex-ante trends than with the same absolute size of operations, since differences in size can be accounted for at the analysis stage. The trajectory of supported SMEs is likely to be shaped substantially by their innovation activity. Both comparison groups showed signs of comparable innovation potential, and our pre-trend analysis gave encouraging results; together, these considerations provide a solid foundation for the DiD analysis.

[25] Similar to the population of supported SMEs, there were only 21 pre-support turnover observations on Beauhurst for the PSM 1:1 group. The mean was £13.1m and median of £2.5m. The equivalent figures for the ESC comparison were: 11 observations, the mean of £21m and the median of £16.7m.

4. Difference-in-differences analysis

Key points

- We estimated the impacts of the Catapult's support using a Bayesian difference-in-differences framework, drawing on both the observed data and evidence from previous evaluations and academic research to strengthen the analysis where appropriate.
- Employment among supported SMEs was found to be, on average, approximately 17% higher than the counterfactual trajectory, with the effects persisting for up to three years after support.
- Supported SMEs were more likely to secure external finance: the support was linked with a 10 percentage point increase in the probability of obtaining some external funding (grants, loans, equity) and a 13 percentage point increase for grant funding specifically.
- The higher likelihood of securing external finance translated into substantially greater funding volumes, with supported SMEs securing c. £791m in external finance after the start of support, c. £300m of which was additional.
- Supported SMEs also accumulated a substantially larger asset base than implied by the counterfactual path, with both total and current assets estimated to be around 73% higher than they would have been without the engagement with the Catapult. This result is consistent with them attracting more finance into the business.
- We found no evidence that the Catapult's support consistently affected turnover or company valuations during the observation period.
- Subgroup analysis did not identify notable differences in impacts by sector or cohort, while evidence on the additional effects of repeat engagement remained inconclusive. These areas remain priorities for future research as the population of supported SMEs grows and additional data becomes available.

4.1 This section presents the key findings from our difference-in-differences (DiD) analysis of the Catapult's impact on the business performance of supported SMEs. We estimated impacts drawing on the comparison groups described in Section 3. However, for conciseness, this

section will focus on our primary comparison group – the PSM 1:1 matched group. Further methodological detail and full estimation results are presented in Annex B.

Overview of methods

4.2 The analysis covered six outcome measures. We examined employment and turnover growth as our primary indicators of business performance, alongside total assets as an alternative measure of company size. We also examined current assets, which tend to be moderately closely correlated with turnover for small companies and may provide an early indication of impacts in cases where turnover data is unavailable, for example for pre-revenue companies.[26] Finally, we examined whether supported SMEs were more likely to attract external finance, in the form of grants, loans or equity investment, and whether their valuations increased.[27] All financial measures (external funding, turnover, and total and current assets) were analysed in real terms, adjusting for inflation, expressed in 2025 prices (as of the end of the year).

4.3 Our choice of statistical models was informed by recent academic discussions of the strengths and limitations of alternative DiD specifications, summarised in, for example, Baker et al. (2025).[28] We considered two types of models: the first estimated the average impact across all years following an SME's first interaction with the Catapult; the second estimated the impact separately for each year after support (an approach known as an event study). Figure 4-1 illustrates the differences between the two approaches.

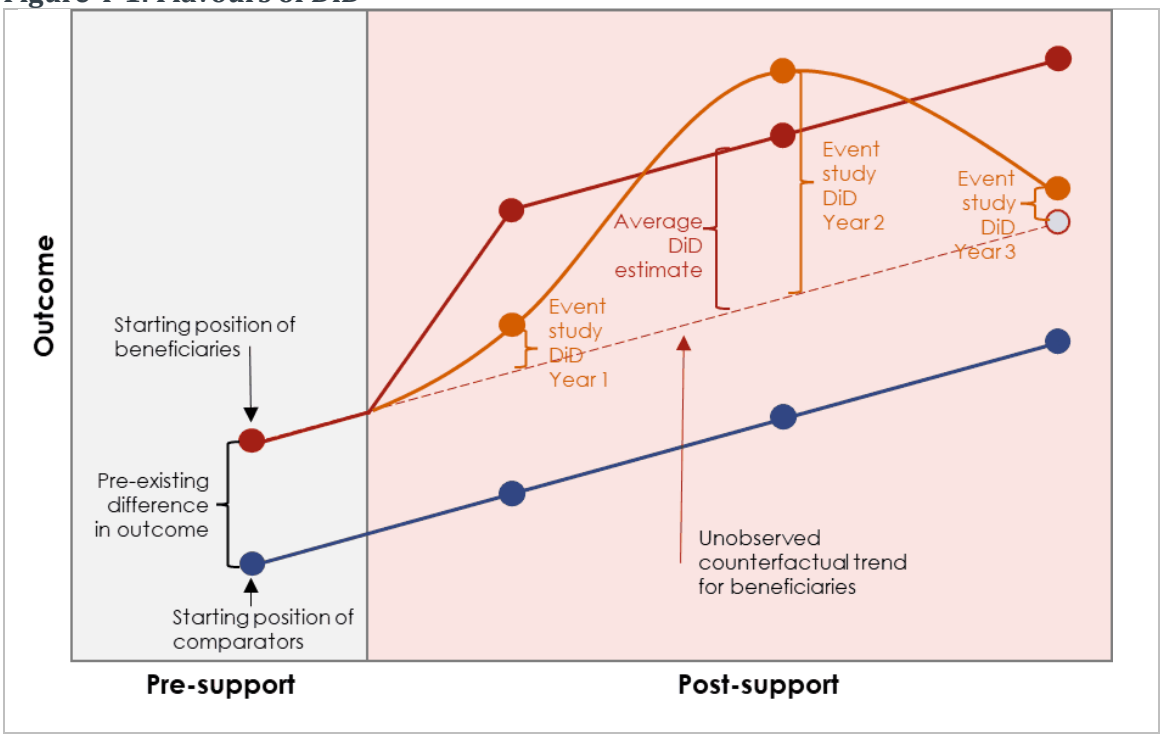
4.4 Since the Catapult's support is not an instantaneous effect, neither of the DiD flavours is a perfect description of reality. The first DiD type ignores the effect dynamics (the fact that it may build up and decay over time), and assumes that supported SMEs quickly move onto a new trajectory. The second approach fleshes out the dynamics and can often provide additional insights into the time profile of the support's effects. However, it relies on smaller sub-samples to estimate the effect in each year and is more sensitive to the assumption that the effects of support are the same over time, i.e. that they do not fundamentally differ depending on the year in which support was provided.

4.5 The remainder of this section focuses on the findings from the average-effects model. Overall, the patterns were consistent across both types of DiD. There was no convincing evidence of a strong dynamic in the effects, although the event study models did provide useful insight into the duration of the effect, which informed our assumptions for the modelling of economic impacts described in Section 6 of this report.

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[26] Where data is available for both indicators, the correlation between turnover and current assets for the SMEs supported by the Catapult is c. 0.6.
[27] For the purposes of impacts analysis, as explained in Section 2, for SMEs with repeat interactions with the Catapult, we treated the date of their first interaction as the start of their support period.
[28] Baker, A., Callaway, B., Cunningham, S., Goodman-Bacon, A. and Sant'Anna, P.H., 2025. *Difference-in-Differences Designs: A Practitioner's Guide.*

Figure 4-1: Flavours of DiD



Source: SQW

Bayesian approach

4.6 As we mentioned in the introduction, we used a Bayesian econometric approach, which allowed us to combine prior information – a best estimate of the scale and nature of the support's impacts – with the observed data, to produce an updated probability distribution of the average effect, known as the posterior.

4.7 A key advantage of the Bayesian approach for this project is in how it describes uncertainty. Rather than reducing the result to a binary significant/not-significant decision based on a conventional cut-off, the Bayesian approach provides a full probability distribution over the possible values of the average treatment effect. This is particularly helpful when working with small samples, and it provides a richer evidence base for the simulation modelling of impacts at the Catapult's level, as described in Section 6.

4.8 The prior estimates were informed by the wider literature and SQW's previous evaluations of business support programmes, including those supporting collaborative R&D. To increase the robustness of our findings, we tested a range of priors and compared the results against a standard frequentist estimate of the average effect (the conventional, non-Bayesian approach).[29]

[29] Frequentist estimation uses only the observed data to estimate an effect, accompanied by a confidence interval and p-value. This approach rests on the idea of repeated sampling: the true average

4.9 One of the challenges with Bayesian estimation is its computational complexity and the associated time demands. We therefore adopted a practical, sequential approach. For outcomes with richer data, and where we had substantial existing evidence to inform our priors, namely employment, turnover, and assets, we used Bayesian methods in the models that compared supported SMEs against our primary comparison group. We then used frequentist estimation for the complementary ESC comparison group, to check whether the point estimates were broadly consistent, or whether the data told a substantially different story that would warrant further investigation. Table 4-1 summarises the estimation approach used across comparison groups and outcome measures.

Table 4-1: Primary estimation approach across outcome metrics and comparison groups

	Employment	Turnover	Assets	Attracting finance	Valuations
PSM 1:1	Bayesian DiD, range of priors	Bayesian DiD, range of priors	Bayesian DiD, range of priors	Logit, Frequentist DiD	Frequentist DiD
ESC comparison	Frequentist DiD	Frequentist DiD	Frequentist DiD	Logit, Frequentist DiD	Frequentist DiD

Source: SQW

4.10 Two of the outcome measures required an alternative modelling approach. One of the measures for attracting external finance was a binary outcome (whether or not a company secured funding), so we estimated this using a logit model rather than the DiD specifications described above. Valuations, meanwhile, are updated irregularly by individual companies, so we used a simpler before-and-after DiD, rather than a richer approach that tracks firms over several years. Further detail on both approaches is provided in Annex B.

Findings

4.11 In the remainder of this section, we present the findings by outcome measure. All models passed our standard suite of diagnostic checks, confirming that the estimation was reliable.

effect is treated as fixed (there is one true value, although we cannot observe it directly). If one were to draw many similar samples from the same population, a 95% confidence interval means that 95% of such intervals, constructed across those hypothetical samples, would contain the true effect. The Bayesian approach treats the observed data as fixed and combines them with prior evidence or beliefs to produce a probability distribution over the effect itself. Its credible interval can therefore be read directly as the range within which there is a 95% probability the true effect lies, given the data and priors. We present the frequentist estimate as a benchmark so the reader can compare the findings to the results that would be obtained using that approach.

Employment

4.12 Before we present the results of impact analysis on employment, we would like to discuss the differences between data sources. Beauhurst data is self-reported by firms to Companies House, whereas BSD combines PAYE administrative records with survey data, and is often the preferred source for evaluation work. Having examined both datasets, however, we identified substantial discrepancies between them: both of them had data for c. 70% of the companies we analysed, however BSD data showed a considerably higher proportion of firms 'stuck' at one employee for a prolonged period, in some cases for the entirety of the analysis window. This issue was more pronounced within the PSM matched comparison group, where it affected as many as 20% of firms. Roughly 12% of supported SMEs were affected.

4.13 There are known challenges with linking to BSD, including the possibility that companies are matched to their parent company rather than the correct entity. However, the pattern we observed is more consistent with employment records not being updated through PAYE data once survey data takes precedence, with the resulting figure then persisting in the dataset for an extended period. Since linking to BSD is fully anonymised, we had no way of verifying which specific companies were affected by this issue.

4.14 For these reasons, we treated Beauhurst as our primary source of evidence on employment effects. However, to reflect that BSD-based figures and the corresponding magnitude of estimated impacts were somewhat lower, we used the results of our BSD-based modelling as one of the priors for the Bayesian estimation carried out using Beauhurst data.

4.15 We analysed the effects on employment using four alternative priors, summarised in Table 4-2.

Table 4-2: Priors used for employment models

Prior	Rationale	Specification for the effect of support
Weakly informative	Places minimal constraints on the estimate, allowing the data to drive the results.	A flat distribution, all values are characterised by equal probability density[30]
BSD 'cross-prior' (preferred)	Based on the frequentist estimate obtained using BSD as the data source	Normal distribution: • Mean 0.072 • St. deviation 0.068

[30] A probability density function describes how probability is distributed continuously across possible values of a random variable. For a continuous variable, the probability of any single exact value is zero, however the probability of falling within an interval is not, and it can be obtained by integrating the density over that interval. The normal distribution has a bell-shaped density, the weakly informative prior assigns a flat density to all parameters and lets the data shape the result.

Prior	Rationale	Specification for the effect of support
Vanino et al.[31]	Informed by the work of Enrico Vanino, Stephen Roper and Bettina Becker who estimated the effects of UKRI R&D grant funding and Catapult engagement on employment and turnover of beneficiaries, finding the average treatment effects equivalent to three to four percent additional growth per year. We introduced a skew in the distribution of the treatment effect to reflect the possibility that a small number of highly successful projects could pull up the average effect and to test the robustness of findings to the assumptions of the shape of the distribution.	Skew normal distribution: • Location 0.005 • Scale 0.02 • Shape 7
SQW	Drew on SQW's extensive experience of evaluating business support programmes aimed at improving businesses practices to encourage growth (for example, those delivered by Be the Business), where typical employment effects are often around ten percent.	Normal distribution: • Mean 0.1 • Standard deviation 0.03

Source: SQW

4.16 Table 4-3 presents the estimated average effects on employment of supported SMEs across the priors.[32] Based on our preferred model, the employment of supported SMEs following their engagement with the Catapult was 16.8% higher than the estimated counterfactual trajectory, with the 95% credible interval covering the range between 11.1% and 22.6%. The effect was positive and substantial across all four priors: the central estimates ranged from 6.2% to 18.5%, and all models passed our suite of diagnostic tests, confirming that they were well specified.

[31] Based on Vanino, E. and Roper, S., 2023. *Evaluating the medium-term business performance effects of engaging with Catapults: A propensity score matching - difference-in-difference study*. ERC Insight Paper. Enterprise Research Centre, and Vanino, E., Roper, S. and Becker, B., 2019. Knowledge to money: assessing the business performance effects of publicly-funded R&D grants. Research Policy, 48(7), pp.1714–1737.

[32] The percentage effects were obtained by exponentiating the model coefficients.

[33] A credible interval is a Bayesian equivalent of a confidence interval, which has the following natural interpretation: given the observed data, there is a 95% probability that the 'true effect' falls in this interval.

Table 4-3: Estimated effects of support on employment

Prior	Estimated effect	95% Credible Interval
BSD 'cross-prior' (preferred)	16.8%	11.1% - 22.6%
Weakly informative	18.5%	12.3% - 24.9%
SQW	14.6%	10.0% - 19.6%
Vanino et al.	6.2%	3.0% - 9.5%

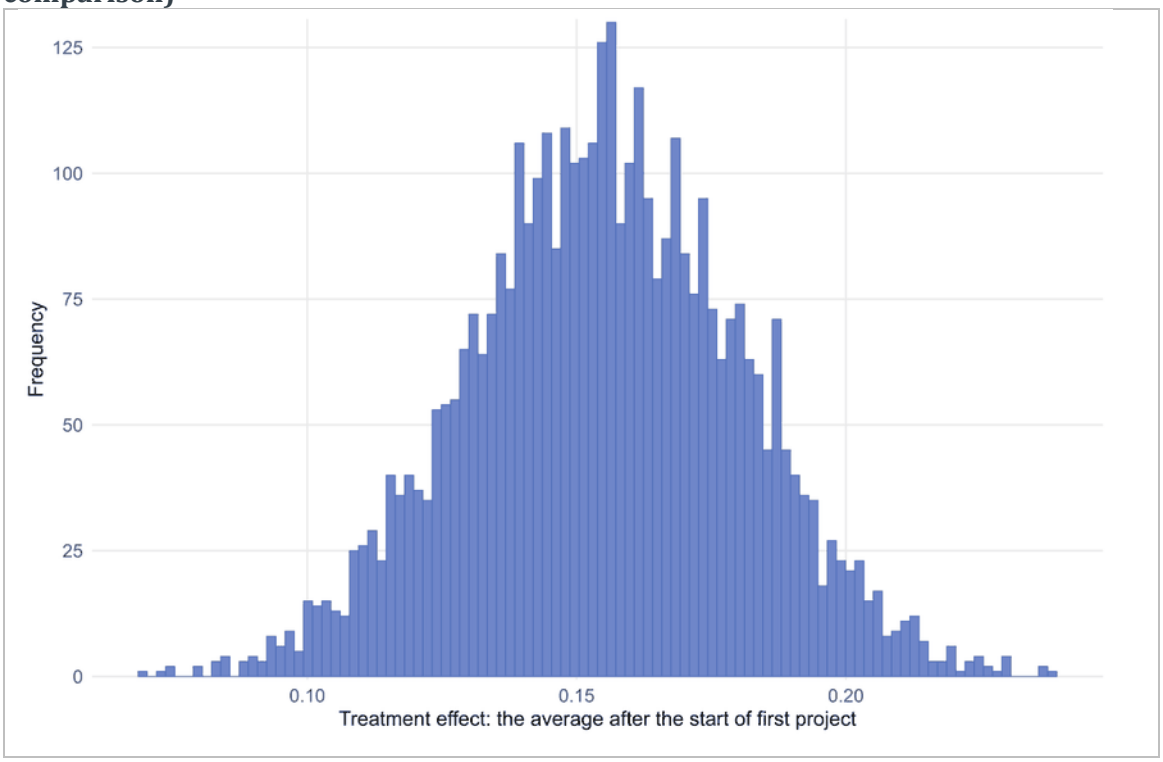
Source: SQW

4.17 The weakly informative prior produced the most optimistic estimate (18.5%). The BSD cross-prior pulled this down slightly, likely reflecting the 'stuck at one employee' issue in the BSD data discussed above. The SQW and Vanino et al. priors adjusted the estimate down further, as a direct result of their more pessimistic expectations about the likely scale of effects.

4.18 To compare the models, we examined their out-of-sample predictive power, that is, how well each model would predict new observations not used in estimation. This comparison found no statistical basis for preferring the weakly informative prior over the cross-prior, or vice versa. The SQW prior showed marginally worse performance, while the Vanino et al. prior proved to be a substantially worse fit for the data. We therefore took the BSD cross-prior as our main result, since it drew on two independent data sources. The results from this estimation underpinned our modelling of economic impacts, described in Section 6.

4.19 Figure 4-2 shows the posterior distribution of the treatment effect on employment, obtained using our preferred prior. In simple terms, Bayesian models are estimated using simulation: across many thousands of replications, a proposed value for the treatment effect is evaluated against the observed data and the prior, building up a distribution of plausible values known as the posterior. Each bar in the figure below represents the frequency with which a particular effect size was sampled during estimation; the height of the bar indicates how likely that value is, given the data and the prior, with values near the centre of the distribution sampled most frequently and therefore most probable. Consistent with the summary statistics in Table 4-3, the distribution has a classic bell shape, is concentrated well to the right of zero and centred around 0.16.

Figure 4-2: Estimated effect of the Catapult's support on the natural logarithm of employment of participating SMEs (posterior distribution, BSD prior, PSM 1:1 comparison)



Source: SQW

4.20 The event study models were consistent with the estimates of the average effects, but provided the additional insight that the effects tend to persist for up to four years, i.e. observed in the year of the support and the following three years. It is possible that beyond this horizon we simply lack sufficient observations to identify impacts, rather than the effects vanishing. Alternatively, the comparison group may be catching up, reflecting a genuine time additionality element of the support provided by the Catapult, though we have no statistical confirmation either way. All these findings were also largely confirmed using the ESC comparison group. The full estimation results, including the event study and ESC group models, are presented in Annex B.

Turnover

4.21 We analysed the effects on turnover using three alternative priors, summarised in Table 4-4. As with the employment analysis, these priors were informed by both existing evidence on the effects of the UK Catapults' support as well as SQW's experience of evaluating similar interventions.

Table 4-4: Priors used for turnover models

Prior	Rationale	Specification for the effect of support
Weakly informative	Places minimal constraints on the estimate, allowing the data to drive the results.	A flat distribution, all values are characterised by equal probability density
Vanino et al.[34]	Informed by the work of Enrico Vanino, Stephen Roper and Bettina Becker who estimated the effects of UKRI R&D grant funding and Catapult engagement on employment and turnover of beneficiaries, finding the average treatment effects equivalent to two to three percent additional growth per year. We introduced a skew in the distribution of the treatment effect to reflect the possibility that a small number of highly successful projects could pull up the average effect and to test the robustness of findings to the assumptions of the shape of the distribution.	Skew normal distribution: • Location 0.01 • Scale 0.02 • Shape 3
SQW	Drew on SQW's extensive experience of evaluating business support programmes aimed at improving businesses practices to encourage growth (for example, those delivered by Be the Business), where typical turnover effects are often around nine percent.	Normal distribution: • Mean 0.09 • Standard deviation 0.02

Source: SQW

4.22 Table 4-5 presents the estimated average effects on turnover of supported SMEs across the three priors. Unlike the results for employment, the estimated effects on turnover were highly sensitive to the choice of prior. Both the central estimates and, importantly, the shape of the obtained posterior distributions closely followed the initial assumptions (Figure 4-3 and Figure 4-4).

[34] Based on Vanino, E. and Roper, S., 2023. *Evaluating the medium-term business performance effects of engaging with Catapults: A propensity score matching - difference-in-difference study*. ERC Insight Paper. Enterprise Research Centre, and Vanino, E., Roper, S. and Becker, B., 2019. Knowledge to money: assessing the business performance effects of publicly-funded R&D grants. Research Policy, 48(7), pp.1714–1737.

