Evaluating the medium-term business performance effects of engaging with Catapults: A propensity score matching - difference-in-difference study

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Evaluating the medium-term business performance effects of engaging with Catapults: A propensity score matching - difference-in-difference study

Enrico Vanino
Department of Economics
University of Sheffield
e.vanino@sheffield.ac.uk

Stephen Roper
Enterprise Research Centre, the Productivity Institute,
the National Innovation Centre for Rural Enterprise
and Warwick Business School
stephen.roper@wbs.ac.uk

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EXECUTIVE SUMMARY

- Catapults have developed over the last decade to play an increasingly important role in the UK innovation system in relation to a number of critical technological areas. In this analysis we evaluate the business performance effects of engaging with Catapults during 2011 and 2016. The analysis builds on an earlier analysis of the positive effects of UKRI grants on sales and employment growth (Vanino et al. 2019).

- The analysis is based on data on business engagements provided by Catapults and longitudinal data for the whole population of UK firms. We consider support offered by Catapults during the 2011 to 2016 period and business growth over the subsequent three and six years. Analysis is based on an econometric analysis which uses propensity score matching and difference-in-difference modelling.

- The main question we consider is:
    - ***Does business engagement with Catapults lead to subsequent improvements in business performance?***

- Our results show that there is a strong positive effect on employment and turnover growth of firms engaging with Catapults. In general, there is a stronger impact in terms of employment, growing by almost 16% faster in 6 years after the start of the intervention.

- Growth effects are particularly strong for services and high-tech companies and micro and small enterprises, while the effect on growth are smaller and statistically weaker for medium and large firms.

- Our findings provide strong support that engaging with Catapults provides an immediate and sustained improvement of the performance of firms, helping them to commercially adopt new innovations and technologies, and leading to faster employment and turnover growth in particular for smaller, high-tech, and firms in the services industry.

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1. INTRODUCTION

Catapults have developed over the last decade to play an increasingly important role in the UK innovation system in relation to a number of critical technological areas. In this analysis we evaluate the business performance effects of engaging with Catapults during 2011 and 2016 and whether business engagement with Catapults exaggerates the performance effects of UKRI R&D grants. The analysis builds on an earlier analysis of the positive effects of UKRI grants on sales and employment growth (Vanino et al. 2019).

Our central research question is: ***Does business engagement with Catapults lead to subsequent improvements in business performance, differentiating between low, medium and high engagement?*** How does this effect vary between different groups of firms? This is based on a comparison of the performance of Catapult supported v unsupported firms.

To address this question we develop an econometric analysis comparing the differences between firms engaging with Catapults to other firms which have never engaged with the public innovation system, before and after the engagement. This kind of estimation is not straightforward, as the decision to engage with Catapults is not an exogenous and randomized treatment, but is very likely to be affected by endogenous factors influencing the decision and the self-selection of firms into this kind of activities. Hence, in order to properly estimate the causal effect of Catapults engagement on the performance of firms, we apply a difference-in-difference propensity score matching technique at the firm-level. The aim is to estimate the difference of the outcome variables between observations which have been treated and similar ones which instead have not been treated, before and after the treatment.

The rest of the report is structured as follows. The next section discusses the data used and provides some initial statistics and evidence. Section 3 presents and discusses the main findings. Methodological details are provided in Annex 1.

