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EVALUATING THE IMPACT OF THE NMS INNOVATION PROJECTS ON SUPPORTED FIRMS

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Evaluating the Impact of the NMS Innovation Projects on Supported Firms

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ABSTRACT
The purpose of this study is to provide evidence of the impact of subsidised National Measurement System (NMS) consultancies on supported firms. The study achieves this by using the consultancy projects offered via Measurement for Innovators (MFI) programme which occurred between 2004 and 2010. This study provides evidence of the key role the NMS plays in the collaborative R&D innovation process in the UK and can be used to extrapolate the impact of the Analysis for Innovators (A4I) programme which commenced in 2017.

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Executive Summary

Context

The purpose of this study is to provide evidence of the impact of subsidised National Measurement System (NMS) consultancies on supported firms. The study achieves this by using the consultancy projects offered via Measurement for Innovators (MFI) programme which occurred between 2004 and 2010. This study provides evidence of the key role the NMS plays in the collaborative R&D innovation process in the UK and can be used to extrapolate the impact of the Analysis for Innovators (A4I) programme which commenced in 2017.

All NMS impact studies take a holistic approach in evaluating the impact of the NMS on supported firms. This is the first time NPL has evaluated a mode of disseminating impact i.e. subsidised consultancy projects.

The MFI programme was led by the National Physical Laboratory (NPL) and delivered by a consortium of UK National Measurement institutes including NPL, LGC, NEL and OPSS.[1] The main objective of the programme was to provide expanded access to the measurement knowledge, skills, and facilities of the NMS laboratories. The benefits of the programme included:

- improving existing products and services of stakeholders;
- developing innovative new products and processes of stakeholders;
- disseminating good measurement practice to all stakeholders;
- collecting information from industry on current challenges and feeding this back into the future formulation of NMS programmes; and
- providing benchmarks for different test methods and creating new test models or methods.

The MFI programme was delivered through three products:

1. **Consultancy projects** – The consultancy projects were used to provide measurement advice to organisations to support the development of process, products, or services. The consultancies were targeted at UK Small and Medium-sized Enterprises (SMEs) and trade associations with majority SME membership, however, some large companies benefited from this product.
2. **Secondments** – The objectives of secondment projects were to improve the performance of the partner organisation by exchanging knowledge and skills in a two-way transfer of people. UK companies, universities, government departments, regional organisations and other bodies were all beneficiaries of this product.
3. **Joint Industry Projects (JIPs)** – Each project brought together a group of companies, public sector organisations or academia to tackle problems of a larger nature than the consultancies and the secondments. These problems were industry-wide issues.

Some aspects of the MFI consultancies and the A4I programme are quite similar. Both programmes aimed to boost a company's/organisation's productivity and competitiveness by providing the capabilities of the NMS to support the development of processes, products, or services.

1 LGC ─ Laboratory of the Government Chemist, NEL ─ National Engineering Laboratory, OPSS – Office for Product Safety and Standards.

Approach

Due to data limitations, the focus will be on the effects of consultancy projects. Given the structure of the MFI consultancies, two things are expected to happen to a company that benefited from the programme.

First, the consultancies are targeted when developing new products and processes or improving existing products and processes, therefore, we should expect an increase in the inventive output of a supported company. To evaluate changes to the inventive output of a company, a dummy variable was used to indicate if a company filed for a patent in a given year. The main hypothesis proposed here is that patent applications are an indicator for inventive output, however, patents do not capture all inventive activities. Companies also use trade secrets to protect ideas. Therefore, the estimates derived from using patents as a proxy should be considered as a lower bound of the effect of the MFI programme on the inventive output of supported firms.

Second, the increase in the inventive activity of a company should lead to some realised benefits in subsequent years. This is because invention enables the supported firms to reduce costs or develop new products. These realised benefits of inventiveness can be measured via growth and productivity. Due to the data limitations, the realised benefits of the inventions were measured via asset growth and firm survival.

The study conducts an empirical analysis of the three waves of the MFI programme with data on 389 companies over 19 years (2000-2018) who applied for the consultancy projects.[2] This dataset was constructed using information from the MFI historical programme management data, FAME (Financial Analysis Made Easy) and ORBIS. The treatment and control group were selected from this dataset. The treatment group consists of companies who completed the consultancy project and the control group consists of companies who had unsuccessful applications or withdrew from the programme.

We employ propensity score matching[3] to analyse the difference-in-differences between the outcomes of the supported firms and the counterfactual. By comparing their outcomes before, during and after the MFI programme we can estimate the causal effect of the programme on the inventive capacity of the firms and the realised benefits from the programme. The models used considered firm heterogeneity in terms of size, inventiveness and other important characteristics that could affect the outcome or determine treatment. We also use parametric regression techniques[4] to test the accuracy of our primary models and ensure robustness in our findings.

Key findings

Our findings show that the MFI programme has a positive impact on companies that completed the programme compared to the control group. On average, the patenting activity of the supported firms increased compared to the counterfactual. Figure B shows the average patenting activity between the treated group and the control group in years before, during and after treatment alongside the difference between these two groups and the confidence interval.

2 Financial data for these companies was gathered for years before and after the duration of the MFI programme in order to measure company behaviour prior to and in response to the programme.

3 and Nearest Neighbour Matching

4 OLS and Panel regressions

We find that in the year of support, the probability of filling for a patent for companies who completed the MFI programme was 11% higher than the companies who received no support from the MFI programme. Evidence from the counterfactual suggests that the companies who had not received treatment still produced patents, but it took them longer to do so.

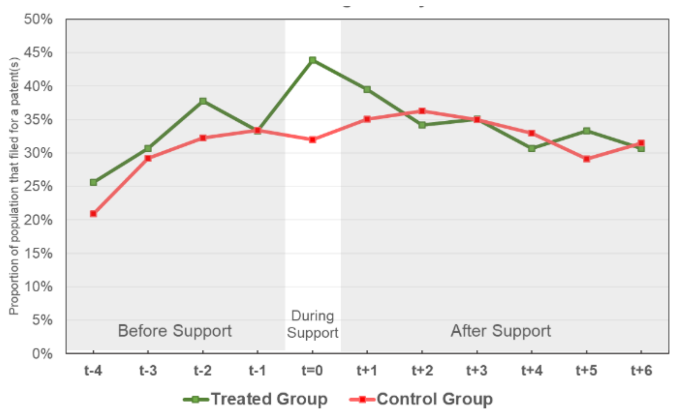


Figure A

Patenting activity

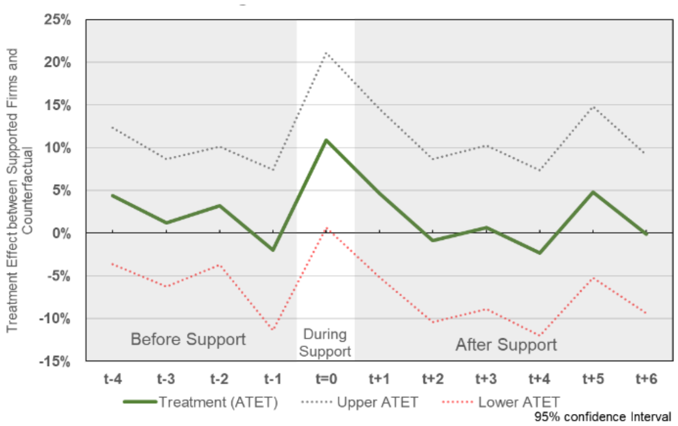


Figure B

Average treatment effect on treated (patenting activity)

Based on the findings on the effect of the MFI programme on inventive activity, we established that it takes the counterfactuals an additional two years before they match the inventive output of the supported firms after treatment. This means we can use the time value of money saved by supported firms that filed for patents two years earlier as an estimated benefit of the programme.

We estimate a benefit-cost ratio of £5:£2. This means for every £1,000 spent on an MFI consultancy by the NMS the supported firm received a value of £2,500. It is worth re-iterating that this estimate of the benefit-cost ratio of the programme is only a lower bound estimate of the effect of the programme on a supported firm's inventive output.

Figure C and Figure D show the survival rates of the treated group and the counterfactual in periods after treatment. We find that the MFI programme does not affect the survival of a supported firm.

Given that the rate of survival between the treated firms and the counterfactual are identical, we can rule out the possibility that firm survival has influenced our estimates of asset growth.

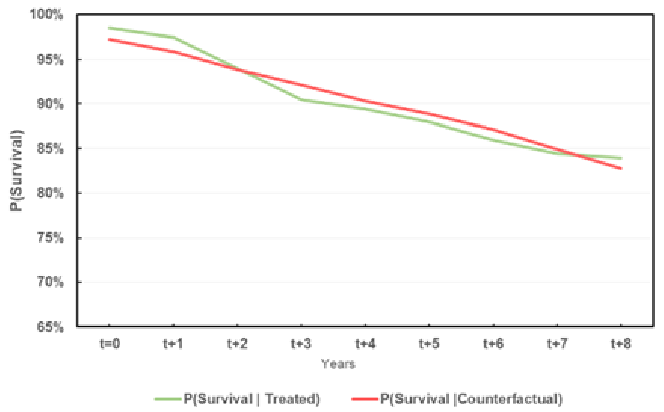


Figure C

Survival rates

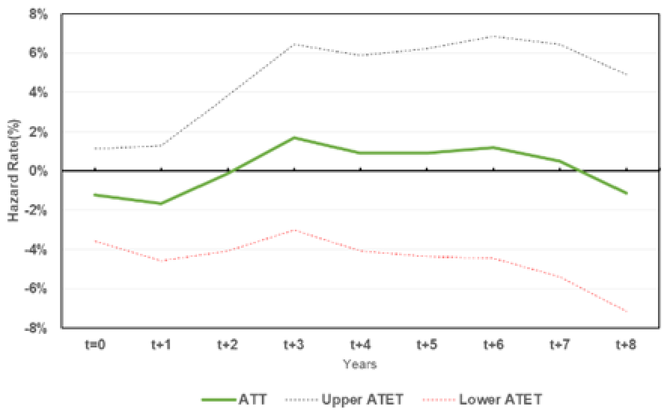


Figure D

Average treatment effect on treated (survival rate)

Finally, we find that the increase in the inventive activity of the supported firms leads to growth in total assets in subsequent years after support. The results from Figure E and Figure F show that the supported firms after receiving treatment grow higher than the counterfactual. This difference in growth is estimated to be about 5% annually.

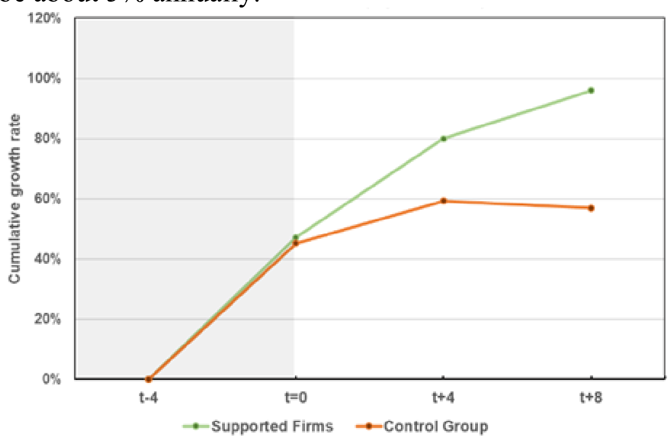


Figure E

Asset growth (4-year intervals)

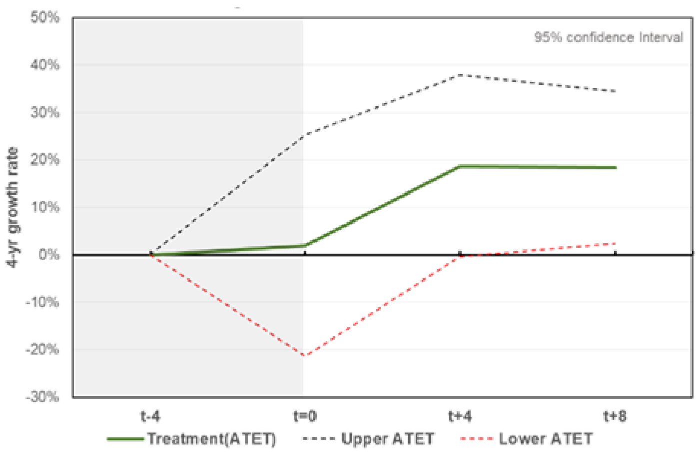


Figure F

Average treatment effect on treated (asset growth)

Furthermore, we notice a period of stagnation for the counterfactual 4 years after the year of treatment. On the other hand, the firms who receive support have a persistent growth trend even 4 years after treatment. The supported firms do not experience the same level of stagnation as the counterfactual. Growth rates this persistent could happen for a couple of reasons. One possibility is that the MFI programme did not only increase the inventive output of the firm but also changed the innovative culture of the supported firms. This means that the supported firms have adopted better ways of acquiring, assimilating and exploiting knowledge for innovating as a result of the MFI programme. Another possible reason is that the increase in inventive output (or patenting activity) has generated large surpluses for the firm, which in turn has provided capital to invest in more assets over time. Thus, leading to a consistent cycle of productivity gains and expansion which we observe in the growth of the firm's assets over time.

CONTENTS

1 INTRODUCTION

The Measurement for Innovators (MFI) Programme commenced in Autumn 2004. The programme was led by the National Physical Laboratory (NPL) but delivered by a consortium of UK National Measurement Laboratories including the Laboratory of the Government Chemist (LGC), the National Engineering Laboratory (NEL) and the Office for Product Safety and Standards (OPSS)[5].

The main objective of the programme was to provide expanded access to the measurement knowledge, skills, and facilities of the National Measurement System (NMS) laboratories to organisations that traditionally have not benefited fully from significant government investment in the UK's national measurement infrastructure.

The programme lasted for 7 years (2004-2010) and within that period there were three individual waves:

MFI Waves	Period	Projects completed
1st Wave	2004-2007	89%
2nd Wave	2007-2009	81%
3rd Wave	2009-2010	89%

Table 1

Timeframe for MFI waves

The benefits of the programme included:

- improving existing products and services of stakeholders;
- developing existing products and services of stakeholders;
- disseminating good measurement practice to all stakeholders;
- collecting information from industry on current challenges and feeding this back into the future formulation of NMS programmes; and
- providing benchmarks for different test methods and creating new test models and methods.

These benefits were delivered through three complementary NMS knowledge transfer products:

- Consultancy on innovation development projects for technology-based companies – mainly Small and Medium-sized Enterprises (SMEs).
- Secondments of specialist staff between the NMS laboratories, technology-based companies and public sector organisations.
- Co-funded Joint Industry Projects (JIPs).

Table 1 shows the characteristics of each product offered during the MFI programme and makes a comparison with the Analysis for Innovators (A4I) programme, a successor to the MFI programme that commenced in Autumn 2017.

The consultancies and secondments focused on collaborating with individual companies to solve challenging technical issues related to developing new or improving current processes, products, or services. The companies who applied for these programmes were unable to solve the problems they were faced with because of the lack of expertise.

There were instances where one or two-day consultations with scientists solved the problem for the company, saving the company time, money and personnel resources so that it may continue its development past a roadblock that it didn't have the expertise to cope with.

5 Formerly the National Weights and Measures Laboratory (NWML)

Characteristic	Consultancies	Secondments	JIPs	A4I
Target Group	Product is targeted at UK SMEs or trade associations with majority SME membership.	UK industry, universities, trade associations, government departments, regional organisations, and other bodies.	Industry, public sector organisations or academia.	Targeted at UK Industry.
Purpose	Provides measurement advice to organisations to support the development of processes, products, or services. No commercial options available for the technical solution provided through the programme.	The objectives of secondments were to improve the performance of the partner organisation by exchanging knowledge and skills in a two-way transfer of people.	The objective of the JIPs was to bring about collaborative projects aimed at solving an industry-wide issue, using metrology as the core underpinning enabler. The focus of a JIP was to remove barriers, helping better enable innovation across a supply chain or industry sector.	Provides measurement advice to organisations to support the development of processes, products, or services.
Duration	Up to 4 days.	1 week-3 months (Full Time or Part-Time).	10-12 months.	Round 1 & 2 – 12 months. Round 3 – 3 to 4 months.
Funding from Supported companies	No.	No.	Co-Funded.	Co-Funded except projects funded via *de minimis*[6].
Application Process	A singular application process with quick turnaround time. The solution to the problem must not be commercially available.	Quite similar to the consultancies. Singular application process.	Five-stage application process and a scoring criterion.	Three-stage application process and a scoring criterion.
Frascati research categories[7]	Experimental Development.	Experimental Development.	Applied research.	Applied research; Experimental Development.

Table 1

MFI and A4I product characteristics

The secondments were also similar to the consultancies; however, the scope of its purpose was much broader. The secondments did not only focus on helping companies develop new products or processes, but also exchanged knowledge and skills between both parties. Unfortunately, there are a significant amount of missing data for the secondment projects and for that reason, they have been excluded from the study. With more effort, the data can be recovered and included in future analyses. Based on the R&D categories in the Frascati Manual 2015, the consultancies and the secondments are experimental developments. This is because the companies supported via the consultancies and secondments draw upon knowledge from the NMS and used this knowledge to develop processes, products, or services.

6 For small scale projects, exempted from the co-funding rules.

7 **Basic research** is experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundations of phenomena and observable facts, without any application or use in view. **Applied research** is an original investigation undertaken to acquire new knowledge. It is, however, directed primarily towards a specific, practical aim or objective. **Experimental development** is systematic work, drawing on knowledge gained from research and practical experience and producing additional knowledge, which is directed to producing new products or processes or to improving existing products or processes. See: Frascati Manual 2015, OECD, (2015).

