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NMS SUPPORT FOR INNOVATION AND BUSINESS OUTCOMES:
A SYNTHESIS OF EVIDENCE FROM BELMANA'S ECONOMETRIC ANALYSIS

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NMS Support for Innovation and Business Outcomes:
A Synthesis of Evidence from Belmana's Econometric Analysis

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ABSTRACT
Belmana Ltd was commissioned by the National Physical Laboratory (NPL) and Innovate-UK (IUK) to conduct an impact assessment of the innovation support provided to a large sample of UK firms. Belmana's analysis examined how this support affected the subsequent performance of these firms in terms of their employment, survival, and wage premiums. Additionally, Belmana provided exploratory analysis for firm productivity, patenting activity and knowledge spillovers. There was, however, a need to distil this analysis to extract key findings specific to NPL and other laboratories funded through the National Measurement System (NMS) programme. The headline findings for innovation support provided by the NMS laboratories are:

- An average annual growth of 6.31 employees per regularly supported firm.
- Only 4% of firms that receive regular support closed during a 7-year period as compared to 12% of firms in the matched control group.
- An average annual wage premium of £4,083 for employees switching to supported firms.

Moreover, this document develops a stylised economic model which helps with the interpretation of the estimates and provides further economic insights. The hope is that this will make it easier for non-specialist audiences to better grasp some its key findings. Hence, this document offers a simplified digest of the original report, spells out some of the implicit assumptions of empirical analysis, and presents a microeconomic model that compliments the econometric estimates.

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PREAMBLE

As the UK's National Measurement Institute and a public corporation that is owned by the Department for Science, Innovation & Technology (DSIT), the National Physical Laboratory (NPL) receives about £100 million in public funding each year. NPL has a responsibility to support the UK's economy and safeguard citizens' quality-of-life, through the programmes it delivers on behalf of government. It follows that it must also frequently monitor its programmes and evaluate their impacts using evidence-based approaches to ensure that they deliver value-for-money to society. In addition to ensuring its accountability to UK taxpayers, insights from such evaluations can strengthen NPL's own ability to design better programmes and inform effective allocation of future funds.

In one very extensive evaluation, consultants from Belmana Ltd[1] performed an econometric analysis of the impacts of support for business innovation being provided by Innovate UK and the National Measurement System Programme (of which scientific work undertaken at NPL accounts for the majority of the programme's funding). The econometric report, resulting from their analysis, provides the depth required by professional economists, but makes it a challenging read for more general audiences. Hence, this document offers a simplified digest of the original report so that non-specialists can better appreciate the key messages distilled from this piece of econometric analysis.[2] Moreover, as our document is wholly focussed on impacts attributable to the NMS programme, it does not cover the economic benefits from the large portfolio of grant-funded projects supplied by Innovate UK.

The goal of this document is to:

i. synthesize the findings from Belmana's analysis that are relevant to the NMS, making them more accessible for a general audience; and
ii. outline a microeconomic model that complements the empirical results in the original report.

To achieve this goal, this document spells out, for non-specialists, all the underlying assumptions of Belmana's empirical analysis that were sometimes left implicit in the original report. We also present a model, rooted in microeconomic theory, that complements Belmana's empirical results by offering an economic story that's consistent with their econometrics. While the original report does not contain any such microeconomic model, we believe that it is consistent with the set-up that researchers may have had in mind while undertaking their analysis. Additionally, this document contains some econometric equations which assume some level of statistical knowledge on part of the readers. These equations are sometimes necessary to fully explain the analysis. However, where possible, such equations have been delegated to textboxes and footnotes to reduce disruption for readers with minimal technical background (or interest). Moreover, the equations are accompanied by text that provides non-technical explanations of the mathematical notation. Finally, this document discusses potential caveats associated with the main findings, along with ideas for future work that would build on Belmana's analysis. By making explicit what was sometimes left implicit in Belmana's original report, this document aims to serve as an accessible digest of the original report and, thereby, help its finding reach a wider audience.

EXECUTIVE SUMMARY

Belmana Ltd. conducted a study to measure the impact of business support provided by Innovate UK and the National Measurement System (NMS). Innovate UK grants, exceeding a

[1] http://www.belmana.co.uk/
[2] The full report from Belmana's analysis is available upon request.

total funding of £2.4 billion since 2004, have driven business innovation in products and services mainly through collaborative R&D. The NMS is formed of six core laboratories that deliver technical infrastructure and measurement standards that underpin the UK's trade, industry, and regulation.[3] The NPL constitutes a major part of the NMS, accounting for more than 80% of all NMS funding, and it supports businesses through different interventions including paid-for R&D and measurement services, contracted collaborations, and free website downloads.

Belmana's original report, hereafter referred to as Belmana (2019), is a technical report detailing their robust econometric analysis. This report contains evidence that NMS-supported businesses perform better than groups of similar unsupported businesses across various measures of economic activities such as employment growth, patenting, and business survival. This evidence is further complemented by improvements in productivity indicators such as real turnover, quality of patents, and wage premiums received by employees in supported businesses. However, the technical depth of the report renders many of its novel findings difficult to understand for non-technical audiences.

In this document, we attempt to bridge that gap by producing a more accessible digest to synthesize the main results from Belmana's analysis and provide further economic intuition for these results. We also present an economic framework that we believe underpins the empirical study. Our main contributions are summarized below:

- This document disentangles Belmana's analysis to focus on the headline results for the impacts generated by support from NMS laboratories, and to make these findings more accessible to NPL's stakeholders.
- Belmana (2019) presents sound empirical results that are rooted in robust econometric techniques; however, the theoretical underpinnings and the main takeaways of these results can be somewhat obscure, and so these are brought to the forefront in this digest. For example, a key statistic that *can be inferred* from Belmana's analysis is that the 175 businesses, who were regularly supported by the NMS laboratories between 2009 and 2015, experienced an average growth of 6.31 employees per year because of the support they received. This growth figure is not explicitly reported in Belmana (2019). Rather, the finding presented in the original report is that regularly supported businesses generate an additional 18,800 job years that are not observed in comparator businesses. Moreover, rate of firm closure among regularly supported businesses is one-third that of the comparator businesses, which translates into an additional impact of over 4,400 job years. Stated this way, the significance of these numbers is hard to interpret. However, by performing a simple mathematical exercise, based on an arithmetic series, we show that the numbers roughly translate to a growth of 6.31 employees per business per year, making the main takeaway from the analysis easier to interpret.
- As an empirical study, the mechanisms behind how NMS support translates into employment growth and wage premiums were left unexplored in Belmana's original report. Hence, this digest also introduces a theoretical model to complement the

[3] In the UK, the National Physical Laboratory (NPL) is the UK's National Measurement Institute (NMI) and works in partnership with five designated institutes:

- NML (National Measurement Laboratory at LGC) – designated for chemical and biometrology
- NEL (National Engineering Laboratory) – designated for fluid flow metrology
- OPSS (Office for Product Safety & Standards, which is a part of the Department for Business and Trade) – responsible for legal metrology
- NGML (National Gear Metrology Laboratory) – designated for gears metrology
- NIBSC (National Institute for Biological Standards and Control) – designated for bioactivity metrology

econometric estimates from Belmana's analysis. Our model explores how firm behaviour responds to NMS support, thereby offering a deeper understanding of the likely channels through which support translates into better business outcomes. The insights from the model also make it possible to discern the implications for the scale of impact generated by the NMS support.

- Lastly, Belmana's analysis features some intriguing pilot studies that necessarily leave some important areas needing further exploration. For instance, the headline results are based on comparing outcomes between supported and unsupported businesses (that is, NMS support is treated as a binary variable). However, the level of interaction with the NMS laboratories varies across supported businesses, and it is also reasonable to expect that the impact generated from these interactions varies depending on the level of support provided. A pilot analysis within Belmana (2019) introduces the idea of using dose response functions to estimate marginal impacts, where the number of incidences of NMS support going to a business serves as a continuous treatment variable. Hence, this digest also discusses how such an analysis might be developed in future studies.

In summary, this document condenses the main findings from Belmana's analysis to make it more useable and relevant to NPL. We do not replicate the empirical analyses performed in Belmana (2019) or introduce any new econometric results. However, we discuss some potential shortcomings of the existing analyses and how they might be addressed in a future study. For example, we aim to initiate a discussion on which factors might drive selection into NMS support. That is, if support from the NMS laboratories results in better economic outcomes, then why do some businesses opt into paying for the NPL's services while others do not? It relates such topics to the idea of potential impacts and how it could determine the businesses' decision to engage with the NPL. Finally, to reiterate, this document does not cover the economic benefits from the large portfolio of grant-funded projects supplied by Innovate UK.

1. INTRODUCTION

Belmana (2019) evaluates the causal impacts of the business support from Innovate UK and the National Measurement System (NMS). Using data on support provided by both institutions linked with firm-level data from the ONS Secure Research Service, it estimates the impacts by comparing outcomes for supported businesses with groups of similar unsupported businesses. Since the focus of this report is on the NMS, the discussion henceforth relates to the impact generated by support from the NMS laboratories.

1.1. THE NATIONAL MEASUREMENT SYSTEM AND THE NATIONAL PHYSICAL LABORATORY

The NMS is the backbone of the UK's measurement standards. It ensures that the country has a consistent and internationally recognized basis for measurement that caters to a wide range of activities in trade, industry, and regulation. The Department for Science, Innovation & Technology (DSIT) supports the NMS through six core measurement laboratories that maintain, develop, and disseminate measurement standards. Over 80% of the entire NMS funding goes to the National Physical Laboratory (NPL), which is a public corporation owned by the DSIT and specializes in metrology (measurement science). Much of the remaining NMS funding is received by the National Measurement Laboratory (NML) hosted at LGC (formerly the Laboratory of the Government Chemist) and the National Engineering Laboratory (NEL).

The NPL's research facilitates the development of primary standards and cutting-edge instrumentation. It also interacts with private businesses, hospitals, and academic institutions through collaborative R&D as well as supplying commercial calibration, testing, consultancy, and training services to such organizations.

The following figures provide some characteristics of the NPL and its place within the UK economy[4]:

- 774 scientific and technical staff, 268 administrative staff, as well as over 200 PhD student researchers.
- A turnover of around £104m; £57.3m of that revenue in annual NMS funding.
- Around 534 articles published in peer-reviewed scientific journals; also, its scientists perform over £38m of public research work. The pool of knowledge generated through the NPL's scientific work can be accessed and used by businesses.
- £13m of revenue from sales of measurement services. The R&D performed by NPL supports the introduction of new and improved calibration services, whose benefits fan-out down the calibration chain.
- Around 7% of all business R&D (£1.7 billion) is directed at instrumentation. NPL works closely with instrument manufacturers to develop complementary calibration services.
- Sells services to around 500 UK-based firms each year. And the lab's scientists collaborate on R&D projects with around 200 UK-based firms each year.

Given the magnitude of the NPL's, and more broadly the NMS's, involvement in the UK economy, it becomes important to evaluate the impact that it generates for the supported businesses. Belmana's research builds on earlier work (BEIS, 2017), augmenting it with new data that allows for a more robust analysis and improved impact measures.