Table 4-5: Estimated effects of support on turnover

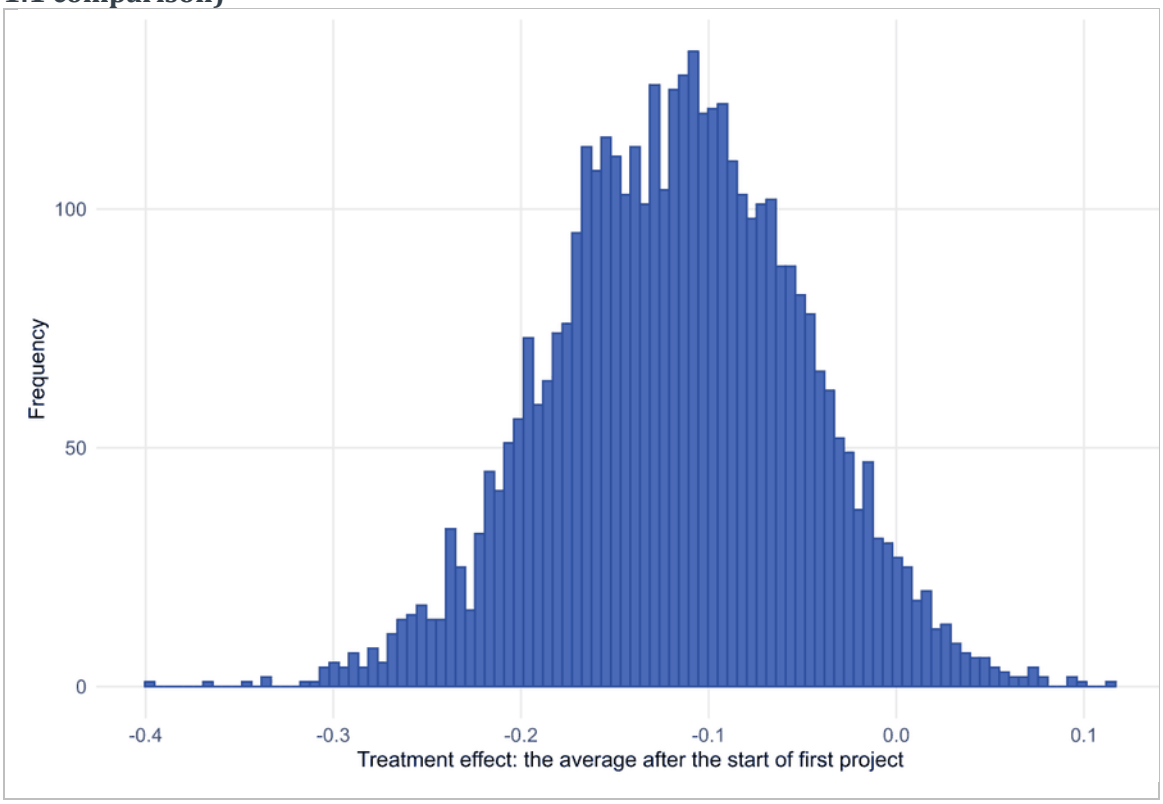
Prior	Estimated effect	95% Credible Interval
Weakly informative	-11.5%	-22.1% - 1.1%
Vanino et al.	1.8%	0.5% - 4.4%
SQW	7.6%	3.6% - 11.5%

Source: SQW

4.23 The model selection criteria found no statistical basis for preferring the weakly informative prior over Vanino et al. (and the other way around), while the SQW prior performed worse. As an additional robustness check, we also estimated a version of the Vanino et al. prior without the skew, which was equally well supported by the data and produced a symmetric posterior distribution centred around 1.5%.

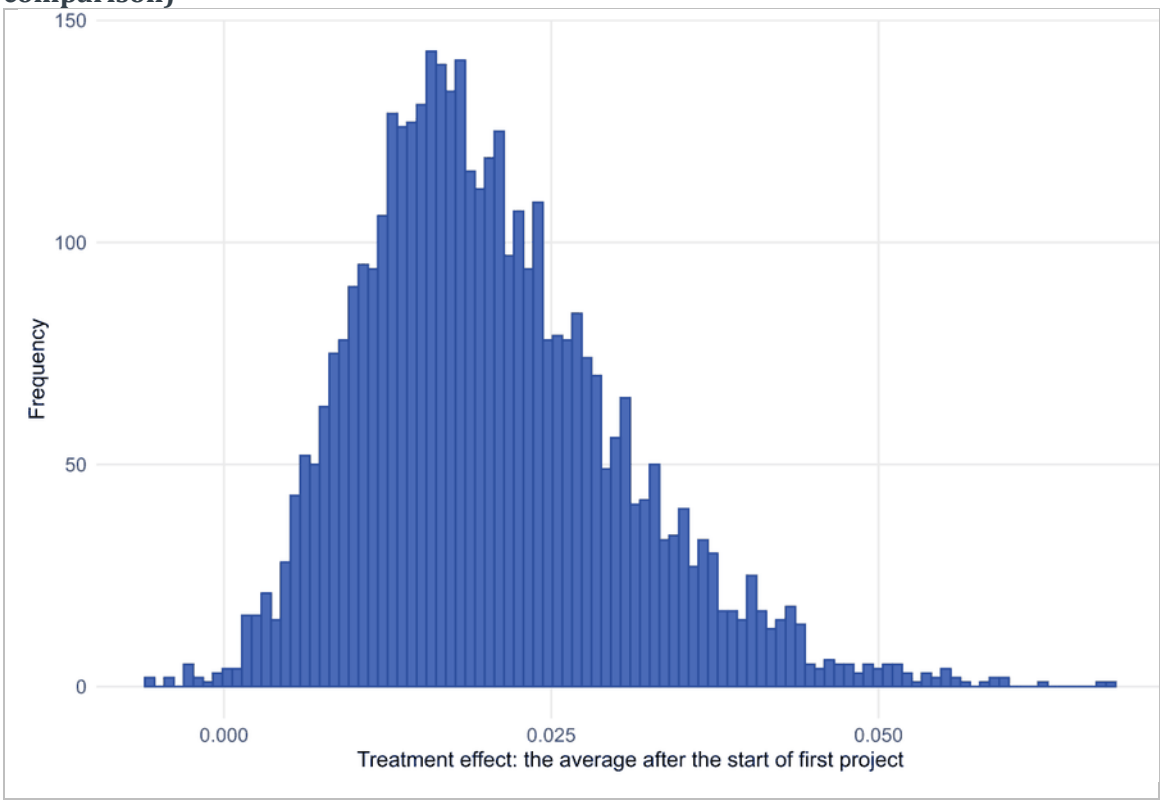
4.24 The frequentist estimations (presented in Annex B) similarly failed to identify an effect. Taken together, these results indicated that the underlying data did not contain a sufficiently strong signal to identify the effect of the Catapult's support on turnover.

Figure 4-3: Estimated effect of the Catapult's support on the natural logarithm of turnover of participating SMEs (posterior distribution, weakly informative prior, PSM 1:1 comparison)



Source: SQW

Figure 4-4: Estimated effect of the Catapult's support on the natural logarithm of turnover of participating SMEs (posterior distribution, Vanino et al. prior, PSM 1:1 comparison)



Source: SQW

Assets

4.25 We analysed the impact of the Catapult's support on assets using two alternative priors, summarised in Table 4-6. We applied the same priors to both total and current assets, since we did not have reliable evidence to differentiate our expectations between the two measures. Also, since current assets are a subset of total assets, for many companies the percentage changes over time could be expected to be similar.

Table 4-6: Priors used for assets models

Prior	Rationale	Specification for the effect of support
Weakly informative (preferred)	Places minimal constraints on the estimate, allowing the data to drive the results.	A flat distribution, all values are characterised by equal probability density
SQW	Drew on SQW's extensive experience of evaluating innovation support as well as programmes aimed at improving businesses practices to encourage growth (including our recent work on the 5G Testbeds and Trials	Skew normal distribution: • Location 0.1 • Scale 0.1 • Shape 3

Prior	Rationale	Specification for the effect of support
	Programme), where typical assets effects are often around 20 percent. We introduced a skew in the distribution of the treatment effect to reflect the possibility that a small number of highly successful projects could pull up the average effect and to test the robustness of findings to the assumptions of the shape of the distribution.	

Source: SQW

4.26 Table 4-7 presents the estimated average effects on total and current assets of supported SMEs across the two priors. Based on our preferred weakly informative prior, following engagement with the Catapult total assets among supported SMEs were estimated to be 72.5% higher than the counterfactual trajectory (with the 95% credible interval between 52.1% and 95.8%). The estimated effect on current assets was very similar, with current assets among supported SMEs estimated to be 73.4% higher than the counterfactual trajectory (50.6% - 99.4% credible interval).

Table 4-7: Estimated effects of support on assets

Prior	Estimated effect	95% Credible Interval
Total assets		
Weakly informative (preferred)	72.5%	52.1% - 95.8%
SQW	50.8%	35.6% - 68.1%
Current assets		
Weakly informative (preferred)	73.4%	50.6% - 99.4%
SQW	48.9%	32.9% - 67.1%

Source: SQW

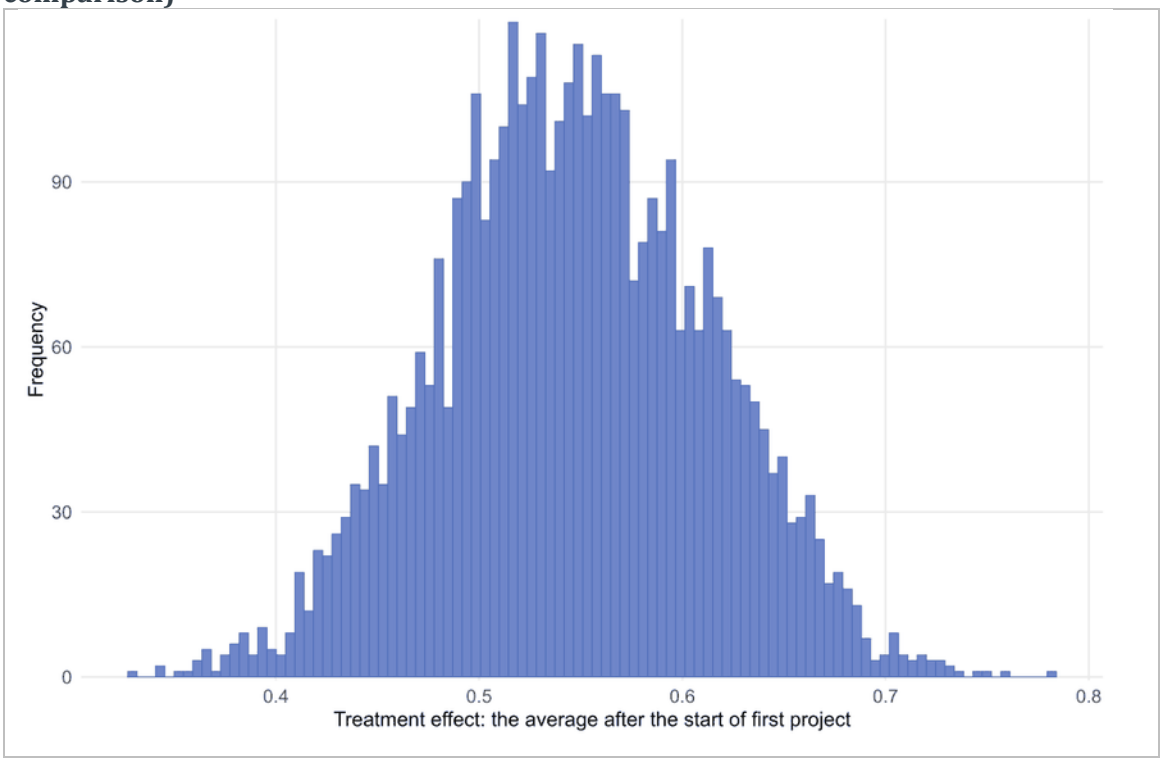
4.27 Across both outcome measures, the estimated effects remained positive and substantial when the alternative SQW prior was applied, at close to 50%. These estimates were lower, reflecting the SQW prior's much more conservative assumptions about the likely scale of impacts. All models passed our suite of diagnostic tests, confirming that they were well specified.

4.28 As with employment, for each outcome measure, we compared the two models using their out-of-sample predictive performance. This comparison found no statistical basis for preferring either, as the differences in predictive performance were small relative to their uncertainty. We therefore used the weakly informative prior as our preferred specification, as

it places fewer assumptions on the likely scale of impacts and allows the observed data to play a greater role in determining the estimated effects.

4.29 Figure 4-5 and Figure 4-6 show the posterior distributions of the treatment effects on total and current assets, respectively, obtained using our preferred weakly informative prior. In both cases, the distributions are concentrated well above zero, with no posterior probability assigned to zero or negative effects. The median of each posterior distribution corresponds to the percentage effects reported in Table 4-7 after transforming the estimated coefficients from the log scale.

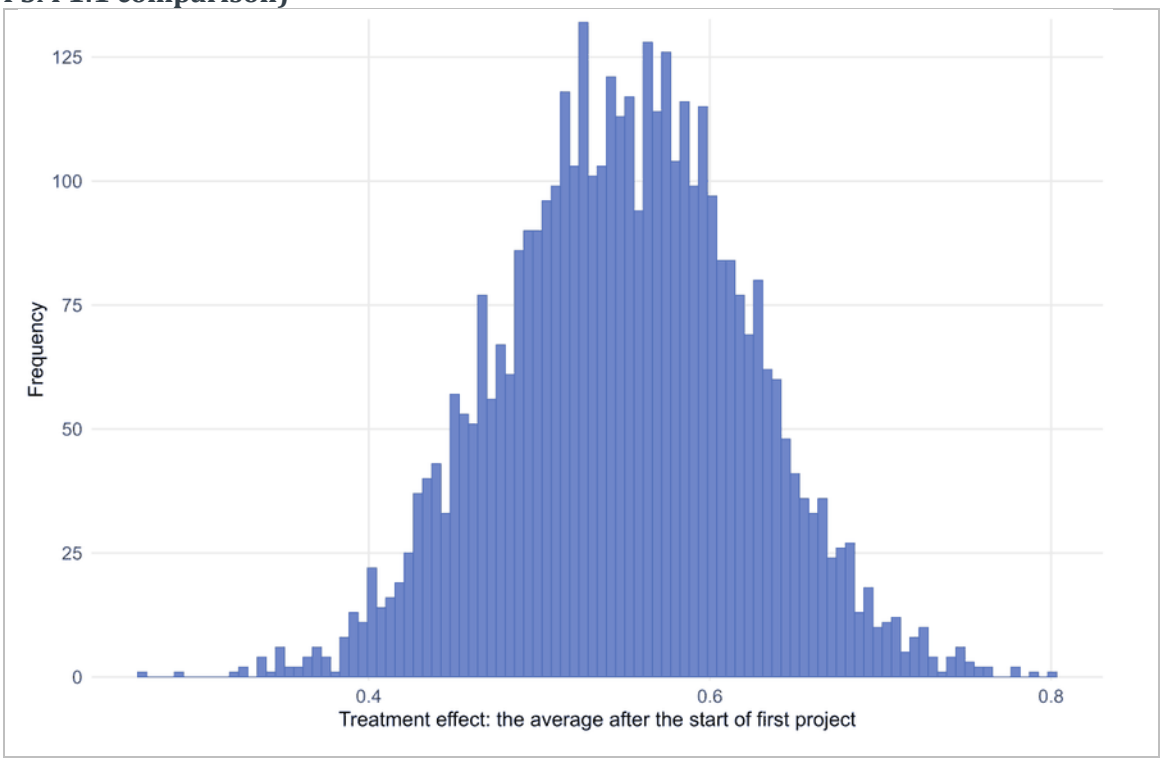
Figure 4-5: Estimated effect of the Catapult's support on the natural logarithm of total assets of participating SMEs (posterior distribution, weakly informative prior, PSM 1:1 comparison)



Source: SQW

4.30 The event study models were broadly consistent with the estimates of the average effects and provided additional insight into the time profile of impacts. Similar to employment effects, the estimated effects on assets emerged in the year of support and persisted for several years thereafter. However, the pattern differed somewhat across the two outcome measures. For current assets, the posterior distributions remained concentrated above zero from the year of support through to the third year following support (i.e. four years in total), whereas for total assets the evidence became considerably weaker by the third year after support. In both cases, the estimated effects were highly uncertain for the fourth year after support.

Figure 4-6: Estimated effect of the Catapult's support on the natural logarithm of current assets of participating SMEs (posterior distribution, weakly informative prior, PSM 1:1 comparison)



Source: SQW

External finance

4.31 Our analysis of the impact of the Catapult's support on SMEs' ability to attract external finance focused on three forms of external funding: grants (primarily from Innovate UK), loans and equity investment. Data on these outcomes was obtained from Beauhurst. The main outcome measure was the cumulative value of finance secured by each company over time. The DiD framework allowed us to examine whether the funding trajectories of supported SMEs diverged from those of the comparison group following engagement with the Catapult.

4.32 Table 4-8 summarises the baseline position of supported SMEs in terms of access to external finance before they first engaged with the Catapult. At that point, fewer than 20% had secured any form of external funding. Loans were the least common source of finance, which may reflect both the challenges of securing debt finance and its relatively high cost for early-stage businesses.

Table 4-8: Cumulative value of external funding accessed by supported SMEs before the support

Finance	Mean	Median	St.dev	Min	Max	N
Grants	£366k	£146k	£637k	£12k	£3,603k	52
Equity	£1,900k	£667k	£3,460k	£23k	£20,021k	42

Finance	Mean	Median	St.dev	Min	Max	N
Loans	£1,648k	£625k	£2,862k	£23k	£7,387k	6

Source: SQW analysis of Beauhurst data

4.33 Before undertaking the DiD analysis, we examined whether supported SMEs were more likely than comparator companies to secure external finance after they had started working on a project with the Catapult. The results of this analysis are summarised in Table 4-9. The reported marginal effect represents the average change in the predicted probability of receiving external finance associated with Catapult support, holding all other observed business characteristics constant.[35]

Table 4-9: Effect on the probability to secure external finance

	Marginal effect of support
All forms of finance	10 p.p. (59% → 69%)
Grants	13 p.p. (47% → 60%)
Equity	Not significant

Source: SQW

4.34 Supported SMEs were more likely than comparator companies to secure external finance after engaging with the Catapult. On average, support increased the probability of obtaining external finance by 10 percentage points. The evidence suggests that this effect was driven primarily by grants rather than equity investment.[36] In particular, support was associated with a 13 percentage point increase in the probability of securing grant funding, while no statistically significant effect was identified for equity investment.

4.35 The higher likelihood of securing external finance translated into substantially larger amounts of funding being raised by supported SMEs than would have been expected based on their counterfactual trajectory. Table 4-10 summarises the estimated average effects on the cumulative value of external finance secured following engagement with the Catapult. Overall, supported SMEs secured more than seven times the level of external finance implied by the counterfactual (on the log scale), reflecting increases in both grant funding and equity investment.[37] We also note that, while we did not identify an increase in the likelihood of

[35] These effects were calculated by first calculating the increase in predicted probability of securing the funding for each company in the sample from changing the Catapult support indicator from "no" to "yes", and then averaging the results across the whole sample.
[36] Loans were included within the aggregate measure of external finance, but the available sample was insufficient to support a separate analysis.
[37] The presented effects were obtained by exponentiating log coefficients. The confidence intervals expressed in % terms are very wide, nevertheless the effects are statistically significant at the 1% level.

securing equity investment, companies that did attract equity funding raised larger amounts than would be expected under the counterfactual.

Table 4-10: Estimated average effect on the cumulative sum of external finance post treatment

	Mean estimate	95% Conf. interval
All forms of finance	735%	234% - 1989%
Grants	375%	141% - 835%
Equity	240%	83% - 530%

Source: SQW

4.36 The 735% estimate should be read as a relative effect, not as a measure of absolute additional funding. As mentioned above, many SMEs held no external finance when support began. The model works on the logarithm of cumulative finance, so each move from zero to a positive amount registered as a large proportional change, and the coefficient reflects those moves.

4.37 To understand the absolute scale of the additional finance, we used the data on amounts raised. Supported SMEs secured £791m in external finance after the start of support. We then simulated the factual and counterfactual paths for the same SMEs, and the predicted gap between the two was approximately £300m.[38] The figure is lower than a simple application of the 735% finding would suggest, since the model estimated an average effect across all companies, and the average was affected by the movement away from zero.

4.38 Consistent with the above, further descriptive analysis indicated that the findings on the scale of additional finance were not driven by a small number of companies securing exceptionally large investments. Instead, the results reflected a broader increase in the number of supported SMEs attracting external finance, consistent with the earlier findings on the increased probability of obtaining funding.

4.39 We further note that the analysis identified a pre-existing negative gap in trends of grant funding and, consequently, in the combined measure of external finance prior to engagement with the Catapult. The modelling approach explicitly controlled for this difference in pre-support trajectories. As a result, the estimated impacts include an element of catch-up growth by supported SMEs relative to the comparison group, which may partially explain the magnitude of the observed effects.

[38] The simulation used a model of the level of cumulative external finance (in £), estimated on the same sample of supported and comparison SMEs. Unlike the specification behind Table 4-10, movements from zero are not treated as proportional changes. The factual path used the observed support status, and the counterfactual path predicted the amount of finance by "switching off" the support.

Valuations

4.40 We explored whether the Catapult's support was associated with changes in company valuations, using data obtained from Beauhurst. Because valuations are updated irregularly, typically when companies raise equity finance, the analysis compared the last valuation observed before support with the most recent valuation available after support.

4.41 Post-support valuation data was available for only 52 supported SMEs, 54 matched comparator companies and 22 ESC comparators, severely limiting our ability to identify any effect. Overall, we found no evidence that the Catapult's support affected company valuations within the observation period, using either frequentist or Bayesian methods. However, the relatively early stage of many supported SMEs means that any valuation effects, if present, may not yet be observable in the available data.