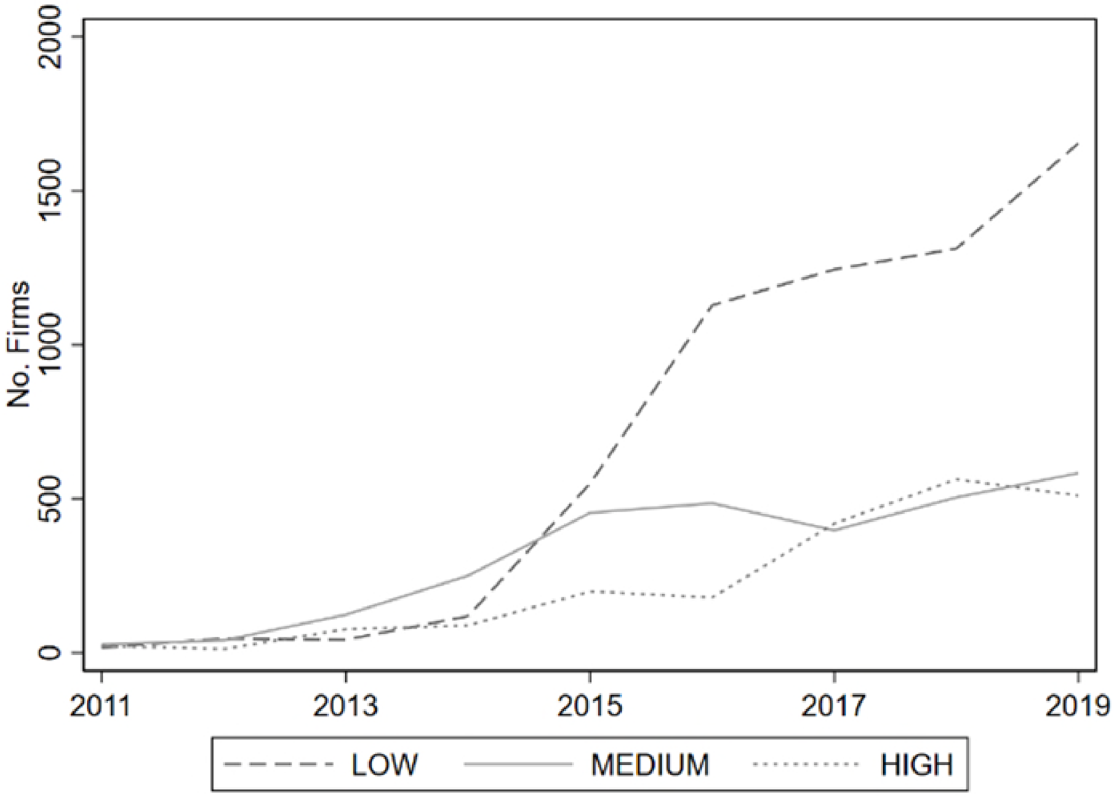
2. DATA AND DESCRIPTIVE ANALYSIS

Our analysis combines administrative data from the Catapults and firm-level data from the ONS. First, we gather administrative data on the list of firms engaging with the Catapults over the period 2011-2019. This data provided the name and corporate reference number of firms contacting Catapults, the year of the action, the specific Catapult contacted, as well as the overall level of engagement, assessed by the Catapults as low, medium or high.

Secondly, we matched both the Catapults data with firm-level data from the ONS Business Structure Database (BSD), accessed through the UK Data Service and covering the whole population of businesses in the UK between 1997 and 2020 (ONS 2021). The BSD provides information on firms' age, ownership, turnover, employment, industrial classification at the SIC 4-digit level and postcode. We have matched this database with the Catapults data using the Company Reference Numbers (CRNs) provided, gathering firm-level information about almost all the UK firms who have engaged with the Catapults combining in this way information on Catapults engagement and firm-level characteristics.

We can first analyse the temporal evolution of the engagement of Catapults with private firms in Figure 1. In the rest of the analysis we focus mostly on firms with a high level of engagement with Catapults. Catapults' engagement with private firms took off mostly after 2014, with a rapid increase in particular in low-engagement activities with companies. Also note that 'high engagement' of firms has overtaken 'medium engagement' around 2017, demonstrating an increasing level of engagement intensity between firms and the Catapults.

Figure 1: Evolution of Catapults engagement and UKRI funded projects with Catapults partners



Notes: Statistics based on administrative data from Catapults and the ONS Business Structure Database.

We can then start exploiting the level of detail of these datasets to analyse the characteristics of firms engaging with Catapults. We see that Catapults are mainly engaging with micro (less than 10 employees) and small enterprises (less than 50 employees), representing three quarters of the entire population of firms supported (Table 1). This evidence could be indicative of the type of activities supported by the Catapults, mainly helping smaller firms to get involved with R&D activities, and with the adoption of new innovations and technologies.