1.2. ECONOMETRIC METHODOLOGY

Randomized experiments are considered the gold standard for evaluating causal effects; however, it is not possible to run them in every setting. In such cases, researchers rely on

[4] These figures are as of 2020. They might differ from the ones in Belmana (2019), which uses NMS support data for firms from 2002 to 2017.

observational data to study the impacts of an intervention/policy. In an experiment, the treatment (NMS support) would be randomly assigned to businesses, and the difference between the average outcomes for supported and unsupported businesses would then provide an estimate of the average causal impact of NMS support. However, in an observational setting, NMS support need not be randomly allocated, and businesses might self-select into support. If there are confounding variables that correlate with the outcomes as well as the likelihood of receiving support, then supported businesses may inherently differ from unsupported businesses and these differences could impact outcomes through channels other than support. For example, if large and R&D intensive firms are more likely to work with the NMS laboratories, then a difference in the research output (e.g., patents) between supported and unsupported businesses need not be attributable only to NMS support. Figure 1 graphically illustrates the causal relationship between different variables in this example, where the arrows represent the direction of causation:

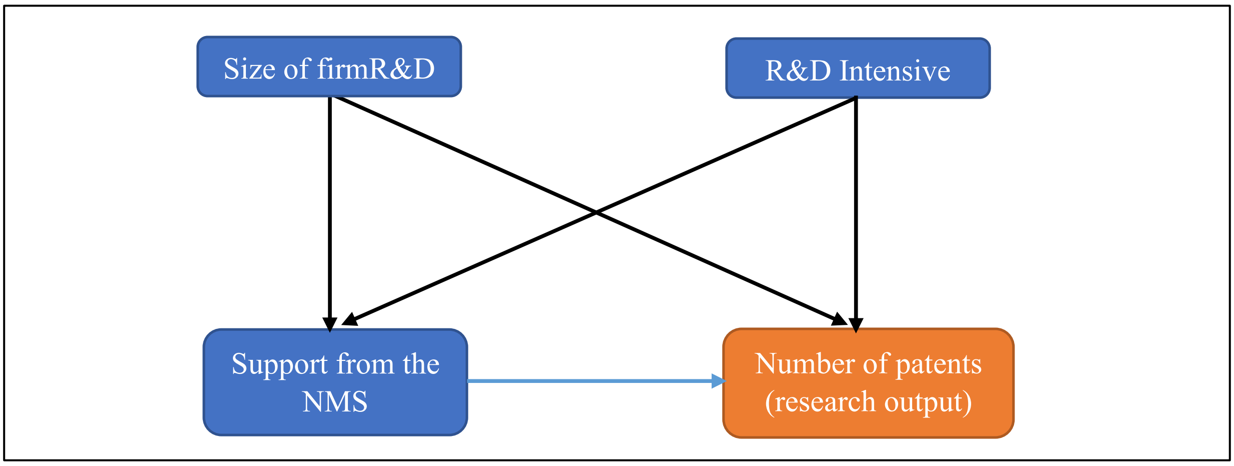


Figure 1: Causal relationships map

To overcome the issue of non-random assignment, Belmana (2019) models selection using a methodology called Propensity Score Matching (PSM). PSM estimates a score for the likelihood of a business receiving support, controlling for observed firm characteristics that can act as confounders, such as industry, age, size, location, whether a business conducts R&D or holds a patent, history of prior engagement with the NMS labs, and so on. Then, PSM matches supported businesses to one or more unsupported businesses based on the propensity score, thereby creating a counterfactual group. In this way, PSM seeks to mimic randomization since the propensity score is a balancing score: the distribution of measured baseline covariates is similar between supported and unsupported businesses, conditional on the propensity score. Figure 2 graphically illustrates the PSM model.

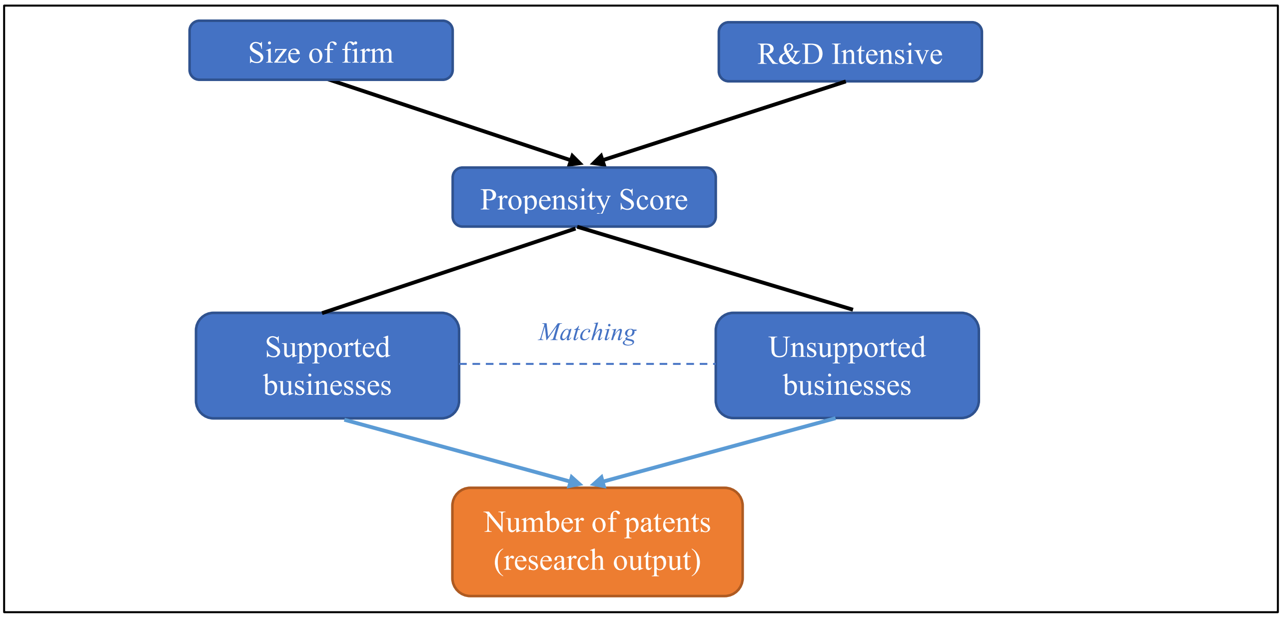


Figure 2: Graphical illustration of Propensity Score Matching

In a cross-sectional analysis, once PSM identifies a control or counterfactual group, comparing outcomes between the supported and unsupported businesses estimates the impact of the support. However, for several outcomes of interest, there is a time series of pre- and post-support performance. In such scenarios, a difference-in-differences (DiD) framework is used in conjunction with PSM to estimate the impact of support. Formal outlines of the PSM model (including a discussion on identifying selection variables) and DiD model are presented in the next section.

1.3. DATA

Belmana's econometric analysis relies on several key databases, as follows:

- The Office for National Statistics (ONS) Business Structure Database (BSD): The BSD is an annual snapshot of all UK businesses based primarily on tax registers (VAT and PAYE records) that goes as far back as 1997. The BSD data are sub-divided into enterprises and local units, and includes information on employment, turnover, sector (SIC code), age, location, business survival, and so on, for all employers and economically significant non-employers in the UK.
- The Annual Respondents Database (ARD) and the Business Enterprise Research and Development (BERD) survey: The ONS Annual Business Survey (ABS) is compiled into a panel called the Annual Respondents Database (ARD) and the ONS Business Expenditure on Research and Development (BERD). These data are derived from random, stratified surveys focused primarily on larger businesses. Therefore, both datasets have low sampling ratios for small and medium-sized enterprises (SMEs) but provide considerable information on impact measures beyond turnover and employment for large businesses. The ARD ranges from 1970 to 2016, and it contains variables on gross value added, capital expenditure, and employment necessary for computing productivity measures. The BERD data starts from 1993. The survey sample is drawn from a running register of firms that engage in R&D activities in the UK, and it records the businesses' R&D expenditure, source of funding for and employment in R&D activities. The sample size of BERD is approximately 5,400 businesses (4,000 Great Britain and 1,400 Northern Ireland). The BERD and the ARD are matched using a 'reporting unit' identifier.

- Financial Analysis Made Easy (FAME) database: Financial data obtained from company annual reports, which includes information on sales, profits, assets, wages, sector (SIC code), R&D expenses, and so on.
- Intellectual Property Office lists of trademarks and patents and the World Patent Statistical Database (PATSTAT): PATSTAT is a database containing bibliographical information relating to more than 100 million patent documents dating as far back as 1844 from leading industrialised and developing countries.
- Annual Survey of Hours and Earnings (ASHE): Microdata on individual employees that allows analysis of the earnings effects of the support. ASHE comprises of a 1% sample drawn from HMRC's PAYE system based on the last two digits of an employees' National Insurance number. Employers of the selected employees then fill out surveys that record information on the employees' occupation, hours, wages (including overtime), bonuses, and so on. Because of large sample size and an expansive coverage of employee jobs, the earning statistics are high-quality and reliable. Moreover, the panel nature of the data allows tracking employees over time, even as they switch jobs or have spells when they are not working.
- NMS data on funding beneficiaries: It contains data for supported firms from 2002 to 2017, where support consists of three different possible interventions: paid for contract R&D or measurement services, contracted collaboration with NMS, and free website downloads. The dataset also includes years of support and organization type. Many businesses sought multiple types of interventions, however, Belmana's analysis excludes businesses that only accessed free website downloads (data on which has been collected since 2007) because it is not expected to generate material impact on the outcomes. However, accessing downloads is used as a characteristic in propensity score calculation in the selection (matching) model.

There are about 500 businesses in the NMS dataset, and many of them receive support more than once and appear across multiple years. The study attempts to deal with the issue of repeat recipients in two ways. First, it adds prior treatment as a characteristic in the selection model to control for the effect of previous treatment. Second, it analyses the recipients in a year and focuses on those businesses that are first-time recipients in that year. However, due to a relatively small number of businesses in the NMS dataset, any analysis by the year of support leaves very few firms. Moreover, the relationship between the NMS and firms that seek support from it displays strong persistence – around half of the beneficiaries in any year had some interaction with the NMS in the preceding year as well. Therefore, it is hard to observe any meaningful results based on an analysis by the year of support.

The study employs a slightly different approach for defining the treatment variable. **Businesses with an incidence of NMS support in more than 85% of the years that they are observed in the ONS data are classified as "regularly supported." This is roughly equivalent to being supported for 5 or more years in a 6-year period. Businesses with one or more incidences of support but are not regular users are classified as "sometimes supported."**

1.4. SUMMARY OF MAIN EMPIRICAL FINDINGS

The study looks at various outcome measures of economic activity that include employment impacts (using the number of jobs as well as in terms of job years), impacts on business survival, and impacts on innovation (patent activity) across businesses. It also examines impacts on productivity measures like real turnover, wage premiums, and the quality of patents. Below are the study's key findings about the impact of NMS support on these outcomes:

- Between 2009 and 2015, 175 regularly supported businesses record an increase of over 23,000 jobs years. This corresponds to an increase of 5.5% in economic activity.

- Around 80% of the employment growth observed in regularly supported businesses is missing in the matched control group businesses, which means that more than 18,000 newly created job years in the regularly supported firms are additional over the comparator businesses.
- Only 4% of the businesses that regularly received NMS support from 2010 had shut down by 2017. In contrast, over 10% of the matched unsupported businesses had closed during this period. The differential impact of support on business survival translates into an additional impact of 4,404 job years.
- Quick divergence in real turnover growth is observed between supported and matched unsupported businesses. For instance, real turnover for business receiving NMS support in 2012 grows almost 11% by 2015. Within the same period, real turnover for matched unsupported businesses falls by 2.3%.
- Businesses supported by the NMS tend to generate patents with higher spillovers, measured using patent citation index. Starting from 2001, the index for supported businesses is consistently higher by 10-70% as compared to unsupported businesses.
- Employees who switch jobs into NMS supported businesses receive about a £78 per week wage premium on average, and the premium stays statistically significant after controlling for employee age and occupation.

1.5. MICROECONOMIC FOUNDATION

An important element that is relatively unexplored in Belmana's analysis is how economic theory can explain the empirical findings. A value added of this report is that it introduces a microeconomic foundation that explores how businesses react to support from the NMS laboratories, thereby explaining the economic mechanisms through which support translates into outcomes. This subsection contains a non-technical outline of the microeconomic framework, and Annex 2 presents a formal model.