Further tests

4.42 Finally, we carried out sub-group analysis to explore whether the effects of the Catapult's support varied across the supported population of SMEs. To test for sector-specific effects, we estimated models that interacted the treatment variables with broad industry categories. We also examined whether effects differed between earlier and later cohorts of supported SMEs by splitting the sample according to the year in which the companies were first supported.

4.43 Across the outcome measures, we did not identify any notable differences in the estimated effects by sector or cohort. However, these findings should be interpreted cautiously because the relevant subsamples were relatively small, reducing the statistical power available to detect differences between groups. Given the absence of informative prior evidence for these subgroup effects, we did not pursue a Bayesian sub-group analysis.

4.44 Separately, we investigated whether SMEs that engaged with the Catapult multiple times experienced larger benefits than those receiving support for the first time. Although the initial estimates suggested the possibility of additional effects from repeat engagement, the results did not prove sufficiently robust. In particular, the models were sensitive to the choice of priors in the Bayesian estimations and did not consistently pass our robustness checks, including tests designed to identify potential bias arising from comparisons between companies treated at different points in time. Therefore, at this stage, we do not draw conclusions on the additional impact of repeat support.

4.45 Both the effects of repeat support and the heterogeneity of impacts across different groups of SMEs remain promising areas for future research as the population of SMEs working with the Catapult continues to grow.

5. Qualitative analysis of the support

Key points

- We carried out a short programme of semi-structured qualitative interviews with supported SMEs. The focus of the interviews was on how companies used the Catapult support and how the support contributed alongside other factors in shaping the outcomes.
- The insights from the interviews helped us to inform the economic impact model described in the following section. However, the limited response to the invitation to participate in the interviews means that the qualitative findings should be treated as illustrative rather than representative of the full population of supported SMEs.
- The Catapult's expertise in energy systems, advice on business development, and network facilitation were the most common types of support accessed by the interviewed SMEs. Most interviewed businesses did not have well-defined expectations about what the support would bring them.
- Although six of seven consultees expected to be able to complete their project without the Catapult, the support was reported to accelerate progress or improve the quality of outcomes. We also note that self-reported evidence on outcomes is often subject to optimism and confidence bias.
- The businesses we spoke to were confident in their in-house technical expertise necessary to develop their product or service. They were looking for technical validation, access to unique facilities (the Living Lab) and crucially investor-readiness and go-to-market support.
- The lack of expertise and experience with commercialisation activities was cited as the main remaining barrier to further development. Other external factors, such as the wider market direction, and related political and regulatory developments were also highlighted as having strong influence on outcomes.
- Overall, the interview evidence supports the conclusion that in most cases the Catapult's support is one contributing factor among several others shaping business progress, with its contribution being relatively high, particularly in the earlier stages of a project.

5.1 Qualitative, semi-structured interviews were included in the design of the impact assessment to supplement the quantitative findings and provide insight into how companies used the Catapult support and how the support contributed alongside other factors in shaping the outcomes reported.

5.2 The original plan was to speak to 20 supported SMEs, and the target sample was stratified to include both SMEs that, according to our records, demonstrated stronger and weaker growth since their first interaction with the Catapult. However, due to a limited response to our requests we were able to reach seven companies and conducted the interviews in August 2026.

5.3 The findings from the interviews provided valuable insights and helped us to inform the GVA model described in the following section. However, given the small sample, they should be viewed as illustrative rather than fully representative of the population of supported SMEs. Annex C describes our approach to sampling and securing interviews.

Profile of interviewees

5.4 The businesses we interviewed were at varying stages of development. Most were at the start-up or early stage (five of seven), with the remainder more established, operating as scale-ups or micro-businesses. As expected, interviewees' companies all offered products and services within the energy sector, with most linked to renewable energy or energy storage (six of seven). One focused on energy efficiency in construction.

5.5 Almost all interviews were conducted with the company's CEO (six of seven), and all interviewees had been directly involved in their business's engagement with the Catapult. Businesses varied in when they first accessed support, ranging from 2020 to 2026; five of the seven had accessed support relatively recently, since 2023. Five companies also reported engaging with more than one type of Catapult support or capability.

5.6 On two occasions, where a relatively long period had elapsed between the business's engagement with the Catapult and our interview, the interviewees found it challenging to recall specific details, or noted that colleagues involved in the original engagement were no longer with the business. But they still were able to comment on the overall effects of the support on the company.

Key findings

5.7 We carried out thematic analysis of the interview evidence, structured around four topics: businesses' expectations of support, the types of support they received, their reflections on the added value of that support, and the contribution of wider factors to their development. The findings below reflect key messages across those topics.

Expectations and objectives

5.8 Most businesses did not have any specific expectations of the Catapult's support that they could recall (5 of 7). Those that did had similar expectations to one another: that the support (for example, transfer of the industry knowledge, identification of funding opportunities, and networking), would help them to move their product from a proof of concept to commercialisation. A couple of businesses raised product or service validation as a key motivation for engaging with the Catapult, which they considered would generate internal confidence in their work, as well as external confidence in the market.

"If you've got a third-party telling you that you're doing something good, that gives confidence internally to continue to develop. I think it's important validation."

Supported business, Consultee 2

5.9 According to consultees, the Catapult's support helped most of them achieve their project objectives, in whole or in part (5 of 7). Where objectives had not been met, two businesses considered this was because the support they received was more generic, shaped by programme requirements rather than fully aligned with their specific business needs.

The type of support and the extent of influence

5.10 The Catapult's expertise in energy systems, advice on business development, and network facilitation were the most common types of support accessed by the interviewed SMEs. Within energy systems expertise, consultees identified support such as demand and competition assessment, product pricing, strategy development, and routes to market. Business development support, meanwhile, was reported to include pitch development, identifying funding routes, and legal or contractual planning. Finally, network support was described as providing direct introductions to relevant contacts, as well as facilitating access to sector events and international business programmes.

"[Neither clients nor funders] care about the bolts and the nuts. Nobody cares about that. What they care about is, what is it going to do for them? What is the business case? What is the user story? What will it do? And the [pitch development] sessions helped, really helped sharpen that up."

Supported business, Consultee 7

5.11 There was little evidence that the businesses we spoke to engaged with the Catapult seeking technical expertise related to their product or service development. Where relevant, businesses reported confidence in their in-house technical expertise, looking only for technical validation or, in one instance, use of the Living Lab environment to facilitate a pilot test.

Reflections on added value

5.12 Interviewees often reported that the Catapult's support added value by either accelerating the progress or improving the quality of the projects. For example, it provided certain financial support or the expertise the SMEs lacked to determine the next steps in the commercialisation process or access to the Living Lab to pilot a product at scale (four out of seven consultees expressed such opinions).

"It definitely accelerated the whole process because whatever grant there was from Catapult, it definitely helped us do the pilot, spend the money, get things done. We are a bootstrapped company, so if it was coming from our own directors funds, it would have taken a little bit longer."

Supported business, Consultee 6

5.13 One business also reported that there was indirect influence on their business growth trajectory from the Catapult's brand – i.e. them validating the product, which resulted in greater visibility and credibility when bidding for various project delivery frameworks.

"Indirectly, yes, the Catapult definitely contributed in a way to [our business'] growth. But again, they don't own the market for PAS [Publicly Available Specification] buying clients, government regulations and statutory [requirements]."

Supported business, Consultee 2

5.14 At the same time, most interviewees expressed confidence that their business would likely have completed its project even without the Catapult's support (six out of seven cases), in other words they did not necessarily see the Catapult's support as critical. However, it is likely that there is a degree of optimism bias in this finding, as the evidence is self-reported and relies on an individual's view of the capability of their own business and its employees.

5.15 Overall, the consultees considered the Catapult's contribution as an important supporting role in shaping their businesses' progress, alongside other factors. The progress was often reported to be strongly influenced by the wider market direction, and by related political and regulatory developments. For example, one business found that the timing of its product development aligned particularly well with the growing momentum towards the greater use of retrofit technologies, with new UK Government regulations on technical insulation making its product a more attractive offer in the market.

5.16 There were also examples of external inhibiting factors. For example, one consultee suggested that their progress was hindered by a shift in the UK Government policy on hydrogen energy: an area that had initially been a strong priority, but was later seen to be stalling, accompanied by substantial policy uncertainty around renewable energy more generally. Separately, low awareness among clients and consumers was also reported to lead to lower levels of engagement and adoption of products and services, hindering growth prospects.

"Certainly, government policy was a big factor as well. And the Catapult understood that. And they were relaying key elements to us, and there were meetings in London around the government policies. So they were very useful. We've taken a bit of a hit, unfortunately, because the hydrogen strategy kind of went backwards for the UK."

Supported business, Consultee 7

5.17 Another example of an inhibiting factor, this time internal to businesses, was a lack of internal commercialisation and sales expertise. This point was highlighted by two of the interviewees. Initial technical product development had required employees with specific technical skill sets; however, both businesses now needed expertise in strategy and marketing to commercialise their products. Both companies accepted that this transition was typical and an expected challenge, however at this point in time it was reported to be the main barrier to further development.

"Well, we don't have the right skills because we're all technical. I've got lots of lovely people who can't sell anything. The support we've had around investor readiness, go to market strategy, marketing segmentation, have been really, really valuable for us but I don't have the tools to be able to apply them."

Supported business, Consultee 1

5.18 Finally, the consultations revealed that a small number of interviewed businesses had benefited from other funded business support (two out of seven). Examples of external support that they accessed included business workshops from Sustainable Ventures, and UK Atomic Energy Authority grant funding.

Overarching assessment

5.19 Overall, the interview evidence supports the conclusion that in most cases the Catapult's support is one contributing factor among several others shaping business progress, consistent with how we modelled attribution in Section 6. SMEs' own assessments, that they would likely have progressed without support, need to be weighed against the potential for optimism bias, discussed above and particularly the tendency to attribute setbacks to external barriers rather than crediting the Catapult for their successes.

5.20 In our opinion, the evidence suggests a relatively high degree of contribution of the support to SMEs achieving their objectives, particularly in the earlier stages of a project and when access to the Living Lab was required. The wider factors, including market conditions, government policy, and SMEs' own commercial capabilities, become more prominent barriers as product/service development progresses towards commercialisation, consistent with our assumption that the Catapult's contribution to outcomes declines over time following the support.

6. Modelling of the Economic Impacts

Key points

- The Catapult's support generated an estimated £210m (95% confidence interval between £176m and £249m) in additional GVA (2025 prices) across the 288 SMEs it has supported, of which £154m has already been realised and £56m is expected to materialise by 2029.
- The estimate is conservative and partial: it captures only direct benefits to supported SMEs and excludes wider indirect effects, such as additional activity generated through the supported SMEs' supply chains. In addition, the estimate excludes potential GVA benefits to the UK from the Catapult's wider work driving innovation in the clean energy sector, for example potential system-level savings from the Catapult's impact in accelerating the development of a lower-cost, flexible future energy system. These benefits are potentially very large but were beyond the scope of this study to quantify.
- We estimated this impact using a bespoke Monte Carlo simulation model, which translated econometric estimates of net employment impacts into Gross Value Added, extrapolated across the full population of supported SMEs.
- Two key assumptions, displacement (20%) and attribution (80%, declining over time), relied on judgement informed by consultation evidence and SQW's wider experience of evaluating similar business support programmes, rather than on direct measurement.
- Although a formal cost-benefit analysis was out of scope, comparing the central GVA estimate against the Catapult's core grant funding (£101.4m since 2018; £37.7m since the start of the current grant period in 2023/24, both in 2025 prices) suggested that every £1 of public investment generated approximately £2 of additional GVA. This result points towards good value for money, subject to confirmation through the Catapult's own full Value for Money assessment.
- Sensitivity testing confirmed that the findings were broadly robust. Even under the most pessimistic combination of assumptions tested, the central estimate exceeded the core grant funding: £126m against £101.4m since 2018, with the whole confidence interval above the investment. For the current grant period, the central estimate (£43m) also exceeded the £37.7m invested, although in that scenario the lower limit of the confidence interval (£32m) fell below it.

6.1 This section quantifies the additional Gross Value Added (GVA) that the Catapult's support generated across supported SMEs, and sets out the methodology, key assumptions and results underpinning the GVA estimates. These figures are based on the econometric estimates of net impacts on the supported SMEs presented in Section 4. They are intended to inform the Catapult's own cost-benefit analysis and Value for Money assessment.

Approach to GVA estimation

6.2 The GVA model used Monte Carlo simulation to estimate the additional economic value generated by the Catapult's support, while considering the uncertainty in the scale of impacts across the supported firms in a systematic and transparent way. Inevitably some supported SMEs will perform better than others over the medium term, generating more additional employment and economic value for the economy. The modelling was informed primarily by the econometric estimates of the Catapult's net impacts on business performance. However, we also drew on qualitative discussions with seven supported SMEs and SQW's wider experience of evaluating business support programmes to select reasonable assumptions in relation to parameters that cannot be fully identified through a quasi-experimental design (for example displacement and attribution).[39]

6.3 The GVA analysis was based on the estimated employment effects and covered both realised and expected benefits. The duration of impacts was derived from the event study econometric model described in Section 4, which identified additional impact on employment over four years following an SME's first engagement with the Catapult. For the SMEs supported more recently, some of these benefits are still expected rather than realised.

6.4 The analysis was carried out in real terms (i.e. adjusting for inflation, prices taken at the end of 2025 / start of 2026). We discounted expected future benefits (expected beyond 2026) at 3.5% per year, in line with HM Treasury Green Book guidance, to reflect social time preference: expected benefits are worth less to society than benefits that have been realised already.

6.5 The modelling of benefits covered all 288 SMEs supported by the Catapult by January 2026, despite the firm-level econometric analysis drawing on a smaller sample of 267 companies due to data availability. The use of Monte Carlo simulations allowed us to extrapolate net impacts to the full population of supported companies, while capturing the uncertainty this introduces for companies outside of the econometric sample.

6.6 The GVA estimates should be interpreted as a conservative view of the additional economic value generated by the Catapult's support, since the modelling captured direct benefits only –

[39] Displacement occurs when a supported company's additional activity displaces economic activity elsewhere in the economy, for example by taking market share from a competitor. Attribution reflects that the Catapult's support is often one of several factors contributing to a supported company's outcomes.

i.e. the additional GVA supported SMEs contributed to the economy. Indirect benefits, such as additional economic activity generated through their supply chains, were not modelled. The estimate also does not include future impacts that may be generated on the back of securing additional external funding by the SMEs.[40] Furthermore, our analysis did not cover any potential GVA benefits to the UK from the Catapult's wider work driving innovation in the clean energy sector, for example, potential system-level savings from the Catapult's impact in accelerating the development of a lower-cost, flexible future energy system. These benefits are potentially very large but were beyond the scope of this study to quantify.

Model structure

6.7 To estimate the additional GVA generated by the Catapult's support, we developed a bespoke simulation model. The process involved the following steps:

- **Step 1: Modelling the baseline**. For each supported SME we constructed their position prior to their first project with the Catapult, including: sector, employment, and the year in which they secured this support.[41,42,43] This step drew on monitoring data and company information available from Beauhurst.

- **Step 2: Projecting employment growth**. For each supported SME, the model projected two growth trajectories. The counterfactual path reflected the growth rate of the comparison group. The post-support trajectory added the additional employment growth observed among the supported SMEs. We derived both trajectories based on the econometric analysis presented in Section 4.

- **Step 3: Estimating additional employment**. This step calculated the difference between the post-support trajectory and the counterfactual path, yielding the number of additional full-time equivalent (FTE) jobs likely generated following each company's engagement with the Catapult.

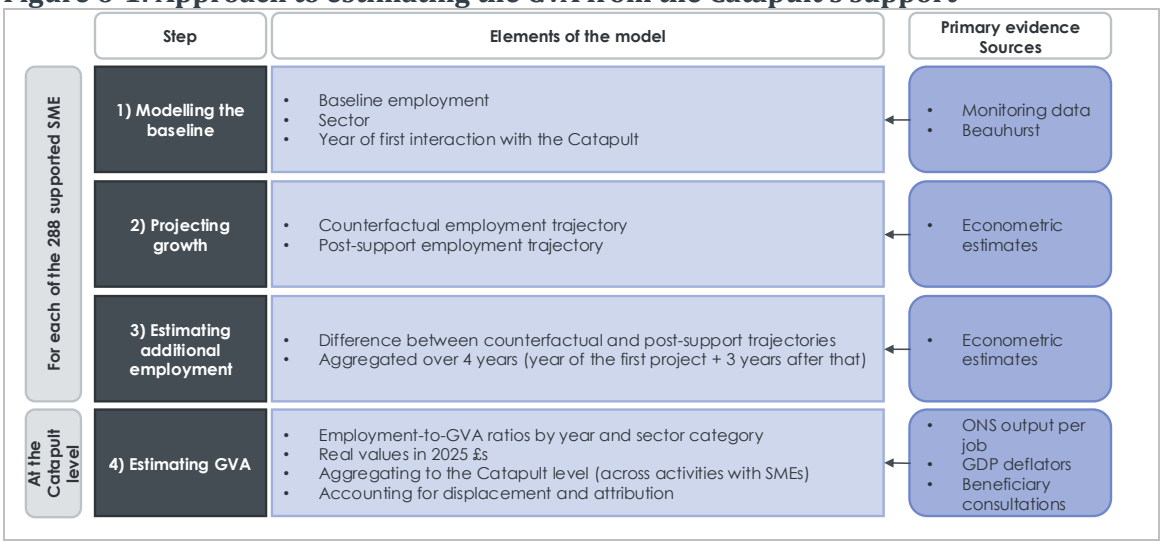
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[40] We adopted this approach because modelling wider effects would have introduced additional uncertain parameters. Focusing on a smaller number of more important parameters reduced the risk of generating confidence intervals too wide for the results to be meaningful or overstating the impacts.
[41] For modelling purposes, we simplified the sector composition of the programme. We grouped companies using high-level SIC chapters, retaining chapters C, J and M as separate categories, as they accounted for the majority of supported SMEs. We combined all remaining sectors into a single 'Other' category.
[42] For firms that engaged with the Catapult on multiple projects, we considered their profile before the start of the first one.
[43] We based the sector definitions at the baseline on the actual sector of each company as recorded in Beauhurst. If the sector information was missing, we assigned that company a sector (C, J, M or Other) based on the distribution of sectors observed among the companies with that data. Similarly, where Beauhurst held baseline employment data, we used the actual values. For companies with missing employment, we imputed values from the sector-specific distribution of firms with non-missing data: each firm was assigned a random percentile between zero and one and an employment value was drawn from the corresponding point in its sector's distribution. This approach reflected that company size may vary systematically across sectors.

- **Step 4: Estimating the GVA across the Catapult's portfolio of SME support**. The model translated the net additional employment generated by each supported SME into GVA in real terms, and aggregated the results across the SMEs.[44] We also accounted for displacement and attribution effects at this stage. This step drew on ONS output-per-job data, GDP deflators, and consultations with supported companies (specifically their perceptions of the Catapult's relative contribution compared with other factors).[45]

6.8 Figure 6-1 summarises the methodology described above.

Figure 6-1: Approach to estimating the GVA from the Catapult's support



Source: SQW

Assumptions

6.9 The table below presents the parameters and parameter values used to estimate the economic benefits of the Catapult's support.

Table 6-1: Parameters and assumptions used in modelling the GVA

Parameter	Value	Evidence
Parameters underpinned by monitoring data and consultations with SMEs		
Number of supported SMEs	288	Monitoring data
Displacement	• 20% central estimate • 10% and 30% sensitivity analysis	SQW's experience of full evaluations of similar programmes

[44] We carried out the employment-to-GVA conversion by year and sector. We used separate estimates for sectors C, J and M, with a combined "Other" category covering the remaining sectors. The "Other" estimate was based on weighted average GVA per job across the remaining SIC chapters, which reflected the composition of those sectors among supported SMEs.

[45] Output per job, UK - ONS; GDP deflators at market prices, and money GDP - GOV.UK

Parameter	Value	Evidence
Attribution of the additional benefits to the Catapult (rather than other factors not captured by the quasi-experimental design)	• Year of support: 80% • 1 year after support: 70% • 2 years after support: 60% • 3 years after support: 50%	Based on consultation evidence
Parameters underpinned by Beauhurst data (descriptive analysis)		
Sector composition	• 20% in sector C • 26% in sector J • 30% in sector M • 24% grouped as 'Other'	Beauhurst
Baseline employment by sector	• Sector C: an empirical distribution of 1 to 184, with a median of 5 • Sector J: an empirical distribution of 1 to 55, with a median of 4 • Sector M: an empirical distribution of 1 to 211, with a median of 4 • 'Other': an empirical distribution of 1 to 219, with a mean of 4	Beauhurst
Parameters underpinned by official statistics		
GVA per job by sector (nominal values)	• Sector J: between £84.3k and £109.5k over 2018-2025 • Sector M: between £55.4k and £77.1k over 2018-2025 • Sector C: between £73.5k and £93.0k over 2018-2025 • 'Other': between £84.0k and £133.9k over 2018-2025	ONS Output per job
Real GVA per job growth over 2026 - 2029	• 1.5% per year	Average real productivity growth based on ONS's Real Time Information administrative data
Parameters based on econometric analysis		

Parameter	Value	Evidence
Counterfactual growth trajectory (non-attributable to the Catapult)	• 7% per year	Econometric analysis (Bayesian)
Additional log employment: average after the first interaction with the Catapult[46]	Empirical posterior distribution (see Figure 4-2) • Median: 0.155 • Credible interval low: 0.105 • Credible interval high: 0.205	Econometric analysis (Bayesian analysis, Beauhurst data, priors informed by analysis of the BSD data)
Duration of the effect on employment	Four years: the year of first support and the three consecutive years	Econometric analysis

Source: SQW

Evidence on attribution of additional jobs to the support and displacement effects

6.10 We did not have formal survey evidence on displacement for this study. Instead, we based this parameter on SQW's wider evidence base from evaluating comparable business support programmes, including 5GTT for DSIT, the British Patient Capital and Debt Funds for the British Business Bank, the suite of support provided by Be the Business, and the activities of High Value Manufacturing Catapult. Displacement for business support interventions typically ranges between 10% and 50%, with lower values associated with more innovative, new-to-market products or applications. Given the nature of the Catapult's support, we consider 20% a reasonable central estimate, and we tested the sensitivity of our results to this assumption (explained below).