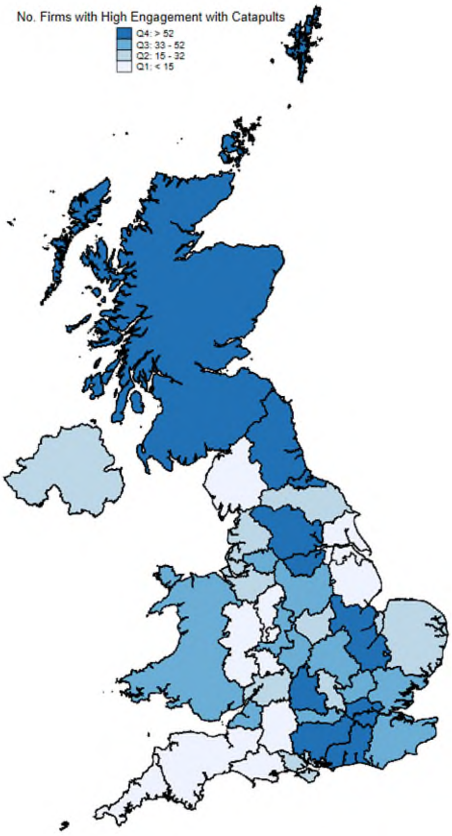
Table 1: Distribution of high engagement with Catapults by firm size

Size	High Engagement
Micro	1064
Small	478
Medium	278
Large	266

Notes: Statistics based on administrative data from Catapults and the ONS Business Structure Database. We define micro enterprises firms with less than 10 employees, small firms with less than 50 employees, medium are firms with less than 250 employees, while large are firms with more than 250 employees.

We continue our analysis by looking at the regional distribution of firms engaging with Catapults. Figure 2 shows the spatial distribution of firms with a high engagement with Catapults across LEPs in England and the three devolved Nations. We can observe several clusters of supported firms across regions, not only located in London and the South-East of England, as usually happening for R&D intensive firms, but also in Oxfordshire and Cambridgeshire, Yorkshire, the Tees Valley and the North-East, and Scotland. This spatial distribution of firms matches the location of some of the Catapults, as the Connected Places Catapult and the Satellite Applications Catapult in Oxfordshire and Cambridgeshire, the Advanced Manufacturing Research Centre and Nuclear Advanced Manufacturing Research Centre in Yorkshire, the Centre for Process Innovation and the Offshore Renewables Energy Catapult in the North-East and the Advanced Forming Research Centre and Offshore Renewables Energy Catapult in Scotland. This spatial clustering of engaging firms around the location of Catapults could create the right conditions for the development of agglomeration externalities, sharing skills, suppliers and knowledge between supported and unsupported companies located close to each other.

Figure 2: Regional distribution of high engagement with Catapults



Notes: Statistics based on administrative data from Catapults and the ONS Business Structure Database. Catapults engagement mapped across LEPs in England and the three devolved Nations. UKRI funded firms collaborating with Catapults mapped at the regional level because of confidentiality issues related to the limited number of concerned firms in each LEP.

It is possible as well to analyse the industrial distribution of firms engaging with Catapults. Here, we observe a very large proportion of engaging firms in the services sector, mainly focusing in the IT and professional services industries. Among the manufacturing industries, firms engaging with Catapults are mostly operating in the chemicals and electronics manufacturing sectors, the manufacturing of machinery, food and beverage products, and the manufacturing of transport equipment.

3. RESULTS

Table 2 examines the short- and medium-term effects on employment and turnover growth of firms engaging with Catapults, while the control group includes not engaged firms. We find that in general there is a stronger impact in terms of employment, growing by almost 16% faster in the 6 years after the start of any interaction. This is particularly relevant for services and high-tech companies, experiencing a turnover growth in the medium term which is 30% faster than non-engaged firms. However, engaged firms operating in manufacturing and low-tech industries do not show any difference in turnover growth in respect to non-engaged firms, only experiencing faster employment growth as a consequence of the engagement with Catapults.