Consider a model where each business produces and sells a portfolio of products that determine its turnover. Businesses adjust their labour employment based on their turnover. Also assume that all products that businesses produce are unique, that is, they behave like monopolists in the product markets. There is a product life cycle such that every year one or more of the existing products either go obsolete (creative destruction) or other competitive businesses enter the market, thereby ending the monopoly profits for the product(s). Businesses can thus be thought of as "temporary monopolists." However, the businesses come up with ideas for new products to replace the older products that exit their portfolio. Figure 3 below represents this product life cycle. The turnover of a business grows (or declines) if the rate of new products entering its portfolio is greater that (or less than) the rate of old products leaving its portfolio. Although not all ideas result in successful innovations because sometimes the new products are not economically viable. For instance, it is possible that the technology available to a business might not be adequate for it to produce a new item in a cost-effective way, meaning that the willingness-to-pay among its potential customers might not exceed the lowest attainable unit cost of its production process. Access to better technology can raise the business's Total Factor Productivity (TFP) and bring down its unit cost, thereby increasing the possibility that an idea successfully leads to a new product.

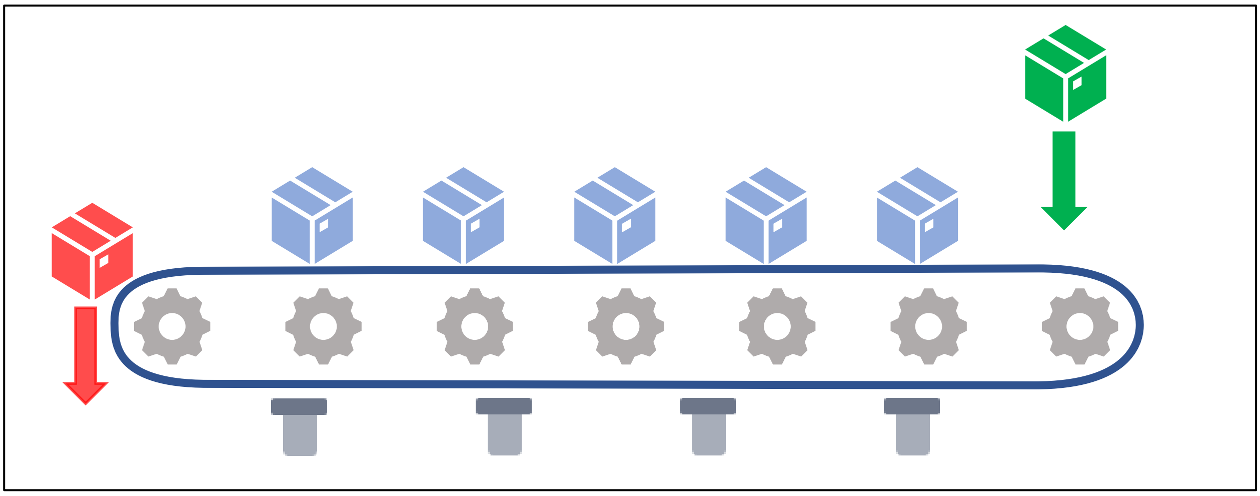


Figure 3: Product life cycle

To gain access to relevant technological knowledge, businesses can seek support from NMS laboratories like the NPL. NPL does not directly help businesses develop ideas for new products, however, it offers them technological know-how in exchange of a fee that helps them bring down the production costs and make these new products more efficiently. Specifically, NPL's unique expertise is particularly relevant to engineering-based businesses that want to secure competitive advantage through access to measurement technologies that underpin effective production techniques. Therefore, the NPL helps the businesses develop their products in a way that would not have been possible without the support. The technology that the NPL provides comes in the form of tacit knowledge that is either embodied in its technical services or accessed through long-term collaborations with its researchers.[5] The businesses can rent this knowledge, but they cannot own it because it is hard for them to develop or sustain such technological knowledge by themselves.[6] It is also reasonable to assume that the 'reliability' of this tacit knowledge tends to degrade over time. For instance, consider the customers who access NPL's comprehensive high-quality calibration services to ensure that the instruments which form a part of their production processes comply with recognized standards. The instruments are likely to go out of calibration with repeated use and thus the customers need to get them recalibrated at regular intervals for proper functioning.[7] Likewise, R&D collaborations with NPL's scientists are often long-term projects. Therefore, businesses must work with NPL over multiple years in order to have continued access to this stock of tacit knowledge and to develop long-term capabilities. This relates to the idea of "regularly supported" businesses that are observed in the data.

In comparison, businesses that are less frequent users or non-users of NPL's services are less likely to have access to cutting-edge technological knowledge that allows them to successfully innovate new products. Since monopoly profits on older products tend to vanish over time, the portfolio of unsupported businesses is likely to shrink as they are unable to innovate new

[5] It is reasonable to think that even NPL does not "own" this tacit knowledge. It is rather "owned" by the specialist staff (scientists and engineers) that are employed by NPL. A part of this knowledge is purely tacit and can only be transmitted by collaborating directly with these specialists. Whereas another part of this tacit knowledge can either be codified (through research papers and standards) or used to create embodied knowledge that can be utilized by businesses through paid-for services.

[6] Consider a cycle repair shop as an analogy. The mechanic at the shop "owns" specialist knowledge about the nuts and bolts of how a bike works. While a general person who uses a bike on an everyday basis can also learn these details, it is often not to their advantage to do so and to invest in tools required to repair their bike every time something breaks down. Rather, most people opt to take their bikes to the mechanics and pay for the specialist service that they offer.

[7] In the cycle repair shop analogy, there is constant wear and tear that comes with regular use. Therefore, one must take their bike to the mechanic every few months for standard servicing and maintenance in order to keep the bike running smoothly.

products at a fast-enough pace. As their turnover falls, they demand less and less labour, resulting in a fall in their employment levels. A falling demand for labour also has a negative impact on the wages paid by these businesses. On the contrary, regularly supported businesses are more likely to successfully innovate new products. As their portfolio expands and turnover increases, they demand more labour to produce these new items. As a result, regularly supported businesses experience a growth in employment. A higher demand for labour and increased labour productivity that comes with access to better technology means that there is a positive impact on the wages paid by regularly supported businesses.

The rest of the report is organized as follows. Section 2 presents a formal outline of the econometric models involved in the analysis: PSM, identifying selection variables, and DiD. Section 3 discusses the main findings from Belmana's analysis. This section focuses on developing an intuitive understanding of the econometric results. The Belmana study also introduces the idea of a continuous treatment variable and dosage modelling, however, it leaves the topic open for further exploration. Section 0 builds on Belmana's pilot analysis to explore how generalized propensity scores can be used to evaluate impacts with alternate treatment definitions. For example, can we use the existing impact estimates with the dose response function to deduce meaningful results if we modify the definition of regularly treated firms? Section 5 concludes with a discussion on possible caveats of the existing analysis and how they can be addressed in a future study. Since the primary goal of the report is to make the findings accessible for a general audience, the attempt in the main text is to keep the exposition simple without using complex mathematics. For those also interested in a more technical exposition, Annex 2 contains a simple theoretical model for how firm behaviour responds to NMS support and provides a deeper understanding of the channels through which support translates into outcomes for businesses. The model attaches a formal structure to complement the existing empirics.

2. ECONOMETRIC APPROACH

Underlying Belmana's empirical analysis is a *"model of change"* that captures how businesses evolve in response to support from NMS laboratories. Consider the following notation: y_i denotes the observed outcome for business i, where the outcome can be employment, real turnover, business survival, number of patents, wages of employees, and so on; and D_i denotes the treatment dummy that is equal to 1 if business i is regularly supported by the NMS, and 0 if it is unsupported. The focus of the analysis is on businesses that record an incidence of support between 2009 and 2015, and businesses that receive support in more than 85% of these years are classified as regularly supported.

2.1. OUTCOME MODEL

To examine the impact generated by NMS support, the goal is to obtain a measure of the causal relationship between treatment status D_i and an outcome of interest y_i. Let us refer to this as the *"outcome model."* An obvious starting point is to regress y_i on D_i, where the regression coefficient captures the difference between the average outcomes for regularly supported and unsupported businesses. However, if there are other factors that influence a firm's outcome as well as its decision to seek NMS support, then failing to account for them in the regression would mean that the coefficient does not capture the true causal impact of support on outcome. To resolve this issue of omitted variables, the regression equation can be modified to include a set of covariates that are expected to impact the outcome and the treatment status. Box A presents the basics of these linear regression models.

BOX A: Linear Regression Models

Suppose the relationship between NMS support and business outcomes is linear, then the "outcome model" can be expressed via following regression equation:

$$y_i = \alpha + \theta \cdot D_i + \varepsilon_i$$

Equation 1

ε_i is an idiosyncratic error term with mean zero that accounts for influences upon y_i from sources other than D_i. If a business goes from being unsupported ($D_i = 0$) to being regularly supported ($D_i = 1$), then its outcome can be expected to change by an amount θ. That is, one could say that θ provides an estimate of the average impact that NMS support generates on the outcome. But for this to be true, D_i must be uncorrelated with ε_i. In other words, there must not be anything contained in the error term that influences the treatment status of businesses. If there are such omitted variables that affect the treatment status and separately affect the outcome, then θ does not capture the true impact of NMS support. A common way to overcome this problem is to include a set of observed covariates in the regression equation that might be correlated with treatment status as well as outcome, as shown below:

$$y_i = \alpha + \theta \cdot D_i + \boldsymbol{X_i^T}\boldsymbol{\beta} + \varepsilon_i$$

Equation 2

where $\boldsymbol{X_i}$ denotes a column vector of observed pre-treatment covariates for business i and $\boldsymbol{X_i^T}$ denotes its transpose; and $\boldsymbol{\beta}$ is a column vector of parameters with the same dimension as $\boldsymbol{X_i}$. Directly controlling for these covariates in the regression reduces the chance that D_i is correlated with ε_i due to omitted variables, thereby making it possible to interpret θ as the causal impact of D_i on y_i.

There is a trade-off between risk of bias and precision as we add covariates to the regression model. A failure to include important variables can lead to unbiased estimate of θ. Thus, it is reasonable to think that a sensible way to minimize this risk is to control for as many covariates as possible in the regression. However, adding extra variables that are unimportant to the model has consequences for the precision of the estimated parameters.

2.2. INCORPORATING SELECTION INTO THE MODEL

Adding covariates to the linear regression model is one approach to account for observable systematic differences between the treated and untreated groups. Belmana's analysis employs a different econometric approach that starts by *"modelling selection into treatment"* to identify a counterfactual group – a set of unsupported businesses that are "similar" to the supported businesses. A comparison of outcomes between the supported businesses and the counterfactual then provides estimates of the economic impacts of the support. Of course, the validity of the estimates relies on how well the counterfactual group can be identified, which requires certain conditions to hold true. This subsection presents a formal outline of Propensity Score Matching (PSM) that was first introduced by Rosenbaum and Rubin (1983).

Let y_i^1 and denote the potential outcome for business i if it is treated, and y_i^0 denote the potential outcome if it is untreated. Then, the impact of support for business i is given by the difference $(y_i^1 - y_i^0)$. And the average treatment effect (ATE) $\hat{\alpha}$ can be calculated as:

$$\textbf{ATE}: \hat{\alpha} = E_i(y_i^1 - y_i^0).$$

Equation 3

where E_i denotes expectation with respect to the distribution of businesses in the sample.[8] However, only one of the two potential outcomes is observed for any business. If business i is treated, then y_i^0 is unobserved and if it is untreated, then y_i^1 is unobserved. The observed outcome y_i can be expressed in terms of the potential outcomes as follows:

$$y_i = D_i \cdot y_i^1 + (1 - D_i) \cdot y_i^0$$

Equation 4

Using observational data, it is possible to compute $E_i(y_i|D_i = 1)$[9] and $E_i(y_i|D_i = 0)$, but the difference $E_i(y_i \mid D_i = 1) - E_i(y_i \mid D_i = 0)$ would not be an unbiased estimate of the average treatment effect in the presence of confounding variables. Confounders are variables that are correlated with treatment as well as the outcome of interest, as depicted in Figure 1. In a randomized experiment, each subject has ex ante an equal probability of receiving treatment.