6.11 The attribution parameter reflects that engagement with the Catapult was often only one of several factors contributing to a project's success and the creation of additional jobs. We informed this parameter through consultations with supported SMEs, who, as we discussed in Section 5, highlighted that the Catapult's contribution varied depending on the type of support received. Specifically, access to the Living Lab, a unique facility of connected homes, was considered to be a critical factor for projects that rely on it. General business advice and market insight, by contrast, was perceived as important alongside other factors rather than critical.

[46] The additional growth figures are based on econometric estimates in logarithmic form. They are approximately equivalent to percentage effect per year. The actual percentage estimate can be found by exponentiating the coefficient. For coefficients with an absolute value closer to zero, the coefficient roughly corresponds to the percentage effect; however, the higher the absolute value the bigger the difference between the estimate and actual effect in percent. The difference reaches 1 p.p. when the estimate is 0.14 (~15%), it is 2 p.p. when the coefficient is 0.2 (~22%). The model corrected for these differences when it simulated additional employment for each company.

Alternative approaches to monetising employment impacts

There are two common approaches to monetising the benefits of additional employment. The approach used in this section estimated the GVA generated by the additional jobs, using output per job in the relevant sector. It then adjusted the result for displacement and attribution.

The alternative method follows the Green Book guidance. For appraisal purposes, the Green Book advises practitioners to generally assume that the national labour supply is constant. Under this principle of full displacement, every job created is filled by a worker who vacates a different job elsewhere in the economy. The benefit of a created job is then in its productivity premium: the difference between productivity in the supported job and the UK average (or a narrower outside option, if sufficient evidence exists).

For this assessment of the Catapult's support for SMEs, we preferred the approach outlined earlier in the main body of this section, for the following reasons:

- **Employment is an intended outcome and impact**: the Catapult's logic model (Annex A) explicitly includes growth in UK employment as an impact and an increase in direct employment of SMEs as an outcome, so the outlined approach is consistent with the agreed programme objectives.
- **Evaluation activities**: the Green Book assumption guides practitioners appraising proposals. This study examined what actually happened, consistent with the Magenta Book's emphasis on the evidence from delivery.
- **Specialist nature of the jobs:** The productivity premium approach implicitly assumes that a worker in an average job could fill a specialist position. The flip side is that a worker at a supported SME, had the job not been safeguarded, would accept an average position. Neither of these assumptions is realistic for the jobs in focus of the research.
- **The approaches differ partly in labelling:** The productivity premium approach is equivalent to assuming a displacement rate equal to UK average productivity as a share of the supported SMEs' sector productivity. The two approaches can therefore be seen as differing in how much effective displacement they assume. Our analysis tested displacement rates of 10-30%, which we considered consistent with the highly innovative activities of the supported SMEs.

We accept that evaluation evidence should also be useful for appraisal. To reduce any further work needed to align the evidence with appraisal requirements, Annex D presents the results of the GVA calculations using the productivity premium approach.

6.12 Notably, when asked about other factors affecting their outcomes, consultees tended to focus on barriers rather than enablers, such as a lack of internal skills, limited market or consumer

awareness, and the challenging regulatory environment in the energy sector. This pattern, together with potential overconfidence bias (the belief among business leaders that they would have succeeded regardless of receiving any support), points towards a high level of attribution to the Catapult.

6.13 On balance of evidence, we concluded that the average contribution of the Catapult's support across projects could reasonably be set at 80%, declining by 10 percentage points each year thereafter. Since this figure reflects our judgement rather than a directly measured value, we tested the sensitivity of our results by varying the starting contribution to 60% and 100%.

Model simulations

6.14 The Monte Carlo model was simulated 10,000 times.[47] In each run, we sampled uncertain parameters from their assumed distributions, including baseline employment and sector for firms with missing data and the additional employment growth attributable to the Catapult's support for each company. Each simulation therefore produced a different estimate of the additional GVA generated, reflecting the range of uncertainty in the underlying parameters.[48]

Subsample analysis for the current core grant period

6.15 We also carried out a supplementary analysis restricted to the group of 90 SMEs first supported by the Catapult from the 2023/24 financial year onwards, corresponding to the Catapult's current core grant period. This subsample analysis used the same model, assumptions and methodology as the full-population estimate.

6.16 The purpose of this analysis was to align the GVA estimates with the current funding period, enabling a more straightforward comparison of monetised benefits against costs. We note, however, that this estimate does not capture the impacts of any companies supported after January 2026. We also note that the subgroup estimate still drew on the results of the

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[47] The simulations were performed using the SimDesign package in R: Chalmers, R.P. and Adkins, M.C. (2020) 'Writing effective and reliable Monte Carlo simulations with the SimDesign package', The Quantitative Methods for Psychology, 16(4), pp. 248–280.

[48] In practice, the true effect of the support is likely to vary across supported SMEs. The model approximated this variation by sampling from the estimated distribution of the average treatment effect from the Bayesian analysis. We recognise that the spread of the posterior for the average effect may be narrower than the true between-firm heterogeneity, because the posterior converges around the mean as the sample size increases.

To test whether this approximation was reasonable, we examined the residuals (differences between observed and predicted values) from the econometric model. Residuals from treated firms before the start of support and from comparison firms capture noise only. Residuals from treated firms after the start of support capture both noise and any treatment heterogeneity. If heterogeneity in the effect of support were substantially wider than the posterior, we would expect a noticeably higher variance in the latter group. In practice, the variance was very similar across the two sets of residuals, and marginally smaller for treated firms after the start of support. This pattern suggests that the posterior distribution of the average treatment effect could be used as a reasonable approximation of the between-firm variation in impacts.

econometric analysis of the whole population of supported SMEs. Our sub-group econometric analysis did not indicate any substantial differences in average effects across cohorts and therefore restricting the underlying sample for the impact assessment would unnecessarily reduce the precision of the estimates.

Results

6.17 The 10,000 simulations of the model produced an estimated net economic contribution of approximately £210m (in 2025 prices) from the 288 SMEs supported by the Catapult, of which £154m have already been realised and the remainder is expected by 2029. The corresponding figures for the subsample of companies supported from the 2023/24 financial year onwards are £72m and £26m (Table 6-2). Figure 6-2 shows the full distribution of the additional GVA estimated through the analysis while Figure 6-3 shows the picture for the more recent subgroup.

Table 6-2: Monte Carlo simulation results for GVA impacts among supported SMEs

	Mean (expected) value	95% confidence interval	Minimum	Maximum
Full population				
Additional GVA	£210m	£176m – £249m	£152m	£291m
Realised	£154m	£126m – £185m	£110m	£213m
Expected	£56m	£44m – £72m	£36m	£90m
Support since 2023/24 onwards				
Additional GVA	£72m	£54m – £94m	£42m	£114m
Realised	£26m	£19m – £35m	£18m	£47m
Expected	£46m	£34m – £63m	£32m	£67m

Note: the mean values for realised and expected GVA sum to the mean for additional GVA. However, the minimum and maximum values do not necessarily sum in the same way, as the lowest or highest realised and expected values did not always occur within the same simulation run. Source: SQW

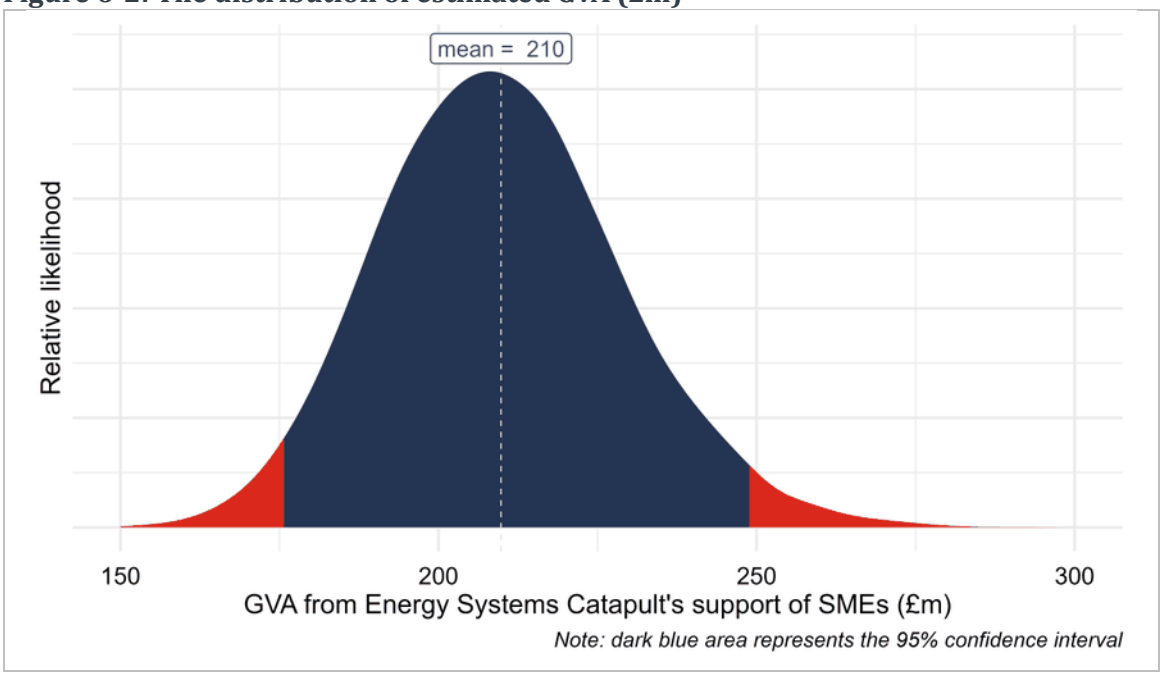
6.18 The Catapult provided us with figures for their core grant funding: £101.4m since 2018, and £37.7m invested since the start of the current grant period (April 2023).[49] On this basis, every £1 of public investment generated approximately £2 of additional GVA: the indicative benefit-

[49] Both expressed in 2025 £s.

to-cost ratio across the full sample is 2.1, and it is 1.9 when the comparison is restricted to the SMEs supported since 2023/24.[5051]

6.19 Although a formal cost-benefit analysis and wider Value for Money assessment remained outside the scope of this assignment, both comparisons pointed towards good value for money, particularly given that the GVA estimates were conservative and partial. Notably, our estimates excluded indirect effects such as supply chain impacts, any economic value that can be expected to be generated in future by the SMEs from additional funding secured with the Catapult's support, and wider non-monetisable benefits. At the same time, the cost figures were not apportioned to SMEs specifically (i.e. they cover all of the Catapult's other activities as well). Furthermore, the entire 95% confidence interval for the additional GVA sits above the corresponding cost figures, suggesting that we can be reasonably confident that the Catapult's support has more than paid for itself in economic terms.

Figure 6-2: The distribution of estimated GVA (£m)

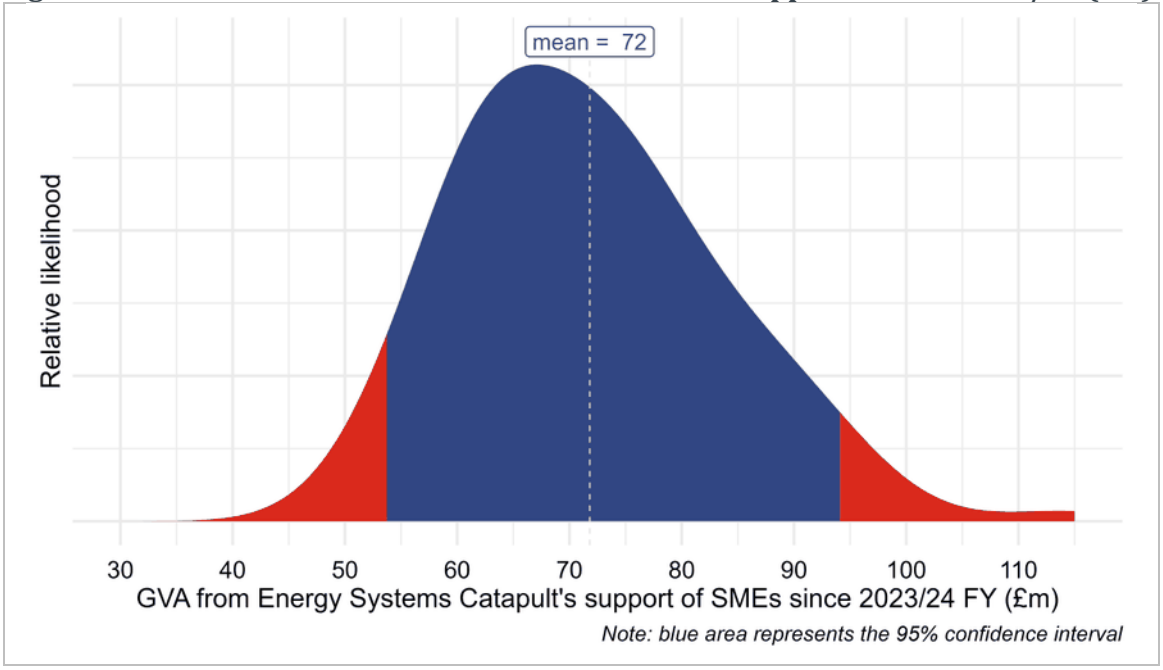


Source: SQW

[50] The analysis of the current grant period covers only the SMEs supported by January 2026 rather than over the whole grant period. Furthermore, a larger proportion of benefits is expected in the future and is therefore subject to discounting. Although the arithmetic ratios are slightly different, we consider the two results to be equivalent.

[51] We note that since baseline data were also incomplete (pre-support employment data were missing for c. 30% of the SMEs) the results of our modelling for the most recent subsample could vary depending on the imputation procedure. To obtain our main results we filled the gaps using the empirical distributions observed across all supported SMEs with data. This approach benefited from a larger pool of data but assumed no structural change in the population of supported SMEs. We observed no such change in the data and to the best of our knowledge there were no strategic decisions by the Catapult to approach SME recruitment differently compared to earlier periods. As a robustness test, we undertook the estimation where we filled the missing baseline data for SMEs supported for the first time in the most recent period using data from their peers supported in the same period. The resulting central GVA estimate was £57m, which lies within the 95% confidence interval of our main estimate.

Figure 6-3: The distribution of estimated GVA for SMEs supported since 2023/24 (£m)



Source: SQW

Sensitivity testing

6.20 Two parameters in the GVA model relied to a greater extent on self-reported evidence and our judgement rather than objective measurement: displacement and attribution. To test the sensitivity of our results to these parameters, we varied both from their central estimates: displacement across 10%, 20% and 30%, and the starting attribution value across 60%, 80% and 100%. Table 6-3 summarises the resulting GVA across the nine combinations of these two parameters, presenting the central estimate and 95% confidence interval for each scenario.

Table 6-3: Sensitivity testing – displacement and attribution

Displacement\starting attribution	100%	80%	60%
Full population			
10%	£309m	£236m	£162m
	(£259m – £367m)	(£198m – £280m)	(£136m – £193m)
20%	£275m	£210m	£145m
	(£230m – £326m)	(£176m – £249m)	(£121m – £171m)
30%	£240m	£184m	£126m
	(£201m – £285m)	(£154m – £217m)	(£105m - £150m)
Support since 2023/24 onwards			

Displacement\starting attribution	100%	80%	60%
10%	£106m	£81m	£56m
	(£79m – £139m)	(£65m – £106m)	(£42m – £73m)
20%	£94m	£72m	£50m
	(£70m – £123m)	(£54m – £94m)	(£37m – £65m)
30%	£82m	£63m	£43m
	(£62m – £108m)	(£47m – £82m)	(£32m - £57m)

Note: 95% confidence intervals are presented in parentheses. Source: SQW

6.21 Both parameters affect the estimated GVA, as expected, though not equally. Varied on its own, with attribution held at its central estimate of 80%, displacement has a relatively modest effect: the additional GVA ranges from £184m to £236m across the 10 – 30% range tested, remaining within the confidence interval for our main result (£176m – £249m). Attribution has a larger effect on the central estimate: holding displacement at its central estimate of 20%, the additional GVA falls outside the main confidence interval both when attribution starts at its highest tested value of 100% (£275m) and at its lowest tested value of 60% (£145m). A similar pattern holds for the subsample of SMEs supported since 2023/24.

6.22 Although the specific estimates varied with the assumptions, the sensitivity testing reinforced our overall conclusion that the Catapult's support was likely to represent good value for money (subject to confirmation by the Catapult's own full Value for Money assessment). Even in the most pessimistic scenario, the central estimate of benefits exceeded the core grant funding. For the full period since 2018, the entire 95% confidence interval (£105m – £150m) in that scenario was above the £101.4m invested. The lower limit of the confidence interval fell below the grant value only for the more recent subsample, where the estimate did not yet cover all SMEs expected to be supported by the end of the grant period. At the other extreme, in the most favourable scenario, even the lower limit of the confidence interval reached over 2.5 times the public investment for the full period since 2018 (£259m), and over double the investment for the current grant period (£79m).

7. Reflections

7.1 This report presents findings from a quasi-experimental analysis of the effects of Energy Systems Catapult's support on SMEs. As set out in the Catapult's Evaluation Framework, this analysis forms one element of a broader programme of evaluation activities guided by the principles of contribution analysis. The findings presented here therefore provide an important source of evidence on the Catapult's effects, but should be interpreted alongside the complementary qualitative evidence, including the feedback presented in Section 5, as well as other theory-based strands of the evaluation.

7.2 To estimate the effects of the Catapult's support, we used a difference-in-differences framework and compared supported SMEs against two complementary comparison groups over time. The analysis examined impacts across six outcome measures covering business growth, access to external finance, and company valuations. To strengthen the analysis where appropriate, we combined the observed data with evidence from previous evaluations and wider research using Bayesian estimation techniques.

7.3 As is often the case with quasi-experimental evaluation work, the main limitation of the analysis relates to the maturity of the evidence base. The monitoring data supplied for the analysis primarily covered activity from April 2018 onwards, although two engagements did begin in January 2018. Over 50% of supported SMEs first engaged with the Catapult in 2022/23 or later. Furthermore, many support activities span multiple years. As a result, the analysis primarily captures short- and medium-term outcomes rather than ultimate long-term impacts. This limitation is particularly relevant for outcomes such as turnover and company valuations, where effects often take longer to emerge than changes in employment, access to external finance or asset growth, which can be viewed as intermediate outcomes that create a foundation for longer-term commercial success.

7.4 A second limitation relates to the ability of quasi-experimental methods to account for factors that are not recorded in the available data. While the use of multiple comparison groups and robustness testing increases confidence in the findings, the analysis cannot fully rule out the influence of unobserved factors, nor can it directly explain the mechanisms through which impacts occur.

7.5 As part of this project, we sought to collect complementary qualitative evidence through consultations with supported SMEs. We were able to speak with seven companies, and these discussions provided valuable insights into how the support was used in practice. In particular, we drew on this evidence to inform several assumptions within the economic impact model and to interpret some of the patterns emerging from the quantitative analysis. However, for reasons outside the control of either SQW or the Catapult, the level of engagement was lower than originally intended. A broader programme of consultations would have allowed us to test our interpretation of the quantitative findings more extensively

and further refine a number of modelling assumptions and parameter values, potentially reducing uncertainty around the resulting estimates.

7.6 Overall, the quantitative evidence suggests that the Catapult's support contributed to the growth of supported SMEs. The strongest and most consistent evidence relates to employment, which was estimated to be approximately 17% higher than the counterfactual trajectory following engagement with the Catapult. The analysis also identified positive effects on SMEs' ability to attract external finance. Supported SMEs were both more likely to secure external funding and raised substantially larger amounts of finance than would be expected under the counterfactual.

7.7 These findings were further supported by the results for total and current assets. Following engagement with the Catapult, supported SMEs accumulated a larger asset base than would be expected based on the path of the comparator companies. Since external funding is ultimately reflected on company balance sheets, the asset results provide an important consistency check for the estimated effects on external finance. Taken together, the evidence suggests that the Catapult's support helped participating SMEs secure additional resources and expand their capacity, laying the foundation for future growth.

7.8 We did not have enough evidence to suggest that the Catapult's support consistently affected turnover or company valuations during the observation period. Supported SMEs continued to grow their turnover following engagement with the Catapult, but at a rate broadly comparable to that observed among the comparison groups. Likewise, although some supported SMEs experienced substantial increases in company valuations, the available evidence did not suggest a systematic effect across the population of firms supported by the Catapult.

7.9 One possible explanation for the lack of impacts on turnover and valuations is that both are later-stage outcomes compared to employment growth and asset accumulation. While the analysis found evidence that supported SMEs were securing additional resources and expanding their organisational capacity, it often takes time for these changes to translate into positive commercial outcomes. Supported SMEs may use the additional finance, assets and staffing capacity identified by our analysis to continue refining products, building partnerships, navigating regulatory requirements or preparing for market entry.

7.10 This pattern is, to a certain degree, corroborated by our qualitative evidence: several supported SMEs reported that, having received the Catapult's support largely at the technical product development stage, they now lacked internal commercialisation and sales expertise, which they identified as the main barrier to translating their progress into commercial success. Other consultees pointed to external market and regulatory conditions as a further factor slowing this transition (see Section 5).