In addition, we identify a particularly strong and positive impact of Catapults engagement for micro and small enterprises, growing in the medium-term by almost 40% faster in terms of employment and by more than 50% in terms of turnover, hinting at a faster growth in labour productivity as well. On the contrary, the growth effect of engaging with Catapults is smaller and statistically weaker for medium and large firms, and only barely significant in terms of turnover growth.

Table 2: Short and medium term employment and turnover growth effect for firms engaging with Catapults

	ST D.Empl.	*MT D.Empl.*	*ST D.Turn.*	*MT D.Turn.*
	General (N=296)			
ATT	0.1141***	0.1620***	0.0439	0.0529
b.s.e.	(0.0306)	(0.0474)	(0.0600)	(0.0866)
	Manufacturing (N=132)			
ATT	0.1162***	0.1589**	0.0362	0.1020
b.s.e.	(0.0447)	(0.0695)	(0.0696)	(0.1248)
	Services (N=164)			
ATT	0.1666***	0.3035***	0.0752	0.3268**
b.s.e.	(0.0473)	(0.0691)	(0.0935)	(0.1327)
	High-Tech (N=160)			
ATT	0.2337***	0.3553***	0.1451	0.3332**
b.s.e.	(0.0531)	(0.0764)	(0.0999)	(0.1357)
	Low-Tech (N=136)			
ATT	0.0596	0.1512**	0.0681	0.1892
b.s.e.	(0.0447)	(0.0698)	(0.0821)	(0.1226)
	Micro-Small (N=153)			
ATT	0.2220***	0.3924***	0.2697***	0.5524***
b.s.e.	(0.0481)	(0.0702)	(0.1022)	(0.1376)
	Medium-Large (N=145)			
ATT	0.0639	0.1191*	0.1156*	0.2092*
b.s.e.	(0.0400)	(0.0649)	(0.0630)	(0.1265)

Notes: Estimation based on administrative Catapults data and the Business Structure Database (BSD). ATT effect estimated using a propensity score nearest-neighbour matching procedure. Abadie and Imbens (2011) standard errors (s.e.) reported in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Short-term refers to growth between t-1 and t+2, medium-term between t-1 and t+5. Number of treated observations reported in title parentheses. The number of control observations included in each subgroup is equal to the number of treated.

4. CONCLUSIONS

Here we use data on firms’ engagement with Catapults to explore potential effects on business growth. The analysis is based on data on business engagements provided by the Catapults and longitudinal data for the whole population of UK firms. We consider support offered by the Catapults during the 2011 to 2016 period and business growth over the subsequent three and six years.

Our results show that there is a strong positive effect on employment and turnover growth of firms engaging with Catapults. In general, there is a stronger impact in terms of employment, growing by almost 16% faster in 6 years after the start of the intervention. This is particularly relevant for services and high-tech companies, experiencing also a turnover growth in the medium term which is 30% faster than non-engaged firms. This is also particularly strong for micro and small enterprises, while the effect on growth smaller and statistically weaker for medium and large firms. On average, these growth effects are marginally smaller than those of UKRI grants in general over a similar period (Vanino et al., 2019), although there is perhaps more variation between the scale of growth effects of the Catapults depending on the types of firm involved.

Our findings provide strong support that engaging with Catapults provides an immediate and sustained improvement of the performance of firms, helping them to commercially adopt new innovations and technologies, and leading to faster employment and turnover growth in particular for smaller, high-tech, and firms in the services industry.

ANNEX: ECONOMETRIC METHODOLOGY

We develop an econometric analysis to evaluate the dynamic effect of engaging with Catapults on the performance of participating firms, in particular in terms of employment and turnover growth. However, engaging with Catapults cannot be considered an exogenous decision, but is very likely to be affected by endogenous factors influencing the self-selection of firms into this kind of activity. To help overcome this issue we apply a propensity score matching (PSM) technique at the firm-level, as developed in previous studies facing similar empirical challenges (Scandura 2016; Vanino et al., 2019), creating a suitable control group of non-treated firms which is as similar as possible to the group of treated firms based on the likelihood of engaging with Catapults. By using a PSM technique we aim to control for any selection bias based on observable covariates by comparing treated with comparable untreated firms, while taking into account unobserved heterogeneity by comparing their differences in performance growth before and after the treatment.