[8] In a sample of N businesses, expectation can be represented as sample mean. That is, $E_i(y_i^1 - y_i^0) = \frac{1}{N}\sum_{i=1}^{N}(y_i^1 - y_i^0)$. More generally, if X is a discrete random variable with a probability mass function (PMF):

$\boldsymbol{x}$	0	1	2	3
$\mathbf{Pr}\ (\boldsymbol{X} = \boldsymbol{x})$	0.2	0.3	0.4	0.1

Then $E(X) = \sum_x x \cdot P(X = x) = 0 * 0.2 + 1 * 0.3 + 2 * 0.4 + 3 * 0.1 = 1.4$

If X is a continuous random variable that takes values in the interval $[x_{low}, x_{high}]$ and has a probability density function (PDF) denoted by $f_X(.)$, then $E(X) = \int_{x_{low}}^{x_{high}} x \cdot f_X(x)dx$. Likewise, if $g(X)$ denotes a measurable function of X, $E\big(g(X)\big) = \int_{x_{low}}^{x_{high}} g(x) \cdot f_X(x)dx$.

[9] Let X and Y denote two events, then $\Pr(X \mid Y)$ is the conditional probability of X occurring given Y occurs. It can also be understood as the fraction of probability of Y occurring that intersects with X. That is, $\Pr(X \mid Y) = \frac{\Pr(X \cap Y)}{\Pr(Y)}$. When X and Y are random variables, the conditional probability $\Pr(X = x \mid Y = y)$ can be interpreted in a similar way.

The conditional expectation $E(X|Y)$ is defined analogously to conditional probability.

- If X is a discrete random variable and Y is an event with nonzero probability, then $E(X|Y) = \sum_x x \cdot \Pr(X = x|Y) = \sum_x x \cdot \frac{\Pr(\{X=x\} \cap Y)}{\Pr(Y)}$, where the sum is taken over all possible outcomes of X.
- If X and Y are discrete random variables, then $E(X|Y = y) = \sum_x x \cdot \Pr(X = x|Y = y) = \sum_x x \cdot \frac{\Pr(X=x, Y=y)}{\Pr(Y)}$, where $\Pr(X = x, Y = y)$ is the joint probability mass function of X and Y and the summation is taken over all possible values of X.
- If X and Y are continuous random variables, then $E(X|Y = y) = \int_{-\infty}^{\infty} x \cdot f_{X|Y}(x|y)dx = \frac{1}{f_Y(y)}\int_{-\infty}^{\infty} x \cdot f_{X,Y}(x, y)dx$, where $f_{X,Y}(x, y)$ denotes the joint PDF of X and Y, $f_Y(y)$ denotes the PDF of Y, and $f_{X|Y}(x|y)$ denotes the conditional PDF of X given the event $Y = y$.

Thus, if the sample size is large enough, randomization ensures that confounders are balanced on average across the treatment and control groups. However, in observational data, subjects often self-select themselves into treatment which leads to selection bias. As defined by Angrist (1998) and Heckman et al. (1998), selection bias can be mathematically expressed as the difference between average untreated potential outcomes of the treated and untreated groups:

$$\textbf{Selection Bias}: E_i\left(y_i^0 \middle| D_i = 1\right) - E_i\left(y_i^0 \middle| D_i = 0\right).$$

Equation 5

It represents a systematic difference between the treated and untreated subjects that might impact the likelihood of treatment as well as outcomes. PSM attempts to reduce this bias by finding a counterfactual group that is like the treatment group in all observable respects except the exposure to treatment, thereby rendering the comparison between these groups more meaningful. If $\boldsymbol{X_i}$ denotes a vector of observed pre-treatment covariates for business i, then propensity score is defined as the probability of treatment conditional on $\boldsymbol{X_i}$. That is,

$$\textbf{Propensity Score}: p(\boldsymbol{x}) = \Pr(D_i = 1 | \boldsymbol{X_i} = \boldsymbol{x})$$

Equation 6

Rosenbaum and Rubin (1983) show that the propensity score is a balancing score. That is, for a given value of propensity score, the distribution of covariates is the same across treated and untreated businesses. That makes it possible to directly compare treated and untreated businesses with similar propensity scores. PSM relies on two key assumptions. Box B discusses these assumptions, their implications, and how Belmana's analysis attempts to ensure that these assumption hold. In addition to the two assumptions discussed below, there is another assumption standard across all inferential tests referred to as the Independent Observations Assumption. It says that the observations in the sample are independent of each other, meaning that the measurements for each business in the sample are in no way influenced by or related to the measurement of other businesses.

BOX B: Assumptions in Propensity Score Matching

$$\textbf{Conditional Independence Assumption (CIA)}: (y_i^1, y_i^0) \perp D_i \,\big|\, \boldsymbol{X_i}$$

Assumption 1

CIA implies that selection is solely based on observable covariates and controlling for these covariates would mean that the treatment assignment is "as good as random." In the current setup, this assumption implies that the potential outcomes of businesses are not influenced by NMS support once we account for the covariates that affect the probability of a business seeking support. If this were not the case, that is, if businesses choose NMS support based on their potential outcomes (or expectations about their potential outcomes), then the choice to opt for support is still not "random" after conditioning on $\boldsymbol{X_i}$. The important thing to note here is that this assumption does not mean that the observed outcome is conditionally independent of NMS support. Rather, it posits that once the observable characteristics have been accounted for, the observed outcome is related to the treatment status only via the impact of NMS support. CIA allows the unsupported businesses to be used to construct a counterfactual for the supported businesses, enabling the estimation of the average treatment effect as

$$\textbf{ATE}: \hat{\alpha} = E_x\{E_i(y_i | D_i = 1, \boldsymbol{X_i} = \boldsymbol{x}) - E_i(y_i | D_i = 0, \boldsymbol{X_i} = \boldsymbol{x})\},$$

Equation 7

where E_x denotes expectation with respect to the distribution of $\boldsymbol{X}$ in the entire population of the businesses.[10] For a formal proof, refer to Annex 1. Rosenbaum and Rubin (1983) show that under CIA, it follows from Equation 7 that

$$\textbf{ATE}: \hat{\alpha} = E_{p(x)}\{E_i(y_i|D_i = 1, p(\boldsymbol{x})) - E_i(y_i|D_i = 0, p(\boldsymbol{x}))\},$$

Equation 8

where $E_{p(x)}$ denotes expectation with respect to the distribution of $p(\boldsymbol{X})$ in the entire population of businesses.[11] In words, untreated businesses with the same propensity scores as that of treated businesses can act as their control group in the sense that the expected difference in responses gives the average treatment effect.

The second assumption is as follows:

$$\textbf{Common Support Assumption}: 0 < \Pr(D_i = 1|\boldsymbol{X_i}) < 1 \ \forall \boldsymbol{X_i}$$

Assumption 2

This assumption simply states that there is a sufficient overlap in the characteristics of the supported and unsupported businesses to enable matching. If there were some $\boldsymbol{X_i} = \boldsymbol{x}$ such that $p(\boldsymbol{x}) = 1$ (or $p(\boldsymbol{x}) = 0$), then there would be no unsupported (or supported) businesses for the given values of the covariates. Thus, the common support assumption ensures that the proportion of treated and untreated businesses is greater than zero for all possible values of $\boldsymbol{X}$. Of course, this might not always hold true and there could be outlier values of propensity score for which only supported or unsupported businesses are observed in the data. Belmana's analysis takes care of this issue by trimming the data to remove outliers. That is, the study includes only those businesses that have propensity scores between the 25th and 75th percentiles, thereby excluding businesses that are either very unlikely or highly likely to receive NMS support. As a consequence of trimming, the analysis focuses on more typical businesses.

2.3. IMPLEMENTING PSM

With this result in mind, PSM can be implemented using the following steps to evaluate the impact of NMS support:

Step 1: Estimate propensity score $p(\boldsymbol{x})$ for each business i using a discrete choice model such as probit or logit, where the dependent variable is D_i and the regressors include appropriate confounding variables $\boldsymbol{X_i}$.

The choice of which variables to include in the selection model can be informed by common sense. The variables included in Belmana's analysis can be broadly classified into three categories.

The first category consists of variables related to firm characteristics like size, age, location, and industry.[12] Since NPL sells unique services that are often quite expensive, most of its

[10] A simple toy example of how $E_X\{.\}$ is computed in Equation 7 – Consider the only confounding variables are business size (Small or Large) and business involvement in research intensive activities (R&D or Not-R&D), then the sample of businesses can be split into the following 4 groups: (Small, R&D); (Large, R&D); (Small, Not-R&D); (Large, Not-R&D). First, the average outcomes for treated and untreated businesses are computed separately within each of the 4 groups. The difference between the average treated and untreated outcome within each group provides an estimate of the ATE for that group. ATE for the entire sample of businesses is then calculated as the weighted average of the ATEs for the 4 groups, where the weight for each group represents the fraction of businesses belonging to that group.

[11] Suppose $f_{p(X)}(.)$ denotes the PDF of propensity scores in the sample of businesses, then Equation 8 can be computed as $\int_{p(x)} \left(E_i(y_i|D_i = 1, p(x)) - E_i(y_i|D_i = 0, p(x))\right) f_{p(X)}(p(x))dp(x)$.

[12] "Industry" here refers to sector, like manufacturing versus non-manufacturing, service versus non-service, and so on. The analysis also slices these sectors based on high/medium knowledge intensive (KI) manufacturing and services. However, we believe that the "industry" controls here do not include 2-Digit SIC (Standard Industrial Classification) code dummies. Having these dummies would create problems for the analysis because then we

customers tend to be larger, well-established businesses that tend to operate in advanced manufacturing-related industries and can afford to pay for its services. Geographical location can also impact the probability of treatment, with businesses that are located closer to the NPL more likely to seek support.

The second category includes variables that capture past innovation activity like R&D spending, holding intellectual property such as trademarks and patents. Since R&D collaborations are one mode of NMS support, firms that operate in more innovative and R&D intensive sectors are more likely to build collaborations with the NMS laboratories. Also, it can be argued that there are increasing returns to R&D investments in the sense that existing knowledge helps in the development and growth of new knowledge. Thus, businesses operating in R&D intensive sectors would be more inclined to pursue collaborations with NMS laboratories.

The third category relates to evidence of prior interactions with NMS laboratories. As discussed in Section 1.5, there is an obvious advantage for businesses to work with NMS laboratories over multiple years. Additionally, there can be a non-trivial “search cost” initially for businesses to find out how the NPL and other NMS laboratories can support them, so it could be their best interest to use their services over multiple years once they have developed the know-how and know-who. This is corroborated by the invoicing data of NPL’s beneficiaries, where most businesses are observed to have incidences of support during multiple years. Belmana’s analysis uses these variables as regressors in a probit model to compute propensity scores, and summary statistics on these variables are presented in Section 3.1.

Step 2: Choose a matching algorithm that uses estimated propensity scores to match regularly supported businesses with unsupported businesses.
Belmana’s analysis uses nearest neighbour matching, which matches a treated business to the untreated business with the closest propensity score. There exist other matching algorithms as well, however nearest neighbour is the most straightforward method that requires no arbitrary choices. It is computationally less intensive because the matching is performed on a single metric (propensity score) and tends to perform well where the number of potential matches is high, as is the case with the data used in the analysis. It can be an issue if bad matches occur at a high rate, that is, the nearest neighbour is not very nearby. The analysis employs several tests to check the quality of matches, which are presented with the summary statistics in Section 3.1.

Step 3: Estimate the impact of NMS support within the matched sample and compute standard errors.
Once we construct a treated group and a matched control group, the impact of NMS regular support can be estimated by comparing average business outcomes between the two groups.

have got businesses within the same industry potentially competing for market share. That is, the outcomes for one business would impact outcomes for another business in the same industry, which would violate the independent observations assumption.