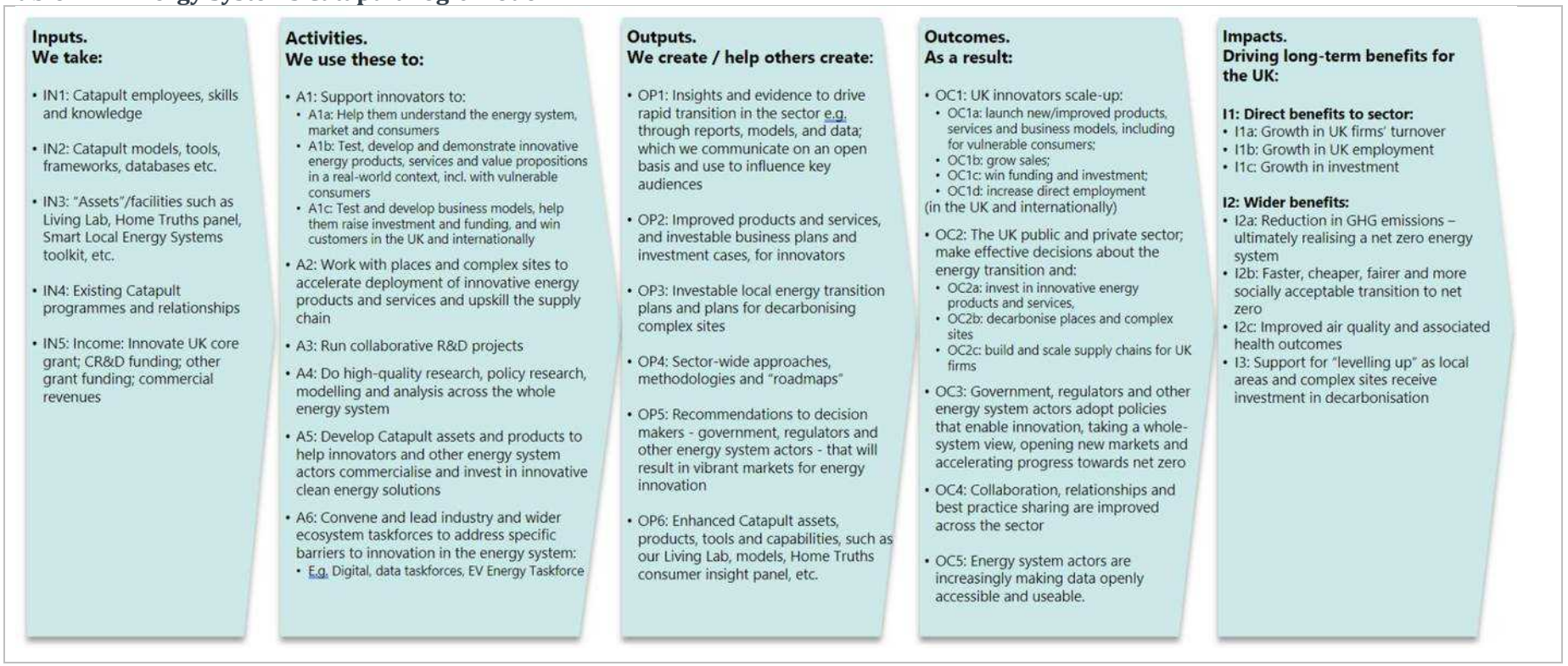
7.11 Based on the impact analysis and simulation modelling used to account for uncertainty in the results, we estimated that the Catapult's support generated approximately £210m in additional GVA (2025 prices) across the 288 SMEs it has supported since 2018, of which

around £154m had already been realised, with a further £56m expected to materialise by 2029. The corresponding estimate for the subsample of SMEs supported since the start of the current grant period in 2023/24 was £72m. Both estimates were conservative and partial: they captured only direct benefits to supported SMEs and excluded wider non-monetisable effects from the Catapult's activities.

7.12 Although a formal cost-benefit analysis was outside the scope of this impact assessment, a comparison of the central GVA estimates against the Catapult's core grant funding (£101.4m since 2018; £37.7m since the start of the current grant period) suggested that every £1 of public funding was associated with approximately £2 of additional GVA. These findings suggest a strong return on public investment and provide an important piece of evidence for the wider Value for Money assessment.

Annex A: The Catapult's logic model

Table A-1: Energy Systems Catapult Logic Model



Source: Energy Systems Catapult Evaluation Framework

Annex B: Further statistical detail

B.1 This annex provides further detail on the statistical analysis used to estimate the impact of the Catapult's support on the business performance of SMEs, as presented in Section 3 (Comparison groups) and Section 4 (DiD analysis) of the main report. All statistical analysis was performed in R with extensive use of its core functionality (R Core Team, 2023), as well as the dplyr (Wickham, 2023), Matching (Sekhon, 2011), cobalt (Greifer, 2024), ggplot2 (Wickham, 2016) and brms (Bürkner, 2017) packages. The simulation work described in Section 6 (Modelling of the economic impacts) used the SimDesign package (Chalmers & Adkins, 2020).[52]

Propensity Score Matching

B.2 PSM was our primary selection technique for identifying the comparison group. Table B-1 presents the results from the estimation of the PSM matching model. It shows which company characteristics were associated with a higher or lower likelihood of receiving the Catapult's support.[53]

Table B-1: PSM estimation results

	estimate	std.err.	statistic	p-value	conf. low	conf. high
(Intercept)	-3.21	0.28	-11.61	0.00	-3.77	-2.68
SIC section: C	0.50	0.25	1.99	0.05	0.01	1.00
SIC section: F	-0.37	0.38	-0.97	0.33	-1.17	0.34
SIC section: J	0.40	0.24	1.71	0.09	-0.05	0.87

[52] R Core Team (2023) R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing; Wickham, H. et al. (2023) *dplyr: A Grammar of Data Manipulation*; Sekhon, J.S. (2011) Multivariate and propensity score matching software with automated balance optimization: the matching package for R. *Journal of statistical software*, *42*, pp.1-52.; Greifer, N. (2024) Covariate balance tables and plots [R package cobalt version 4.5.5]; Wickham, H. (2016) *ggplot2: Elegant Graphics for Data Analysis.* s.l.:Springer-Verlag New York; Bürkner, P.-C. (2017) brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software*, 80(1), pp.1–28; Chalmers, R.P. and Adkins, M.C., 2020. Writing effective and reliable Monte Carlo simulations with the SimDesign package. The Quantitative Methods for Psychology, 16(4), pp.248–280.

[53] The table presents the estimation outputs from a logistic regression, where the outcome is whether a company was supported by the Catapult. In simple terms, positive coefficients indicate characteristics that were relatively more common among supported SMEs, while negative coefficients indicate characteristics that were less common. The p-values and confidence intervals indicate the strength of evidence for these relationships, with lower values (typically below 0.05) and confidence intervals that exclude zero providing stronger evidence of an association between a characteristic and programme participation. The propensity score for each company was generated by combining these estimated coefficients with each company's own characteristics to produce a single predicted probability of receiving the support.

	estimate	std.err.	statistic	p-value	conf. low	conf. high
SIC section: M	-0.05	0.22	-0.21	0.83	-0.48	0.40
SIC section: N	-0.08	0.35	-0.22	0.82	-0.80	0.59
Region: East Midlands	-0.68	0.47	-1.45	0.15	-1.70	0.17
Region: East of England	-0.46	0.31	-1.48	0.14	-1.10	0.12
Region: North East	-0.50	0.50	-0.99	0.32	-1.61	0.40
Region: North West	0.15	0.27	0.55	0.58	-0.41	0.67
Region: Northern Ireland	-1.05	0.79	-1.33	0.18	-2.95	0.28
Region: Scotland	0.04	0.26	0.17	0.87	-0.48	0.55
Region: South East	0.29	0.21	1.36	0.17	-0.13	0.70
Region: South West	-0.06	0.27	-0.23	0.81	-0.61	0.45
Region: Wales	-0.10	0.42	-0.25	0.80	-0.99	0.66
Region: West Midlands	0.83	0.26	3.21	0.00	0.31	1.32
Region: Yorkshire and The Humber	0.03	0.36	0.08	0.94	-0.72	0.70
Any RTIC code	0.84	0.15	5.62	0.00	0.55	1.14
On high growth list	-0.35	0.20	-1.71	0.09	-0.76	0.04
Innovate UK funding (pre-support)	1.55	0.20	7.94	0.00	1.17	1.94
Environmental Accolades signal	1.92	0.21	9.03	0.00	1.51	2.34
Clean Energy signal	0.61	0.18	3.38	0.00	0.26	0.97
Academic spinout	-0.16	0.27	-0.59	0.56	-0.71	0.36
Any other environmental	-0.22	0.27	-0.82	0.41	-0.74	0.30

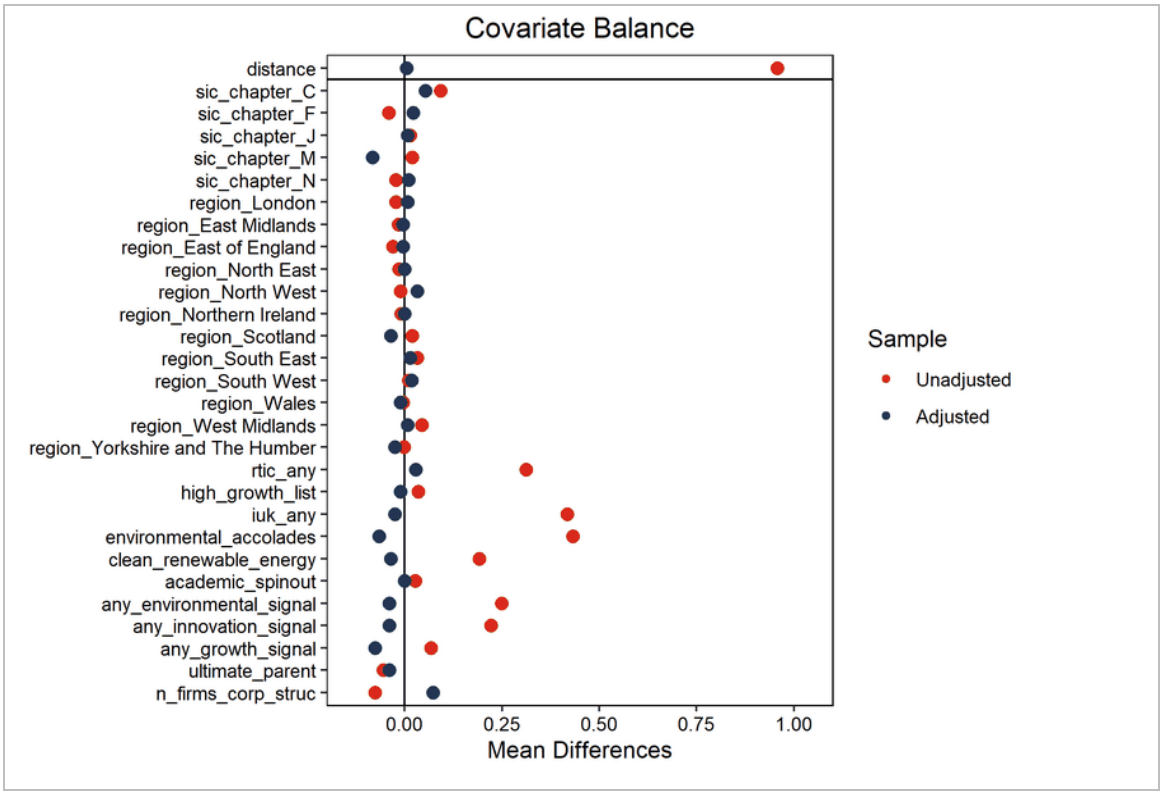
	estimate	std.err.	statistic	p-value	conf. low	conf. high
signal (beyond Accolades and Clean Energy)						
Any innovation signal	-1.04	0.21	-5.05	0.00	-1.44	-0.64
Any growth signal (beyond high growth list)	-0.73	0.17	-4.19	0.00	-1.07	-0.39
Ultimate parent	-0.63	0.18	-3.45	0.00	-0.99	-0.27
Number of firms in corporate structure	-0.01	0.00	-1.77	0.08	-0.01	0.00
Model statistics						
N	4,089					
Log-likelihood	-796					
AIC	1648					
BIC	1825					
McFadden R2	0.22					

Note: Due to small cell counts, sectors G and S were merged with all other sectors not mentioned in the table and used as a reference category. Source: SQW

B.3 Figure B-1 shows the average differences between the groups for each individual characteristic, across all companies in the sample. The closer the dots sit to the vertical line, the more similar the group averages. Figure B-2 shows the distribution of propensity scores ('distance') before and after matching. The more similar the shapes above and below the middle line, the more like-for-like the two groups are. The latter comparison reflects the combined characteristics of each business, rather than the average of each characteristic considered individually.

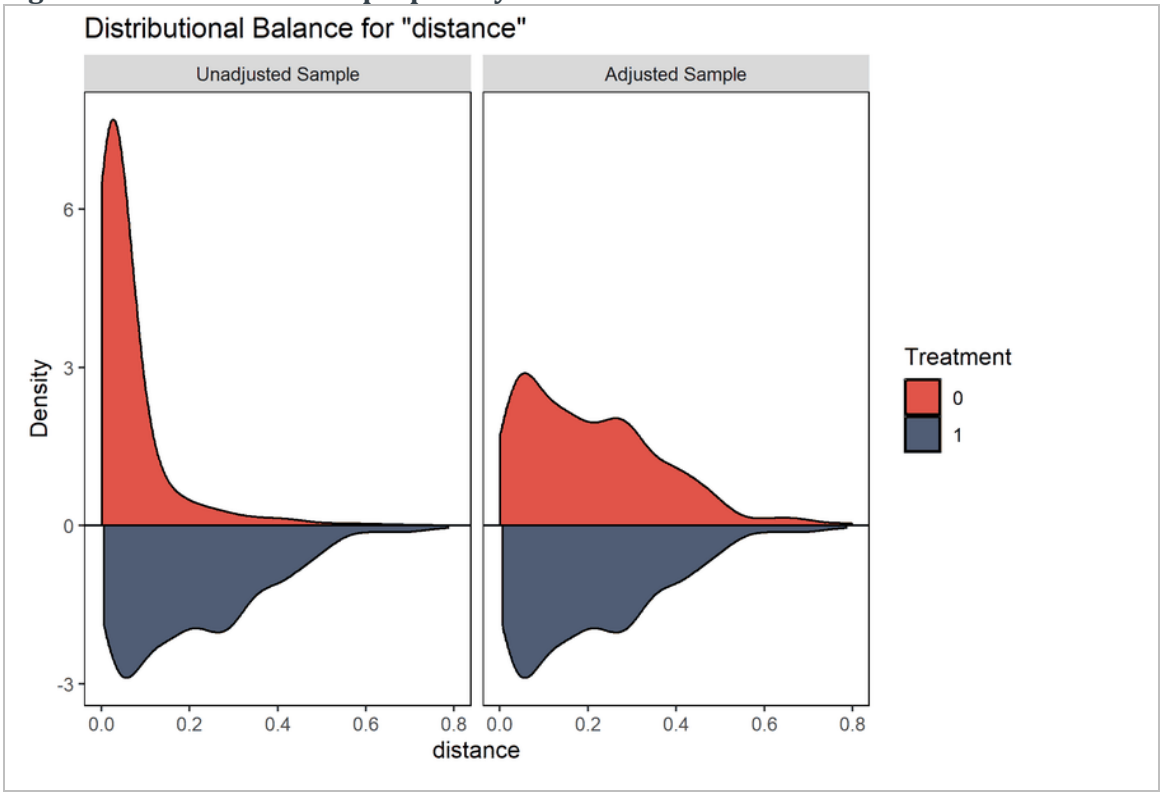
B.4 Checking the balance figures provided initial evidence that PSM successfully selected comparator companies with observable characteristics similar to those of the supported SMEs. PSM cannot identify a group of unsupported companies that are absolutely identical to the supported companies, but it aims to narrow the differences between the two, and the results confirmed that it was successful in this.

Figure B-1: Balance between the supported SMEs and comparison firms by characteristics before and after PSM



Note: unadjusted sample is the whole wider pool of c. 4,000 companies we identified using simple filters on age, sector, tracking status and buzzwords (both based on Beauhurst data). Source: SQW

Figure B-2: Distribution of propensity scores before and after PSM

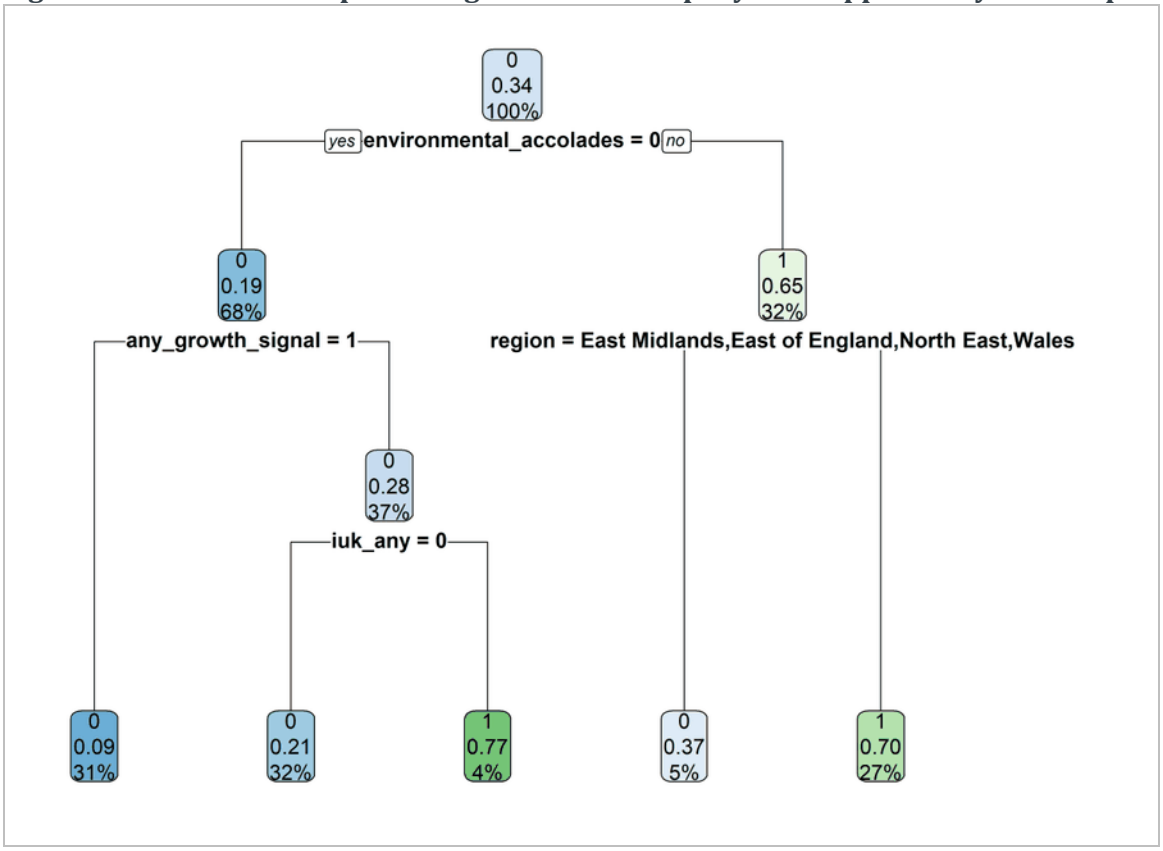


Source: SQW

Decision trees

B.5 As described in the main text of the report, we used decision trees to complement PSM. This approach drew on the same underlying information and identified the same important characteristics as PSM, but considered them sequentially rather than simultaneously. We trained the decision tree algorithm on a random sample from the Beauhurst and Data City comparator pool, and the algorithm selected the tree shown in Figure B-3 as the best predictor of whether a company was supported by the Catapult.[54]

Figure B-3: Decision tree predicting whether a company was supported by the Catapult



Source: SQW

[54] Each box in the tree contains three pieces of information: the top number (0 or 1) is the predicted classification (0 for comparator, 1 for a supported SME); the middle number is the likelihood that a company in that group was supported; and the bottom percentage is the share of the total sample falling into that group. A decision tree works by repeatedly splitting companies into smaller groups based on their characteristics, choosing at each step the characteristic that best separates supported SMEs from comparators. Starting at the top with the full sample, each split creates two branches based on a yes/no question about a company characteristic. Rather than splitting the data until every group is fully separated, which would risk fitting to noise in this particular sample, the tree was kept deliberately shallow, stopping once further splits would add little reliable separation between supported SMEs and comparators.

Analysis of pre-treatment trends

B.6 Improved balance between supported SMEs and the comparator pool was one indicator of comparison group quality. As a further check, we examined trends in the key outcome measures across the comparison groups. For conciseness, the pre-trend tests presented in this annex focus on employment, the outcome variable that formed the foundation of our impact modelling; equivalent graphs and tests were also carried out for other key outcome variables, and the outputs are available on request.

B.7 Figure B-4 plots average log employment over the period from three years before support to five years after for supported SMEs, the PSM-matched comparison group, the comparator companies selected using decision trees, and the ESC comparison group. The vertical dashed line marks the last year before support began.[55] No companies in the ESC comparison group had data available five years after their interaction with the Catapult, and the number of supported SMEs with data at that point was also small; the 'kink' visible in their line towards the far right of the graph should therefore not be interpreted as evidence of typical impacts.