Our identification strategy relies on comparing the performance of treated firms before and after their engagement with Catapults compared to the performance of a control group of similar but non-engaging firms. Through the construction of a valid control group based on the observable differences between engaging and non-engaging, our matching approach should control for endogeneity bias. The final step is to assess the average treatment effect on the engaging firms, the ATT effect, to estimate the difference in the outcome variables between firms which engaged and did not engage with Catapults using a linear regression model as developed by Leuven and Sianesi (2017).

We consider two possible treatments: first, we focus on the impact of 'high-intensity' engagement with Catapults. We focus on the impact of the first engagement with Catapults in order to better identify this causal effect (Scandura, 2016). We then measure the average growth rate of the outcome variables y^1_{t+n}, employment and turnover[1], as the difference between the pre-treatment log level at time *t-1* and the levels in the short-term 3 years after the treatment, and in the medium-term (MT) 6 years after the treatment.[2] Since we are

[1] Due to the limited number of variables included in the BSD database, it is not possible to estimate the impact of Catapults engagement on measures of firms' productivity such as total factor productivity or gross value added.
[2] Superscript 1 in y^1_{t+n} indicates the engagement with Catapults; n denotes the number of years after the first engagement.

interested in identifying the differences in firms' performance after the first engagement, we can express the average treatment effect (τ_{ATT}) in terms of performance growth after the beginning of the collaboration at time *t+n* as $E(y^1_{t+n}|\, S_t = 1)$, and the counterfactual performance growth for the same group of firms had they not participated as $E(y^0_{t+n}|\, S_t = 1)$:

$$\tau_{ATT} = E(y^1_{t+n} - y^0_{t+n}|\, S_t = 1) = E(y^1_{t+n}|\, S_t = 1) - E(y^0_{t+n}|\, S_t = 1)$$

where *S* denotes the two groups of firms, *S=1* is the treated group engaging with Catapults and *S=0* is the untreated group. The fundamental problem is that only one of the two possible cases is observed for each firm, i.e., whether the firm has engaged with Catapults $E(y^1_{t+n}|\, S_t = 1)$ or not $E(y^0_{t+n}|\, S_t = 0)$. Hence, we need to build a suitable control group by considering instead the effect of no treatment on the performance growth of similar firms which did not engage.

Table A1: Propensity score estimation and balancing test for matched observations in the analysis of engagement with Catapults

Variable	Coeff.	S.E.	Treated	Control	Mean Bias	Bias Reduction	t-value	p-value	V(T)/V(C)
Employment	0.1123***	(0.0255)	4.9057	4.8595	2.1	95.8	0.2	0.841	1.06
Productivity	-0.041	(0.0289)	4.6857	4.7489	-4.3	59.1	-0.51	0.609	1.4
Age	-0.069	(0.0663)	3.0106	2.9764	4.5	73.6	0.63	0.532	1.03
Employment Growth	-0.077	(0.0522)	0.15597	0.13521	3.5	48.5	0.39	0.699	1.6
Productivity Growth	0.0271	(0.0322)	0.10719	0.16732	-6.1	-129.6	-0.75	0.453	1.02
Group	0.0584	(0.0753)	0.73469	0.72245	2.5	92.6	0.3	0.761	-
Foreign	0.0321	(0.0713)	0.29796	0.25306	10.8	66.7	1.11	0.267	-
Agglomeration	-0.002	(0.0027)	5.2091	6.3315	-9.3	-2.4	-0.81	0.419	0.91
Entry Rate	-0.775	(1.2592)	0.01194	0.01265	-2.9	-32.6	-0.4	0.689	0.65
Reg-Ind. Productivity	-0.067	(0.0491)	4.7987	4.8075	-1.1	80	-0.12	0.905	0.99
Reg-Ind. Employm.	0.0525**	(0.0216)	7.8471	7.8352	0.6	91.9	0.07	0.945	1.05
Market Share	-0.018	(0.1342)	0.29879	0.30174	-0.9	97.4	-0.09	0.931	0.99
Single Plant	0.1051	(0.0896)	0.19592	0.22449	-6.2	76.3	-0.77	0.439	-
Patents	0.1848***	(0.0220)	0.82862	0.9085	-7.3	83.2	-0.49	0.626	0.89
	No. Obs.	R-sq	Ps R-sq	LR Chi-sq	p-value	Mean Bias	Median Bias	B	R
	18382	0.116	0.007	4.91	0.987	4.4	3.9	20	0.89