2.4. Difference-in-differences

Implicit in PSM is also the assumption that there is no selection on unobservables. In other words, PSM does not account for unobserved firm characteristics that might affect outcomes as well as the probability of businesses to seek NMS support. However, it is still possible to estimate causal impacts by tweaking the "outcome model" slightly if unobserved confounders have certain features. Specifically, when the data contains a time series of pre- and post-support performance (as is the case in Belmana's analysis) and the unobserved confounders are assumed to be time-invariant, their effect can be cancelled out by taking the difference in outcomes before and after the support. This method is called Difference-in-Differences (DiD). Figure 4 graphically depicts the DiD method.

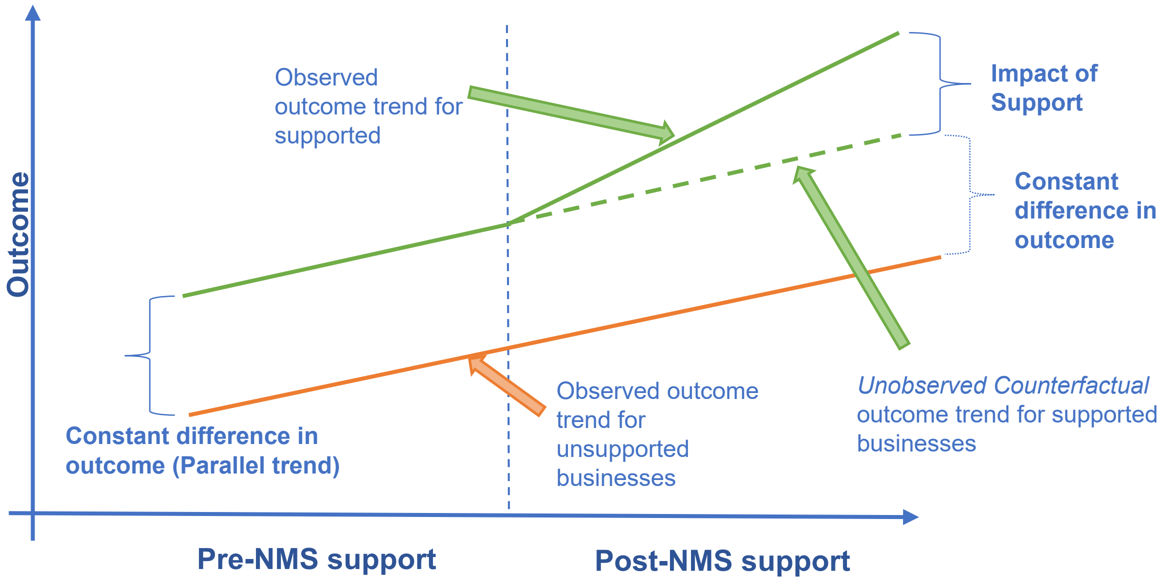


Figure 4: Graphical representation of Difference-in-Differences estimator

Implementing PSM with DiD is similar to the cross-sectional version discussed above, except that the average treatment effect is now measured for changes in outcomes between the pre- and post-support periods instead of levels of the outcomes. Thus, the dependent variable is the difference between outcomes in the pre- and post-support periods for both the treated and the untreated groups. That is,

$$\Delta y_i = y_{i,post} - y_{i,pre}$$

Equation 9

An advantage of combining DiD with PSM is that it allows relaxing the CIA. The counterfactual outcome of treated businesses can differ from the observed outcome of untreated businesses, as long as their trend is the same. This is also called the parallel trend assumption and is important for the DiD to work. It requires that in the absence of support, the difference in outcomes between the supported and unsupported businesses is constant. That is, the two groups were (and would have continued to stay) on a similar trajectory before one group received NMS support. The parallel trends assumption can be mathematically expressed as:

$$E\left(y^0_{i,post} - y^0_{i,pre} \middle| D_i = 1, \boldsymbol{X_i}\right) = E\left(y^0_{i,post} - y^0_{i,pre} \middle| D_i = 0, \boldsymbol{X_i}\right) \forall \boldsymbol{X_i}$$

Equation 10

Unlike CIA, it allows for unobserved imbalances to exist between the supported and unsupported businesses after matching. The DiD specification can eliminate any bias resulting from such imbalances as long as they are stable over time in their impact on the probability of businesses to seek NMS support and on the outcomes. Therefore, PSM in conjunction with DiD helps to control for any time-invariant unobserved heterogeneity that may exist between the treatment and control groups after matching.

The DiD matching estimator is simply implemented by calculating the propensity scores using covariates from the pre-support period and applying the steps described in Section 2.3 to the differenced outcome Δy_i. That is, the average treatment effect is calculated as follows:

$$\textbf{ATE}: \hat{\alpha} = E_{p(\boldsymbol{X})}\{E_i(\Delta y_i | D_i = 1, p(\boldsymbol{x})) - E_i(\Delta y_i | D_i = 0, p(\boldsymbol{x}))\}$$

Equation 11

When outcomes in the above model are measured as logged variables, then the DiD estimate can be interpreted as the difference in growth rates between the treated and untreated businesses resulting from the NMS support.[13] Belmana's analysis applies the econometric methodology described in this section to evaluate the impact of NMS support on various business outcomes. The key findings from the analysis are discussed in the next section.

[13] When outcomes are log transformed, the dependent variable in the DiD setup is given by:

$$\Delta \ln (y_i) = \ln (y_{i,post}) - \ln (y_{i,pre}) = \ln\left(\frac{y_{i,post}}{y_{i,pre}}\right).$$

Ignoring $p(x)$ in Equation 11 for simplicity, the DiD estimate for the ATE can be expressed as:

$$\hat{\alpha} = E\left(\ln\left(\frac{y_{i,post}}{y_{i,pre}}\right) \middle| D = 1\right) - E\left(\ln\left(\frac{y_{i,post}}{y_{i,pre}}\right) \middle| D = 0\right).$$

Suppose the first term is calculated to be 0.05. That is, $E\left(\ln\left(\frac{y_{i,post}}{y_{i,pre}}\right) \middle| D = 1\right) = 0.05 \Rightarrow E\left(\left(\frac{y_{i,post}}{y_{i,pre}}\right) \middle| D = 1\right) = e^{0.05}$.

The Taylor series expansion of e^x is given as $e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \cdots \approx 1 + x$ (for small values of x). Using this, the first term can then be expressed as $E\left(\left(\frac{y_{i,post}}{y_{i,pre}}\right) \middle| D = 1\right) \approx 1 + 0.05 \Rightarrow E\left(\left(\frac{y_{i,post}}{y_{i,pre}}\right) - 1 \middle| D = 1\right) \approx 0.05 \Rightarrow$ $E\left(\left(\frac{y_{i,post}-y_{i,pre}}{y_{i,pre}}\right) \middle| D = 1\right) \approx 0.05 \Rightarrow E\left(100 * \left(\frac{y_{i,post}-y_{i,pre}}{y_{i,pre}}\right) \middle| D = 1\right) \approx 5\%$.

In words, the first term is an approximate measure of the average growth rate (% change) in outcomes for the supported businesses. Likewise, the second term is an approximate measure of the average growth rate in outcomes for the unsupported businesses. And their difference represents the impact of NMS support on average growth.

3. MAIN FINDINGS FROM BELMANA'S ANALYSIS

3.1. SUMMARY STATISTICS

Table 1: Summary statistics, 2009 (Baseline Year)

Variable	Measure	All BSD	NMS Non-Users	Downloads Only	Regularly Supported†
Panel A					
Count‡		391049	387899	223	175
Employment	Mean	58.40	53.65	734.35	332.34
	Median	10	10	83	32
	Geometric Mean	9.14	9.02	89.60	44.33
Real Turnover (in £'000)	Mean	111.39	94.25	1894.22	747.31
	Median	8.87	8.83	97.50	37.83
	Geometric Mean	7.83	7.71	114.42	53.84
Patents	Mean	0.07	0.05	11.01	0.51
	Median	0	0	0	0
	Geometric Mean	1.86	1.75	4.44	2.02
Trademarks	Mean	0.16	0.12	6.99	4.08
	Median	0	0	0	0
	Geometric Mean	3.38	3.13	7.30	8.90
Live RU	Mean	1.06	1.06	1.79	1.35
	Median	1	1	1	1
	Geometric Mean	1.04	1.04	1.40	1.23
Panel B					
Age Category	< 2 years	14.8%	14.8%	0.0%#	0.0%#
	2-5 years	23.0%	23.0%	0.0%#	0.0%#
	6-10 years	23.4%	23.4%	7.7%	13.1%
	> 11 years	38.8%	38.8%	67.1%	86.9%
Employment Category	1-2 employees	70.6%	70.7%	17.1%	6.8%
	3-9 employees	20.4%	20.4%	10.1%	14.2%
	10-19 employees	4.6%	4.6%	9.4%	16.5%
	20-49 employees	2.7%	2.7%	12.2%	17.6%
	50-249 employees	1.3%	1.3%	29.4%	22.7%
	250+ employees	0.3%	0.3%	21.7%	22.2%
Other Categorical Variables	High KI Manufacturing	0.4%	0.3%	13.3%	24.4%
	High/Medium KI Manufacturing	1.2%	1.2%	27.3%	34.1%
	Manufacturing	5.6%	5.5%	38.8%	42.0%
	Scale-up	0.7%	0.7%	0.0%	0.0%#

NOTES: **† -** The regularly supported businesses included here are the ones that have propensity scores between the 25th and 75th percentiles and do not receive any Innovate UK funding.
‡ - Counts represent the number of businesses in each category, however, not all variables are available for each business.
# - True values are not reported as the count of businesses in the corresponding cell is less than 10.

Table 1 presents summary statistics in the baseline year (2009) to tease out the differences between four different groups of businesses: the entire BSD population, non-users of NMS laboratories, those that only accessed downloads, and businesses that were regularly supported by an NMS laboratory between 2009 and 2015. Regularly supported businesses tend to be larger and more innovation active compared to non-users of NMS services, as is evident from the variables in Panel A. They are also older, with around 87% of regularly supported businesses having been established for more than 10 years at baseline, compared to 39% in the non-users group. A much larger proportion of regularly supported businesses operate in the manufacturing sector (42%) compared to 5.5% for the non-users. And almost a quarter of the regularly supported businesses operate in high knowledge intensive manufacturing sector. These differences provide evidence that businesses self-select into receiving regular support by NMS laboratories. That is, a direct comparison of outcomes for regularly supported businesses and non-users will not provide a true picture of the impact of support because any differences in their outcomes could be driven by a combination of NMS support and underlying systematic differences between the two groups. PSM helps construct a control group of businesses that is similar at baseline to the regularly supported businesses.