The JIPs were also collaborative. Each project involved a consortium of a National Metrology Institute (NMI) and several other organisations from industry, academia, or other sectors to use measurement expertise to create an innovative solution to a specific problem. The solutions had a generic aspect that could be disseminated throughout relevant market sectors. However, the solution to the problem is not always guaranteed. On the Frascati Manual 2015, the JIPs would be considered as applied research projects.

An initial attempt to evaluate the effects of the JIPs showed no significant effect. This is primarily because the model we used measures the direct impact of the project to the stakeholders. However, the JIPs were primarily focused on industry-wide impact rather than the direct benefits to stakeholders involved in the project. An example of a JIP project was one that focused on creating a methodology for measuring the accuracy of 3D face imaging systems that will generally aid the adoption of 3D face recognition systems.

This made our approach for measuring the impact of the JIPs inappropriate. For this reason, we exempted the JIPs from the study. Only the consultancies were used in this study. Nevertheless, the analysis provides evidence of the benefits UK businesses derive when they directly collaborate with the NMS on firm-specific problems.

The rest of the study is organised as follows. Section 2 contains an overview of the conceptual and empirical framework used to build our model and test our hypotheses. In Section 3, the sources, variables, and data of the study are described. The explanatory variables, control variables and specification for all the empirical models are discussed in further detail in Section 4. The results of the econometric models are presented and discussed in Section 5. Section 6 concludes.

2 FRAMEWORK

As explained in Section 1, our analysis is based on the causal effect of the consultancies on firms who benefited from the programme. In this section, we give an outline of the conceptual framework and the empirical framework used in these analyses.

2.1 CONCEPTUAL FRAMEWORK

To determine the causal effect of the consultancies on firms who benefited from the programme, the study carries out a two-step approach. The conceptual framework would be guided by the following hypotheses:

Hypothesis 1 (H1): Given the nature of the MFI programme, we expect the programme to increase the inventive capacity of companies who received support in comparison to the constructed counterfactual group.

Hypothesis 2 (H2): The increase in the inventive capacity of the supported firm via the MFI programme should lead to some realised benefits for the firm over time when compared to the counterfactual.

These hypotheses could be addressed using the Knowledge Production Function[8] which is represented in a simplified path analysis diagram in Figure 1.

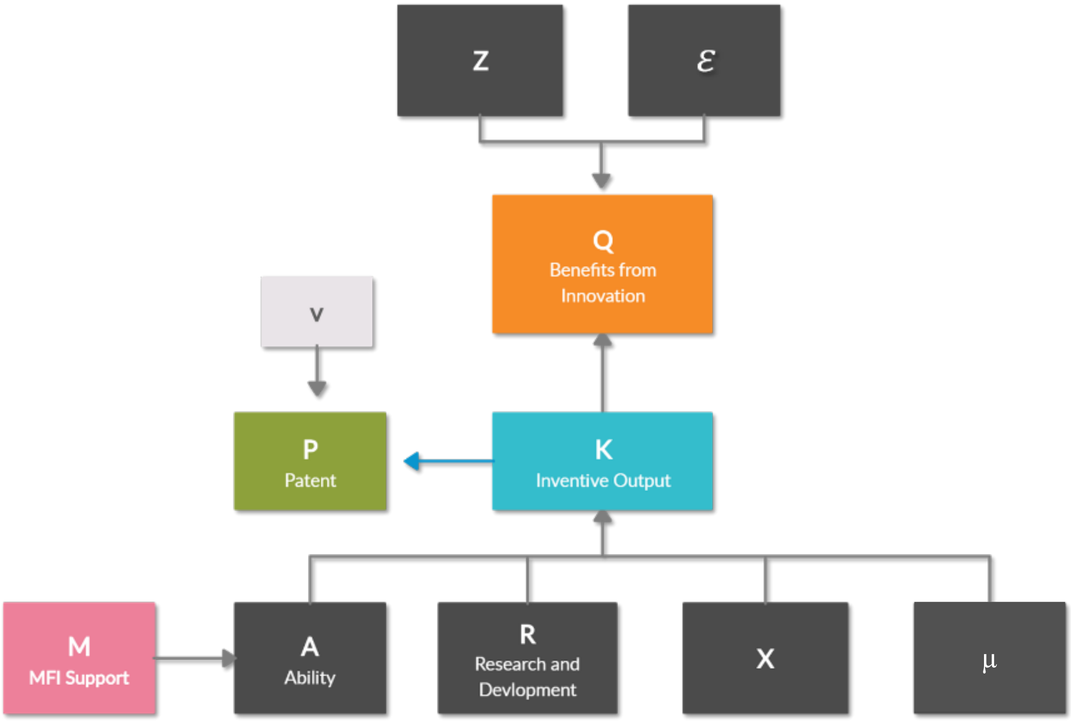


Figure 1

A simplified path analysis diagram of the overall model

Focusing on the bottom half of the diagram, the model suggests that there are inventive inputs required to increase a firm's inventive output denoted as *K*. Assuming the model to be of the Cobb-Douglas form we represent it as follows:

$$K = A\, R^{\gamma}\, X^{\delta}\, e^{\mu} \quad (1)$$

8 Pakes and Griliches, (1984).

where A represents the private productivity of research effort, R represents R&D investment, X represents a vector of underlying characteristics of the firm that influence its inventive output, γ and δ are output elasticities of R and X, respectively, and e^{μ} is an error term that represents randomness and unmeasured factors that influence K. Equation (1) can be written in linear form as[9]:

$$\boldsymbol{k} = \boldsymbol{a} + \gamma \boldsymbol{r} + \delta \boldsymbol{x} + \mu \tag{2}$$

In equation (2), $\boldsymbol{r}$ represents the real R&D investments of the firm. The real R&D investment of a firm can be written as follows:

$$\boldsymbol{r} = \ln(R_t) = \ln(RD_t + (1-\sigma)R_{t-1}) \tag{3}$$

where RD_t represents R&D investments at time t, and σ is the depreciation rate of the cumulative R&D investment of the firm at t-1.

Here it is necessary to highlight the importance **of $\boldsymbol{a}$** in equation (2). This is an efficiency parameter that represents the private productivity of research effort which is primarily influenced by the firm's work-force expertise, ability, or skill. A firm with a better-skilled workforce is more efficient at transforming its research activities into inventive outputs. Given the structure of the MFI consultancies, one can say that the provision of expert advice from the NMS to a firm increases their existing ability. More specifically, we assume that $\boldsymbol{a}$ (efficiency parameter) can be written as:

$$\boldsymbol{a} = \ln(A) = \ln(\alpha + \beta M) \tag{4}$$

Where α is the firm's current level of expertise and β is the additional expert knowledge given to the firm from the MFI programme. M is a dummy variable representing firms who received support from the programme, when M=1 the firms receives β and when M=0 the firms has no β.

It is also important to note that $\beta < \alpha$ (i.e. the knowledge obtained from the consultancy is not more than the firm's existing level of expertise). We impose this constraint on β because the consultancy projects were focused on providing support to organisations to aid the development of a process or product. This indicates that the firm has gotten past the stage of fundamental research and has a significant amount of expertise before it participates in the MFI programme. The firm has invested resources to develop the product or process up until a certain level where it needed support from the NMS via the MFI programme to make further advancement. Upon making this advancement with the help of the NMS, there is a simultaneous increase in the firm's inventive output.

To be more explicit about the effect of the MFI programme we substitute (4) into (2):

$$\boldsymbol{k} = \ln(\alpha + \beta M) + \gamma \boldsymbol{r} + \delta \boldsymbol{x} + \mu$$

$$\boldsymbol{k} = ln(\alpha) + ln\left(1 + \frac{\beta}{\alpha}M\right) + \gamma \boldsymbol{r} + \delta \boldsymbol{x} + \mu$$

Because $\beta < \alpha$ or $\frac{\beta}{\alpha} < 1$, and $M \in \{0,1\}$ therefore[10] $\ln\left(1 + \frac{\beta}{\alpha}M\right) \approx \frac{\beta}{\alpha}M$

$$\boldsymbol{k} = ln(\alpha) + \frac{\beta}{\alpha}M + \gamma \boldsymbol{r} + \delta \boldsymbol{x} + \mu \tag{5}$$

The problem we face is that $\boldsymbol{k}$ in itself is unobservable. However, we can use a proxy of $\boldsymbol{k}$ to evaluate the effect of the MFI programme on the inventive output of a company. Some papers[11] have suggested that patents are likely a good measure of inventive output. This is because patents are temporary property rights on an invention which excludes others from making, using, or selling the patented

9 Logs are represented in shorthand i.e. $\boldsymbol{r} = \ln(R)$

10 Using Taylor series, $\ln(1+x) \approx x$ if x is small.

11 Griliches, Z. (1990) and Cohen and Levin, (1989)

property for a given period. This invention which is patented comes as a result of combining various inventive inputs. Thus, patents can be used as an output measure of prior inventive efforts.
Patent as a proxy for inventive capacity can be represented as follows:

$$P = K^{\omega}\, e^{v} \tag{6}$$

Which can be linearised as follows:

$$\boldsymbol{p} = \omega \boldsymbol{k} + v \tag{7}$$

Where $\boldsymbol{p}$ represents patenting activity, $\boldsymbol{k}$ is inventive output and v accounts for disturbances and unobserved factors that influence patenting activity ($\boldsymbol{p}$) which are not explained by the firm's inventive output ($\boldsymbol{k}$). ω is the elasticity of patents with respect to inventive outputs of the firm.[12]
We can substitute (5) into (7):

$$\boldsymbol{p} = \omega\left(ln(\alpha) + \frac{\beta}{\alpha} M + \gamma \boldsymbol{r} + \delta \boldsymbol{x} + \mu\right) + v$$

$$\boldsymbol{p} = \omega ln(\alpha) + \omega \frac{\beta}{\alpha} * M + \omega\gamma * \boldsymbol{r} + \omega\delta * \boldsymbol{x} + \omega\mu + v \tag{8}$$

The direct effect of the MFI consultancies on a firm's patenting activity is explained by $\omega * \left(\frac{\beta}{\alpha}\right)$.[13] The variance of Equation (8), is made up of three components. The first component, $Var(\omega\mu)$, represents the randomness and unmeasured factors that affect inventive output which also influences a firm's patenting activity. The second component, $Var(v)$, accounts for disturbances and unobserved factors that influence patenting activity ($\boldsymbol{p}$) which are not explained by the firm's inventive output ($\boldsymbol{k}$). The third component, $\omega ln(\alpha)$, accounts for the idiosyncratic difference in firm's ability that cannot be observed.

With this model, we can test our first hypothesis (H1).

Shortcomings of this approach

Not all inventions are patented. Some studies use sectorial differences to explain the propensity to patent an invention. Alongside controlling for sectorial differences, we use the size of the firms to control for the propensity to patent an invention. This is because larger companies are generally more likely to protect their Intellectual Property (IP) through patents as they have greater resources to do so, as shown in Table 2. It is also worth noting that not all patents are converted to commercial products or viable processes. We only use patents as a proxy to measure the changes in inventive output rather than a direct increase the viable products created.

Patents differ in both economic and technical significance. We address this issue by applying the "law of larger numbers" i.e. "The economic . . . significance of any sampled patent can also be interpreted as a random variable with some probability distribution" (Scherer 1965b, p. 1098). The assumption is that some random fraction of inventive output (K) is selected for patenting. We know that this is not the case. Firms will choose to patent an invention based on the premise that the benefits gained from protecting the invention through a patent outweighs the cost of applying for the patent. For this reason, our approach to using patents should only be considered as a statistical technique which indicates some sort of inventive output by a firm.

12 $0 \le \omega \le 1$. When $\omega = 0$ it indicates that the firm does not patent any of its inventions. When $\omega = 1$ it indicates the firm patents all its inventions.

13 The elasticity of the firms patenting activity with respect to support from the MFI consultancies is $\frac{dlnP}{dM} = \omega * \frac{\beta}{\alpha}$

No. Employees	0-9	10 - 49	50 - 249	250+	Total
Patents	9%	16%	28%	31%	10%
Trademarks	24%	48%	65%	81%	28%
Copyright	60%	48%	47%	63%	59%
Database rights	14%	21%	25%	29%	15%
Other	25%	23%	9%	12%	25%

Table 2

Overall IP ownership levels from the UK Intellectual Property Awareness Surveys[14]

Another issue is that not all inventions are patentable. This is a much harder issue to overcome. This is because it would require asking each firm in our sample, what number of inventions they had that were unpatentable over the years. It's a fair assumption to make that most firms do not keep such records.

A consequence of the first and third issues mean that elasticity of patents with respect to inventive outputs is:

$$0 \leq \omega < 1$$

This constraint means that our analysis of the effect of the MFI programme on the inventive output of firms is only a partial estimate of the true effect of the MFI programme on the inventive output of supported firms, i.e.:

$$\omega * \left(\frac{\beta}{\alpha}\right) < \left(\frac{\beta}{\alpha}\right)$$

The upper half of the model focuses on the benefits of innovation. Evolutionary economists[15] have long argued that innovation is an activity that creates asymmetries in firm capabilities bestowing the innovating firms with a competitive advantage that allows them to grow. This asymmetry works through two channels. First, innovation leads to differential products or service characteristics lending a competitive advantage to firms with superior goods.[16] Second, innovation implies organisational learning, which will strengthen dynamic capabilities and generate unique knowledge which is hard to imitate.

A firm increasing its inventive capacity is one thing but the firm's ability to innovate (i.e. use this invention (idea)) is another. A firm's ability to transform its invention into a viable product or process can be evaluated through the benefits it would gain. This is because invention either reduces the cost of production, develops/modifies products which allow the firm to charge a premium or increase its' market share.

These benefits are reflected in the company's growth and productivity. These are measured through the revenue, survival, profit, assets, stock market value or the employment metrics of the firm. In Figure 1 these realised benefits from innovation are denoted as **Q**.

The model used to evaluate the benefits of innovation from the inventive output is:

$$Q = K^b Z^\rho e^\varepsilon \qquad (9)$$

which can be linearised as follows

14 Banking on IP? (2020).

15 Dosi, (1988).

16 Dasgupta, (1986).

$$\boldsymbol{q} = b\boldsymbol{k} + \rho\boldsymbol{z} + \varepsilon \tag{10}$$

Where $\boldsymbol{z}$ are other observable characteristics that influence the growth/capacity of a firm, $\boldsymbol{k}$ is the inventive output of the firm and ε are assumed random and mutually uncorrelated errors.
We then substitute $\boldsymbol{k}$ from equation (5) back into equation (10):

$$\boldsymbol{q} = b\left(ln(\alpha) + \frac{\beta}{\alpha}M + \gamma\boldsymbol{r} + \delta\boldsymbol{x} + \mu\right) + \rho\boldsymbol{z} + \varepsilon$$

$$\boldsymbol{q} = bln(\alpha) + b\frac{\beta}{\alpha} * M + b\gamma * \boldsymbol{r} + b\delta * \boldsymbol{x} + b\mu + \rho\boldsymbol{z} + \varepsilon \tag{11}$$

Where the coefficient $b * \frac{\beta}{\alpha}$ measures the rate of increase in benefits to innovation as a result of the MFI programme.

For this analysis, we use growth in total assets as a measure of the realised benefits from innovation. The total asset of a company is a well-populated financial metric in comparison to turnover, profits, and employment in our sample. The rationale for this metric is that an increase inventive output can lead to the successful development of products or processes. Successful products or process would lead to a surge in economic opportunities (profits, revenue, etc.) for the company. A surge in economic opportunities allows the company to increase its capital investment or expand its workforce.

An appropriate measure to identify an increase in capital investments is observing changes in the company's total assets (gross assets adjusted for depreciation). The total assets of a company is an appropriate measure as it does not just include investments in fixed assets (such as machinery) but also include investments in intangible assets (such as IP) and current assets (such as cash in bank and inventory). We also explore the influence of the MFI programme on the probability of firm survival. A firm's survival can be seen as a benefit of innovation. This is because innovation enables firms to maintain a competitive advantage in their markets.

2.2 EMPIRICAL FRAMEWORK

Given that we have established the conceptual framework behind the MFI programme, it would be helpful to outline the estimation strategy used to evaluate the hypotheses. Fundamentally, we apply a common estimation technique called Difference-in-Differences (DiD). The DiD approach is a research design for estimating causal effects of treatment which is based on the potential outcome approach developed by Rubin[17]. This is a common technique used to estimate the difference between the outcomes of two groups – the treated group and the treated group had it not received the treatment (counterfactual) – before and after receiving support.

Figure 2 is an illustration of how the DiD estimator works. In Figure 2, discrete time is measured in years, where $t = -n$ represents n years before participation in the programme, $t = 0$ represents the year the firm participated in the programme, and $t = +n$ represents the years after participation in the programme.

$Y_S(-n)$ and $Y_C(-n)$ are the observed outcomes of both the treated and the control group n years before receiving the programme respectively. $Y_S(0)$ and $Y_C(0)$ are the observed outcomes of both groups at the point of intervention.