Notes: Propensity score estimation and matching balancing test reported in this table refers to the results shown in Table 3 (engagement with Catapults versus no engagement). Estimations and tests for the other analysis are similar and consistent, and available upon request. The second and third columns report the results of the propensity score estimation using a probit model. Robust standard errors (s.e.) reported in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Columns 4 and 5 present the mean value of each control variable for firms in the treated and control groups after the implementation of the matching technique. In column 6 we display the median standard bias across all the covariates included in the logit estimation after the matching procedure. Columns 7 and 8 report the t-tests for the equality of the mean values between treated and untreated firms in the matched sample. Column 9 shows the ratio of variance of residuals orthogonal to linear index of the propensity score in treated group. The bottom row presents a summary of statistics regarding the whole sample: the pseudo R2 from the probit estimation and the corresponding χ^2 statistic and p-value of likelihood-ratio test of joint significance of covariates; the mean and median bias as summary indicators of the distribution of bias across the samples; the Rubin's B shows the absolute standardized difference of means of linear index of propensity score in treated and matched non-treated groups, while the Rubin's R is the ratio of treated to matched non-treated variances of the propensity score index. Finally, the total number of treated and control observations in the support sample is included.

To build the control group we use a propensity score matching technique in order to select suitable controls from the very large group of untreated firms, matching observed characteristics as closely as possible to those of treated firms before the beginning of the engagement (Vanino et al., 2019). We estimate the probability of engagement, the so-called propensity score, based on a set of relevant observable characteristics which have been found to influence the likelihood of participation in the previous literature. We use a probit model with industry, region and year fixed-effects to estimate the propensity score for all observations, using several covariates which may explain the probability of participation. We include a set of firm-level variables such as employment, turnover, firm age, employment and productivity growth in the 2-years period before the engagement, firms market share, group membership, foreign ownership and single-plant firm dummies to control for firms' characteristics, and the total number of patents owned to control for firms' previous innovation activities.[3] In addition, we take into account other control variables at the industry-region level to control for location and sector specific factors, such as the agglomeration index per region and industry, the regional R&D intensity,[4] the region-industry competition level measured with the net entry-exit rate, region-industry employment and turnover per employee levels, and finally year, region (LEP or NUTS 2-digit level) and industry (SIC 2-digit) dummies.

We estimate a separate propensity score for each treatment and sub-sample of interest (see below), in order to take into account the heterogeneous likelihood of being treated for firms with different characteristics. For the analysis of the effect of engaging with Catapults (RQ1), we draw a sample of control untreated firms from the general population of firms

[3] Data on firms' patents was provided by the UK Intellectual Property Office.
[4] We have measured region and region-industry R&D intensity using data from the UK CIS dataset (BIS-ONS, 2018) as the average ration between R&D expenditure and turnover at the regional NUTS 2-digit level or at the regional NUTS 2-digit and industry SIC 2-digit level.

operating within the same industry and regions. For the evaluation of the participation in UKRI funded project in partnership with Catapults (RQ), we instead considered as a group of control untreated firms participating in other UKRI funded project, but not collaborating with Catapults, in order to assess the added value of the Catapults contribution to these projects. Finally, in a last set of results (RQ3), we also compare the performance of firms collaborating with Catapults in UKRI funded projects vis-à-vis firms with a high engagement with Catapults but not participating in UKRI funded project with them. Table A1 reports the results of the propensity score estimation for the general engagement with Catapults, which is consistent with previous studies. In particular, large and more innovation intensive firms seem to be more likely to engage with Catapults, in particular if located in highly agglomerated regions and industries.