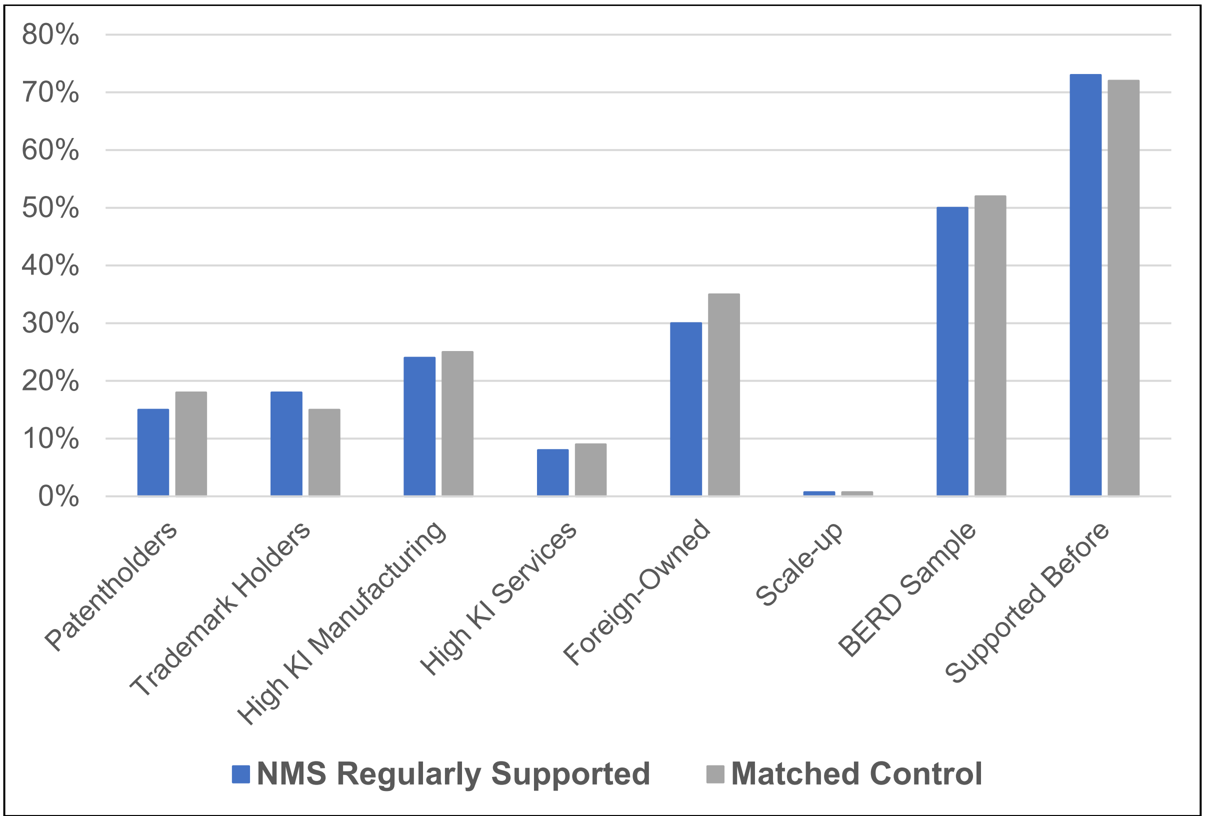


Figure 5: Characteristics of NMS regularly supported and matched control businesses

Figure 5 explores the characteristics of regularly supported businesses, looking at the fraction of businesses that hold a patent or trademark, industry and ownership categories, and whether businesses participated in the ONS Business Expenditure on R&D (BERD) survey. The effect of PSM in achieving a balance along these characteristics is quite marked, implying that the matched control group is very similar to the treatment group at baseline. Similarly, PSM also removes the imbalance observed in the age of the regularly supported businesses in comparison to the wider business population.

3.2. EMPLOYMENT GROWTH

The main analysis sample in Belmana’s study consists of a subset of businesses that are regularly supported by the NMS laboratories after 2009. This subset only includes businesses with propensity scores between the 25th and 75th percentiles. By doing so, it removes outliers that might contaminate the analysis. For example, very small firms that employ few people can potentially grow a lot within a year. In contrast, very large firms can relatively grow only by a small amount even in a good year. Trimming ensures that such extreme businesses are less likely to be included in the analysis.[14] Besides such trimming, the main analysis sample also excludes businesses that won Innovate UK grants in addition to being regularly supported by the NMS laboratories. These are generally large businesses with multiple innovation streams that tend to have overlapping support from Innovate UK and the NMS. Excluding businesses that also won Innovate UK grants ensures that any differences in outcomes between the treated and comparison groups can be attributed to NMS support (and not some combination of NMS and Innovate UK support). The untrimmed data consists of 358 businesses that are regularly supported by the NMS after 2009, of which 217 businesses have propensity scores between the 25th and 75th percentiles. Excluding firms that also received Innovate UK funding leaves 175 businesses in the main analysis sample.

Table 2 presents employment for these 175 regularly supported businesses between 2009 and 2015. The first row shows that they experience a growth in gross employment such that by 2015, they have 6,801 more jobs that they had in 2009. Adding up employment between 2009 and 2015 leads to a total of 430,693 job-years.[15] The second row tracks the yearly change in employment and the final column shows that between 2009 and 2015, a total of 23,573 job-years were added by these businesses.[16]

Table 2: Employment trends in regularly supported businesses

Regularly Supported	2009	2010	2011	2012	2013	2014	2015	Change in Jobs From 2009 to 2015	Job-Years
Gross employment for NMS supported businesses	58,160	57,622	59,554	61,693	62,684	66,019	64,961	6,801	430,693
Jobs added each year		-538	1,932	2,139	991	3,335	-1,058		23,573
Additional job-years†		-429	1,542	1,707	791	2,661	-844		18,809

[14] There is significant variation in the size of businesses even in the trimmed sample, which is evident from the numbers presented in Table 1. For instance, arithmetic mean (AM) and geometric mean (GM) of employment in the trimmed sample of regularly supported businesses at baseline are 332.34 and 44.33, respectively. For a list of k non-negative real numbers $(x_1, x_2, \dots, x_k)$, AM is defined as $\frac{x_1+x_2+\cdots+x_k}{k}$ and GM is defined as $\sqrt[k]{x_1 \cdot x_2 \cdots x_k}$. The AM-GM inequality states that the AM of a non-negative list of numbers is always greater than or equal to the GM, and the two means are equal if and only if every number in the list is the same (i.e., $x_1 = x_2 = \cdots = x_k$). Thus, a large difference between the AM and GM represents significant variation in the underlying list of numbers.

[15] A job-year is equivalent to one year of full-time work for one person. If a person is employed at a job for 3 years, then it amounts to 3 job-years even though it will be counted as one job. But if a person is employed at two jobs for 6 months each (or if two people are employed each for 6 months), it amounts to one job-year even though they will be counted as two separate jobs. Job-years is a more precise measure of employment activity than number of jobs because it also accounts for how long a job lasts.

[16] By definition, a job added (or lost) in the early years contributes more to the job-years calculation through the end of 2015 than a job added (or lost) in the later years. For instance, regularly supported businesses saw a fall of 538 jobs from 2009 to 2010, which is then multiplied by six years to understand the effect of this fall through the end of 2015. The fall was quickly reversed, with 1,932 jobs added between 2010 and 2011, which is multiplied by five years to understand the effect of this increase through the end of 2015. Overall, the job-years calculation becomes: -538*6 + 1,932*5 + 2,139*4 + 991*3 + 3,335*2 + -1,058*1 = 23,573.

†Additional job years are calculated using the additionality ratio that is computed in Table 3 below. Some statistics may appear internally inconsistent due to rounding.

To understand the causal impact of NMS support, the change in employment that is seen in regularly supported businesses needs to be compared to the change in employment that is seen in the counterfactual. It is possible to undertake this calculation using number of jobs as the outcome, but that can skew the estimated impact of NMS support. That is because regularly supported businesses tend to be larger firms that start with a very different average level of employment than matched controls. Thus, small growths in regularly supported businesses could reflect huge changes in their levels of employment. While huge growths in the matched controls would still reflect relatively small changes in their levels of employment. To avoid this issue, log of employment is used as the outcome variable instead of level of employment in the DiD model to estimate the employment growth rates for the two groups of businesses. An "additionality ratio" is then calculated as the proportion of growth that is seen in the treated group but not seen in the counterfactual group.[17]

Belmana's analysis focuses on the period between 2009 and 2013 for calculating the additionality ratio. As shown in Table 3, the growth rate during this period for the treated group is around 23% and that for the counterfactual group is around 5%. The resulting additionality ratio is approximately 0.80, which is used in the bottom row of Table 2 to estimate that out of the 23,573 job-years added by regularly supported businesses between 2009 and 2015, around 18,809 (=0.80*23,573) job-years are additional that are not observed in the matched counterfactual businesses. This avoids additional employment estimates being influenced by the differences in the size of businesses in the two groups.

Table 3: Estimates of additionality in jobs growth in regularly supported businesses

Growth in Treatment Group	Growth in Control Group	Difference-in-differences Estimate	Additionality Ratio
0.23	0.05	0.18*** (= 0.23 – 0.05)	0.8 (= 0.18/0.23)

**** significant at the 1% level; ** at 5%; * at 1%. Some statistics may appear internally inconsistent due to rounding.*

Note that the additionality ratio of 0.8 is based on employment growth observed between 2009 and 2013. Therefore, using it to calculate additional job-years throughout the 2009-2015 period involves an implicit assumption that this additionality ratio reasonably captures the average impact of NMS support on job growth through all the years. For an even more robust analysis, it is possible to estimate the additionality ratios separately by year to calculate the additional job-years, as shown in Table 4. The first row presents the estimated additionality ratios for each year from 2010 to 2015, which are based on employment growth observed from 2009 up until that year. These ratios are used to estimate that approximately 24,261 job-years in the regularly supported businesses are additional that are not observed in the matched counterfactual businesses, which is higher than the employment growth of 23,573 job-years observed in the regularly supported businesses. This calculation implies that without NMS support, employment in these businesses would have shrunk by around 688 (=24,261 – 23,573) job-years. Comparing results from Table 4 and Table 2 implies that Belmana's analysis might be slightly undercounting the actual impact of regular NMS support on employment growth.

[17] As shown in Subsection 2.4, growth in the treatment group is computed as $E(\ln(y_{i,post}) - \ln(y_{i,pre})|D=1)$ and growth in the matched control group is computed as $E(\ln(y_{i,post}) - \ln(y_{i,pre})|D=0)$. The DiD estimate is $\hat{\alpha} = E(\ln(y_{i,post}) - \ln(y_{i,pre})|D=1) - E(\ln(y_{i,post}) - \ln(y_{i,pre})|D=0)$, and the additionality ratio is computed as $\frac{\hat{\alpha}}{E(\ln(y_{i,post}) - \ln(y_{i,pre})|D=1)} = 1 - \frac{E(\ln(y_{i,post}) - \ln(y_{i,pre})|D=0)}{E(\ln(y_{i,post}) - \ln(y_{i,pre})|D=1)}$.

Table 4: Estimates of additionality in job growth in regularly supported businesses (by year)

	2009	2010	2011	2012	2013	2014	2015	Job-Years
Additionality Ratio		2.91	1.95	0.96	0.80	0.76	0.71	
Jobs added each year		-538	1,932	2,139	991	3,335	-1,058	23,573
Additional job-years‡		-1568	3777	2054	752	2553	-752	24,261

‡Additional job-years are calculated separately for each year as the product of that year's additionality ratio and the number of jobs added. Some statistics may appear internally inconsistent due to rounding.

Figure 6 plots employment trends for the NMS regularly supported businesses and the matched control group. To focus on employment growth, the 2009 employment levels in both groups are indexed to 100. The difference in growths between the two groups is consistent with the DiD estimate in Table 3. While the DiD estimate focuses on growth until 2013, it is clear from Figure 6 that these differentials persist for much of the 2009-2015 period.