17 Rubin Casual Model; Rubin, D. (1978). Rubin, D. B. (1974).

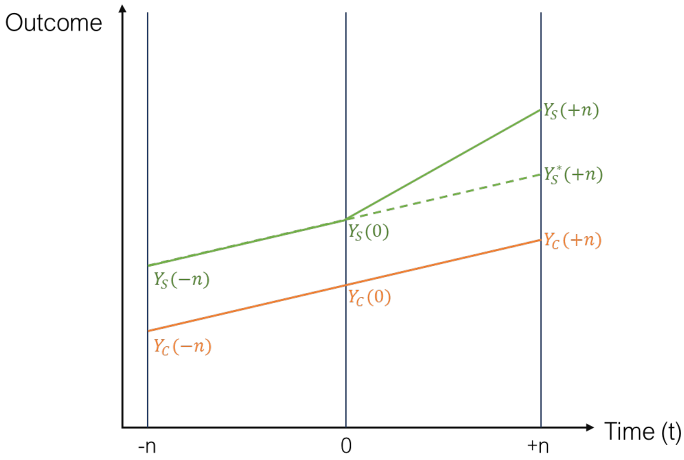


Figure 2

Difference-in-Differences approach

After the programme, there are three outcomes, $Y_S(+n)$ which is the observed outcome of the treated group *n* years after treatment, $Y_S^*(+n)$ which is the unobserved outcome of the treated group if they had not received treatment *n* years after treatment, and $Y_C(+n)$ which is the observed outcome of the control group.

$$DiD(+n) = Y_S(+n) - Y_S^*(+n)$$

The difference between $Y_S(+n)$ and $Y_S^*(+n)$ is our treatment effect *n* years after treatment. This is because if we take the difference between $Y_S(+n)$ and $Y_C(+n)$ as the treatment effect we do not account for the constant difference between both the treated group and control group, thereby leading to a 'self-selection' bias of the true effect of the programme.

With this in mind we can express the DiD as the average treatment effect on the treated (ATET)[18].

$$ATET(t) = E(Y_S(t)|M = 1) - E(Y_C(t)|M = 1)$$

Where $Y_S(t)$ is the outcome of interest for firms that receive support at time t, $Y_C(t)$ is the outcome for a firm that did not receive treatment at time t, and M is an indicator for whether the firm received support from the programme. $E(Y_C(t)|M = 1)$ is not observed, however, $E(Y_C(t)|M = 0)$[19] is observed. Because of a potential selection bias due to the fact that the receipt of treatment is not entirely random, $E(Y_C(t)|M = 1) \neq E(Y_C(t)|M = 0)$ and the counterfactual cannot simply be the average outcome of the non-participants.

We can use several methods to construct an appropriate substitute for the counterfactual, $E(Y_C(t)|M = 1)$ using $E(Y_C(t)|M = 0)$.

The methods used are:

- DiD model using propensity score matching; and
- DiD model using nearest neighbour matching.

Propensity score matching (PSM) calculates the probability (p) of treatment assignment conditional on observed baseline characteristics and finds a comparison group made up of members who are not exposed to the treatment but, given their observable characteristics, had the same probability of receiving treatment as the individuals who were treated. One of the assumptions made is that the

18 The proof can be found in Abadie (2005) and Athey & Imbens (2006).

19 The outcome of the control group.

observable characteristics are not affected by treatment and are adequate to determine treatment status and the observed outcomes. This is known as the 'conditional independence assumption' coined by Rubin (1977).[20] This assumption is often written as:

$$[Y_S(t)\,, Y_C(t)] \perp M|\, p(X)$$

The conditional independence assumption means, given the characteristics we've selected as controls, outcomes are independent of treatment. Treatment is essentially randomised because we have accounted for self-selection bias. This is a strong assumption and is difficult to prove. We use both the economic intuition, knowledge from the structure of the programme and the statistical significance of variables to select the variables that affect treatment assignment and the observed outcomes.

Another assumption made is the 'overlap/common support assumption'. This states that for each characteristic, there is a positive probability of being treated and untreated. This assumption is often written as:

$$0 < p(M = 1|X) < 1$$

If both assumptions hold, we can construct the counterfactual using the propensity scores we have computed. The PSM estimator for the average treatment effect on the treated ($ATET$) would be:

$$ATET_t = E[Y_S(t)|\, M = 1, p(X)] - E[Y_C(t)|\, M = 0, p(X)]$$

DiD model using nearest neighbour matching (NNM) holds the same assumptions as the PSM. The difference between both methods is their matching techniques. PSM calculates the probability of receiving treatment based on the covariates selected and then matches the firms in the treated groups with those in the control group using the propensity scores. The NNM uses the distance between covariate patterns to define an appropriate match from the control group for each observation in the treated group.

The distance between observations in the treated and control group based on the selected covariates can be measured using several methods, however, we have used the Mahalanobis distance metric. This is because the Mahalanobis distance metric also accounts for the correlation between the chosen variables by considering the covariance between observations in the distance calculation.
We have also used additional parametric estimation techniques to check the robustness of the results obtained from the matching estimation techniques. We use repeated cross-sectional and panel linear estimators to estimate the DiD between supported firms and the control group by regressing the outcome on the covariates, including an indicator variable for treatment status.
The data generation process can be stated as follows:

$$Y_{i,t} = \alpha + \delta_i treated_{t-j} + \varphi \boldsymbol{X}_i + B_t + \mu_i \qquad (12)$$

Where B_t accounts for year-specific effects, $\boldsymbol{X}_i$ represents the relevant individual controls, δ_i is the estimated impact[21] of the MFI programme, and μ_i is the term accounting for random differences in $Y_{i,t}$ unaccounted for in the model. The $treated_{t-j}$ variable is an interaction term between time and the treatment group dummy variables. It is worth breaking down this equation.

$$treated_{t-j} = t_{i(t-j)} * d_i$$

Where i is the firm, j is the number of periods before or after treatment, and d_i is a dummy that takes the value 1 for firms that were treated. This is slightly different from the conventional form of DID because we are looking at lagged treatment (i.e. Ordinary Least Squares (OLS) with lagged treatment) but still shares the same characteristics as the conventional DID. The reason we have used this method

20 Rubin, D. (1977).

21 Average treatment effect on treated (*ATET*).

is because it conveniently allows us to analyse the effect of treatment at multiple periods. For example, if we wanted to evaluate the effect of receiving treatment on the outcome after a year, we simply lag the $treated_{t-j}$ variable by one year (i.e. $j = 1$), therefore:

$$treated(t-j) = treated_{t-1}.$$

Secondly, this method also allows us to analyse the effect of treatment using a dynamic model. The programme ran over 6 years which meant that a company could receive treatment in 2005 and another company could receive treatment in 2008. Using this method, we can analyse the effect of treatment dynamically (i.e. collectively analyse the relative effect of treatment on the outcomes t years before/later).

For consistency in our estimates, we ensure all the OLS assumptions are upheld, particularly the Zero Conditional Mean. We also ensure that we control for variables that affect treatment assignment and outcome. Failure to do so would mean that $E(\mu_i|Treated) \neq 0$ (i.e. some variables affect both treatment assignment and outcome that we have excluded from the variable, therefore leading to a bias in our estimates).

In addition to checking the consistency of our estimates across different models, we can carry out standard diagnostic and specification tests with the parametric regression methods that are impossible with the matching techniques described earlier.

3 DATA

Following on from the conceptual framework as detailed in Section 2, this section provides on the data, its sources and the variables used to test the framework. The dataset contains 389 unique companies and financial data that span from 2000 to 2018. This totals up to 7,391[22] observations in our dataset. The data, however, is unbalanced such that the variables in the dataset have an unequal number of observations. The reason behind that is because of sample attrition in the dataset. The dataset was constructed to track observations before and after applying to the MFI programme. Consequently, some companies did not exist in certain periods before and after the MFI programme. This is the reason why the dataset is unbalanced.

3.1 DATA SOURCES

This study is an empirical analysis of companies who applied for the MFI programme between 2004 and 2010. This analysis is made possible by linking data from the following sources:

- MFI Historical Programme Management Data.

  This dataset was used by the project managers of the programme to keep track of applications made by companies. It contained information on the company name, the year the company received treatment, the project type and the project status (completed, withdrawn, rejected, etc.)

- FAME (Financial Analysis Made Easy) by Bureau van Dijk.

  Programme management data did not include unique identifiers for the companies neither did it have the historical financial information of these companies. Through some data cleaning process, we were able to extract the following information from FAME:

  1. Company House Reference Number which served as our unique identifier for observations;
  2. Firm level characteristics e.g. age, size, sector, and accounts status; and
  3. Financial data from 2000-2018 for the companies e.g. total assets and intangible assets.

- ORBIS provided by Bureau van Dijk.

  We used ORBIS to extract data on the intellectual property portfolio for the firms i.e. patents trademarks.

These data sources were linked together using the Company House Reference Numbers of the companies.

3.2 DATA CLEANING

We performed several trimming exercises to the data. The MFI programme supported all types of organisations including businesses, charities, universities, trade associations and so on. As a first process, we excluded organisations which were not businesses. Observations in our dataset that did not have a Company House Reference Number were also excluded. We also manually reviewed the dataset to exclude charities, universities and public bodies who have a Company House Registration Number.

After this cleaning process, the sample contained 565 companies (approximately 90% of the organisations in the original dataset).

The MFI programme was made up of three different waves and applicants could make multiple applications across those three waves. To avoid double-counting, we ignored multiple treatments given to a company. Instead, the first product used by the company has been recorded as the only product used during the programme. The data also showed that only 29 out of 281 companies received

22 389 companies over 19 years.

multiple consultancy treatments. This was not enough data to make any robust inference on the effect of multiple treatments.

Treatment period

Companies in the MFI programme received treatment in different years. To amalgamate these results, rather than observe treatment in absolute years, we observed treatment in relative (offset) years.
The consequence of this approach is that all observations are measured with respect to the same base period. The base period is defined as the year in which the organisation applied for the MFI programme. For example, a zero value ($t=0$) refers to the period in which the observation applied for the MFI programme. Negative values ($t-n$) refer to periods before application and positive values ($t+n$) refer to periods after application to the programme.

Treatment group

An observation is recorded as one which received treatment if the first mode of support from the MFI programme was through a consultancy project. If a JIP or secondment was its first project, then it was exempted from the dataset and analysis as described in the earlier part of this study.
A consequence of this additional data cleaning process is that we lost approximately 38% of the population. After trimming the data, we ended up with 389 unique companies.

Control group

Initially, the control group comprised of companies who applied for the programme but the project was either rejected, cancelled, or withdrawn. The application process of the consultancies was not as rigorous as the JIPs. The application process did not require independent assessors with relevant sector expertise to choose what projects were accepted. The only criterion for an application was that the problem submitted by the firm did not have a commercially available solution. A consequence of this lenient application process is that treatment assignment, to some degree, is random.

Also, the high completion rate of projects under the MFI programme meant the number of treated companies were considerably higher than the control group. To increase the number of controls in our dataset, we also used the treated observations as control variables in the periods before they received treatment.

For Example, in Table 3, Company "G02" applied for the MFI programme and received support in 2009. In our dataset, "G02" would be considered as an observation in the control group for financial years before 2009. In 2009, it will become a treated variable. Post-2009, the data points for the company would be excluded from the sample. This is to avoid the observation contaminating the control sample after receiving support.

This gives us two types of control groups in our sample:

- **Control Group A** – Companies who never received support but applied for the programme.
- **Control Group B** – Companies that received support but are considered as controls up until the year before they applied for the programme. The rationale behind this is that they have not received treatment in those years, therefore they can be used as a control group.

Financial Year	ID	Treated
2006	G02	0
2007	G02	0
2008	G02	0
2009	G02	1
~~2010~~	~~G02~~	.
~~2011~~	~~G02~~	.
~~2012~~	~~G02~~	.

Table 3

Example of Control Group B

In other words, Control Group A does not include any company that would have received any form of treatment through the entirety of the programme. Control Group B is made of state of the companies before treatment. Although Control Group B, was setup to avoid contamination at the point of treatment, it is hard to avoid contamination at longer time periods. For illustrative purposes, if Firm A received treatment in 2007, our data set control group would comprise of data for Firm A from 2000 to 2006. If treatment effects on an outcome was evaluated at t=0, then we would take the average outcome of Firm A in 2002 to 2006 and difference that against its outcome in 2007 when it received treatment. Most of the control group will contain data of years that are not contaminated, however, Firm A data in 2006 (i.e. t+1 would be 2007 outcomes) is essentially an outcome when the company has received treatment. We do recognise this setup could reduce the treatment effects we observe, i.e. as we analyse more periods (i.e. t+n, as n increases) contamination in the control group increases, which could provide weaker results for our treatment effect. However, we do not necessarily see this as an adverse condition because if one could still observe treatment under such conditions then our estimates could be considered as, to some extent, muted.

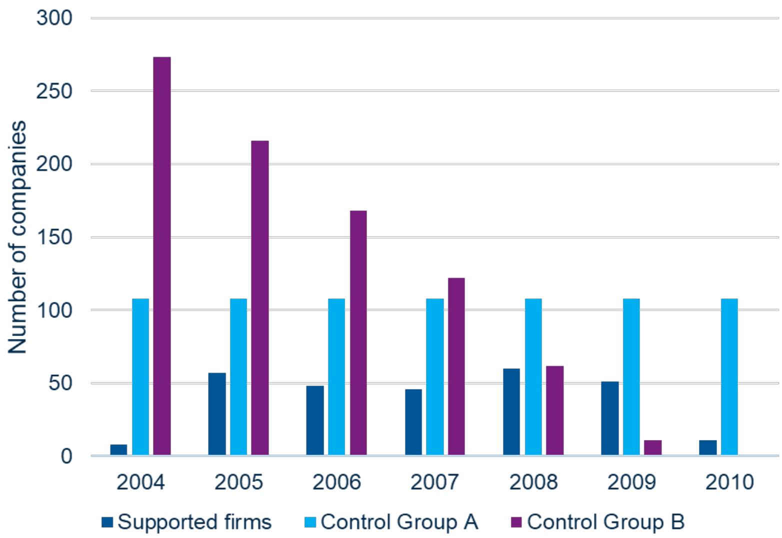


Figure 3

The sample size for each treatment year

Figure 3 shows the sample size for each year applicants took part in the MFI programme at time t=0. Only a very small number of firms were supported in 2004. This is because the programme started in the last quarter of that year which is not enough time for the NMS scientists and project managers to assimilate to the processes of the programme effectively. For this reason, the effectiveness of the programme on its recipients in 2004 is uncertain. Introducing 2004 into the sample might reduce the measure of the quality of our hypotheses. Robustness tests show that the inclusion of the year does not affect the estimates attributed to support, however, it increases the standard errors of our estimates. For this reason, we have exempted observations in 2004 from the analysis.

Cohort selection

It is very important to highlight what we refer to as the cohort in this study. We restrict our observations to a specific cohort with the intention to consistently identify the effects of the MFI programme on our outcomes of interest at different points in time as illustrated in Figure 4. There are two requirements for an observation to be included in the cohort:

1. It needs to be within the years the NMS ran the MFI programme. This refers to the years 2005 to 2010 and we have explained why we dropped 2004 previously.

2. Control group B cannot include observations post-treatment as explained in Table 3. Without restriction, we contaminate our control group with observations that have received treatment.

We then use our cohort to analyse the effect of the MFI programme at different points in time.

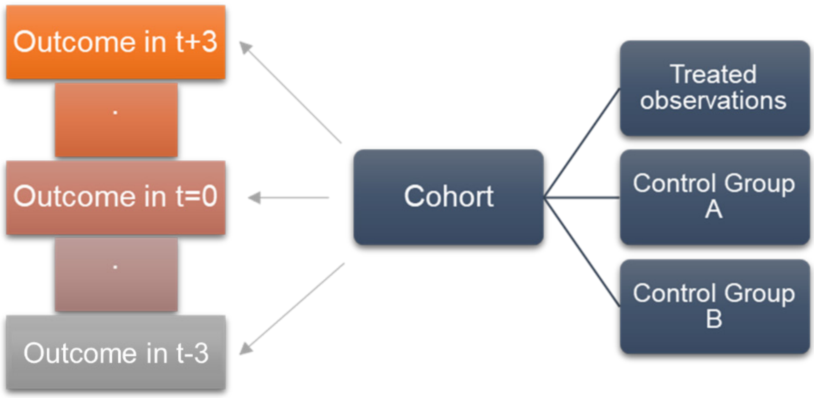


Figure 4

Illustration of cohort selection

3.3 VARIABLES

In this section, we highlight the variables used in the analyses.

Outcome variables

Variables	Description
Patenting activity	In the conceptual framework, the inventive output is denoted as ***K***. However, ***K*** is unobservable. Consequently, we used patents as a proxy to measure the inventive output of a firm. We constructed a binary variable which indicates if a company filed for at least a patent in that year to measure the patenting activity of the company.
Asset growth rate	In our conceptual framework, the benefits of innovation are denoted as **Q**. One of the measures for **Q** in our case is asset growth. The asset growth is obtained by taking the log difference of assets between two points in time. We believe that these benefits for innovation are accumulated slowly and evaluating the short-run (year-to-year) fluctuations in growth would be insufficient in capturing the full effects of the programme. We construct longer periods for assessing the compounded effect of the change in the inventive activity of these companies over longer periods. In this case, we've calculated the change in the asset base of a company for over 4 years. Mathematically represented as $$\Delta y_t = y_t - y_{t-4}$$ where y_t denotes log of assets at period t. Assets are measured in constant prices before log transformation.
Firm survival rate	Another measure of the benefits of innovation (**Q**) is Firm survival. To evaluate the effect of the MFI programme on the survival rate of firms we use a metric called Hazard rate. The Hazard rate is a dummy which indicates if a firm becomes inactive at time t – this is conventionally referred to as the hazard function at time t. An organisation is inactive if it was in liquidation or was dissolved at time t. We use this to evaluate the effect of the MFI programme on firm survival.

Intangible asset	We determine the value of a company having at least a patent in a year by using the intangible assets as an outcome variable. This is because the value of an organisation's knowledge, if recognised, are recorded as intangible assets. Given that intangible assets are the recorded value of knowledge assets, we can provide an estimate of the value of knowledge gained for filing for at least one patent in a year.

Variable of interest

Variables	Description
Treatment	Treatment is a dummy variable that is used to distinguish between the treated and control group in a given treatment year. The treatment year is defined as the year in which the company applied for the MFI programme. This variable is also used as a distributed-lag model in our parametric estimation techniques because the effect of being treated on the outcome variables might occur over time rather than all at once or might have a delayed effect rather than being instantaneous.