Figure B-4: Pre-support trends in log employment



Note: this graph is based on Beauhurst data. Source: SQW

B.8 This graphical analysis focused on the period to the left of the vertical line, that is, the pre-support trajectories of the averages. Both the levels and trends were broadly similar before support began, with the exception of the group comprised of unsuccessful applicants

[55] The year of support for companies that had multiple projects was determined based on the earliest interaction with the Catapult.

B.9 (UAs) and companies that participated in the SME Surgery, where the level was somewhat lower. This pattern was consistent with the key assumption underpinning the difference-in-differences models which requires similarity of trajectories rather than levels.

B.10 However, the graphical analysis presented only a partial picture, since it did not account for the timing of support for individual companies or the size of each group. For example, the left and right tails of the graph were underpinned by fewer observations, each of which carried a higher weight in the calculation of the average and could 'pull' the line to a greater extent.

B.11 To further investigate the parallel trends assumption, we carried out two formal tests at the analysis stage. The first added 'leads' to the event study model, testing for anticipatory effects in the years before support began. Informed by the number of available datapoints, we investigated anticipatory effects for up to three years prior to treatment. The second was a placebo test, in which we isolated the pre-support period for all companies, split it into placebo 'before' and 'after' subperiods, and tested for differences in outcomes between the comparison groups and supported SMEs over a two-year window before the support began. The results of both tests are presented in Table B-2 and Table B-3.

Table B-2: Test for anticipatory effects

	estimate	std. error	p-value
PSM 1:1 group			
Anticipatory effect – 3 years before	0.13	0.15	0.41
Anticipatory effect – 2 years before	0.13	0.15	0.42
Anticipatory effect – 1 year before	0.09	0.14	0.54
Model statistics			
N	2,039		
Fixed effects	Firm and year		
Standard errors	Two-way clustered		
Firm clusters	442		
Year clusters	10		
Adj. R^2 (overall)	0.53		
Within R^2	0.01		
ESC comparison group			
Anticipatory effect – 3 years before	-0.17	0.20	0.41

	estimate	std. error	p-value
Anticipatory effect – 2 years before	-0.12	0.19	0.55
Anticipatory effect – 1 year before	-0.10	0.18	0.59
Model statistics			
N	1,691		
Fixed effects	Firm and year		
Standard errors	Two-way clustered		
Firm clusters	388		
Year clusters	10		
Adj. R^2 (overall)	0.56		
Within R^2	0.02		
Decision trees group			
Anticipatory effect – 3 years before	0.37	0.12	0.002
Anticipatory effect – 2 years before	0.33	0.12	0.003
Anticipatory effect – 1 year before	0.27	0.11	0.013
Model statistics			
N	2,625		
Fixed effects	Firm and year		
Standard errors	Two-way clustered		
Firm clusters	566		
Year clusters	10		
Adj. R^2 (overall)	0.48		
Within R^2	0.01		

Source: SQW

Table B-3: Test for the effects of placebo treatment on log employment over a two-year period before the start of the Catapult support

	estimate	std. error	p-value
PSM 1:1 group			

	estimate	std. error	p-value
Placebo support over the two years prior to engaging with the Catapult	0.04	0.06	0.57
Model statistics			
N	867		
Fixed effects	Firm and year		
Standard errors	Two-way clustered		
Firm clusters	319		
Year clusters	9		
Adj. R^2 (overall)	0.67		
Within R^2	0.001		
ESC comparison group			
Placebo support over the two years prior to engaging with the Catapult	0.08	0.06	0.24
Model statistics			
N	773		
Fixed effects	Firm and year		
Standard errors	Two-way clustered		
Firm clusters	287		
Year clusters	10		
Adj. R^2 (overall)	0.66		
Within R^2	0.003		
Decision trees group			
Placebo support over the two years prior to engaging with the Catapult	0.01	0.05	0.81
Model statistics			
N	1,098		
Fixed effects	Firm and year		
Standard errors	Two-way clustered		

	estimate	std. error	p-value
Firm clusters	401		
Year clusters	10		
Adj. R^2 (overall)	0.64		
Within R^2	0.008		

Source: SQW

B.12 The placebo test did not identify any unexpected changes in the trend of supported SMEs before their interaction with the Catapult. The test for anticipatory effects carried out using the PSM 1:1 and ESC comparison groups provided further encouragement that the parallel trends assumption held.

B.13 However, we identified substantial pre-existing differences in pre-support trends when the analysis was carried out relative to the decision tree comparison group, possibly reflecting that this method was less selective, drawing in a larger number of comparators from across the wider pool.

B.14 On the basis of the above checks, we discounted the decision tree (DT) comparison group and as a precautionary measure we incorporated a variable capturing any differences in pre-support growth trends between the groups directly into the final regression models, as described below in this annex.

Impact analysis

DiD models

B.15 Our estimates for the average DiD model came from a two-way fixed effects specification (a DiD model that controls both for fixed differences between companies and for changes over time common to all of them), applied over the calendar timeline, with treatment switching on for each business at the relevant point in time. As discussed in detail in Goodman-Bacon (2021),[56] in such a model the treatment effect is estimated using two sources of comparison: how supported SMEs' outcomes changed relative to the comparison group, and relative to other supported SMEs that first engaged with the Catapult at different points in time (a design sometimes called the pipeline approach). Drawing on both sources is particularly useful when analysing relatively small samples. Our models also included a linear group-specific trend to capture pre-existing differences in growth between supported SMEs and comparators that could not be attributed to support.

[56] Goodman-Bacon, A., 2021. 'Difference-in-differences with Variation in Treatment Timing'. Journal of Econometrics, 225(2), pp.254-277.

B.16 The following equation describes the general model:

$$Y_{it} = \alpha_i + \gamma_t + \beta_1 D_{it} + \beta_2 X_{it} + \beta_3 (C \cdot t) + \varepsilon_{it},$$

where:

- Y_{it} – is the outcome measure of interest for company i in time t
- α_i – is a company 'fixed-effect' capturing potentially unobserved time-invariant characteristics of each particular company (e.g., their management style, risk attitudes etc.)
- γ_t – is the time 'fixed effect' capturing the influence of general macro-economic conditions in the economy and tracing out the growth over time that is common for supported companies and comparators
- D_{it} – takes the value of one for the supported SMEs when $t \geq \tau_i$ (τ_i is the year in which the firm first engaged with the Catapult) and zero otherwise. β_1 is the coefficient of interest (the DiD estimate). It represents the average uplift in the outcome of interest observed in the years after the start of the Catapult support
- X_{it} – is a vector of additional variables that could be included to control for specific business characteristics[57]
- $C \cdot t$ is the pre-existing linear group trend. C takes the value of one for all supported SMEs and t is a linear trend
- ε_{it} – is the error term.[58]

B.17 The event study models differed in that, instead of a single treatment indicator covering all post-support years, they included separate variables for the year in which an SME first engaged with the Catapult and for each subsequent year after the start of support:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{\tau=t_i}^{t_i+4} \beta_{1_\tau} D_{i\tau} + X_{it} + \beta_3 (C \cdot t) + \varepsilon_{it.}$$

[57] For example, we used additional controls to investigate the differences in effects for companies that engaged in multiple projects, by including an interaction: $D_{it} \cdot multiple\ projects$, however that interaction term was poorly identified and did not feature in any of the final models. Our main models did not include any additional controls, since the overall approach was mimicking a randomised control trial with the allocation performed by PSM and fairly equal balance on observable characteristics across the groups.

[58] We tested an alternative non-linear specification for the trend that does not assume monotonicity (i.e. that the supported SMEs are on a constantly increasing trajectory relative to the comparison companies), however we found the linear approximation to be a better fit for the data.

B.18 The analysis period in all our DiD models was restricted to three years prior to the start of the support and four years afterwards. This restriction was necessary because of the small number of observations available outside that window, which would otherwise have had a disproportionate effect on the estimates.

B.19 As a further check, we tested whether our two-way fixed effects specification was vulnerable to bias that can arise when comparisons between already-treated and not-yet-treated companies are affected by treatment effects that vary across cohorts. Applying the decomposition proposed by de Chaisemartin and D'Haultfœuille (2020),[59] we found that, for example in our employment model, of 534 underlying comparisons, 42 (8%) received a negative weight; however, these contributed only around 1.3% of the total weight to the overall estimate of the treatment coefficient. We therefore concluded that, although present, this bias had a limited effect on our results, and proceeded with our chosen specification rather than alternative estimators such as Callaway and Sant'Anna (2021).[60] Such estimators are based on estimating effects separately by cohort; in our case, individual cohorts were too small to allow us to reliably identify effects.

B.20 The analysis of valuations used a simpler 2×2 DiD model, in which the last available pre-support valuation was taken as the 'before' observation, and the latest available post-support valuation as the 'after' observation. This adjustment was necessary because valuations are updated irregularly.

B.21 Finally, to estimate the effect of the Catapult's support on the probability of attracting external finance, we used a logit model:

$$P(Y = 1|X) = \Lambda(\beta_1 D_i + X_i + \varepsilon_i),$$

where Λ is the cumulative distribution function of a logistic distribution and P is the probability of a positive outcome. This model was analysed using maximum likelihood estimation. We ran the models both controlling for companies' observable characteristics and without the controls (following the quasi-experimental logic and relying on the balance of characteristics across the groups). The findings in relation to the effects of the Catapult's support were consistent.

Estimation results

B.22 Before presenting the results that were not included in the main body of the report, we note that all of the Bayesian models passed the standard suite of diagnostic tests. These included convergence diagnostics (visual analysis of trace plots, R-hat below 1.01, and adequate

[59] de Chaisemartin, C. and D'Haultfœuille, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9), pp.2964–2996.
[60] Callaway, B. and Sant'Anna, P.H., 2021. Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), pp.200–230

effective sample sizes for all key parameters), posterior predictive checks confirming that the models reproduced the key features of the observed data, and leave-one-out (LOO) based model comparison across prior specifications.

B.23 The Bayesian models produced four key outputs for each estimated effect, summarised in Table B-4. The median reports the 50th percentile of the posterior distribution and serves as our central estimate (an equivalent of the point estimate from the standard models). The 95% credible interval gives the range within which the true effect falls with 95% probability, given the observed data. The probability of direction reports the probability that the effect has the same sign as the median, providing a continuous measure of confidence in the direction of the impact. Finally, the percentage in the Region of Practical Equivalence (ROPE) reports the probability that the effect is too small to be meaningful from a policy perspective, defined here as within plus or minus 2% for employment and turnover effects, and plus or minus 10% for assets. These are summary statistics; the models also produce full posterior distributions, which can be shown graphically alongside the tabular results.

Table B-4: Interpreting the summary of a Bayesian model

Output	Description
Median	The 50th percentile of the impact distribution
95% credible interval (CI)	Given the observed data, there is a 95% probability that the 'true effect' falls in this interval
Probability of direction (pd)	The probability that the parameter has the same sign as the median
% in Region of Practical Equivalence (ROPE)	The probability the effect is in the region where it is deemed too small to be meaningful from the policy perspective (assumed to be +/-2% for employment and turnover effects, and +/-10% for current and total assets)

Source: SQW

B.24 Unless otherwise stated, the estimates presented in this annex are regression coefficients from the regression models. The actual percentage estimate can be found by exponentiating the coefficient. For coefficients with an absolute value closer to zero, the coefficient roughly corresponds to the percentage effect; however, the higher the absolute value the bigger the difference between the estimate and actual effect in percent. The difference reaches 1 p.p. when the estimate is 0.14 (~15%), it is 2 p.p. when the coefficient is 0.2 (~22%), 5 p.p. when the estimate is 0.3 (~35%), etc.

Employment: average DiD model

B.25 Table B-5 presents the average Bayesian DiD estimates for employment under all four informative priors considered for the PSM matched comparison group. The table also lists key diagnostic indicators across the models. Overall, all models generated the probability of

direction (pd) of c. 100%, and none of the posterior distribution within ROPE, indicating high confidence in both the direction and practical significance of the effect.

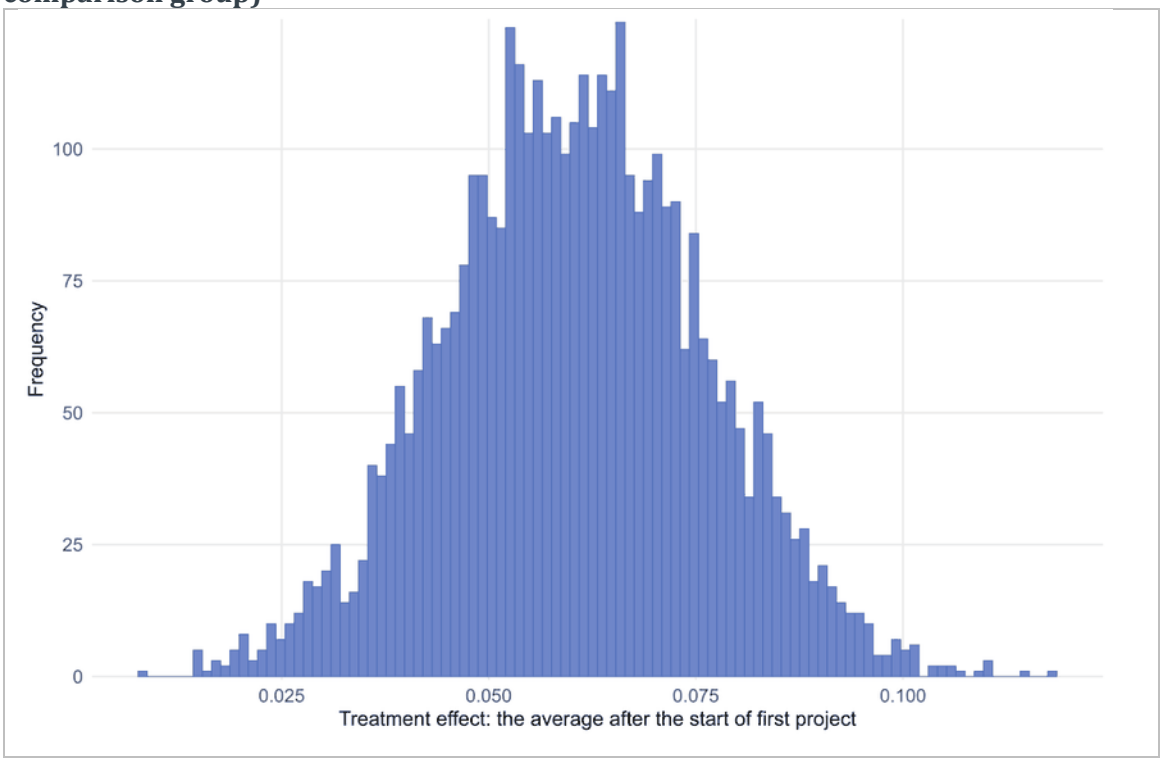
Table B-5: Bayesian results for employment effects in the average DiD (PSM 1:1 comparison group)

Prior	Median	CI low	CI high	pd	% in ROPE
BSD 'cross-prior' (preferred)	0.16	0.10	0.20	100%	0%
Weakly informative	0.17	0.12	0.22	100%	0%
SQW	0.14	0.10	0.18	100%	0%
Vanino et al.	0.06	0.03	0.09	100%	0%
Model statistics					
N (observations)	2,039				
Group-level effects	Firm and year				
n (firms)	442				
$\hat{R}$ *(max)*	1.002				
Min bulk ESS / min tail ESS	3252 / 2978				
MCMC	4 chains; 4,000 post-warmup draws; 0 divergent transitions				

Source: SQW

B.26 Figure B-5 shows the posterior distribution obtained using the Vanino et al. prior. Consistent with that specification being more conservative about the scale of impacts, the distribution is shifted to the left compared with our preferred model. Importantly, however, the skewed shape assumed by us in this prior is not supported by the data: the posterior remains symmetric. This finding provides reassurance about the strength of the signal in the data regarding the relationship between the Catapult's support and employment growth.

Figure B-5: Estimated effect of the Catapult's support on the natural logarithm of employment of participating SMEs (posterior distribution, Vanino prior, PSM 1:1 comparison group)



Source: SQW

B.27 To select our preferred prior, we compared the out-of-sample predictive performance of the four specifications using leave-one-out (LOO) cross-validation. LOO estimates how well each model would predict new observations not used in estimation, providing a data-driven basis for comparing priors. The key statistic is the difference in expected log pointwise predictive density (ELPD) relative to the best-performing model, effectively a measure of relative predictive accuracy: values close to zero indicate equivalent predictive performance, while the standard error of the difference indicates whether any gap is meaningful.

B.28 Table B-6 shows that the ELPD differences across the weakly informative prior, BSD cross prior and SQW prior were negligible and well within one standard error of zero. The data therefore provided no basis for preferring one prior over another – changing our starting assumptions about the likely size of the effect made almost no difference to the results, with all three priors leading to very similar conclusions. The Vanino et al. prior, by contrast, showed materially worse predictive performance. On this basis, we retained the BSD cross-prior as our preferred specification, since it incorporated information from two independent data sources.

Table B-6: LOO comparison of out of sample predictive power of employment models

Prior	ELPD difference	s.e. of the difference
BSD 'cross-prior' (preferred)	0.0	0.0

Prior	ELPD difference	s.e. of the difference
Weakly informative	0.0	0.5
SQW	-0.2	1.1
Vanino et al.	-6.5	3.5

Source: SQW

B.29 Table B-7 presents the frequentist average-effects DiD estimate for employment, using the PSM 1:1 comparison group. The point estimate (0.17) is consistent with our Bayesian findings, and the effect is statistically significant at any conventional threshold. The pre-existing trend variable was statistically insignificant, confirming that the matching was successful in aligning pre-support trends between the two groups.

Table B-7: Frequentist results for employment effects in the average DiD (PSM 1:1 comparison group)

	estimate	CI low	CI high	p-value
Effect of support	0.17	0.07	0.26	0.00
Pre-existing group trend	-0.03	-0.08	0.02	0.22
Model statistics				
N	2,039			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	442			
Year clusters	10			
Adj. R^2 (overall)	0.56			
Within R^2	0.006			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect Source: SQW

Employment: the event study model

B.30 Table B-8 presents the results from our Bayesian estimation of the event study DiD. Table B-9 provides the estimates of the same model obtained using the standard frequentist approach. The Bayesian results are based on the weakly informative prior, to allow for a direct comparison between the estimation approaches rather than the choices of assumptions about the scale of the effects.

Table B-8: Bayesian results for employment effects in the event study DiD (weakly informative prior, PSM 1:1 comparison group)

	Median	CI low	CI high	pd	% in ROPE
Support year	0.14	0.06	0.21	100%	0%
One year after support	0.15	0.08	0.23	100%	0%
Two years after support	0.19	0.10	0.27	100%	0%
Three years after support	0.12	0.01	0.22	98%	1%
Four years after support	0.01	-0.13	0.16	56%	23%
Pre-existing group trend	-0.02	-0.02	-0.02	100%	0%
Model statistics					
N (observations)	2,039				
Group-level effects	Firm and year				
n (firms)	442				
$\hat{R}$ *(max)*	1.001				
Min bulk ESS / min tail ESS	2327 / 2613				
MCMC	4 chains; 4,000 post-warmup draws; 0 divergent transitions				

Source: SQW

Table B-9: Frequentist results for employment effects in the event study DiD (PSM 1:1 comparison group)

	estimate	CI low	CI high	p-value
Support year	0.14	-0.01	0.29	0.07
One year after support	0.15	-0.05	0.36	0.15
Two years after support	0.19	-0.09	0.46	0.18
Three years after support	0.11	-0.23	0.46	0.52
Four years after support	0.01	-0.42	0.44	0.97

	estimate	CI low	CI high	p-value
Pre-existing group trend	-0.02	-0.09	0.05	0.57
Model statistics				
N	2,039			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	442			
Year clusters	10			
Adj. R^2 (overall)	0.52			
Within R^2	0.01			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect Source: SQW

B.31 The two approaches produce very similar central estimates across all years, with point estimates and medians of posterior distributions ranging from 0.14 in the year of support to 0.19 two years after support, before declining to close to zero by year four. However, under the frequentist approach, the effect in the years following support is not statistically significant at conventional thresholds, with p-values well above 0.05 in every year except the year of support itself, where the effect is significant only at the 10% level. The Bayesian approach characterises the uncertainty around these estimates more fully. Rather than a binary significant/non-significant judgement, it shows that the posterior distribution is concentrated well away from zero in the first three years following the support.[61]

B.32 Statistical significance in the frequentist framework is heavily influenced by sample size: as the event study splits the sample into progressively smaller yearly sub-groups, the resulting confidence intervals widen, making it harder to reject the null hypothesis of no effect, even where the underlying point estimate is similar in magnitude to that for the year of support. The Bayesian approach is less susceptible to this issue.

B.33 As the sample size gets smaller, the Bayesian uncertainty about the effect grows, but it is expressed in terms of a widening of the fully characterised posterior distribution. When a

[61] Note that the Bayesian model identifies the pre-existing trend with unusually high precision. However, this is by design since the variable is capturing the arithmetical difference between the average time trends of the two groups, there is little uncertainty about the exact value. The pre-trend tests described earlier in this annex, together with the statistical insignificance of the trend variable in the frequentist estimations, give us confidence that the comparison group moved along a broadly similar trajectory to supported SMEs before the Catapult's support began.

weakly informative prior is used, the estimated distribution is driven by the data rather than a prior belief about the effect.

B.34 In this case the distributions do widen (compared to the average DiD) but still stay concentrated above zero. Given that the central estimates are consistent across the two approaches, we consider the Bayesian results to provide the more reliable characterisation of the effect's persistence over time.