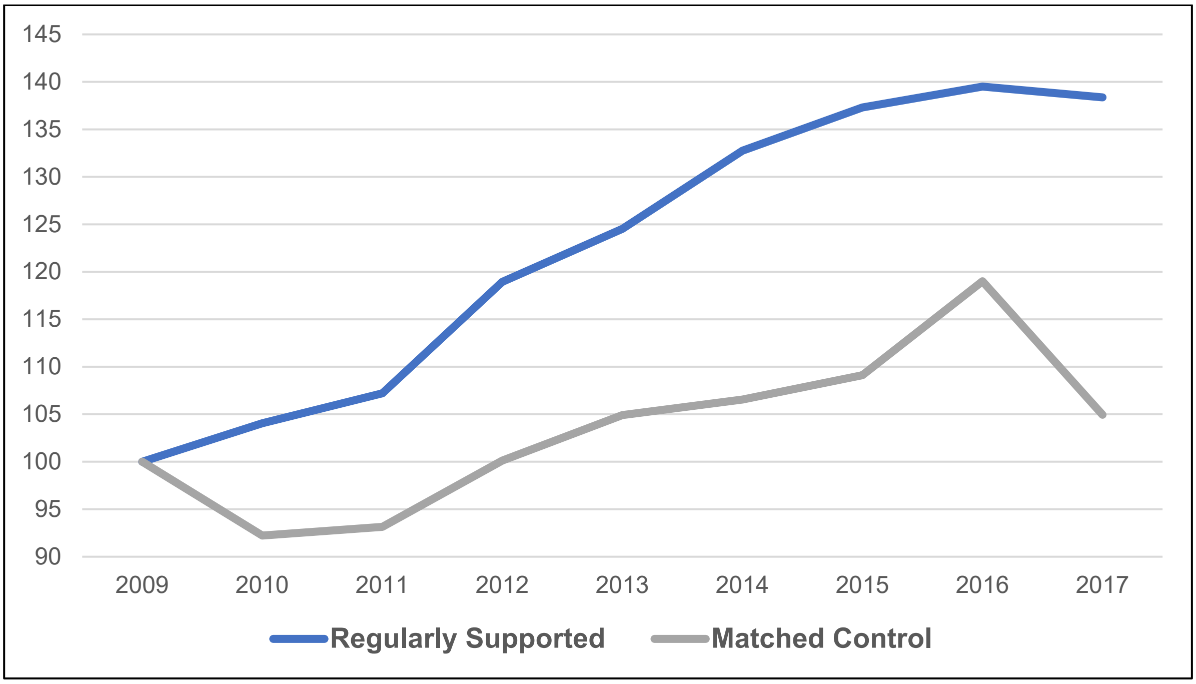


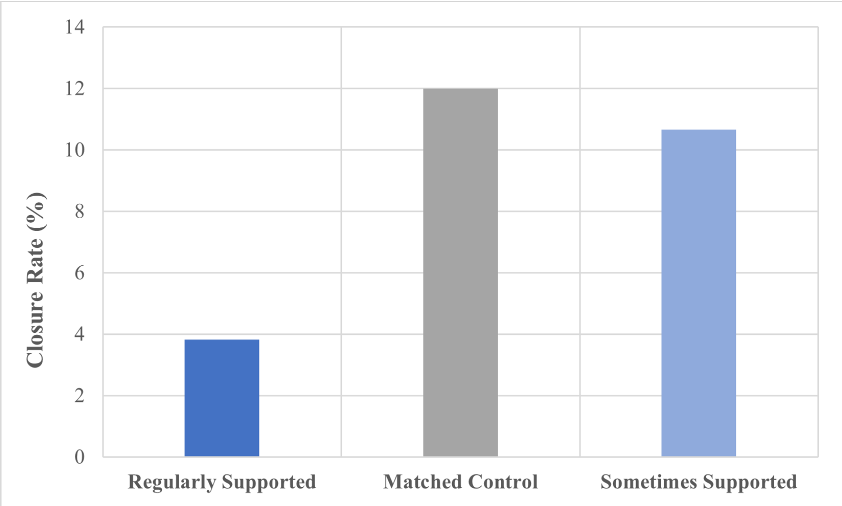
Figure 6: Employment growth for NMS regularly supported businesses vs matched controls

The empirical evidence of employment growth attributable to NMS support corroborates the theoretical hypothesis discussed in Subsection 1.5. Regular support from NMS laboratories enables businesses to successfully innovate new products at a higher rate. As their portfolio expands and turnover increases, they demand more labour to produce these new items. As a result, regularly supported businesses experience a growth in employment. Thus, the analysis so far can be thought of as capturing the employment impacts generated through the creation of new jobs due to NMS support.

3.3. BUSINESS SURVIVAL

The microeconomic framework in Subsection 1.5 introduces the idea of product life cycle where existing products either go obsolete and are replaced by new ones (creative destruction) or other competitive businesses enter the market, thereby ending the monopoly profits for the existing product(s). The portfolio of businesses shrinks over time if they cannot innovate regularly, and they run the risk of closing if they are unable to make any profits. It is reasonable to believe that NMS support should have a positive effect on the probability of business survival. As a result, supported businesses are also better able to safeguard existing jobs in addition to creating new ones.

Panel A: Business closure rate by 7 years



Panel B: Business survival functions (Kaplan-Meier curves)

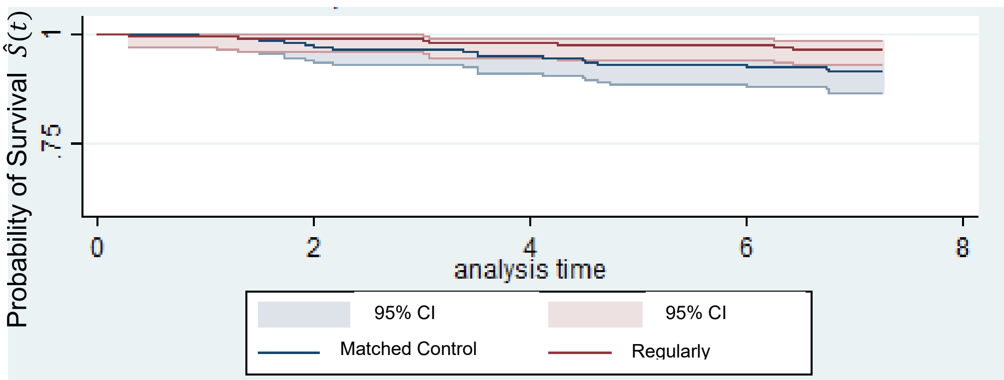


Figure 7: Survival of NMS regularly supported businesses vs matched controls

Panel A of Figure 7 shows that only 4% of businesses that receive regular NMS support after 2009 had closed by 7 years as compared to 12% of businesses in the matched control group. For comparison, 11% of businesses that only sometimes received NMS support after 2009 had closed by 7 years, which is similar to the closure rate in the matched control group. Panel B presents the survival functions (Kaplan-Meier curves) [18] through the seven-year period (2009-2016) for the two groups, which show that the matched control group is less likely to survive at each year following the start of NMS support. Although there is some overlap in the

[18] The Kaplan-Meier estimate of the survival function (Kaplan and Meier, 1958) is given by: $\hat{S}(t) = \prod_{i:t_i \le t}\left(1 - \frac{d_i}{n_i}\right)$, where $\hat{S}(t)$ denotes the probability that a business survives beyond t years after 2009; t_i is a time when at least one firm closed; d_i denotes the number of businesses that closed at time t_i; and n_i denotes the number of businesses that have survived up to time t_i.

confidence intervals for the two groups, particularly in the initial years, significant imbalance remains that suggests that NMS support has a positive impact on business survival.

To understand the employment impacts of differential business survival across the two groups, Belmana (2019) performs an additional analysis studying the effect on job-years. The analysis shows that higher chance of businesses surviving in the supported group results in an estimated 5,122 additional job-years. However, an increase of around 718 job-years occurs in businesses that would have closed without support.[19] Thus, the net employment impact of support through higher business survival is 4,404 (=5,122 – 718) job-years.

3.4. OVERALL EMPLOYMENT IMPACT

The overall employment impact attributable to NMS support comprises of the additional job-years from higher employment growth (18,809 job-years) and firm survival (4,404 job-years) in the supported group.[20] Putting these two numbers together gives 23,213 additional job-years among the sample of 175 regularly supported businesses. To obtain the average number of jobs added each year, we could also model this as the result of an arithmetic series. Of course, this is a simplification as it abstracts from variation across years occurring due to random noise. The sum of an arithmetic series containing n terms, with the first term a and common difference d, is given by:

$$S_n = a + (a + d) + (a + 2d) + \cdots + (a + (n - 1)d) = \frac{1}{2} \cdot n \cdot (2a + (n - 1)d).$$

Hence, the sum of additional job-years is given by:

$$S_n - na = d + 2d + \cdots + (n - 1)d = \frac{1}{2} \cdot n \cdot (n - 1)d,$$

where in this instance: $S_n - na = 23{,}213$, and $n = 7$. Thus, the expression for additional job-years becomes:

$$23{,}213 = \frac{1}{2} \cdot 7 \cdot (7 - 1)d$$
$$\Rightarrow d \approx 1{,}105.$$

On a per firm basis, this means that each of the 175 regularly supported businesses creates about 6.31 additional jobs each year. Although, it might be easier to think of this as saying that each regularly supported business creates 6.31 more new jobs per year than a matched control business, this difference is a combination of employment growth and survival effects. A breakdown shows that employment growth effects and survival effects lead to 5.12 and 1.20 additional jobs on average, respectively, among NMS regularly supported businesses.[21]

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[19] We believe that the analysis uses Kaplan-Meier estimates to obtain the additional job-years. However, the underlying calculations are not explicitly explained in the report and there is scope to make it clearer in a future analysis.

[20] Additional job-years due to higher employment growth reflect the period 2009-2015, while the corresponding number due to higher business survival seems to reflect the period 2009-2016. Since the underlying calculations for the latter are not explicitly explained in the Belmana report, we assume for simplicity that both numbers reflect the seven-year period 2009-2016 for calculating the average number of new jobs added each year. The result obtained represents a conservative estimate; a similar analysis as in Table 1 but for the period 2009-2016 shows that approximately 25,838 additional job-years result from employment growth among the NMS supported businesses.

[21] Total job-years coming from higher employment growth in regularly supported businesses = 18,809. Treating it as a sum of an arithmetic series as discussed above, let d_1 denote the employment growth effect each year. Then we get $S_n - na = 18{,}809 = \frac{1}{2} \cdot 7 \cdot (7 - 1)d_1 \Rightarrow d_1 \approx 896$. On a per firm basis, this means that each of the 175 regularly supported businesses creates about 5.12 additional jobs each year.

3.5. PRODUCTIVITY – TURNOVER

The results so far show a positive employment impact on NMS regularly supported businesses. As discussed in the microeconomic framework in Section 1.5, support that fosters innovation and provides access to better technology can also be expected to have direct effects on business performance by raising Total Factor Productivity (TFP). One measure of productivity may be real sales per employee, as the Business Structure Database (BSD) tracks turnover. Belmana (2019) does not attempt a similar econometric analysis of the turnover impacts of NMS support like it does for employment, rather it only presents some preliminary qualitative results. However, these qualitative results point towards positive turnover impacts of NMS support.

For instance, Figure 8 presents the trend in real turnover among businesses that received NMS support in 2012 and the matched control group. The wider unmatched population of businesses from the BSD is also included for reference. Real turnover for each group in 2011 is indexed at 100. The figure indicates that the turnover growth for supported businesses diverged rapidly from the matched and unmatched controls, and the difference persists over time. By 2014, real turnover of the supported businesses grew almost 11.4% from the 2011 level, while that of the matched control businesses shrank 2.3% during the same period.