Control Variables

Variables	Description
Size[23]	Historical Data on firm size is not available, size estimates on FAME are based on the latest accounts date. To obtain the historical size of companies, we employ an ordinal logit model using the natural log of assets and sectors to predict what size class the organisation would have been for a given year. This allows us to observe the size class of an observation at several points in time.
Patent Holder	We have a variable that identifies if a company has previously filed for a patent. This enables us to account for the propensity to patent if a firm filed for a patent in the past (i.e. two years before participation in the programme). A suitable alternative is R&D expenditure, but unfortunately, we have very infrequent data on R&D expenditure for our sample. There is no requirement at the firm level for small companies to report their R&D expenditures in the UK.
Year dummy	In some cases, we controlled for year-specific invariant effects that were not accounted for in our model. We used it to improve the specification of the model and improve our point estimates and associated inference.
Pre-Financial Crisis Dummy	For cases where the analysis was based on the cohort, we did not use year-specific variables as a control. Instead, we have used a dummy variable to indicate years before the crash. This is because most of the time-specific effects that occurred during the period of the MFI programme were as a result of the Global Financial Crisis. So, we used this dummy variable to control for the macro-economic effects that occurred during and after the financial crisis.
Age of the company	The age variable records how old the organisation is in a given period. We placed these ages into quartiles. The youngest companies were 5 years and below; the second category is 6-12 years; the third category is 13-22 years; and the last category is for companies over 22 years. The youngest group in our sample are described as new market entrants.

23 The details of this estimation are provided in the Annex A.

Research & Development Intense Sectors	Empirical studies frequently employ Standard Industrial Classification (SIC) codes as a method for segmenting firms to test predictions that may differ with respect to the technological intensity of the firm. We use this technique to identify companies that fall into sectors which engage intensively with research and development. This variable includes the following sectors: 1. Research and experimental development on biotechnology [72110] and, 2. Other research and experimental development on natural sciences and engineering [72190]. Research and experimental development are comprised of creative and systematic work undertaken to increase the stock of knowledge and to devise new applications of available knowledge.[24]

3.4 DESCRIPTIVE STATISTICS

Table 4 shows the summary statistics in the variable used in our model. Overall, we find that the average total asset base of the companies in the sample is £610,000 with an annual growth rate of 5.6%. The annual growth of non-financial assets in the UK is about 4.8% from 2009 to 2018.[25] This shows that the set of companies that applied for the MFI programme have a higher expected growth rate than companies in the general UK population.[26] Further analysis into the panel variation of asset growth shows a small amount of between (time-invariant) variation in comparison to the within (time-variant) variation of the data. This is because the growth data involves taking the difference between two time periods and consequently, we have reduced the time-invariant effects in the data.

Secondly, the average annual growth of the firms in our sample is within the bounds of common sense with a maximum annual growth rate of 868% and maximum negative annual growth rate of -692%. These values do not seem absurd and show no signs of being coding errors. The same applies to four-year growth rates.

A plausible reason behind the high asset growth rate of the firms in our sample compared to the UK population might be the inventive nature of these firms. Of the companies with patenting data, about 30% file for a patent in a year. This excludes companies where patenting data is not available on ORBIS. This indicates that within 3-4 years, these companies are expected to have filled for at least a patent. The UK patents office recorded that less than 1% of UK SMEs published patents and 4% of large companies published patents.

24 More information about the breakdown of our sectors is provided in Annex E.

25 The UK national balance sheet estimates, (2019, 2020).

26 For simplicity, this estimate assumes that the firms who applied for the MFI programme and all other UK firms are homogenous which is not the case. If we control for firm-specific effects this expected value might change, however, that analysis is beyond the scope of this study.

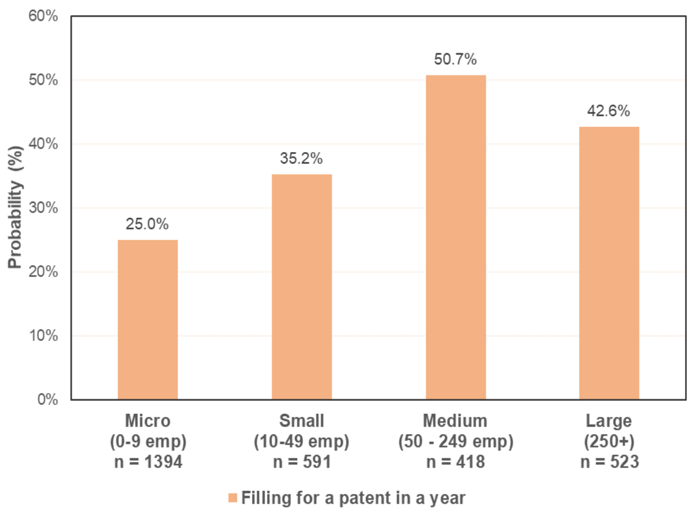


Figure 5

Patenting behaviour by class

The panel variation from the patent data is from within observations in the sample rather than between. This means over time the patenting activity of these companies tends to vary. We breakdown patenting activity by size class in Figure 5. Further analysis of patenting activity by size class shows that the patenting activity for the micro firms is lower than the average patenting activity per year of the firms in the sample. On the other hand, the medium and large firms in our sample file for at least a patent every two years.

Using our classification of what R&D intense sectors are, the primary business activity of 20% of the companies in our sample are in research and experimental development on biotechnology, natural sciences and engineering.

Variable	n	Mean	Std. Dev.	Min	Max	Between Std. Dev.	Within Std. Dev.
Total Assets	5,592	610,562.50	3872658.00	0	5.29E+07	3,275,716	1,084,807
Intangible Assets	1,854	514,768.20	2797992.00	-203.31	3.32E+07	1,827,051	1,080,831
Ln(Total Assets)	5,353	7.563	3.282	0	17.783	3.192	0.918
Ln(Intangible Assets)	1,848	6.105	3.926	-6.866	17.317	3.547	1.249
Δ Ln(assets)	4,935	0.057	0.654	-6.924	8.680	0.257	0.628
Δ Ln(assets) 4yr	3861	0.220	1.116	-7.322	8.420	0.841	0.925
Filed for a patent in a given year	3,553	0.295	0.456	0	1	0.278	0.362
Age of company in a given period	7,391	17.490	20.405	0	124	19.770	5.145
R&D Intense sector	7,391	0.195	0.397	0	1	0.397	0

Table 4

Descriptive statistics

We compare the mean of the treated group and the control group in the selected cohort in Table 5. There are some noticeable differences between the treated group and the control group. The treated group has a higher proportion of SMEs than the control group. Whilst the control group had more large firms than the treated group. This is supported by the structure of the consultancy programme, which tried to support more SME businesses.

Variable	Treated Group				Control Group				
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	*diff*
Ln(Assets)	6.37	2.51	0.17	15.01	7.92	3.61	0.25	17.53	*-1.55****
ΔLn(Assets)	0.12	0.77	-3.16	4.03	0.12	0.73	-6.87	7.22	*0.00*
Filled for a patent (Dummy)	0.39	0.49	0	1	0.28	0.45	0	1	*.11****
R&D Intense Sector (Dummy)	0.24	0.43	0	1	0.17	0.38	0	1	*.089****
Age Quantiles									
5 years and younger	0.42	0.49	0	1	0.39	0.49	0	1	*0.03*
6-12 years	0.27	0.44	0	1	0.23	0.41	0	1	*0.04*
13- 22 years	0.13	0.33	0	1	0.17	0.37	0	1	*-0.04**
23 years and older	0.21	0.39	0	1	0.19	0.40	0	1	*0.02*
Size Class									
Micro (0- 9 emp)	0.70	0.46	0	1	0.58	0.49	0	1	*0.12****
Small (10-49 emp)	0.18	0.39	0	1	0.13	0.34	0	1	*0.05**
Medium (50-249 emp)	0.10	0.29	0	1	0.11	0.31	0	1	*0.01*
Large (250)	0.02	0.15	0	1	0.18	0.38	0	1	*-0.15****

*** p<0.01, ** p<0.05, * p<0.1 indicates significance levels in a t-test in the equality of proportions between both groups.

Table 5

Comparison between means of treated group and control group

Due to the difference in size class between both the treated and the control group, it is important to include this as a control variable as it determines treatment assignment. Figure 6 shows the distribution of the treated group and the control group by size class in the cohort. About 90% of the observations in the cohort sample are made up of SMEs.

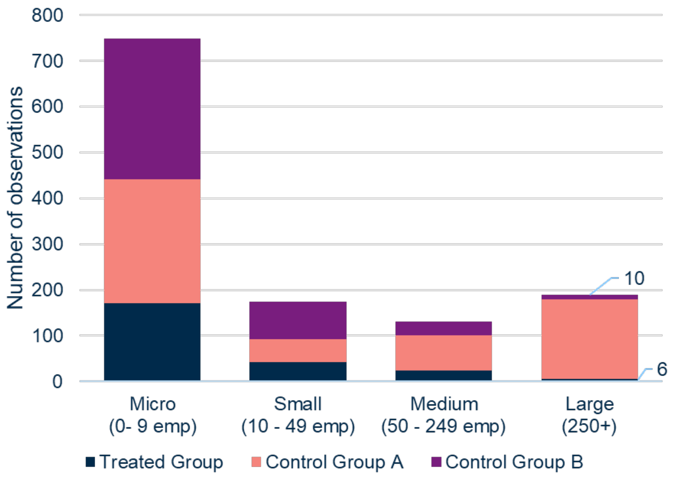


Figure 6

Treated and control groups by size class

The size difference between the control group and the treated group is also reflected in the value of total assets. The average value of total assets for the control group is almost 2.5 times larger than that of the treated group. However, the average asset growth rate of both groups is 12% and this does not significantly differ at the point of intervention.

The patenting activity of the treated group is about 11% higher than that of the control group at the point of intervention. We believe this caused by the support the firms received through the MFI programme. Table 5 only focuses on the point of intervention; thus, we cannot prove if this difference in patent activity is a persistent trait that has been there before treatment. In later parts of this study, we show if there any differences between the patenting activity of both groups before and after treatment whilst controlling for other variables that might influence the outcome and assignment of treatment.

4 MODEL SPECIFICATION AND VARIABLE CHOICE

In Section 2, the conceptual framework and estimation strategy required for the analysis of the effect of the MFI programme were described. This section gives an outline of the choice of the confounding variables and the econometric outline of the conceptual framework.

Confounding can occur when covariates that predict the treatment assignment and the outcome of interest are excluded from the model. In the presence of confounding, the confounding variable can influence any marginal association between treatment and the outcome, thereby violating the conditional-independence assumption.[27] Violation of the conditional-independence assumption means $E(Y_C(t)|M = 0)$ is not a valid substitution for $E(Y_C(t)|M = 1)$ because we have failed to control for the confounding variables.

Rubin[28] suggests that including variables that are strongly related to treatment, but unrelated to the outcome, can decrease the efficiency of an estimated treatment effect. However, Rubin argues that if such a variable had even a weak effect on the outcome, the bias resulting from its exclusion would dominate any loss of efficiency for a reasonably sized study.

The choice of variables for this study has been guided by economic theory and our underlying knowledge of the programme's structure. We also ensure that the variables selected are unaffected by participation or the anticipation of participation. The variables selected are either fixed over time or are measured before participation. For the latter, we measured such variables two years before participation in the programme.

As an additional approach to our choice of variables, we test the statistical significance of our carefully chosen variables against two models: the treatment assignment model and the outcome model. The treatment assignment model is used to investigate how well the selected variables influence treatment. The specification for the treatment model is given by:

$$P(M = 1 \mid \boldsymbol{X}) = \alpha + \varphi \boldsymbol{X} + \varepsilon_{i,t} \tag{13}$$

Where M is a dummy for receiving treatment, $\boldsymbol{X}$ are covariates which we have chosen to address the *'strong ignorability'* assumption[29], with *i* representing the company
The outcome model is used to investigate how well the selected variable influences the outcome of interest. The specification of the outcome model is given by:

$$Y_{i,t=0} = \alpha + \varphi \boldsymbol{X} + \varepsilon_i \tag{14}$$

Where t=0 is the year of participation in the programme, $Y_{i,t=0}$ is the outcome of interest, $\boldsymbol{X}$ are covariates which we have chosen to address the *'strong ignorability'* assumption.
Furthermore, this approach helps us evaluate the strength of higher order terms and interactions of the variables. Adding higher order terms and interactions as covariates were also suggested in Rosenbaum and Rubin (1984).

27 i.e. the outcome is independent from treatment conditional on the propensity score.

28 Rubin, (1997b).

29 'Strong ignorability' occurs when the conditional independence assumption and common support are held. The phrase was coined by Rosenbaum and Rubin (1983).

It is worth noting that unobservable variables might play an additional role in determining the selection process and the outcome of interest. Therefore, conditioning on observables alone might not enable us to avoid selection bias. Nevertheless, conditioning on observables might reduce this problem.

4.1 INVENTIVE OUTPUT

For the analysis on the inventive output, we need to determine the control variables which we would use irrespective of the estimation technique. We use the following variables as controls:

- Dummy for patent holders two years before receiving treatment. The rationale behind this is that firms which were patent holders two years (t-2) before being included in the cohort had previously engaged in R&D. This indicates that the firm had the resources or capabilities to do so. Therefore, firms who had patents in previous years should have a higher propensity to patent in subsequent years than does who did not.
- The size of the organisation. This variable was included for two reasons. First, the programme design was mostly targeted towards the SMEs and this was shown in the descriptive statistics. The treated firms have a higher proportion of SMEs than the control group, showing that this is a characteristic that determines selection into treatment. Second, larger firms have a higher propensity to patent than the small or micro firms. This is because of their ability to mobilise sufficient financial resources, economies of scale in research, and greater efficiency in implementation due to experience. We also lag these variable two years before treatment (t-2) to eliminate the possibility of the size of the organisation being influenced by a firm's participation in the programme. Our size variable was interacted with previous patent ownership because we believe large firms who have engaged in R&D up to the level of patenting ideas are different to large firms who have no record of inventions.
- Pre-Financial Crisis. The Global Financial Crisis occurred within the period of the MFI programme. The Global Financial Crisis had negative effects on the UK economy. We believe that the demand for the expertise of the NMS grew during the period of the crash. This means firms were more likely to receive treatment during/after the crisis.
- Age of company. We control for new entrants to the market. These new market entrants are defined as companies who are 5 years or younger. New companies tend to be smaller. This increases the chances of them being selected into treatment because the consultancies were setup to primarily support SMEs. New firms are more willing to take riskier innovative steps and exploit external knowledge. This is because their stocks of firm-specific knowledge are almost at zero, so they try to quickly accumulate knowledge and capabilities. The age of the company can contribute to its willingness to invent. We also interact the pre-financial crisis with the age variable because we believe that new market entrants during the global financial crisis would have been the companies who probably needed the support of the NMS.

We check the statistical significance of these controls using the treatment model in Equation 13 and the outcome model in Equation 14. Table 6 shows the outcome and treatment models for the analysis of inventive output.

Our interpretation of the effect of the control variables on treatment assignment is in line with the coefficients reported in Table 6 for the treatment model. With the medium-sized firms used as our base group to understand the differences between the size classes, we find that the small and micro firms have the same probability of receiving treatment as the medium-sized firms and the larger firms were less likely to be treated.

Previous patent ownership did not affect receiving the propensity to receive treatment as this was not a criterion that determined treatment in the design phase of the programme. Furthermore, we find that younger firms (new market entrants) were more likely to receive treatment, more so during/after the period of the global financial crisis.

Variables	Outcome model coefficient/(Standard Error)	Treatment Model coef/(se)
Patent holder (t-2)	0.461*** (0.094)	0.021 (0.089)
Micro (0-9 employees)	0.047 (0.073)	0.052 (0.078)
Small (10-49 employees)	0.108 (0.089)	0.011 (0.090)
Large (250+ employees)	-0.071 (0.070)	-0.146** (0.073)
Patent holder (t-2) & Micro	-0.294*** (0.110)	0.090 (0.105)
Patent holder (t-2) & Small	-0.032 (0.132)	0.060 (0.124)
Patent holder (t-2) & Large	0.277*** (0.107)	-0.024 (0.093)
Pre-Financial crisis	0.031 (0.037)	-0.032 (0.034)
New market entrant (0- 5 years) (t-2)	0.231** (0.103)	0.180* (0.095)
Pre-Financial Crisis & New market entrant	-0.165 (0.117)	-0.240** (0.104)
Intercept	0.102 (0.069)	0.189** (0.075)
Number of observations	618	618
R2	0.265	0.095
Adjusted R2	0.253	0.080
F	28.365	9.285
Prob > F	0.000	0.000

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust Standard Error in Parenthesis. In the table above we report the results of the OLS regression for both models. The dependent variable for the outcome model is patenting activity (Binary variable indicates if the company produced a patent in that year). The dependent variable of the treatment model is a dummy that takes the value 1 for the year in which the company received treatment.

Table 6

Variable choice models for patents

For the outcome model, we find that previous patent ownership has a significant influence on future patenting activity. We also find that micro firms with no previous patent ownership are less likely to patent than small or medium-sized firms, however, large-sized firms with previous patent ownership are more like to patent than all other firms. The model also suggests that without previous patenting activity, size does not influence current patenting activity. However, a joint significant test on the size variables indicates that they are not equal to zero, which justifies the inclusion of them in our matching model.

Furthermore, we find that younger firms (new market entrants) are more likely to produce a patent. This is because once you control for the resources a firm is pre-disposed to (i.e. the size of a firm), the age variable becomes an indicator for the company's willingness to invent. We find that the Financial Crash period does not affect firm patenting behaviour. The interaction between the period before the global financial period and the firm age shows that there was a drop in the willingness to patent during this period, however, this it is not statistically significant.