Employment results obtained using the ESC comparison group

B.35 Table B-10 and Table B-11 present the equivalent frequentist results for employment using the ESC comparison group. Both the average-effects DiD and event study models closely mirror the results obtained using the PSM 1:1 comparison group: the average effect (0.18) is very similar in magnitude and remains statistically significant, and the year-by-year pattern in the event study follows a similar shape: the point estimates peak around two years after the support, with only the estimate for the year of support being statistically significant. This consistency across two independently constructed comparison groups increased our confidence in the findings, and did not, in our view, warrant further investigation.

Table B-10: Frequentist results for employment effects in the average DiD (ESC comparison group)

	estimate	CI low	CI high	p-value
Effect of support	0.18	0.08	0.28	0.00
Pre-existing group trend	0.01	-0.05	0.08	0.67
Model statistics				
N	1,691			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	388			
Year clusters	10			
Adj. R^2 (overall)	0.56			
Within R^2	0.006			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect Source: SQW

Table B-11: Frequentist results for employment effects in the event study DiD (ESC comparison group)

	estimate	CI low	CI high	p-value
Support year	0.13	0.02	0.24	0.02
One year after support	0.14	-0.12	0.40	0.25
Two years after support	0.16	-0.15	0.48	0.27
Three years after support	0.08	-0.37	0.52	0.71
Four years after support	-0.07	-0.66	0.53	0.81
Pre-existing group trend	0.03	-0.05	0.11	0.39
Model statistics				
N	1,691			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	388			
Year clusters	10			
Adj. R^2 (overall)	0.56			
Within R^2	0.008			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect. Source: SQW

Assets: average DiD model

B.36 Table B-12 and Table B-13 present the average Bayesian DiD estimates for total and current assets, respectively, under the two priors considered for the PSM matched comparison group. The tables also list key diagnostic indicators across the models. Overall, both models generated the probability of direction (pd) of c. 100% for both total and current assets, and none of the posterior mass fell within ROPE, indicating a high degree of confidence in both the direction and practical significance of the effects.

Table B-12: Bayesian results for total assets effects in the average DiD (PSM 1:1 comparison group)

Prior	Median	CI low	CI high	pd	% in ROPE
Weakly informative (preferred)	0.55	0.42	0.67	100%	0%

Prior	Median	CI low	CI high	pd	% in ROPE
SQW	0.41	0.30	0.52	100%	0%
Model statistics					
N (observations)	2,008				
Group-level effects	Firm and year				
n (firms)	468				
$\hat{R}$ *(max)*	1.000				
Min bulk ESS / min tail ESS	5355 / 3064				
MCMC	4 chains; 4,000 post-warmup draws; 0 divergent transitions				

Source: SQW

Table B-13: Bayesian results for current assets effects in the average DiD (PSM 1:1 comparison group)

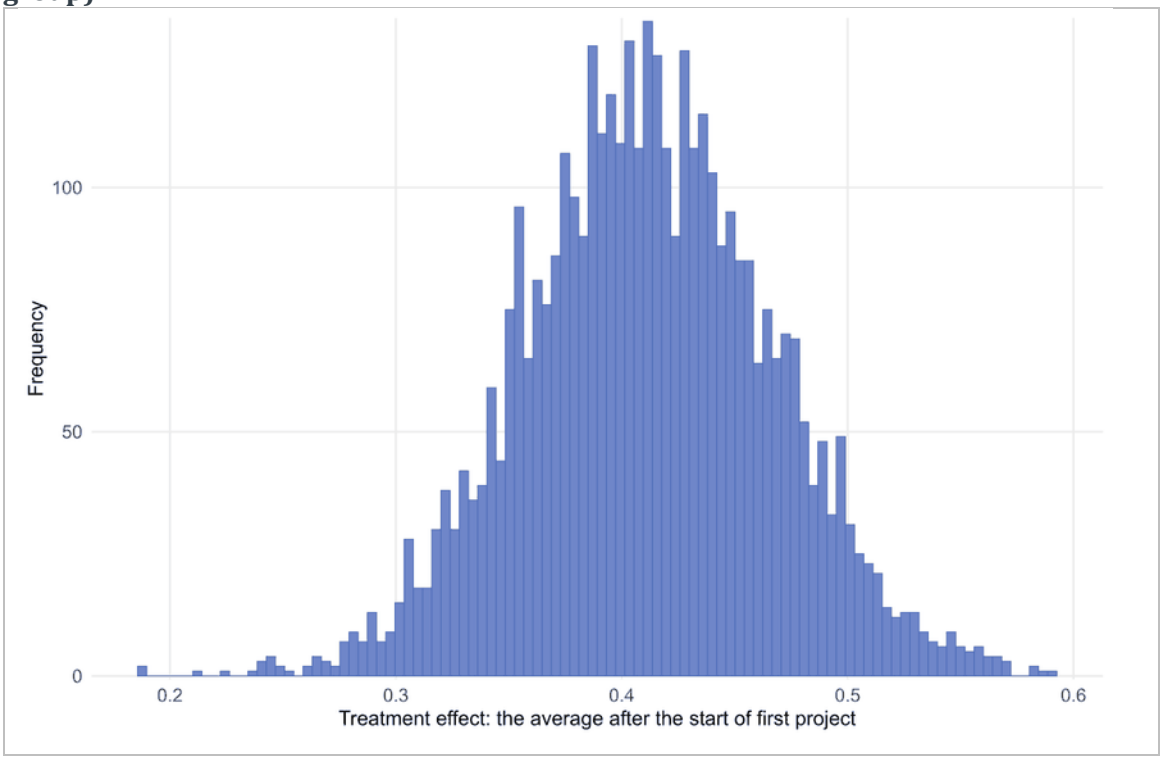
Prior	Median	CI low	CI high	pd	% in ROPE
Weakly informative (preferred)	0.55	0.41	0.69	100%	0%
SQW	0.40	0.28	0.51	100%	0%
Model statistics					
N (observations)	2,008				
Group-level effects	Firm and year				
n (firms)	468				
$\hat{R}$ *(max)*	1.000				
Min bulk ESS / min tail ESS	5494 / 2350				
MCMC	4 chains; 4,000 post-warmup draws; 0				

Prior	Median	CI low	CI high	pd	% in ROPE
	divergent transitions				

Source: SQW

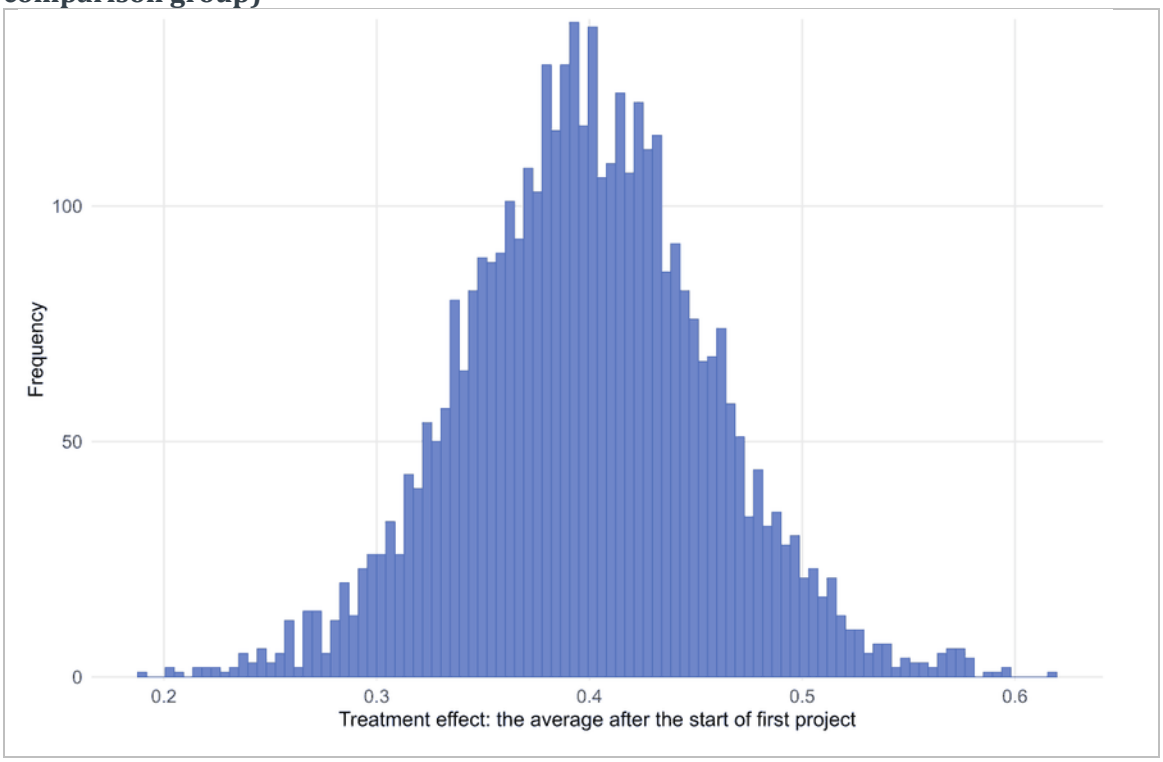
B.37 Figure B-6 and Figure B-7 show the posterior distributions obtained using the SQW prior. Consistent with that specification being more conservative about the scale of impacts, the distributions are shifted to the left compared with our preferred model. Importantly, however, the strong positive skew assumed in the SQW prior is not reflected in the posterior distributions, which remain approximately symmetric and bell-shaped. This suggests that the observed data, rather than the prior assumptions, are driving the estimated effects and provides further reassurance regarding the strength of the relationship between the Catapult's support and SME asset growth.

Figure B-6: Estimated effect of the Catapult's support on the natural logarithm of total assets of participating SMEs (posterior distribution, SQW prior, PSM 1:1 comparison group)



Source: SQW

Figure B-7: Estimated effect of the Catapult's support on the natural logarithm of current assets of participating SMEs (posterior distribution, SQW prior, PSM 1:1 comparison group)



Source: SQW

B.38 Table B-14 shows that for both total and current assets, the ELPD differences across the weakly informative and SQW priors were small relative to their standard errors. The data therefore provided no statistical basis for preferring one prior over the other. Changing our starting assumptions about the likely scale of impacts had little effect on the models' predictive performance, with both priors leading to the same substantive conclusions.

Table B-14: LOO comparison of out of sample predictive power

Prior	ELPD difference	s.e. of the difference
Total assets		
Weakly informative (preferred)	0.0	0.0
SQW	-1.7	1.8
Current assets		
Weakly informative (preferred)	0.0	0.0
SQW	-1.5	2.0

Source: SQW

B.39 Table B-15 and Table B-16 present the frequentist average-effects DiD estimates for total and current assets, respectively, using the PSM 1:1 comparison group. The point estimates (0.55

for both) are consistent with our Bayesian findings, and the effects are statistically significant at any conventional threshold. The pre-existing trend variable was statistically insignificant in both cases, confirming that the matching was successful in aligning pre-support trends between the treatment and comparison groups.

Table B-15: Frequentist results for total assets effects in the average DiD (PSM 1:1 comparison group)

	estimate	CI low	CI high	p-value
Effect of support	0.55	0.20	0.89	0.01
Pre-existing group trend	-0.09	-0.27	0.08	0.25
Model statistics				
N	2,008			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	468			
Year clusters	9			
Adj. R^2 (overall)	0.83			
Within R^2	0.01			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect Source: SQW

Table B-16: Frequentist results for current assets effects in the average DiD (PSM 1:1 comparison group)

	estimate	CI low	CI high	p-value
Effect of support	0.55	0.17	0.93	0.01
Pre-existing group trend	-0.08	-0.25	0.09	0.31
Model statistics				
N	2,008			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	468			
Year clusters	9			

	estimate	CI low	CI high	p-value
Adj. R^2 (overall)	0.79			
Within R^2	0.01			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect Source: SQW

Assets: the event study model

B.40 Table B-17 and Table B-18 present the results from our Bayesian estimation of the event study DiD for total and current assets, respectively. Table B-19 and Table B-20 provide the estimates of the same models obtained using the standard frequentist approach. The Bayesian results are based on the weakly informative prior, to allow for a direct comparison between the estimation approaches rather than the choices of assumptions about the scale of the effects.

Table B-17: Bayesian results for total assets effects in the event study DiD (weakly informative prior, PSM 1:1 comparison group)

	Median	CI low	CI high	pd	% in ROPE
Support year	0.33	0.17	0.49	100%	0%
One year after support	0.42	0.24	0.59	100%	0%
Two years after support	0.37	0.17	0.57	100%	0%
Three years after support	0.04	-0.19	0.28	65%	58%
Four years after support	-0.26	-0.59	0.07	94%	15%
Pre-existing group trend	0.00	0.00	0.00	90%	100%
Model statistics					
N (observations)	2,008				
Group-level effects	Firm and year				
n (firms)	468				
$\hat{R}$ (max)	1.000				
Min bulk ESS / min tail ESS	3475 / 2530				
MCMC	4 chains; 4,000 post-warmup draws; 0				

	Median	CI low	CI high	pd	% in ROPE
	divergent transitions				

Source: SQW

Table B-18: Bayesian results for current assets effects in the event study DiD (weakly informative prior, PSM 1:1 comparison group)

	Median	CI low	CI high	pd	% in ROPE
Support year	0.34	0.16	0.52	100%	0%
One year after support	0.56	0.37	0.74	100%	0%
Two years after support	0.57	0.36	0.78	100%	0%
Three years after support	0.29	0.04	0.54	99%	6%
Four years after support	-0.27	-0.64	0.10	93%	16%
Pre-existing group trend	-0.03	-0.03	-0.03	100%	100%
Model statistics					
N (observations)	2,008				
Group-level effects	Firm and year				
n (firms)	468				
$\hat{R}$ (max)	1.000				
Min bulk ESS / min tail ESS	3846 / 2881				
MCMC	4 chains; 4,000 post-warmup draws; 0 divergent transitions				

Source: SQW

Table B-19: Frequentist results for total assets effects in the event study DiD (PSM 1:1 comparison group)

	estimate	CI low	CI high	p-value
Support year	0.33	-0.07	0.74	0.09
One year after support	0.42	-0.08	0.92	0.09

	estimate	CI low	CI high	p-value
Two years after support	0.37	-0.29	1.04	0.23
Three years after support	0.04	-0.86	0.95	0.91
Four years after support	-0.26	-1.45	0.93	0.63
Pre-existing group trend	0.00	-0.23	0.23	1.00
Model statistics				
N	2,008			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	468			
Year clusters	9			
Adj. R^2 (overall)	0.83			
Within R^2	0.02			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect Source: SQW

Table B-20: Frequentist results for current assets effects in the event study DiD (PSM 1:1 comparison group)

	estimate	CI low	CI high	p-value
Support year	0.35	-0.05	0.74	0.08
One year after support	0.56	0.04	1.08	0.04
Two years after support	0.57	-0.14	1.29	0.10
Three years after support	0.29	-0.65	1.24	0.50
Four years after support	-0.27	-1.51	0.97	0.63
Pre-existing group trend	-0.03	-0.27	0.22	0.81
Model statistics				
N	2,008			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	468			

	estimate	CI low	CI high	p-value
Year clusters	9			
Adj. R^2 (overall)	0.80			
Within R^2	0.02			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect Source: SQW

B.41 For both total assets and current assets, the Bayesian and frequentist approaches produce very similar central estimates across all years. The estimated coefficients are positive and sizeable in the support year and the following two years for total assets, and in the support year and the following three years for current assets. Beyond these periods, the estimated coefficients are close to zero or negative.

B.42 Under the frequentist approach, only the effect on current assets one year after support is statistically significant at the 5% level. The remaining estimates are not statistically significant at conventional thresholds, although some effects are significant at the 10% level.[62]

B.43 However, as discussed in relation to employment, the Bayesian approach provides a fuller characterisation of uncertainty than a binary significant/non-significant assessment. Although the frequentist estimates are mostly not statistically significant, the Bayesian posterior distributions remain concentrated above zero for three years from the point of support for total assets and four years for current assets, providing evidence of positive impacts on both outcome measures. This difference largely reflects the smaller samples available in the event study, which reduce the precision of the frequentist estimates even where the central estimates remain positive and similar in magnitude to those obtained from the Bayesian models.

Assets results obtained using the ESC comparison group

B.44 Table B-21, Table B-22, Table B-23 and Table B-24 present the equivalent frequentist results for total and current assets using the ESC comparison group. Both the average-effects and event-study DiD models closely replicate the results obtained using the PSM 1:1 comparison group. The average treatment effects (0.54 for total assets and 0.55 for current assets) are almost identical in magnitude and remain statistically significant, while the event-study estimates show a very similar temporal pattern, with effects peaking around one year after support for total assets and two years after support for current assets. The statistical significance patterns are also broadly consistent across the two comparison groups. As discussed in relation to employment, this consistency across independently constructed

[62] Specifically, the effects on total assets in the support year and one year after support, and on current assets in the support year.

comparison groups increases our confidence in the robustness of the findings and does not, in our view, warrant further investigation.

Table B-21: Frequentist results for total assets effects in the average DiD (ESC comparison group)

	estimate	CI low	CI high	p-value
Effect of support	0.54	0.20	0.88	0.01
Pre-existing group trend	-0.05	-0.22	0.11	0.48
Model statistics				
N	1,636			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	415			
Year clusters	9			
Adj. R^2 (overall)	0.88			
Within R^2	0.02			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect Source: SQW

Table B-22: Frequentist results for current assets effects in the average DiD (ESC comparison group)

	estimate	CI low	CI high	p-value
Effect of support	0.55	0.16	0.93	0.01
Pre-existing group trend	0.00	-0.18	0.18	0.96
Model statistics				
N	1,636			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	415			
Year clusters	9			
Adj. R^2 (overall)	0.86			

	estimate	CI low	CI high	p-value
Within R²	0.02			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect Source: SQW

Table B-23: Frequentist results for total assets effects in the event study DiD (ESC comparison group)

	estimate	CI low	CI high	p-value
Support year	0.35	-0.07	0.78	0.09
One year after support	0.45	-0.09	1.00	0.09
Two years after support	0.43	-0.29	1.14	0.21
Three years after support	0.13	-0.85	1.10	0.77
Four years after support	-0.18	-1.45	1.10	0.76
Pre-existing group trend	0.02	-0.18	0.23	0.80
Model statistics				
N	1,636			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	415			
Year clusters	9			
Adj. R² (overall)	0.89			
Within R²	0.03			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect. Source: SQW

Table B-24: Frequentist results for current assets effects in the event study DiD (ESC comparison group)

	estimate	CI low	CI high	p-value
Support year	0.36	-0.05	0.77	0.08
One year after support	0.58	0.03	1.13	0.04
Two years after support	0.60	-0.15	1.36	0.10
Three years after support	0.34	-0.64	1.32	0.45

	estimate	CI low	CI high	p-value
Four years after support	-0.21	-1.54	1.11	0.72
Pre-existing group trend	0.04	-0.20	0.28	0.71
Model statistics				
N	1,636			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	415			
Year clusters	9			
Adj. R^2 (overall)	0.86			
Within R^2	0.03			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect. Source: SQW

External finance

B.45 Table B-25 – Table B-30 present the outputs from the logistic regression models used to examine whether Catapult support was associated with a higher probability of attracting external finance after support commenced. The results were broadly consistent across both the PSM 1:1 matched comparison group and the ESC comparison group. The estimated increase in the probability of securing external finance was driven primarily by grant funding, while we did not identify statistically significant effects for equity investment. All models controlled for a range of observable company characteristics.