After estimating the propensity scores, we proceed by matching the untreated and treated observations based on this. First, we impose a common support condition, dropping the treated and untreated observations whose propensity scores are larger or smaller than the maximum or minimum of the other category. Secondly, we apply a Nearest-Neighbour matching technique with a strict Caliper bandwidth, matching each treated observation only with the closest untreated observation within a 0.05 range in the propensity score. We restrict the matching to firms located in the same region at the LEP or NUTS 2–digit level and operating within the same sector at the SIC 2-digit level.[5] Finally, we have clustered the standard errors following the Abadie and Imbens (2011) methodology for the Nearest-Neighbour matching procedure to take into account the additional source of variability introduced by the estimation of the propensity score. Table A1 also reports the results of the balancing tests verifying the consistency of the construction of the control group and the overall quality of the matching procedure. To check the propensity score balancing we report mean differences across the treated and control group for the set of variables used to estimate the propensity score after matching. Where differences between treated and untreated firms were observed before matching, these are significantly reduced after matching. The bias after matching for all covariates is reduced below the 25% critical threshold, and the t-values for differences in the means are not significant, suggesting a consistent and balanced matching, and that there are no systematic differences in the observable characteristics of treated and untreated firms before the engagement with

[5] To test the sensitivity of the matching method, as a robustness check we apply a Kernel matching technique with a strict bandwidth of 0.05, using a kernel-weighted distribution which down-weights the contribution to the outcome of non-treated firms which are further from the propensity score of treated observations within a certain range.

Catapults. Overall, the matching procedure satisfies the balancing property, suggesting that the conditional independence assumption is not violated, since y_{t+n}^{1} and y_{t+n}^{0}, respectively are statistically independent for firms with the same set of exogenous characteristics.

Finally, we are able to estimate a linear regression model following the Leuven and Sianesi (2017) methodology on a pooled cross-sectional dataset where for any given firm we observe the treatment dummy, the propensity score, the different control variables and the dependent variables of employment and turnover growth between period *t-1* and the short-term (*t+2*) and the medium term (*t+5*) periods. We start by estimating the overall effect, before exploring the heterogeneity of this effect by differentiating between firms operating in manufacturing and services sectors, high-tech and low-tech companies,[6] and between micro-small and medium-large enterprises. By matching based on the propensity score and controlling for year, region and industry fixed-effect, along with other control variables, we get a reliable estimate of the impact of engaging with Catapults. However, it is important to bear in mind the limitations of this methodology. First, despite being widely adopted in innovation policy research because of its ability to deal with potential common support problems, propensity score matching does not fully reduce the concerns of unobservable factors explaining grant allocation and post-grant performances. Second, this methodology cannot establish the impact of the treatment beyond the eligible groups of treated and control observations included in the analysis, potentially biasing the estimation of the overall economic effect if these groups are not representative of the entire population.

[6] Following the ONS-Eurostat classification, we consider as high-tech firms in the following SIC 2007 industries: (20) chemicals; (21) pharmaceuticals; (26) computer, electronic and optical products; (27) electrical equipment; (28) machinery; (29) motor vehicles; (30) transport equipment; (50) water transports; (51) air transports; (58) publishing activities; (59) motion picture, video and television programme production, sound recording and music publish activities; (60) programming and broadcasting activities; (61) telecommunications; (62) computer programming, consultancy and related activities; (63) information service activities; (64) financial intermediation; (65) insurance; (66) auxiliary activities to financial intermediation; (69) legal and accounting activities; (70) activities of head offices, management consultancy activities; (71) architectural and engineering activities, technical testing and analysis; (72) scientific research and development; (73) advertising and market research; (74) other professional, scientific and technical activities; (75) veterinary activities; (78) employment activities; (80) security and investigation activities; (85) education; (86) human health and social work activities; (90) arts, entertainment and recreation.

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Enterprise Research Centre

Centre Manager
Enterprise Research Centre
Warwick Business School
Coventry, CV4 7AL
CentreManager@enterpriseresearch.ac.uk

Centre Manager
Enterprise Research Centre
Aston Business School
Birmingham, B1 7ET
CentreManager@enterpriseresearch.ac.uk

Economic and Social Research Council
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