We also ran specification tests on both the treatment and outcome model. They passed, indicating that there is not enough evidence to suggest that the model is incorrectly specified or there is an omitted variable.

It is important to assess if the matching procedure was able to balance the distribution of the relevant variables in both the control group and treatment group. One suitable indicator to assess how effective the matching algorithm was at reducing the differences between the treated and control group for each covariate is to measure the standardised mean differences between the treated group and the control group before and after matching. For each covariate *X*, the standardised mean difference is defined as the difference between the sample mean of the treated and control group sub-samples divided by the square root of the average sample variances in both groups. This is a common approach used in many evaluation studies.[30] We can visually infer how successful the matching procedure was, however, we can't measure if the differences between both groups are statistically significant before and after matching using this approach.

Figure 7

Covariate balance summary

Figure 7 shows the standardised differences between the treated group and the control group before and after matching with propensity scores for each covariate. Standardised mean differences between {-1,0} indicate that there is a higher representation of the control group than the treated group for that covariate, and vice versa. Figure 7 shows us that the differences between the control group and the treated group have noticeably reduced after the matching procedure.

4.2 BENEFITS OF INNOVATION

Asset Growth

The confounding variables for the inventive output model would differ from that which evaluates if the supported firms incurred any benefits from innovations. This is because the variables that influence patenting could differ from those that affect asset growth.
For the analysis of the effect of the MFI programme on asset growth we use the following variables:

- We have included all the variables that affected treatment in our previous models (i.e. size, age, and the pre-financial crisis dummy variable). However, it is worth explaining how these variables could affect our new outcome variable (i.e. 4-year asset growth rate). Analysis of the

30 Lechner, (1999) and Sianesi, (2004)

mean (Table 5) shows that the average annual growth rate of the micro companies is much higher than every other size class. For that reason, we introduce a dummy variable indicating if the observation is a micro firm.

- The Global Financial Crisis had a significant negative impact on economic activity and businesses. However, given that the outcome variable is the growth of assets over four periods, the outcome variable during the period of the crash would also contain information on growth trends from the period before the crash. This might mute the effects of the financial crisis on asset growth.
- We control for the R&D intensity of the firms that the sectors belong to. The R&D sector variable is a dummy which indicates if a firm's primary activity is research and experimental development on biotechnology, natural sciences, or engineering. The rationale behind this is that firms who intensively engage in R&D do so with the expectation of creating innovative processes or products which would result in a risk premium because of the competitive advantage they have gained.
- We also interact the age variable with all our other variables because we have established that the young firms are dynamic, willing to take riskier innovative steps and exploit external knowledge.

Variables	Outcome model	Treatment Model
	coef/(se)	coef/(se)
R&D Intense Sector	0.571*** (0.185)	0.163*** (0.050)
Micro (0-9 employees)	0.223*** (0.080)	0.088*** (0.026)
Pre-Financial crisis	-0.127 (0.082)	-0.013 (0.026)
New market entrant (0-5 years) (t-2)	-0.129 (0.497)	0.221** (0.088)
New market entrant (0-5 years) (t-2) & R&D Intense Sector	-1.011 (0.864)	-0.112 (0.080)
New market entrant (0-5 years) (t-2) & Micro	0.520 (0.597)	-0.006 (0.080)
New market entrant (0- 5 years) (t-2) & Pre-Financial crisis	0.668 (0.573)	-0.268*** (0.073)
Intercept	0.221*** (0.070)	0.117*** (0.021)
Number of observations	886	1,085
R2	0.058	0.054
Adjusted R2	0.050	0.048
F	5.757	6.710
Prob > F	0.000	0.000

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis. In the table above we report the results of the OLS regression for both models. The dependent variable for the outcome model is the four-year asset growth rate. The dependent variable of the treatment model is a dummy that takes the value 1 for the year in which the company received treatment.

Table 7

Variable choice models for assets

Table 7 shows the OLS regression used to identify the statistical significance of these variables on treatment assignment and outcome. There is an overlap between the variables used in the treatment model for the inventive output analysis and the benefits of innovation analysis. For succinctness, we only discuss the effect of the new variables introduced to the treatment model used for the benefits of innovation model. The new variables included in the treatment model are the R&D intense sectors and an interaction between age and firms in R&D intense sectors. We find that a firm was more likely to receive treatment if they belonged to an R&D intense sector. Additionally, the interaction between the age and the firms in the R&D sector shows that younger firms in the R&D sector have a lower probability of receiving treatment, however, it is not statistically significant.

Furthermore, given the nature of the outcome variable, we find that there are no significant differences between growth rates before the crash and after the crash. R&D intense sector and size are the only variables that statistically influence asset growth rate.

Specification tests carried out on the outcome and treatment model shows no signs of misspecification. Figure 8 shows the standardised differences between the treated group and the control group before and after matching with propensity scores for each covariate. Figure 8 shows us that the differences between the control group and the treated group have noticeably reduced after the matching procedure, particularly for the R&D intense sectors and Micro firms.

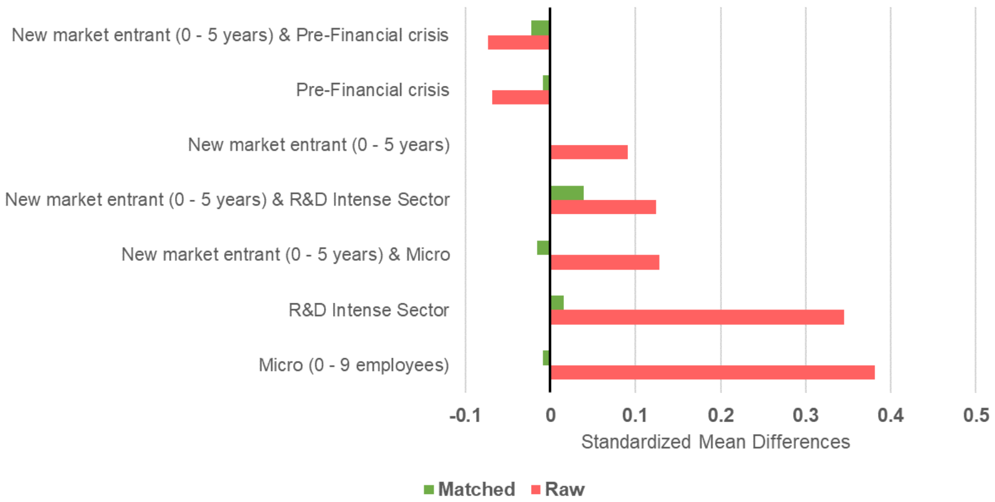


Figure 8

Covariate balance summary

Survival Rates

We examine if the MFI programme influences the survival rates of the firms using the same estimation technique (i.e. propensity score matching). Using these estimation techniques enables us to estimate the difference between the probability of survival if the supported firm received treatment and the probability of survival if the supported firm did not receive treatment whilst ensuring that the *'strong ignorability'* condition is upheld.[31] In comparison to using the conventional cox proportional model, the propensity score match method ensures the treated observations have an appropriate match from the control group and we can include multiple matches between the treated observation and the control group.

The previous sections have identified that firm size, age, financial crisis and sector influences treatment assignment, however, we explain how these variables could influence survival as well. The first covariate we examine is the size of the firm. We pay particular interest to the larger firms. Numerous studies have shown that larger firms have lower failure hazard rates than smaller ones.[32] Larger firms have fewer restrictions to capital markets leading to a lower risk of insolvency and illiquidity. Large firms tend to have a higher proportion of highly qualified labour forces. Lucas (1978) explains that the higher failure risk of small firms is because the talent of management in small

31 'Strong ignorability' occurs when the conditional independence assumption and common support are held. The phrase was coined by Rosenbaum and Rubin (1983)

32 Mata and Portugal, (1994).

firms is on average lower than that of larger firms. For these reasons, we have included firm size as one of our covariates.

Second, we control for the age of the organisation. New market entrants tend to face the same difficulties small firms face. These characteristics are highly correlated. New firms are more willing to take riskier innovative steps and exploit external knowledge. This is because their stocks of firm-specific knowledge are almost at zero, so, they must quickly accumulate knowledge and capabilities. If these firms are unable to accumulate the knowledge and capabilities after a certain period, competition drives them out of the market.

Previously, we have indicated that firms who intensely engage in R&D are those who declared their primary activity as research and experimental development. The possibility that a firm in an intense R&D sector engages in projects that could, in turn, lead to the company's failure could be higher than those of firms outside these sectors. This is because the technological uncertainty[33] of R&D projects is very high.

Variables	Outcome model	Treatment Model
	coef/se	coef/se
Large (250 + employees)	-0.001 (0.010)	-0.172*** (0.020)
R&D Intense Sector	0.007 (0.016)	0.116*** (0.039)
New market entrant (0-5 years)	0.038** (0.016)	0.013 (0.032)
Pre-Financial crisis	-0.005 (0.009)	-0.066*** (0.025)
Intercept	0.012* (0.007)	0.232*** (0.022)
Number of observations	1,085	1,085
R2	0.014	0.050
Adjusted R2	0.010	0.046
F	2.484	27.419
Prob > F	0.042	0.000

Note: *** p<0.01, ** p<0.05, * p<0.1. The standard error in parenthesis. In the table above we report the results of the OLS regression for both models. The dependent variable of the outcome model is the hazard rate at the time of participation. The dependent variable of the treatment model is a dummy that takes the value 1 for the year in which the company received treatment.

Table 8

Variable choice models for survival

Table 8 shows the OLS regression used to identify the statistical significance of these variables on treatment assignment and survival. For brevity, we do not discuss the results of the treatment model because the effects of the covariates on treatment assignment have been discussed earlier.
For the specification of the outcome model, we have been very cautious with the number of covariates included in the model. In comparison to the previous outcome models,[34] we have found the F-test of this model to be quite low although significant at a 5% level. An attempt to understand how the selected variables affect survival rates when they are interacted showed that they were insignificant and consequentially led to an overall F-test which was statistically insignificant. For this reason, we have not included any interactions between the fundamental variables.

A firm's age is the only variable that had a significant association with survival. The new market entrants have a higher failure hazard rate than firms that have been established for 6 years or more. In previous sections, we described how the size of a firm can affect survival rates. Although the model shows size effects are not statistically significant, the coefficient of the size variable is meaningful (i.e. the failure hazard is lower for large firms). We find the coefficient of companies in the R&D sector to

33 Technological uncertainty is the inability to perfectly foresee the connections between an R&D project and the actual introduction of a new product, process, or service.

34 Growth of total assets and patenting activity.

be in line with our economic intuition explained earlier, however; the coefficient is not statistically significant.

Figure 9 shows the standardised difference between the treated group and the control group before and after matching based on the propensity score for each covariate. The summary shows that after matching there are no differences between the treated and control group for each covariate.

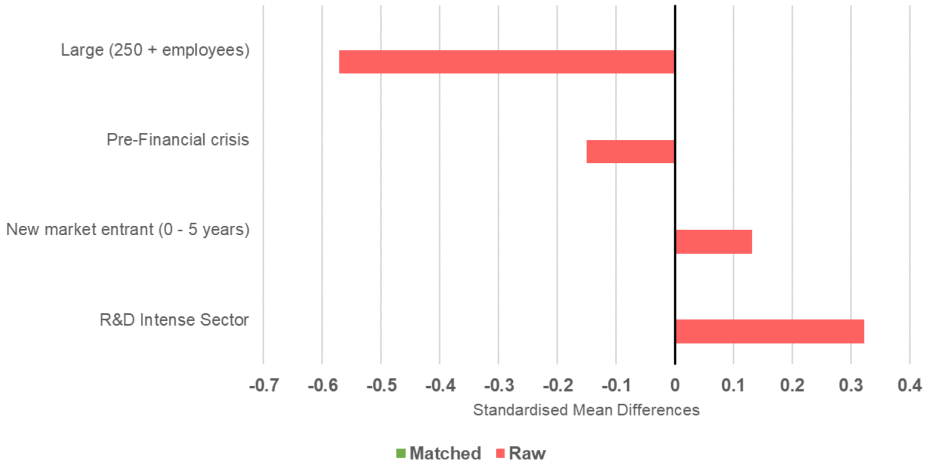


Figure 9

Covariate balance summary

5 RESULTS AND INTERPRETATION

This section presents the results where we explore: the impact of the MFI programme on the inventive output of the supported firms; and the benefits of innovation derived by firms supported via the MFI programme.

5.1 EFFECT OF THE MFI PROGRAMME ON INVENTIVE OUTPUT

First, we examine how well our results determine *Hypothesis 1 (H1)* which states: "*Given the nature of the MFI programme, we expect the programme to increase the inventive capacity of companies who received support in comparison to the constructed counterfactual group.*"

Table 9 compares the estimations from the propensity score matching method with that of the nearest neighbour matching and ordinary least square method. We find that the size and significance of our estimates are consistent regardless of the estimation technique used. The OLS technique enables us to perform diagnostic tests and we have no evidence that shows any sign of misspecification in the models.[35]

	Patents at t-4	Patents at t-3	Patents at t-2	Patents at t-1	Patents at t=0	Patents at t+1	Patents at t+2	Patents at t+3	Patents at t+4	Patents at t+5	Patents at t+6
Propensity Score Matching	0.044	0.012	0.032	-0.020	0.109**	0.047	-0.009	0.007	-0.023	0.048	-0.001
	(0.042)	(0.038)	(0.037)	(0.048)	(0.052)	(0.05)	(0.05)	(0.05)	(0.048)	(0.05)	(0.048)
Nearest Neighbour Matching	0.058	0.031	0.060	-0.006	0.110**	0.042	-0.008	0.010	-0.026	0.040	-0.006
	(0.042)	(0.038)	(0.037)	(0.049)	(0.054)	(0.052)	(0.051)	(0.051)	(0.052)	(0.053)	(0.049)
OLS Regression	0.048	0.020	0.057	0.003	0.112**	0.053	-0.013	0.004	-0.024	0.037	-0.009
	(0.042)	(0.037)	(0.035)	(0.046)	(0.052)	(0.05)	(0.048)	(0.048)	(0.048)	(0.049)	(0.047)
n	478	618	618	618	618	618	618	618	618	618	618

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard Errors in Parenthesis.

Table 9

35 Linktest and omitted variable test for the models are provided in the Annex B.

The impact of the MFI programme in the patenting activity of supported firms

We present the results from the propensity score matching estimation techniques alongside the confidence interval of the treatment effect on the treated in Figure 10. The results show that the firms who applied for the MFI consultancies are generally innovative regardless of the period of observation. Before the treatment period (*t=0*), we find that the differences between the treated group and the counterfactual are insignificant which supports the conditional independence and the common trends assumption. During the year of support, the supported firms were 11%[36] more likely to file for patents than the counterfactuals. Figure 10 shows the differences between the treated and counterfactual group in each period alongside a 95% confidence interval. These results support the first hypothesis (H1).

Another inference that we make from the results about the effect of the MFI programme is that it enabled treated firms to file for their patents two years earlier. A visual inspection of the patenting activity of the treated group and the counterfactual after t=0 in Figure 10 shows that the treated group gradually returns to its normal trend of patenting after two years (i.e. the trend of the counterfactual group).[37]

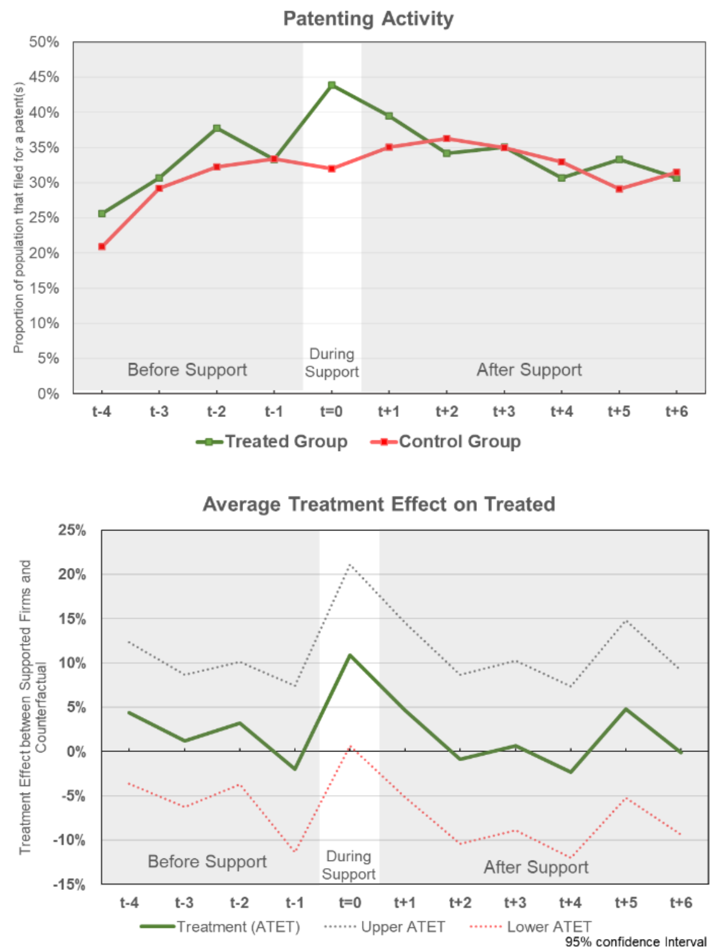


Figure 10

Patenting activity of the treated group and the counterfactual

36 Significant at 5 percent level

37 Figure C1 (in Annex C) shows the cumulative average patenting activity of the matched control group and the treatment group from two periods before treatment to 6 periods after treatment. In periods before support the treatment and counterfactual group have a common trend. However, in the period of treatment the common trend between the treatment and control group deviates with the treated group having a higher level of cumulative patenting activity. Two periods after support the matched control group catches up with the treated group and have common trend afterwards.