Table B-25: Effect on the probability to secure any external finance after the support (PSM 1:1)

	estimate	std.error	statistic	p-value
Intercept	392.29	155.69	2.52	0.01
The Catapult's support	0.87	0.28	3.09	0.00
Year of support	-0.20	0.08	-2.55	0.01
SIC section: C	0.44	0.48	0.92	0.36
SIC section: F	-0.31	0.84	-0.36	0.72
SIC section: J	0.62	0.43	1.44	0.15

	estimate	std.error	statistic	p-value
SIC section: M	0.22	0.41	0.53	0.59
SIC section: N	1.36	0.72	1.91	0.06
Region: East Midlands	0.73	0.89	0.82	0.41
Region: East of England	0.23	0.57	0.41	0.68
Region: North East	0.29	0.96	0.30	0.76
Region: North West	-0.77	0.56	-1.36	0.17
Region: Northern Ireland	-2.20	1.29	-1.70	0.09
Region: Scotland	0.12	0.47	0.26	0.79
Region: South East	0.43	0.43	1.00	0.32
Region: South West	-0.63	0.51	-1.25	0.21
Region: Wales	1.23	0.80	1.55	0.12
Region: West Midlands	0.53	0.53	1.01	0.31
Region: Yorkshire and The Humber	0.42	0.61	0.68	0.50
Any RTIC code	0.23	0.28	0.82	0.41
On high growth list	0.15	0.44	0.36	0.72
Innovate UK funding (pre-support)	0.60	0.32	1.85	0.06
Environmental Accolades signal	1.32	0.35	3.72	0.00
Clean Energy signal	-0.11	0.34	-0.33	0.74
Academic spinout	0.09	0.67	0.14	0.89
Any other environmental signal (beyond Accolades and Clean Energy)	0.82	0.54	1.52	0.13
Any innovation signal	0.84	0.33	2.57	0.01
Any growth signal (beyond high growth list)	1.85	0.32	5.76	0.00
Ultimate parent	1.21	0.36	3.41	0.00
Number of firms in corporate structure	0.00	0.01	0.06	0.95
Model statistics				

	estimate	std.error	statistic	p-value
N	539			
Log-likelihood	-199			
AIC	457			
BIC	588			
McFadden R2	0.44			

Source: SQW

Table B-26: Effect on the probability to secure grants after the support (PSM 1:1)

	estimate	std.error	statistic	p-value
Intercept	525.41	153.84	3.42	0.00
The Catapult's support	1.01	0.26	3.88	0.00
Year of support	-0.26	0.08	-3.45	0.00
SIC section: C	0.53	0.46	1.14	0.26
SIC section: F	-0.03	0.85	-0.03	0.98
SIC section: J	-0.17	0.43	-0.39	0.70
SIC section: M	0.09	0.41	0.22	0.82
SIC section: N	0.64	0.70	0.91	0.36
Region: East Midlands	0.46	0.89	0.52	0.60
Region: East of England	-0.04	0.52	-0.07	0.94
Region: North East	0.12	0.94	0.13	0.90
Region: North West	-0.49	0.55	-0.90	0.37
Region: Northern Ireland	-1.72	1.25	-1.37	0.17
Region: Scotland	0.03	0.43	0.07	0.94
Region: South East	-0.08	0.39	-0.22	0.83
Region: South West	-0.58	0.49	-1.20	0.23
Region: Wales	0.91	0.73	1.23	0.22
Region: West Midlands	0.36	0.49	0.73	0.46
Region: Yorkshire and The Humber	0.17	0.61	0.29	0.77

	estimate	std.error	statistic	p-value
Any RTIC code	0.14	0.27	0.52	0.60
On high growth list	-0.13	0.34	-0.37	0.71
Innovate UK funding (pre-support)	1.38	0.31	4.51	0.00
Environmental Accolades signal	1.87	0.37	5.04	0.00
Clean Energy signal	-0.11	0.29	-0.36	0.72
Academic spinout	-0.37	0.47	-0.80	0.43
Any other environmental signal (beyond Accolades and Clean Energy)	0.83	0.61	1.38	0.17
Any innovation signal	0.80	0.29	2.74	0.01
Any growth signal (beyond high growth list)	0.67	0.34	1.98	0.05
Ultimate parent	1.04	0.37	2.83	0.00
Number of firms in corporate structure	0.01	0.01	1.27	0.20
Model statistics				
N	539			
Log-likelihood	-218			
AIC	498			
BIC	627			
McFadden R2	0.42			

Source: SQW

Table B-27: Effect on the probability to secure equity after the support (PSM 1:1)

	estimate	std.error	statistic	p-value
Intercept	258.98	750.15	0.35	0.73
The Catapult's support	0.32	0.24	1.32	0.19
Year of support	-0.14	0.07	-1.86	0.06
SIC section: C	0.12	0.44	0.27	0.79
SIC section: F	0.62	0.98	0.63	0.53

	estimate	std.error	statistic	p-value
SIC section: J	0.04	0.42	0.10	0.92
SIC section: M	0.07	0.41	0.16	0.87
SIC section: N	2.63	1.16	2.26	0.02
Region: East Midlands	0.03	0.96	0.03	0.98
Region: East of England	0.51	0.63	0.82	0.42
Region: North East	0.11	0.92	0.12	0.91
Region: North West	-1.31	0.53	-2.45	0.01
Region: Northern Ireland	-0.02	1.37	-0.01	0.99
Region: Scotland	-0.37	0.43	-0.86	0.39
Region: South East	-0.31	0.36	-0.87	0.39
Region: South West	0.19	0.50	0.38	0.70
Region: Wales	-0.25	0.68	-0.36	0.72
Region: West Midlands	-0.74	0.45	-1.64	0.10
Region: Yorkshire and The Humber	-0.50	0.57	-0.88	0.38
Any RTIC code	0.08	0.27	0.31	0.75
On high growth list	1.07	0.33	3.28	0.00
Innovate UK funding (pre-support)	-0.61	0.33	-1.84	0.07
Environmental Accolades signal	-0.29	0.41	-0.72	0.47
Clean Energy signal	-0.26	0.29	-0.88	0.38
Academic spinout	0.56	0.46	1.20	0.23
Any other environmental signal (beyond Accolades and Clean Energy)	0.46	0.73	0.64	0.52
Any innovation signal	0.96	0.31	3.10	0.00
Any growth signal (beyond high growth list)	20.06	734.84	0.03	0.98
Ultimate parent	1.13	0.43	2.60	0.01
Number of firms in corporate structure	-0.02	0.02	-1.24	0.21

	estimate	std.error	statistic	p-value
Model statistics				
N	539			
Log-likelihood	-212			
AIC	484			
BIC	613			
McFadden R2	0.41			

Source: SQW

Table B-28: Effect on the probability to secure any external finance after the support (ESC comparison)

	estimate	std.error	statistic	p-value
Intercept	532.6	206.86	2.57	0.01
The Catapult's support	1.15	0.38	3.04	0
Year of support	-0.27	0.1	-2.6	0.01
SIC section: C	0.96	0.54	1.78	0.07
SIC section: F	0.89	0.85	1.06	0.29
SIC section: J	0.58	0.52	1.11	0.27
SIC section: M	0.49	0.5	0.98	0.33
SIC section: N	1.26	0.79	1.6	0.11
Region: East Midlands	0.26	1.09	0.24	0.81
Region: East of England	0.88	0.56	1.55	0.12
Region: North East	0.06	1.18	0.05	0.96
Region: North West	0.18	0.58	0.31	0.76
Region: Northern Ireland	-2.89	1.23	-2.34	0.02
Region: Scotland	-0.68	0.6	-1.13	0.26
Region: South East	0.61	0.54	1.14	0.26
Region: South West	0.21	0.6	0.36	0.72
Region: Wales	-0.69	0.79	-0.87	0.39

	estimate	std.error	statistic	p-value
Region: West Midlands	0.38	0.52	0.73	0.47
Region: Yorkshire and The Humber	-0.03	0.76	-0.04	0.97
Any RTIC code	-0.15	0.35	-0.44	0.66
On high growth list	-0.57	0.54	-1.04	0.3
Innovate UK funding (pre-support)	1.48	0.4	3.68	0
Environmental Accolades signal	0.79	0.42	1.89	0.06
Clean Energy signal	-0.34	0.42	-0.81	0.42
Academic spinout	0.67	0.8	0.84	0.4
Any other environmental signal (beyond Accolades and Clean Energy)	0.78	0.53	1.49	0.14
Any innovation signal	-0.17	0.4	-0.42	0.67
Any growth signal (beyond high growth list)	3.2	0.39	8.28	0
Ultimate parent	1.58	0.49	3.24	0
Number of firms in corporate structure	0.01	0.01	0.94	0.35
Model statistics				
N	582			
Log-likelihood	-161			
AIC	383			
BIC	514			
McFadden R2	0.59			

Source: SQW

Table B-29: Effect on the probability to secure grants after the support (ESC comparison)

	estimate	std.error	statistic	p-value
Intercept	387.54	204.30	1.90	0.06
The Catapult's support	1.24	0.37	3.34	0.00
Year of support	-0.19	0.10	-1.92	0.05

	estimate	std.error	statistic	p-value
SIC section: C	1.21	0.54	2.26	0.02
SIC section: F	0.31	0.89	0.35	0.73
SIC section: J	0.03	0.53	0.06	0.96
SIC section: M	0.26	0.52	0.51	0.61
SIC section: N	-0.21	0.78	-0.27	0.79
Region: East Midlands	-0.49	1.33	-0.37	0.71
Region: East of England	0.32	0.58	0.56	0.58
Region: North East	-0.74	1.74	-0.42	0.67
Region: North West	0.73	0.61	1.20	0.23
Region: Northern Ireland	-2.10	1.47	-1.43	0.15
Region: Scotland	0.04	0.57	0.07	0.94
Region: South East	-0.25	0.51	-0.49	0.62
Region: South West	-0.38	0.59	-0.64	0.52
Region: Wales	-0.24	0.78	-0.31	0.76
Region: West Midlands	0.47	0.54	0.88	0.38
Region: Yorkshire and The Humber	-0.15	0.71	-0.22	0.83
Any RTIC code	-0.36	0.34	-1.05	0.29
On high growth list	-0.10	0.50	-0.20	0.84
Innovate UK funding (pre-support)	1.51	0.37	4.10	0.00
Environmental Accolades signal	1.97	0.43	4.61	0.00
Clean Energy signal	0.24	0.37	0.64	0.52
Academic spinout	1.05	0.73	1.43	0.15
Any other environmental signal (beyond Accolades and Clean Energy)	0.34	0.56	0.60	0.55
Any innovation signal	0.26	0.37	0.72	0.47
Any growth signal (beyond high growth list)	1.11	0.38	2.92	0.00

	estimate	std.error	statistic	p-value
Ultimate parent	0.82	0.47	1.75	0.08
Number of firms in corporate structure	0.01	0.01	1.77	0.08
Model statistics				
N	582			
Log-likelihood	-162			
AIC	386			
BIC	517			
McFadden R2	0.56			

Source: SQW

Table B-30: Effect on the probability to secure equity after the support (ESC comparison)

	estimate	std.error	statistic	p-value
Intercept	479.55	912.05	0.53	0.60
The Catapult's support	0.58	0.42	1.37	0.17
Year of support	-0.25	0.11	-2.25	0.02
SIC section: C	0.19	0.53	0.35	0.73
SIC section: F	2.32	1.21	1.91	0.06
SIC section: J	0.27	0.54	0.50	0.62
SIC section: M	0.40	0.53	0.76	0.45
SIC section: N	3.23	1.27	2.54	0.01
Region: East Midlands	1.08	1.26	0.86	0.39
Region: East of England	1.01	0.68	1.50	0.13
Region: North East	-0.75	1.15	-0.65	0.51
Region: North West	-1.31	0.64	-2.04	0.04
Region: Northern Ireland	-1.20	1.03	-1.17	0.24
Region: Scotland	-0.27	0.57	-0.48	0.63
Region: South East	0.16	0.49	0.33	0.74

	estimate	std.error	statistic	p-value
Region: South West	1.03	0.65	1.58	0.11
Region: Wales	-1.72	0.95	-1.81	0.07
Region: West Midlands	-0.52	0.51	-1.01	0.31
Region: Yorkshire and The Humber	-0.75	0.78	-0.97	0.33
Any RTIC code	0.30	0.35	0.87	0.38
On high growth list	0.50	0.43	1.16	0.25
Innovate UK funding (pre-support)	-0.14	0.45	-0.31	0.76
Environmental Accolades signal	-0.82	0.47	-1.72	0.08
Clean Energy signal	-0.56	0.39	-1.43	0.15
Academic spinout	0.88	0.60	1.48	0.14
Any other environmental signal (beyond Accolades and Clean Energy)	0.44	0.70	0.62	0.54
Any innovation signal	0.51	0.43	1.17	0.24
Any growth signal (beyond high growth list)	21.37	884.34	0.02	0.98
Ultimate parent	1.73	0.70	2.48	0.01
Number of firms in corporate structure	-0.02	0.02	-1.24	0.21
Model statistics				
N	582			
Log-likelihood	-143			
AIC	346			
BIC	477			
McFadden R2	0.57			

Source: SQW

B.46 Table B-31 – Table B-36 present the estimation results from the DiD models of the cumulative value of external finance secured by supported SMEs, using both the PSM 1:1 matched comparison group and the ESC comparison group. For this outcome measure, we estimated average treatment effects only. The external finance data was less granular and exhibited

substantially less variation over time than the employment and turnover data. As a result, a meaningful event study analysis was not feasible.

Table B-31: Effect of support on cumulative sum of all external finance (PSM 1:1)

	estimate	CI low	CI high	p-value
Effect of support	2.12	1.21	3.04	0.00
Pre-existing group trend	-0.40	-0.67	-0.12	0.01
Model statistics				
N	3,776			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	539			
Year clusters	11			
Adj. R^2 (overall)	0.78			
Within R^2	0.01			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect. Source: SQW

Table B-32: Effect of support on cumulative sum of grants (PSM 1:1)

	estimate	CI low	CI high	p-value
Effect of support	1.56	0.88	2.24	0.00
Pre-existing group trend	-0.30	-0.52	-0.08	0.01
Model statistics				
N	3,776			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	539			
Year clusters	11			
Adj. R^2 (overall)	0.81			
Within R^2	0.009			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect. Source: SQW

Table B-33: Effect of support on cumulative sum of equity finance (PSM 1:1)

	estimate	CI low	CI high	p-value
Effect of support	1.22	0.61	1.84	0.00
Pre-existing group trend	-0.12	-0.34	0.09	0.22
Model statistics				
N	3,776			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	539			
Year clusters	11			
Adj. R^2 (overall)	0.77			
Within R^2	0.008			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect. Source: SQW

Table B-34: Effect of support on cumulative sum of all external finance (ESC comparison)

	estimate	CI low	CI high	p-value
Effect of support	2.30	1.30	3.31	0.00
Pre-existing group trend	0.10	-0.17	0.37	0.44
Model statistics				
N	3,717			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	585			
Year clusters	11			
Adj. R^2 (overall)	0.80			
Within R^2	0.05			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect. Source: SQW

Table B-35: Effect of support on cumulative sum of equity finance (ESC comparison)

	estimate	CI low	CI high	p-value
Effect of support	1.32	0.66	1.98	0.00
Pre-existing group trend	0.22	0.02	0.42	0.04
Model statistics				
N	3,717			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	585			
Year clusters	11			
Adj. R^2 (overall)	0.80			
Within R^2	0.04			

Note: a low within R^2 is expected in a difference-in-differences model, where the fixed effects absorb most of the variation in the outcome, and does not indicate weak identification of the treatment effect. Source: SQW

Table B-36: Effect of support on cumulative sum of grants (ESC comparison)

	estimate	CI low	CI high	p-value
Effect of support	1.66	0.92	2.40	0.00
Pre-existing group trend	0.22	0.03	0.42	0.03
Model statistics				
N	3,717			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	585			
Year clusters	11			
Adj. R^2 (overall)	0.80			
Within R^2	0.05			

Source: SQW

Valuations

B.47 Table B-37 – Table B-38 show the estimates from the 2x2 DiD models of companies' valuations.

Table B-37: Estimated effect on valuations (frequentist, PSM 1:1 comparison)

	estimate	CI low	CI high	p-value
Effect of support	-0.12	-2.76	2.51	0.66
Model statistics				
N	212			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	106			
Year clusters	2			
Adj. R^2 (overall)	0.53			
Within R^2	0.005			

Source: SQW

Table B-38: Estimated effect on valuations (frequentist, ESC comparison)

	estimate	CI low	CI high	p-value
Effect of support	-0.17	-3.72	3.38	0.65
Model statistics				
N	114			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	74			
Year clusters	2			
Adj. R^2 (overall)	0.65			
Within R^2	0.03			

Source: SQW

Turnover: average DiD model

B.48 Table B-39 presents the average Bayesian DiD estimates for turnover under all three informative priors considered for the PSM matched comparison group and an additional robustness prior (Vanino but without a skew). The table also lists key diagnostic indicators across the models. The results were highly sensitive to the choice of the prior.

Table B-39: Bayesian results for turnover effects in the average DiD (PSM 1:1 comparison group)

Prior	Median	CI low	CI high	pd	% in ROPE
Weakly informative	-0.11	-0.25	0.01	95%	5%
Vanino et al.	0.02	0.00	0.04	100%	55%
Vanino et al. (no skew)	0.01	-0.02	0.05	80%	62%
SQW	0.07	0.03	0.11	100%	0%
Model statistics					
N (observations)	2,494				
Group-level effects	Firm and year				
n (firms)	465				
$\hat{R}$ *(max)*	1.00				
Min bulk ESS	4024				
MCMC	4 chains; 4,000 post-warmup draws; 0 divergent transitions				

Source: SQW

B.49 Table B-40 shows the ELPD differences across the turnover models. The differences between the weakly informative and Vanino priors were negligible with the SQW prior performing somewhat worse. The additional Vanino prior without a skew (i.e. expecting a normal distribution around the average effect) was also equally supported by the data as the weakly informative prior.[63] This pattern reinforced our view that the results conformed to the priors both in terms of the expected value of the average effects as well as its probability distribution.

[63] The symmetric prior was specified as $\mathcal{N}(0.025, 0.02)$.

Table B-40: LOO comparison of out of sample predictive power of turnover models

Prior	ELPD difference	s.e. of the difference
Weakly informative	0.00	0.00
Vanino et al.	-1.20	1.97
Vanino et al. (no skew)	-0.88	1.90
SQW	-3.08	2.72

Source: SQW

B.50 Table B-41 shows the results from the frequentist estimation. As expected, the central estimate was nearly identical to the Bayesian estimate under the weakly informative prior. The effect was found to be statistically insignificant. Table B-42 presents the findings using the ESC comparison group.

Table B-41: Frequentist results for turnover effects in the average DiD (PSM 1:1 comparison group)

	estimate	CI low	CI high	p-value
Effect of support	-0.12	-0.38	0.14	0.37
Pre-existing group trend	0.06	-0.04	0.17	0.23
Model statistics				
N	2,494			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	388			
Year clusters	10			
Adj. R^2 (overall)	0.66			
Within R^2	0.001			

Source: SQW

Table B-42: Frequentist results for turnover effects in the average DiD (ESC comparison group)

	estimate	CI low	CI high	p-value
Effect of support	-0.11	-0.30	0.07	0.29
Pre-existing group trend	0.10	-0.01	0.21	0.13

	estimate	CI low	CI high	p-value
Model statistics				
N	2,045			
Fixed effects	Firm and year			
Standard errors	Two-way clustered			
Firm clusters	465			
Year clusters	10			
Adj. R^2 (overall)	0.69			
Within R^2	0.003			

Source: SQW

Annex C: Sampling for the qualitative research

C.1 This annex outlines our approach to sampling for the qualitative discussions with SMEs and the outreach strategy.

Method

C.2 The study targeted 20 interviews with businesses that received support from the Catapult. We sought to speak to companies that both performed well since their first interaction with the Catapult and those who did not necessarily reach expected outcomes. To achieve this, we stratified 288 supported SMEs according to three criteria:

- being in the top or bottom half of the population by achieved employment growth since support
- having exactly one or more than one project with the Catapult, and
- having secured external finance after the start of support.

C.3 The segmentation across the three criteria gave us eight strata. Within each of these strata we initially identified three companies whose employment growth was relatively well explained by our impact models, and two that did not fit the models' predictions as well, in total five companies per stratum. This gave us a target list of 40 firms.

C.4 In total, 94 SMEs were contacted about the research. The Catapult initially contacted the 40 businesses we identified on behalf of SQW to invite them to participate in a short, 30-minute online interview about their experience. There was a low rate of response to the initial request, and a further 54 businesses were contacted (that were selected using the same procedure).

C.5 In total, nine businesses responded positively to the Catapult request, and seven businesses were interviewed. One business did not respond to follow up contact from SQW, and one business did not have availability in the time period required. The overall limited response could be partly related to other primary research activities undertaken by external organisations across all Catapults and the resulting survey fatigue.

Annex D: Productivity premium approach to GVA

D.1 The main report estimated the GVA from additional employment as the output of the additional jobs, adjusted for displacement and attribution (see Section 6). The HM Treasury Green Book instead recommends, for appraisal, a productivity premium approach under full displacement of jobs. This annex presents the results obtained using that alternative method, so that the evidence can feed into appraisal and business cases.

Method and assumptions

D.2 The calculations followed the approach described in Section 6 and used the same assumptions as Table 6-1, with three changes (Table D-1). First, in line with the productivity premium approach, we valued each additional job at the difference between the productivity of that job (annual GVA) and the GVA of the average job in the UK. Second, we set displacement to zero, because this approach assumes that every additional job is taken from elsewhere in the economy and counts only the productivity uplift for these jobs (rather than the full output but only for a certain proportion of them). Third, we did not apply an attribution adjustment, which is equivalent to setting attribution to 100%. The econometric estimates already compared supported SMEs with a matched comparison group, and the Green Book approach relies on that counterfactual to isolate the effect of the intervention. The main model applied a further cautious adjustment for other contributing factors, informed by consultation evidence and judgement.

Table D-1: Assumptions for the productivity premium GVA model

Parameter	Value (over 2018-2025)	Evidence
GVA per job (UK average, nominal values)	• Between £51.6k and £68.8k	ONS Output per job
Productivity premium: GVA difference from the average per job by sector (nominal values)	• Sector J: between £32.0k and £40.1k • Sector M: between £1.7k and £8.2k • Sector C: between £19.5k and £25.2k • 'Other': between £24.9k and £68.9k	ONS Output per job
Displacement	• 0%	Consistent with the job redistribution and productivity premium assumptions
Attribution	• 100%	The estimate relies on a quasi-experimental comparison against similar companies

Source: SQW

Results

D.3 The 10,000 simulations of the productivity premium GVA model produced an estimated net economic contribution of £132m (2025 prices), of which £89m had been realised. The corresponding figures for the SMEs supported since 2023/24 were £50m and £15m (Table D-2).

Table D-2: Monte Carlo simulation results for GVA impacts (productivity premium)

	Mean (expected) value	95% confidence interval	Minimum	Maximum
Full population				
Additional GVA	£132m	£107m – £163m	£91m	£194m
Realised	£89m	£70m – £113m	£59m	£138m
Expected	£43m	£33m – £56m	£27m	£71m
Support since 2023/24 onwards				
Additional GVA	£50m	£37m – £66m	£31m	£83m
Realised	£15m	£10m – £22m	£8m	£30m
Expected	£35m	£26m – £47m	£21m	£60m

Source: SQW

D.4 The productivity premium approach produced mean estimates which were 37% lower than the main estimate for the full population (£132m against £210m) and 31% lower for the SMEs supported since 2023/24 (£50m against £72m). Nevertheless, the mean estimates exceeded the core grant funding in both periods, giving indicative BCRs of approximately 1.3. The lower bound of the confidence interval was above the funding for the full period (£107m) and about equal to it for the recent period (£37m against £37.7m). The results were therefore consistent with the positive conclusions of the main report.

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