Furthermore, we excluded the variable which indicates if a firm belongs to an R&D intense sector from the inventive output analysis. Table 10 shows the impact of the MFI programme on R&D intense sectors and the non-R&D intense sector at time *t=0* based on our current specification. We find that the impact of the MFI programme on firms in non-R&D intense sectors is higher in *t=0* than the firms in the R&D intense sectors.

	R&D Intense Sector Patents *t=0*	Non-R&D Intense Sector Patents *t=0*
Nearest Neighbour Matching	0.074 (0.054)	0.127** (.062)

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard Errors in Parenthesis.

Table 10

The impact of the MFI programme on patenting activity by sector at *t=0*

This is because our model identifies if a company filed for a patent (patenting activity) rather than the number of additional patents (patent intensity) they have in a year because of the programme. As a result of this, even if the MFI programme had an impact on the inventive activity of a firm in an R&D intense sector, our model cannot capture these additional impacts. This is because the firms in these sectors have a high patenting culture and they will always have some patenting activity with or without the MFI programme each year.

To test the assumption that the MFI programme influenced the patenting activity of firms in the R&D intense sector we ran an alternative model with a different outcome variable. We created a four-level categorical variable (coded 0 – No patents; 1 – 1 Patent; 2 – 2 to 5 patents; 3 – more than 5 patents) which describes the patenting behaviour of a firm in a year. This way we can observe patenting intensity. As a firm moves from one category to another, one can infer that there's a shift in the firm's patenting intensity. We use an ordered logistic model to determine the odds of moving into a higher category conditional on the independent variables in the treatment year.

The same independent variables used in the previous specification were used in this model for consistency. We also included a variable that indicates if a firm belongs to an R&D intense sector to control for the patenting behaviour of such firms as described earlier. We interact the treatment variable with the R&D intense sector to identify if there is any difference between the marginal effects of treated firms from the R&D intense sectors and the treated firms from the non-R&D intense sectors.

```
Ordered logistic regression                     Number of obs     =        618
                                                LR chi2(13)       =     252.04
                                                Prob > chi2       =     0.0000
Log likelihood = -520.60244                     Pseudo R2         =     0.1949

------------------------------------------------------------------------------------------------
                    ordered_pat |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------------------+---------------------------------------------------------------
                       1.treats |    .596445    .285103     2.09   0.036     .0376533    1.155237
            1.biotech_life_eng |   1.076702   .2628292     4.10   0.000     .5615662    1.591838
                                |
        treats#biotech_life_eng |
                            1 1 |  -.4607148   .4602434    -1.00   0.317    -1.362775    .4413457
                                |
                 1.L2_pat_holder |   2.108853   .6138852     3.44   0.001       .90566    3.312046
                                |
               L2_predicted_size |
                              1 |  -.0942066   .5959469    -0.16   0.874    -1.262241    1.073828
                              2 |   .3131151   .6491392     0.48   0.630    -.9591742    1.585405
                              4 |  -.9854245   .7586369    -1.30   0.194    -2.472325    .5014764
                                |
L2_pat_holder#L2_predicted_size |
                            1 1 |  -1.259968   .6718544    -1.88   0.061    -2.576779     .056842
                            1 2 |  -.2129808   .7452598    -0.29   0.775    -1.673663    1.247702
                            1 4 |   2.776859   .8303168     3.34   0.001     1.149468     4.40425
                                |
                    1.pre_crash |   .1838491   .2132132     0.86   0.389    -.2340411    .6017393
                      1.qb_year |   .9024512   .4153011     2.17   0.030     .0884759    1.716426
                                |
               pre_crash#qb_year |
                            1 1 |  -.7021965   .4917097    -1.43   0.153     -1.66593    .2615368
--------------------------------+---------------------------------------------------------------
                          /cut1 |   2.097298   .5788937                       .962687    3.231909
                          /cut2 |   3.036448   .5877337                      1.884511    4.188385
                          /cut3 |   4.433933   .6049213                      3.248309    5.619557
------------------------------------------------------------------------------------------------
```

Table 11

Alternative specification for identifying the effects of the MFI programme on patenting

The results from this specification are presented in Table 11. We find that the probability of a treated observation from a non-R&D intense sector increasing its patenting activity is 64%[38] higher than a control observation in a non-R&D intense sector. The interaction between the sector and treatment variable examines the partial effect of the programme on supported firms in R&D intense sectors in comparison to the firms in the non-R&D intense sectors. The magnitude of the coefficient shows that the effect of treatment on firms in the R&D sector is much lower than those firms in the non-R&D intense sectors. However, this effect is not significant. Therefore, we do not have enough evidence to suggest that the MFI programme had a lesser effect on supported firms in R&D intense sectors than the supported firms in the non-R&D intense sector. We can conclude that the firms in the R&D intense sector supported via the MFI programme also experienced an increase in patenting activity.

Panel Data

Variables	Pooled OLS coef/se	Random Effects Model coef/se	Fixed Effects Model 1 coef/se	Fixed Effects Model 2 coef/se
Treatment	0.103**	0.085**	0.082**	0.082*
	(0.046)	(0.040)	(0.040)	(0.046)
Treatment (t-1)	0.041	0.031	0.029	0.029
	(0.043)	(0.038)	(0.038)	(0.043)
Treatment (t-2)	-0.025	-0.021	-0.014	-0.014
	(0.042)	(0.038)	(0.038)	(0.042)
Treatment (t-3)	-0.020	-0.019	-0.016	-0.016
	(0.042)	(0.038)	(0.038)	(0.041)
Treatment (t-4)	-0.032	-0.043	-0.047	-0.047
	(0.042)	(0.037)	(0.037)	(0.040)

38 Ordinal logit regression coefficient are log odds ratios, therefore, to obtain the odds ratio we take the exponent of the log odds ratio. *Prob(x) = odds/(1 + odds)*

Treatment (t-5)	0.048	0.036	0.034	0.034
	(0.042)	(0.037)	(0.037)	(0.040)
Patent holder (t-2)	0.353***	0.250***	0.108	0.108
	(0.058)	(0.066)	(0.073)	(0.102)
Micro Firm (t-2)	-0.072	-0.056	-0.084	-0.084
	(0.055)	(0.069)	(0.088)	(0.117)
Small Firm (t-2)	-0.012	0.082	0.089	0.089
	(0.063)	(0.074)	(0.088)	(0.116)
Large Firm (t-2)	-0.164***	-0.078	0.121	0.121
	(0.062)	(0.081)	(0.106)	(0.107)
Micro Firm & Patent Holder (t-2)	-0.153**	-0.178**	-0.141*	-0.141
	(0.063)	(0.071)	(0.078)	(0.109)
Small Firm & Patent Holder (t-2)	-0.082	-0.156**	-0.141*	-0.141
	(0.072)	(0.079)	(0.085)	(0.116)
Large Firm & Patent Holder (t-2)	0.302***	0.130	-0.127	-0.127
	(0.072)	(0.088)	(0.104)	(0.098)
Pre-Financial Crisis	0.139***	0.123***	0.070	0.070
	(0.052)	(0.045)	(0.046)	(0.047)
New Market Entrant (0-5 years)	0.099**	-0.017	-0.079*	-0.079
	(0.044)	(0.043)	(0.045)	(0.059)
Pre-Financial Crisis & New Market Entrant (0-5 years)	-0.028	-0.033	-0.026	-0.026
	(0.067)	(0.062)	(0.063)	(0.083)
Intercept	0.082	0.178**	0.283***	0.283***
	(0.062)	(0.070)	(0.079)	(0.100)
Number of observations	2,507	2,507	2,507	2,507
R2	0.161	-	0.028	0.028
Adjusted R2	0.151	-	-0.072	0.017
Sigma_u	-	0.219	0.311	0.311
Sigma_e	-	0.368	0.368	0.368
F	16.925	-	2.358	2.031

Note: *** p<0.01, ** p<0.05, * p<0.1. Controls for year-specific were included on regressions but were exempted from the results for brevity. The dependent variable for the outcome model is patenting activity (binary variable indicates if the company produced a patent in that year). Pooled OLS regression passed the linktest and show no evidence of functional form misspecification using the Ramsey RESET test. The F-test on the endogenous effect from the Fixed effects model is *F(206, 2272) = 6.09 | Prob > F = 0.0000*. The base group for size variables are medium-sized firms. Fixed Effects Model 2 reports standard errors clustered by firm. It might make sense to generate clustered standard errors at firm level since the unit of randomisation is individual and there might me be unobservable variations that are correlated across time (i.e. some serial correlation within each company. We ran the FE model with errors clustered at firm level).

Table 12

Panel results evaluating the impact of the MFI programme

We also use panel data techniques to test if *Hypothesis 1* is true. Table 12 shows the results from our panel data. We use Pooled OLS, Random Effects and Fixed Effects as comparators. Our preferred DiD estimator is the average treatment effect on treated (ATT) estimated using propensity score methods. We find that firms who receive support filed for more patents in the year of support. Subsequent years show no significant differences between firms who received support and the counterfactual.

We find the treatment effects estimated using the Random-effects and Fixed-effects model are consistent, however, the treatment effect for the Pooled OLS model is larger than the other models. This suggests that there are fixed individual-specific effects that we have omitted from our model. The omission of these variables has led to upward bias on the estimates we see in the Pooled OLS model. However, when we clustered standard errors at firm-level, we observe the same treatment effect, but the confidence interval of our treatment effect increases. The treatment effect only becomes significant at a 10% level.

Value of the inventive output

We established that the MFI programme enabled firms to apply for patents approximately 2 years earlier than they would have. In this section, we determine the time value of money saved by the organisations that filed for the patents two years earlier because of the support they received via the MFI programme.

To do this we must first estimate the value of a patent for the companies in the sample. Patents are classed as one of the knowledge assets of a firm. Knowledge assets refer to the accumulated intellectual resource of an organisation used to create competitive advantage. Knowledge assets come in several forms, these include processes, databases, intellectual property, agreements etc. An analysis of the types of knowledge assets is beyond the scope of this study.

Most literature[39] on patent valuation tends to construct the value of patents based on indicative factors such as patent citations or the stock market valuation of the firm's intangible stock of knowledge. The former approach is a measure of value but does not lend itself flexible enough to be appraised in monetary terms. The latter approach can be assessed in monetary terms, however, the stock market value approach can only be used for firms quoted in well-functioning and thickly traded stock markets. This is not the case for our sample of firms. This has led us to use an alternative approach for which we have reasonable data.

The rationale behind this approach is that the value of the firm's knowledge assets - if recognised - are recorded as intangible assets. Given that intangible assets are the recorded value of knowledge assets, we can provide an estimate of the value of intangible assets attributed to filing for at least one patent in a year.

We use the following linearly estimable equation to the derive the relationship between filling for a patent and the growth in intangible assets:

$$\Delta y_{i,t} = \alpha + \beta_i P_{i,t} + B_t + \mu_{i,t}$$

Where $\Delta y_{i,t}$ is the growth in intangible assets for an observation at time *t*. This is calculated by taking the log difference of intangible assets between $y_{i,t=0}$ and $y_{i,t-1}$. $P_{i,t}$ is a binary variable indicating if an observation filed for a patent at time *t*. β_i is a semi-elasticity that shows the percentage change in intangible assets when we file for at least a patent. Because this is a panel dataset we control for time-specific effects which are denoted as B_t in the equation above.

Table 13 presents the results of our estimate. The results show that filing for at least one patent in a year results to 11% increase in the value of knowledge assets (intangible assets). If we evaluate the semi-elasticity (β_i) at the average value of intangible assets, we can deduce what this value is in monetary terms. In our sample, the average value[40] of knowledge assets for a firm is £450,000. This means on average a patent is valued at £52,000 for the firms in our sample.

We also compare values from other studies that attempt to find the average value of a patent. Kogan et al. (2017) used the stock market reaction to a patent grant to obtain an approximation of the value of a patent. The estimated median value of a patent from the study was around \$3.2 million. Giuri et al. (2007) conducted a survey of inventors for a sample of 7,752 European patents. The inventors were asked to estimate the minimum price at which the owner of the patent, whether the firm, other organisations, or the inventor would have sold the patent rights on the day on which the patent was granted. About 68% of all the patents in their sample have a minimum value of less than €1 million.

39 Bloom et al. (2002), Hall et al. (2005), Hall and MacGarvie, (2006).

40 This average is based on the geometric mean. This is because, as discussed earlier, intangible assets are not measured using the same method across firms. This way we can normalise the disparity that comes through different valuation systems. Secondly, there are very large positive outliers in the data and taking the geometric mean accounts for these large outliers in the dataset.

Both of these studies have high patent value estimates. However, we should note that these estimates are largely based on a sample of public firms; these firms may attach higher valuations to individual patents in comparison with smaller organisations.

```
. * Model 1
. reg D_log_intassets bin_pat i.fyear, r

Linear regression                               Number of obs     =      1,233
                                                F(17, 1215)       =       2.28
                                                Prob > F          =     0.0022
                                                R-squared         =     0.0200
                                                Root MSE          =     .92091
```

D_log_inta~s	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
bin_pat	.1016327	.0505474	2.01	0.045	.0024627	.2008026
fyear						
2003	-.2376871	.1370197	-1.73	0.083	-.5065086	.0311345
2004	-.248283	.1782193	-1.39	0.164	-.5979348	.1013687
2005	-.0099181	.1592156	-0.06	0.950	-.3222861	.30245
2006	.0393002	.183093	0.21	0.830	-.3199133	.3985138
2007	.0409013	.1131844	0.36	0.718	-.1811574	.2629599
2008	-.0813283	.1504607	-0.54	0.589	-.3765198	.2138633
2009	.0814493	.1566111	0.52	0.603	-.2258089	.3887075
2010	-.0877463	.1176031	-0.75	0.456	-.3184739	.1429813
2011	-.1688437	.1222284	-1.38	0.167	-.4086458	.0709584
2012	-.0370506	.1525088	-0.24	0.808	-.3362605	.2621592
2013	-.2692033	.1270672	-2.12	0.034	-.5184988	-.0199079
2014	-.2294979	.1614828	-1.42	0.156	-.546314	.0873182
2015	.0715269	.1653673	0.43	0.665	-.2529104	.3959641
2016	-.0076801	.1530863	-0.05	0.960	-.308023	.2926628
2017	-.293804	.1171284	-2.51	0.012	-.5236003	-.0640078
2018	-.1037463	.1326178	-0.78	0.434	-.3639316	.156439
_cons	.0343987	.0987465	0.35	0.728	-.159334	.2281314

Table 13

Value of a patent

We also estimate a ballpark figure of the average value of a patent using figures from the UK Intellectual Property Office (IPO), Office of National Statistics (ONS) and World Intellectual Property Organisation (WIPO). The IPO reports that 6% of total UK investment in intangible assets was in assets protected by patent.[41] The ONS report stated that the total value of intangible assets in the UK as of 2015 is £134.2 billion. Consequently, we can estimate that the total value of patents in the UK was around £8.1 billion in 2015.[42] According to the WIPO, the total counts of patents in force owned by UK applicants in 2015 was roughly 133,264.[43] Therefore, the average value of a patent given these values is around £60,800.

The plausibility of all these patent values is difficult to assess. One thing we can say is the value calculated by our model is the lowest estimate compared to all other values we have reported. However, there are some caveats to our approach. There is not one standardised system that is sufficiently developed and globally accepted for quantifying the value of intangible assets. Some firms use the income method. This approach assumes that the value of the patent is based on the discounted future returns that are expected to be generated by that patent. A less speculative method used by firms to value their patents is the cost method. This approach values the patents based on the costs that are

41 UK Intangible Investment and Growth, Intellectual Property Office, (2016).

42 Developing experimental estimates of investment in intangible assets in the UK: 2016, Office for National Statistics, (2019).

43 WIPO Patent Statistics Data Centre.

associated with the underlying invention. A consequence of the varied ways of valuing a patent is that the reported values are all measured differently.

Secondly, this approach only evaluates the value recorded from filing a patent. It does not assess the value of other unpatentable inventive outputs that came off as a result of support from the NMS via the MFI programme.

To estimate the time value of filing for this patent 2 years earlier, we need to model the future returns expected from investing in a patent. This can be written as:

$$P_\tau = P_0 \cdot e^{r\tau}$$

Where τ indicates time, P_τ is the expected value of the patent at time τ, P_0 is the value of the patent at the time of inception,[44] and r is the expected rate of return for the investment.
Therefore, the value obtained from the investment at time τ could be represented as:

$$V_\tau = P_\tau - P_0$$
$$V_\tau = P_0 \cdot e^{r\tau} - P_0$$
$$V_\tau = P_0 \cdot (e^{r\tau} - 1)$$

Where V_τ is the value obtained from the investment at time τ. V_τ can also be interpreted as the opportunity cost of not having the investment for τ years (i.e. how much money would the firm have lost because the patent was made τ years later). In the case of the MFI programme, V_τ represents the additional value the company gained from filing the patent two years earlier.

To calculate V_τ we need to know the expected rate of return for investing in a patent. The expected return rate is difficult to observe because of the limited data we have. An alternative approach to modelling the expected rate of return of the firm is to identify the hurdle rate of the firm. The hurdle rate is the minimum rate of return on a project or investment required by a firm to undertake a project. Therefore, we can use the hurdle rate to identify the minimum expected rate of return for a firm investing in a patent.

We use data from the Bank of England Finance and Investment Decisions (FID) Survey[45] that explicitly asks firms to reveal their hurdle rates. The data suggests that the most common hurdle rate was in the 10%-15% range. We use the midpoint of this range, which is 12%, as the hurdle rate in our estimate. This is similar to the net rate of return that private non-financial corporations reported by the ONS[46]. The inclusion of the renewal cost of a patent does not make any difference to our estimates. The value of filing the patent two years earlier is approximately £14,000. The average cost of an MFI consultancy is about £5,500[47]. This means that the benefit-cost ratio of the MFI consultancies on the inventive output of a firm has a lower bound of £5:£2. It is worth noting that our estimate of the benefit-cost ratio to the supported firm is only a lower bound estimate. Patents only capture a fraction of the inventive output of a firm. Therefore, our estimate is only based on that fraction of inventive output.

44 Our estimates show this is £52,000.

45 FID survey (2017) had 1,220 respondents and was broadly representative across industries, firm size, and UK regions.

46 Profitability of UK companies, Office for National Statistics, (2018).

47 Average cost of the MFI programme is £4000 in 2004 – 2010 , considering inflation is about £5,500 as at 2018.

5.2 EFFECT OF THE MFI PROGRAMME ON THE BENEFITS OF INNOVATION

The previous section showed that the MFI programme increases the inventive capacity of an organisation, however, the second stage of this analysis was to identify if the knowledge gained via the MFI programme has resulted to some benefits.

Effect of the MFI programme on Firm Growth

We examine how well our results determine *Hypothesis 2 (H2)* which states: "*The increase in the inventive capacity of the supported firm should lead to some realised benefits for the firm over time when compared to a constructed counterfactual group.*"

Table 14 presents the results of the estimation technique[48] used to evaluate growth rates between the supported firms and the control group. The values indicate the average treatment effect on the treated (ATET) between our treated group and the counterfactual in different time periods.

Estimators	4 yr growth rate at *t=0*	4 yr growth rate at *t=4*	4 yr growth rate at *t=8*
Propensity Score Matching	0.019	0.187*	0.184**
	-0.119	-0.098	-0.082
Nearest Neighbour Matching	0.045	0.189*	0.183**
	-0.125	-0.097	-0.082
OLS Regression	0.031	0.174*	0.188**
	-0.116	-0.092	-0.074

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard Errors in Parenthesis.
Growth rates are calculated in 4 yr intervals i.e. $\Delta y_t = ln(y_t) - ln(y_{t-4})$.
As a robustness check we have provided the average asset growth rate on shorter time periods in Annex D.

Table 14

The impact of the MFI programme on firm growth

The first period (*t=0*) is the average treatment effect on the treated from *t-4* to *t=0*. We find that there are no significant differences between the growth rate of both groups in periods before treatment. The second period (*t=4*) is the first period where we try to evaluate what has happened to the asset growth rate of both the treated firms and the counterfactuals after treatment. Four years after treatment, we find that the supported firms have grown at an additional rate of 5%[49] annually in comparison to the counterfactual. The third period (*t=8*) examines the average treatment effect on the treated from *t+4* to *t+8*. The supported firms still grow at an additional 5%[50] annually in comparison to the counterfactual. Figure 11 shows a graphical representation of our estimates using propensity score matching. We find that the supported firms and the counterfactual have very similar growth rates before the period of treatment which validates the common trends assumption. Four years after treatment both the supported firms and the counterfactuals grow, however, the supported firms grow at a faster pace. This shows that if the supported firms did not receive any support, they would still grow albeit at a much lower rate in comparison to receiving treatment. The value of the knowledge obtained by the supported firms through the MFI programme enables them to grow at a much higher rate.

48 Diagnostic test for OLS estimations shows no evidence of misspecification for all models.

49 Significant at 10% level. Annualised growth figure i.e. 18.7/4 years.

50 Significant at 5% level. Annualised growth figure i.e. 18.4/4 years.

Between *t+4* and *t+8*, we notice a period of stagnation for the counterfactual. Firms in that group do not seem to be making any growth, however, there is no significant decline either. The firms who receive support have a persistent growth trend even 8 years after treatment. The supported firms do not experience the same level of stagnation as the counterfactual.

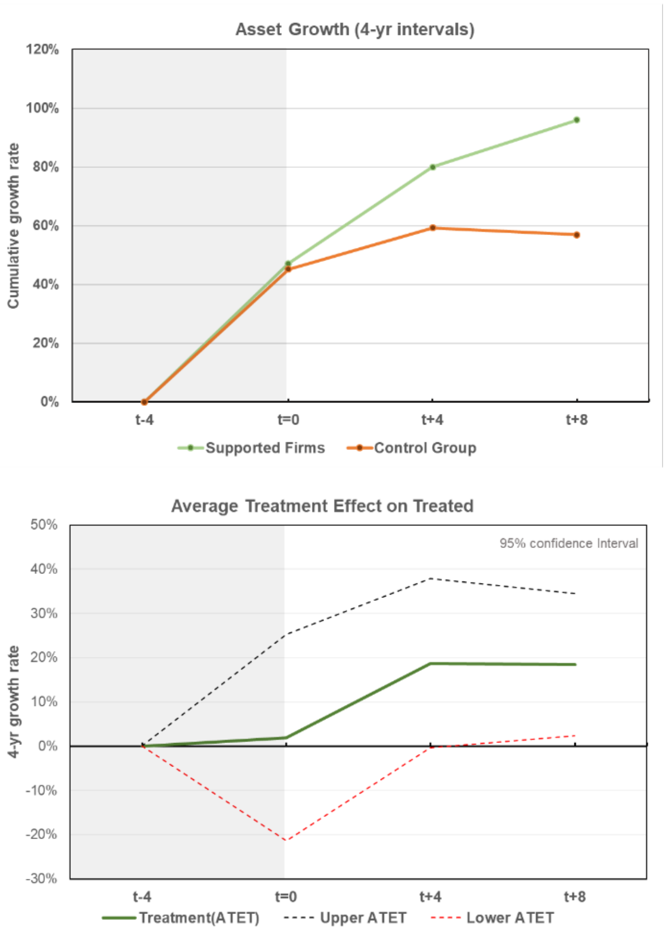


Figure 11

The cumulative growth rate of the treated group and the counterfactual from *t-4* to *t+8*

Growth rates this persistent could happen for a couple of reasons. One of them being that the MFI programme did not only increase the inventive output of the firm but also changed the innovative culture of the supported firms. This means that the supported firms have adopted better ways of acquiring, assimilating, and exploiting knowledge for innovating as a result of the MFI programme. Another possible reason is that the increase in inventive output (or patenting activity) has generated large surpluses for the firm, which in turn has provided capital to invest in more assets over time. This leads to a consistent cycle of productivity gains and expansion which we observe in the growth of the firm's assets over time. Further analysis on the asset growth,[51] indicates that persistent growth rate four years after receiving treatment is experienced by 1 in 10 companies.

It is somewhat hard to estimate the proportion of the additional growth which is solely as a result of the MFI programme. This is because even though the programme contributed to the innovative output of the firm, the firm has made some efforts, before and after the MFI programme.

This result supports the second hypothesis (H2) which states that *"The increase in the inventive capacity of the treated firm should lead to some realised benefits for the firm"*. These realised benefits

51 Extend analysis on asset growth in Annex F.

were measured via asset growth. It shows that the companies supported via the MFI consultancies have higher growth rates than the counterfactual and this growth is sustained over time.

Effect of the MFI programme on Firm Survival

Table 15 shows the results from the hazard rates (mortality rate) estimation in each period. The estimates are the differences between the hazard rates of the treated group and the counterfactual. The magnitude of the estimates across all periods suggests that the differences between the hazard rates of both groups are very small. We find that the differences between the hazard rates of both groups are not statistically significant.

Traditionally, the cox proportional hazards model[52] is most commonly used in empirical studies in the firm survival literature and we tried to use this model for the firm survival analysis in this study. A key assumption of the Cox proportional hazard model is proportional hazards. This means that the changes in covariates produce proportional changes in the hazard regardless of time. Thus, the relative risk of two individuals with different covariate values is independent of time and only influenced by the coefficient of the covariate. We found the same results as the matching models and the parametric regression above. However, some of our variables failed the meet the proportional hazards assumption and for that reason, we excluded these results from the analysis.

	Survival at *t=0*	Survival at *t+1*	Survival at *t+2*	Survival at *t+3*	Survival at *t+4*	Survival at *t+5*	Survival at *t+6*	Survival at *t+7*	Survival at *t+8*
Propensity Score Matching	-0.012	-0.016	-0.001	0.017	0.009	0.009	0.012	0.005	-0.011
	(0.012)	(0.015)	(0.02)	(0.024)	(0.025)	(0.027)	(0.029)	(0.03)	(0.031)
Nearest Neighbour Matching	-0.012	-0.016	-0.001	0.017	0.009	0.009	0.012	0.005	-0.011
	(0.012)	(0.015)	(0.02)	(0.024)	(0.025)	(0.027)	(0.029)	(0.03)	(0.031)
OLS Regression	-0.008	-0.012	0.003	0.019	0.009	0.008	0.011	0.006	-0.011
	(0.01)	(0.013)	(0.018)	(0.023)	(0.024)	(0.025)	(0.027)	(0.028)	(0.029)

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard Errors in Parenthesis. Estimates are based on the differences between the hazard rate estimates of the treated group and the counterfactual.

Table 15

The impact of the MFI programme on firm survival

Figure 12 is a graphical examination of the survival rate[53] between the treated group and the counterfactual. The rate of survival is generally quite high but as time goes by the survival rates reduces. We see that both groups track each other and there are no significant differences between them. This says a lot about the general population of firms in the sample. We previously established

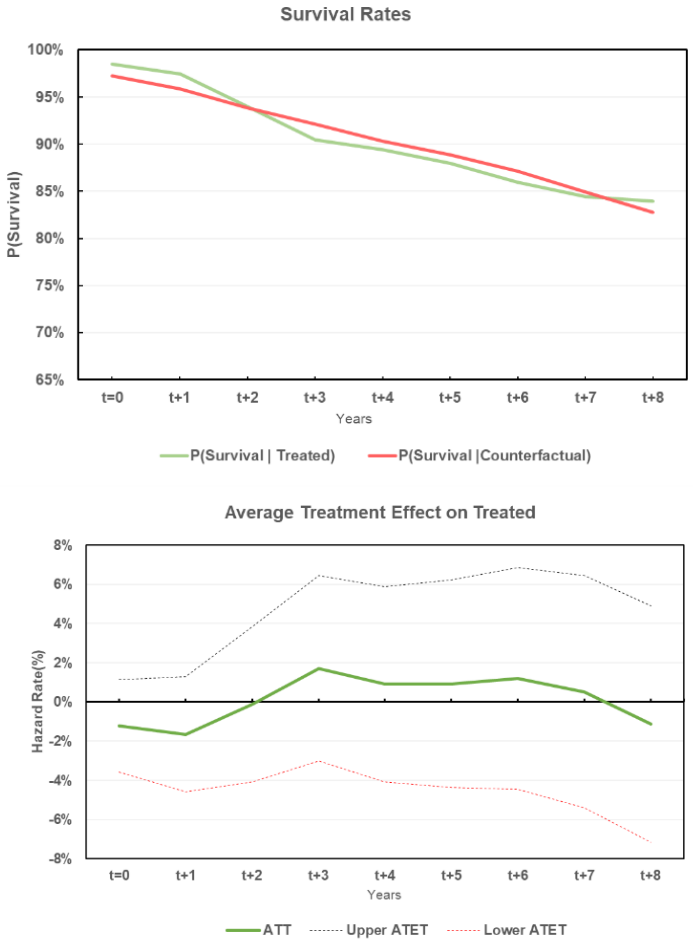
52 Cox, (1972), D.R. Cox Regression models and life-tables. J. R. Stat. Soc. Ser. B, 34 (2) (1972), pp. 187-220.

53 *P(Survival) = 1 – Hazard Rate*

that these firms are very innovative in comparison to the general population of UK firms. Their innovative nature might have a positive effect on their survival rates.

Figure 12

Survival rates between the treated group and the counterfactual



This result deduces that the MFI consultancies do not affect a firm's chances of survival. Therefore, we cannot accept the hypothesis that the MFI programme has an impact on the survival rates of the supported firms. However, given that the rate of survival between the treated firms and the counterfactual are identical, we can rule out the possibility that our estimates on the effect of the programme on asset growth generate a bias attributed to survival.

It is worth noting that our survival rate estimate is based on closure/inactivity reported by FAME. This approach neglects the fact that inactivity from a firm could reflect different exit strategies from acquisition, asset relocation, mergers, and in some cases name changes. There might be a considerable number of firms that did not close as inferred in our analysis above but in fact had one of the exit strategies listed above.

5.3 SENSITIVITY ANALYSIS

Although we found statistically significant effects for patenting activity and asset growth, we still have to consider the possibility that our estimates might be influenced by unobservable characteristics that simultaneously determine treatment assignment and the outcome of interest.

Rosenbaum (2002) developed "sensitivity analysis" to explore the robustness of matching estimates to a selection of unobservable characteristics. Rosenbaum (2002) invites us to imagine a number Γ (gamma) ≥ 1, where Γ represents the ratio of the probability that the treated have these unobserved characteristics to the probability that the controls have the same unobserved characteristics. When $\Gamma=1$

the unobservable effect does not affect treatment assignment. However, for values of Γ higher than 1, the hidden bias is increasing the likelihood of an observation being assigned to one group compared to being assigned to the other group.

The Rosenbaum bounds test shows us at what value of Γ does our unobserved characteristics make the observed treatment effect insignificant. We perform this test on the two outcome variables that showed significant treatment effect (i.e. patenting activity and asset growth).

For the patenting activity model, we find that the upper bounds on the significance levels for $\Gamma = 1$, 1.05, 1.1, and 1.15 are 0.034, 0.056, 0.085 and 0.123 respectively. This means that the study is sensitive to unobservable characteristics that could increase the odds of being assigned to the treatment group by 5% and above at a 5% significance level. Given these results, we have to be cautious with the treatment effect estimated.

In comparison to the patenting activity model, the asset growth model is robust to the possible presence of selection bias even for unobservables that could increase the odds of treatment assignment by 80%. The critical level of Γ at which we would have to question our conclusion of a positive effect is between 1.8 and 2 (i.e. an unobserved covariate causes the odds ratio of treatment assignment to differ between treatment and control cases by a factor of about 1.8).

It is important to recognise that these results are worst-case scenarios. For example, a value of $\Gamma=1.8$ does not mean that there is no true positive average treatment effect on the treated. The results simply mean that the confidence interval for our estimated treatment effects for asset growth would include zero if an unobserved variable caused the odds ratio of treatment assignment to differ between treatment and control group by 1.8. The unobserved variable must be so strong as to almost perfectly predict whether the 4-year asset growth would be bigger for the treatment or the control group in each pair of matched observations in the data. In the case where the unobserved confound variable has a strong effect on treatment assignment, but a weak effect on the asset growth, the confidence interval for the treatment effect would not contain zero.

6 CONCLUSION AND FURTHER WORK

In this report, the effects of the MFI programme on the inventive output as well as the benefits of innovation of supported firms were analysed. The analyses are based on one of the products offered during the MFI programme called the consultancies. The other products were excluded due to data limitations. With more effort, we would like to recover the data for the other products and expand the analyses on the effects of the MFI programme on supported firms.

We use several estimation techniques[54] to obtain the DiD between the outcome for the treated firms and the counterfactual. According to our results, we find that the MFI consultancies increased the patenting activity of the treated firms in the year of support in comparison to the counterfactual by 11% with a lower bound benefit-cost ratio of £5:£2. This supports the hypothesis (H1) that the MFI programme increases the inventive output of the supported firms, albeit that the proxy of inventive output is a lower bound estimate because it accounts for a fraction of the inventive output of a firm. Additionally, we find that the MFI programme has an impact on the growth rate of the supported firms. After receiving support, the average annual growth rate of the firms who received support was 5% higher than the counterfactual. We found this difference in growth rate to be persistent even eight years after treatment. These results support the second hypothesis (H2) which states that "*The increase in the inventive capacity of the supported firm via the MFI programme should lead to some realised benefits for the firm*".

This work only gives evidence of the effect of the MFI consultancy projects on the supported firm. In recent years, the NMS has rolled out programmes that share similarities with the MFI programme, such as the Analysis for Innovators programme (A4I), and the Measurement for Recovery programme (M4R). This gives the National Physical Laboratory and its partners the opportunity to extend and replicate the study. Some of the areas we would want to explore include using generalised propensity scores to estimate a dose-response and the effect of the treatment intensity (such as duration of project) on observable outcomes. We also intend on exploring how NMS programmes improve the success rate of patents, the quality of patents through measure such as citations, and what technology areas (patent families) benefit from programmes akin to the MFI programme.

54 Propensity Score Matching; Nearest Neighbour matching; and Linear Estimation techniques.

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ANNEX A: FIRM SIZE ESTIMATION

One of the challenges with our data was that the size of an organisation was based on the year the firms filed its last accounts. Choosing such variables as controls could violate the assumption that the treatment variable should not influence the control variable.

To obtain the historical size of companies we employ an ordinal logit model using the natural log of assets and sectors to predict what the size classes the organisation would have been for a given year.

```
. ologit size log_assets i.sectors if fyear==laccounts_date

Iteration 0:   log likelihood = -308.45926
Iteration 1:   log likelihood = -185.73953
Iteration 2:   log likelihood = -143.88875
Iteration 3:   log likelihood = -141.19531
Iteration 4:   log likelihood = -141.17718
Iteration 5:   log likelihood = -141.17717

Ordered logistic regression                     Number of obs     =        289
                                                LR chi2(8)        =     334.56
                                                Prob > chi2       =     0.0000
Log likelihood = -141.17717                     Pseudo R2         =     0.5423

------------------------------------------------------------------------------
        size |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  log_assets |   1.559881   .1545431    10.09   0.000     1.256982     1.86278
             |
     sectors |
          2  |  -1.426981   .6132921    -2.33   0.020    -2.629012   -.2249511
          3  |  -.5511543   2.238848    -0.25   0.806    -4.939215    3.836907
          4  |  -.1897966   .8845897    -0.21   0.830    -1.923561    1.543967
          5  |  -.4918812   .4588859    -1.07   0.284    -1.391281    .4075187
          6  |   .3197364   .4925964     0.65   0.516    -.6457348    1.285208
          7  |  -.6107072   .9667133    -0.63   0.528     -2.50543    1.284016
          8  |  -1.010321   .7114739    -1.42   0.156    -2.404784    .3841418
-------------+----------------------------------------------------------------
       /cut1 |   11.67921   1.228742                      9.270916     14.0875
       /cut2 |   14.33813   1.396774                      11.60051    17.07576
       /cut3 |   17.47832   1.678685                      14.18815    20.76848
------------------------------------------------------------------------------
Sectors: 1 - Biotechnology and Life Sciences; 2 - Business Services;
3 -Construction, Mining & Utilities; 4 - IT;
5 - Industrial, Electric & Electronic Machinery; 6 - Manufacturing;
7 - Other services; 8 - Wholesale, Retail and Support Services.
```

Figure A1

Regression output for historical size of supported companies

ANNEX B: SPECIFICATION TESTS

The linktest by Tukey (1949), which was further described by Pregibon (1980), is used to check for misspecification of the dependent variable in the OLS models used. The motivation behind the linktest is to assess if a regression model is affected by the so-called link error, such that the dependent variable needs a transformation or link function to properly relate to the independent variables. To verify that this is not the case, the link test regresses the dependent variable against the original regression's predicted values and the squared values of this prediction. If the squared prediction regressor in the test regression is significant, there is evidence misspecification. It is also expected that the coefficient for the prediction regressor is highly significant.

Patent Models

Parametric regression link test for OLS models. Table B1 shows the linktest of each period of interest where the dependent variable is the patenting activity in that period.

Dependent Variable	Predicted values	Squared prediction	R^2	Number of obvs.
patents(t-4)	0.760***	0.350	0.49	478
	(0.22)	(0.33)		
patents(t-3)	0.829***	0.241	0.53	618
	(0.22)	(0.31)		
patents(t-2)	0.811***	0.256	0.59	618
	(0.26)	(0.35)		
patents(t-1)	0.974***	0.030	0.33	618
	(0.28)	(0.32)		
patents(t)	1.384***	-0.449	0.27	618
	(0.27)	(0.32)		
patents(t+1)	0.992***	0.009	0.22	618
	(0.27)	(0.34)		
patents(t+2)	0.908***	0.114	0.19	618
	(0.27)	(0.34)		
patents(t+3)	1.264***	-0.340	0.17	618
	(0.33)	(0.45)		
patents(t+4)	1.130***	-0.175	0.16	618
	(0.33)	(0.46)		
patents(t+5)	0.968***	0.045	0.16	618
	(0.27)	(0.40)		
patents(t+6)	1.236***	-0.336	0.16	618
	(0.30)	(0.46)		

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis.

Table B1

Linktest outputs where the dependent variable is patenting activity.

Asset growth models

Parametric regression link test for OLS models. Table B2 the linktest of each period of interest where the dependent variable is the 4-year growth rate in that period.

Dependent Variable	Predicted values	Squared prediction	R^2	Number of obvs.
Δassets(t)	1.114**	-0.094	0.06	886
	(0.49)	(0.38)		
Δassets(t+4)	0.740**	0.241	0.53	982
	(0.34)	(0.31)		
Δassets(t+8)	0.703*	1.266	0.59	880
	(0.42)	(1.57)		

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis.
Growth rates are calculated in 4yr intervals i.e. $\Delta y_t = ln(y_t) - ln(y_{t-4})$

Table B2

Linktest outputs where the dependent variable is 4-year growth rate

ANNEX C: CUMULATIVE PATENTING ACTIVITY

Figure C1 illustrates the cumulative patenting activity of the treatment group and the matched control group.

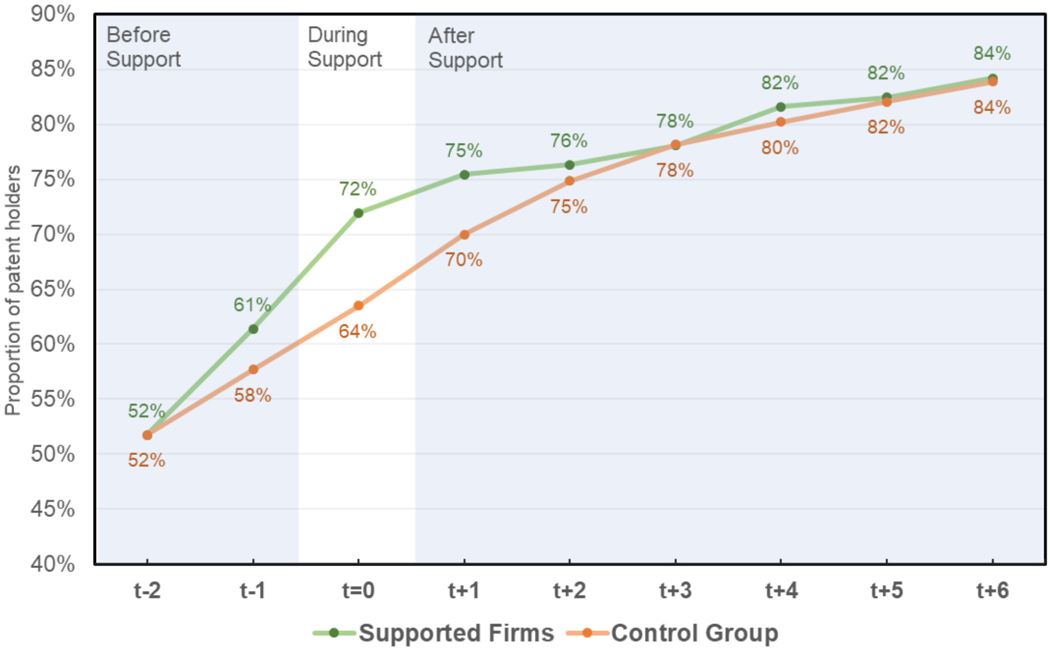

Figure C1

Cumulative patenting activity

ANNEX D: ASSET GROWTH RATE AT SHORTER TIME PERIODS

As a robustness check we provide the treatment effect on assets growth rate for shorter time periods.

Time period	ATT	Variance	Standard Error	t-statistic
t+1	4%	0.0034	0.0583	0.7630
t+2	3%	0.0056	0.0746	0.4449
t+3	10%	0.0078	0.0882	1.1810
t+4	19%	0.0095	0.0976	1.9174

Table D1

Treatment effect on assets growth rate at 1-year time intervals

We choose the four-year period as preferred interval for evaluation for two reasons. The first is that, even after support from the programme, the company has certain commercialisation steps to take before realising the full benefits of the new products. Therefore, we expect to see some lags before the company starts accruing benefits. The second reason is that the effect of a new product or process is accumulated over time. The treatment effect over smaller time periods, although positive, are not strong enough to firmly reject that these changes did not happen randomly. Table D1 reports the treatment effect at shorter time intervals up until the four-year interval used in the report.

ANNEX E: SECTOR BREAKDOWN

Annex E provides a breakdown of the sectors in our sample and the distribution of firms in each sector. Due to the relatively small sample size of firms and the widespread distribution of companies in our sample it was impractical to adopt the standard two-digit SIC code classification. Therefore, we had to define industries based on a combination of two-digit and three-digit SIC Code (in some case sectors are defined based on five-digit SIC Codes) as well as Bureau Van Dyke’s industry classification to assign a company to a sector.

Table E1 presents a breakdown of how sectors were identified and number of companies in each sector.

In our propensity score models, with the “Manufacturing Sector” as our base group for comparison, we found no significant difference in the propensity to receive treatment between the manufacturing sector and most other sectors. Nevertheless, the companies in “Construction, Mining & Utilities” and companies classified as “Other” were less likely to receive treatment relative to the manufacturing sector. The reason behind this is because firms in the “Construction, Mining & Utilities” sector failed the common support assumption (i.e. most companies in this sector did not receive treatment). Generally, we found no significant difference in our observed outcomes (patents and asset growth) between sectors, except for the case of the Research & Development intense sector who had a higher propensity to file for patents than other sectors. Given that the only industry-fixed effect that found an observed outcome was the Research & Development intense sector, we decided to create a dummy for companies in this sector.

Industry Classification	n	Description
Research & Development Intense Sectors	76	This includes companies with the five-digit SIC Codes 72110 and 72190. The primary activities of these companies are described are research and experimental development in biotechnology, natural sciences, or engineering.
Business Services	78	Companies classified under this category have primary activities that cover generic business services. This classification was derived from the Bureau van Dijk sector classification called "business

		services" which includes SIC Codes such as 45, 62, 64, 70, 71, 72, excl. 72110 or 72190, 73, 74, 80, 82. It includes a rather vague two-digit 70 code such as "Activities of Head offices".
Construction, Mining & Utilities	9	This classification includes companies in Construction, Mining & Extraction, and Utilities. This is the amalgamation of three Bureau van Dijk sectors namely Construction, Mining, and Utilities and includes SIC Codes such as 42, 43, 09, 35, 37, 36.
IT	15	This classification includes companies that operate in the communications, computer software and hardware sector. This includes SIC Codes such as 61, 62, 263, 262.
Industrial, Electric & Electronic Machinery	93	This classification includes organisations that manufacture industrial, electronic machinery. This includes SIC sectors such as 26 excl. 263 or 262, 28 excl. 2896 or 2893, 33, 325.
Manufacturing	63	This classification includes all forms of manufacturing excluding that of industrial and electronic machinery or equipment. For example, companies that manufacture chemicals, petroleum, rubber, plastic, wood, textiles, and metal products. This includes SIC codes such as 32, 30, 20, 25, 2896, 2893, 17, 16, 23, 22, 24, 31, 21, 13.
Other	33	This classification includes services such as transport, leisure, property services and third sectors such as public administration and Education.
Wholesale & Retail activities	22	This classification includes companies that engage in retail/wholesale of products. This covers 46 and 47 two-digit SIC Codes.
Total	**389**	

Table E1

Description of sectors

ANNEX F: FURTHER ANALYSIS ON ASSET GROWTH RATE

Although the growth rates are observed and there is no reason to believe these are measurement errors, as these were all obtained from the company fillings by FAME, we still wanted to ensure that the results were not driven by a few extra ordinary companies. We removed a few outliers, about 10 of the largest growth rates observed from both ends of the distribution, and the treatment effects were still consistent, which ruled out claims that a few outliers are driving the results.

However, it could still be the case that there a substantial group of companies that experience more growth than other firms in the sample. This is also a sensible assumption to make because support received by some companies might be more beneficial in comparison to other companies that were also supported, however, we would not class these groups of companies as outliers, instead they are a subsample that experienced above average treatment effects.

To test this assumption, we used a robust regression technique. The robust regression attempts to apply downward weights and use Cook's Distance (normalised change in the fitted response values due to the deletion of an observation) to reduce the effect of extreme values. The robust regression was used to evaluate the effect of these subset of companies that experienced abnormal growth rates.

For our model on four-year asset growth after treatment [Δ*assets(t, t+4)*], 38 observations were assigned a weight of 0 because they had a Cook's Distance of greater than 1, and it also reduced the observed outcome of 90 observations by 50%. Altogether, almost 13% of our sample size were either reduced to nothing or reduced by at least half the original value observed. Table F1 shows the results of adjusting for these companies that experienced tremendous growth. We find that the treatment effect for Δ*assets(t, t+4)* grows by about 10% over four years (annualised growth rate 2.5%). This shows that even after excluding the group of companies that had high growth rates, we still obtain a good treatment effect from the programme.

Outcome	Model 1	Model 2
Δassets(t, t+4)	0.172* (0.093)	0.104* (0.054)
Δassets(t+4, t+8)	0.175** (0.083)	0.042 (0.044)

Note: *** p<0.01, ** p<0.05, * p<0.1.

Table F1

Modelling asset growth, excluding companies that had high growth rates. Model 1 represents the original estimates of our treatment effect on four-year asset growth using OLS. Model 2 represents treatment effect estimates by also controlling for the outliers using Stata's robust regression command (rreg). Standard Error reported in parenthesis.

We ran the same analysis on the four-year growth rates reported four years after treatment. 47 observations were assigned a weight of 0 because they had a Cook's Distance of greater than 1, and an outcome of 67 observations were reduced by 50%. This means 13% asset growth observed in our sample was reduced by at least half. We found that the average treatment effect reduces significantly from an annualised growth rate of 4.4% to 1%. The likelihood of that average treatment effect occurring by chance also increased. This shows that the tremendous annualised growth rate 4 years after treatment is mostly experienced by a smaller number of companies in the sample, potentially 1 in every 10 companies.

This does not invalidate our treatment effect, however, it does suggest that there a group of companies in our sample that go on to do tremendously well. It is important to look into the characteristics of these firms and inform the design of future programmes akin to the MFI programme.annex g:rosenbaum bounds test

Annex G presents post estimation bounds tests to determine whether an unmeasured variable is affecting selection into the treatment group.

Patents

Figure G1

Test results using the patenting activity at t=0 as the outcome variable

Mantel-Haenszel (1959) bounds for variable bin_pat

Gamma	Q_mh+	Q_mh-	p_mh+	p_mh-
1	1.82473	1.82473	.034021	.034021
1.05	1.59333	2.05977	.055543	.01971
1.1	1.37177	2.2831	.085068	.011212
1.15	1.16045	2.49719	.122933	.006259
1.2	.95843	2.70286	.168923	.003437
1.25	.764883	2.90083	.22217	.001861
1.3	.579094	3.09174	.281263	.000995
1.35	.400433	3.27613	.344419	.000526
1.4	.228343	3.45451	.40969	.000276
1.45	.062332	3.62732	.475149	.000143
1.5	-.098041	3.79494	.53905	.000074
1.55	.042138	3.95774	.483194	.000038
1.6	.192552	4.11604	.423655	.000019
1.65	.338362	4.27011	.367545	9.8e-06
1.7	.479857	4.42023	.315664	4.9e-06
1.75	.617304	4.56662	.268517	2.5e-06
1.8	.750943	4.70951	.226343	1.2e-06
1.85	.880994	4.8491	.189161	6.2e-07
1.9	1.00766	4.98557	.156809	3.1e-07
1.95	1.13112	5.11908	.129002	1.5e-07
2	1.25155	5.24979	.105367	7.6e-08

```
Gamma : odds of differential assignment due to unobserved factors
Q_mh+ : Mantel-Haenszel statistic (assumption: overestimation of treatment effect)
Q_mh- : Mantel-Haenszel statistic (assumption: underestimation of treatment effect)
p_mh+ : significance level (assumption: overestimation of treatment effect)
p_mh- : significance level (assumption: underestimation of treatment effect)
```

Asset Growth

Figure G2

Test results using the growth of assets 4 years after participation

```
. rbounds F4_S_log_assets if $observation_period, gamma(1 (0.1) 2)
```

Rosenbaum bounds for F4_S_log_assets (N = 1130 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	.21773	.21773	.176528	.260414
1.1	0	0	.188231	.247968	.147312	.291643
1.2	4.0e-14	0	.161791	.275735	.120729	.320743
1.3	1.1e-10	0	.137794	.302056	.096278	.348547
1.4	5.6e-08	0	.11534	.326835	.074131	.374869
1.5	6.8e-06	0	.094513	.350543	.053133	.399805
1.6	.000271	0	.075507	.373123	.033636	.424185
1.7	.004324	0	.057462	.394588	.01489	.447407
1.8	.032714	0	.040687	.415768	-.002663	.469059
1.9	.135062	0	.024326	.435368	-.019302	.490855
2	.34387	0	.008763	.454732	-.034989	.512308

```
* gamma  - log odds of differential assignment due to unobserved factors
  sig+   - upper bound significance level
  sig-   - lower bound significance level
  t-hat+ - upper bound Hodges-Lehmann point estimate
  t-hat- - lower bound Hodges-Lehmann point estimate
  CI+    - upper bound confidence interval (a=  .95)
  CI-    - lower bound confidence interval (a=  .95)
```

Figure G3

Test results using the growth of assets 8 years after participation

```
. rbounds F8_S_log_assets if $observation_period, gamma(1 (0.1) 2)
|
Rosenbaum bounds for F8_S_log_assets (N = 1118 matched pairs)

Gamma          sig+      sig-    t-hat+    t-hat-       CI+       CI-
----------------------------------------------------------------------
    1       6.9e-15   6.9e-15   .144089   .144089    .10881   .179595
  1.1       1.3e-10         0   .119157   .168989   .083786   .204855
  1.2       1.8e-07         0   .096665   .191779   .061318   .228255
  1.3       .000039         0   .075927   .212821   .039448   .249927
  1.4       .001801         0   .056635   .233024   .019045   .270837
  1.5       .025935         0   .038119   .251381  -.000288   .290254
  1.6       .148735         0   .020524   .269221   -.01883   .309176
  1.7       .422593         0   .003788   .286099  -.036667    .32685
  1.8       .726668         0  -.012013   .302377  -.054143   .343957
  1.9       .912781         0  -.027411   .317765  -.070595    .36018
    2       .981032         0  -.042353   .332504  -.086622   .375996

* gamma  - log odds of differential assignment due to unobserved factors
  sig+   - upper bound significance level
  sig-   - lower bound significance level
  t-hat+ - upper bound Hodges-Lehmann point estimate
  t-hat- - lower bound Hodges-Lehmann point estimate
  CI+    - upper bound confidence interval (a=  .95)
  CI-    - lower bound confidence interval (a=  .95)
```