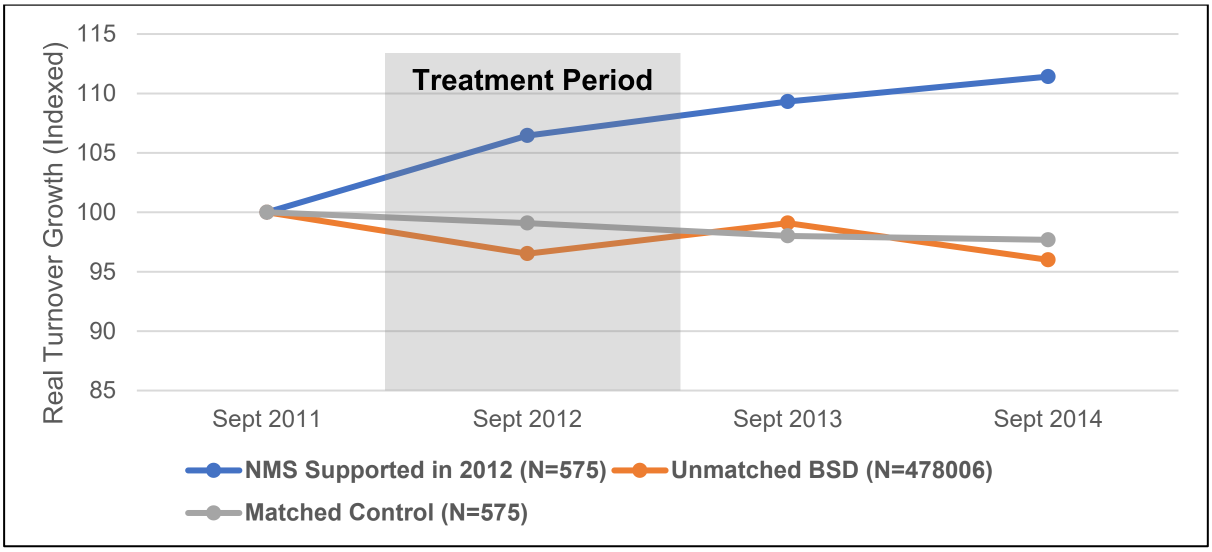


Figure 8: Turnover growth in businesses collaborating with or using an NMS service, 2012

3.5.1. Gross Value Added (GVA) Impacts

The results so far focus on employment and turnover impacts using the BSD. In an exploratory analysis, Belmana also combines the Annual Respondents Database (ARDx)[22] with FAME balance sheet data to conduct a GVA analysis. GVA can be a preferred measure of output because it is less effected by variation in the procurement that businesses make as a part of

A similar calculation can be performed for the firm survival impacts. Let d_2 denote the additional survival effect on employment each year. Then, $S_n - na = 4{,}404 = \frac{1}{2} \cdot 7 \cdot (7-1)d_2 \Rightarrow d_2 \approx 210$. On a per firm basis, this means that the survival effects for each of the 175 regularly supported businesses lead to 1.20 additional jobs every year as compared to a matched control business.

[22] The Annual Respondents Database (ARDx) is constructed from a compulsory business survey. Until 1997 it was created out of the *Annual Censuses of Production and Construction* (ACOP and ACOC), which were combined into the *Annual Business Inquiry* (ABI) in 1998. From 2009 onwards, the ABI has been referred to as the *Annual Business Survey* (ABS), and some changes were made to the survey instruments during the transition. Belmana's analysis of the ARD focuses on the period from 2009-2016. Sample sizes decrease as the overlap between businesses that respond to a sample survey and those that receive NMS support is imperfect. However, respondents that are NMS beneficiaries provide detailed information about business performance measures like sales, employment, purchases, remuneration to employees and capital investment.

their production process. Unfortunately, data limitations mean that this analysis can only be performed for large firms in the ARD. Table 5 highlights that the average GVA among the reporting units of enterprises that ever received NMS support is almost eight times that of all businesses in the ARDx. Turnover and purchases are also more than six times higher among the supported businesses. However, the per employee values of these output and input measures are very similar for the beneficiaries and non-beneficiaries.

Table 5: NMS beneficiaries in the ARD, 2009-2016

Measure		All	NMS
Real Gross Value Added	£'000 mean	22,387	173,120
Real Turnover	£'000 mean	88,777	577,222
Employment		138	949
Real Purchases	£'000 mean	65,358	397,690
Capital stock plant	£'000 mean	4,423	82,991
Capital stock vehicles	£'000 mean	638	6,911
Industry shares			
Manufacturing		14%	54%
High-Tech		3%	10%
Low Paid		25%	6%
Number of Reporting Units		28,016	1,204

NOTE: Real measures in 2010 prices. The averages are for reporting units. As one enterprise can have multiple reporting units, the total number of reporting units will be higher than the number of enterprises.

3.5.2. Using Productivity Decomposition to Explore Reallocation

Belmana also employs productivity decomposition methods: the analysis focuses on the sample of manufacturing businesses in the ARDx, since more than half of the NMS beneficiaries tend to be in manufacturing as seen in Table 5. It explores two productivity decomposition methods: Foster, Haltiwanger, and Kirzan (2008, hereafter FHK) and Griliches and Regev (1995, hereafter GR). The idea behind both these methods is to disaggregate total productivity growth into underlying components that can be its source. The primary focus is on three sources:

- Productivity effects within a business: Internal improvements such as access to innovation funding that allow businesses to invest in productivity enhancing technologies.
- External drivers: Reallocation of resources to different businesses resulting from productivity differences (restructuring impacts). This is comprised of two terms in the FHK decomposition and just one term in the GR decomposition.
- Entry and Exit Measures: These are sensitive to the economic cycles and are most affected by periods of recession.

The results of decomposing labour productivity (measured in terms of real value added per employee) are presented in Table 6. As mentioned earlier, these results are not obtained within an evaluation framework (causal analysis such as treated versus control); rather they compare what is happening in supported businesses with the productivity performance of the wider population. The top panel presents results for firm-level productivity weighted using employment, and the bottom panel does the same with weighting by value added. These weights allow analysis of productivity growth for the entirety of manufacturing sector by grossing up the individual businesses in terms of their sample weights. Both panels present results from FHK decomposition and followed by results from GR decomposition. The disaggregation “adds up,” i.e., the different decompositions both total to the overall productivity growth for the industry (these totals will differ when weighted by employment and value added).

Table 6: Manufacturing labour productivity decomposition for NMS support, 2009-2016

Design	FHK/ GR	Within	Between	Entry	Exit	Total
Employment weighted, 2009-16						
Unsupported	FHK	-0.80%	-0.57%	-2.97%	2.00%	-2.34%
NMS Supported	FHK	0.19%	-0.22%	-0.11%	-0.69%	-0.83%
Total		**-0.61%**	**-0.79%**	**-3.08%**	**1.31%**	**-3.17%**
Unsupported	GR	-1.31%	0.07%	-2.38%	1.19%	-2.42%
NMS Supported	GR	-0.30%	0.35%	0.08%	-0.87%	-0.75%
Total		**-1.61%**	**0.42%**	**-2.30%**	**0.32%**	**-3.17%**
Value added weighted, 2009-16						
Unsupported	FHK	-0.77%	-0.50%	-1.62%	1.01%	-1.88%
NMS Supported	FHK	0.12%	-0.20%	-0.68%	-0.31%	-1.07%
Total		**-0.64%**	**-0.70%**	**-2.30%**	**0.69%**	**-2.95%**
Unsupported	GR	-0.96%	-0.23%	-1.16%	0.42%	-1.92%
NMS Supported	GR	-0.11%	0.08%	-0.48%	-0.52%	-1.02%
Total		**-1.06%**	**-0.15%**	**-1.64%**	**-0.10%**	**-2.95%**

The top panel shows that between 2009-2016, manufacturing sector experienced a modest fall in labour productivity of roughly 3.17%. However, almost three-fourths of this overall productivity decline happened in unsupported businesses, i.e., the decline in productivity of unsupported businesses was three times that of supported businesses. The decompositions then consider whether the allocation of resources was towards more productive uses at a business level. The first column – within – considers productivity change in the businesses that continued throughout the period. The FHK decomposition shows that while the productivity of unsupported businesses fell by 0.8%, plants run by supported businesses experienced an average productivity growth of 0.19%. The result is particularly impressive when we account for the fact that the analysis period here follows the global economic recession that began in 2008.[23] The result is similar for FHK decomposition with value added weights. The results from GR decomposition seem to suggest that productivity declined for both groups of businesses. However, the decline for unsupported businesses was more than four times that of supported businesses (1.31% versus 0.3%) when considering employment weights and more than eight times (0.96% versus 0.11%) when considering value added weights.

The other three columns focus on resource reallocation. The second column – between – answers whether employment change, or value added, is correlated with productivity such that businesses experiencing productivity growth also tend to attract new employees and value added. Generally, for the GR decomposition, this correlation occurs for the supported businesses (0.35% with employment weights and 0.08% with value added weights). For the FHK decomposition, the correlation is negative but the impacts are more modest than for unsupported businesses. This suggests that supported businesses are performing better than unsupported ones when it comes towards diverting resources towards higher productivity units. As mentioned earlier, the between index differs somewhat in the timing of when reallocation is measured for the two decompositions. The GR decomposition considers the

[23] As per the ONS, between 2008 Q1 and 2016 Q4, labour productivity in the entire UK economy declined 1.13% (this decline was 3.86% by the end of 2015 Q4, following which there was an increase in 2016). In the same period, Multi Factor Productivity (MFP) declined 3.17% (this decline was 4.77% by the end of 2015 Q4). *Source:* https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/articles/multifactorproductivityestimates/latest (Figure 2)

mid-point in the period by averaging share weights at the beginning and end of the period, whereas FHK uses share weights in the base year to then compare what happens at the end of the period. Thus, the fact that the first year of the period immediately followed the 2008 financial crisis might account for the differences in the two decompositions.

The final two columns – entry & exit – are most effected by the 2008 recession. The employment weighted FHK decomposition suggests that much of the decline in total productivity is attributable to new entrant businesses. The finding is unsurprising since this was a period of considerable entry of relatively low productivity businesses that drove the overall productivity growth down. However, there appears to be a huge divide between entrants that received NMS support and those that did not. Supported entrants drive down productivity only very slightly (0.11%) when compared to the decline caused by unsupported entrants (2.97%). In fact, the employment weighted GR decomposition suggests that supported entrants drove up productivity by 0.08%, as opposed to the decline in productivity of 2.38% observed for unsupported entrants. The decompositions with value added weights show that while entrant businesses drove down productivity, the negative impacts due to unsupported entrants was much higher than supported entrants. In Section 3.3, it was noted that regular NMS support improved the likelihood of business survival. The decomposition in Table 6 shows that where exits of supported businesses occurred, it depressed productivity, i.e., the exiting businesses tended to be of average or higher productivity. This suggests that NMS support might have led to the survival of some unproductive businesses that would have died without support. Whereas, in the case of unsupported businesses, exits were productivity enhancing, i.e., the exiting businesses tended to be of lower productivity. Looking at the results for unsupported exiting businesses along with the "within" column suggests that the decline in the productivity among unsupported businesses would have been even higher had it not been for the exit of businesses / plants with very low productivity; although, the situation was not helped by the subsequent entry of businesses / plants with below average productivity.

In summary, the productivity decompositions suggest that NMS support helped in keeping supported businesses more productive than their counterparts during a period of worldwide economic slowdown that followed the 2008 financial crisis.

3.6. PRODUCTIVITY – WAGE PREMIUM

Another measure that is closely linked with firm productivity is wage. In a simple model of the production process, a business's factors of production would include labour and capital. As supported businesses grow with access to better technology, they can also be expected to pay higher wages to their employees that may indicate higher productivity levels in such businesses. Belmana (2019) performs an analysis of the impact of NMS support on wages using microdata on individual employees from the Annual Survey of Hours and Earnings (ASHE).[24] For a first impression of wages at businesses supported by the NMS laboratories, Table 7 contrasts the summary statistics of employees between the NMS supported

[24] ASHE is a dataset on individual employees, drawn randomly from the HMRC's PAYE system based on their National Insurance (NI) numbers. Surveys are completed by their employers from payroll data, so quality and response rates are high. Since all employees registered for PAYE taxes with NI numbers ending in two specific digits are included in the sample, the resulting dataset is a panel that can track individuals even if they change employers or have a spell out of work. Variables collected include weekly earnings (deflated by consumer price index) and hours worked in a reference period, occupation (4-digit SOC code), managerial and supervisory duties, place of work, gender, and age. As ASHE is a 1% sample of all employees, many employees of supported business are included, however usually just with a few employees for each business. Thus, the wages available for an individual business may not be very representative of that business. For example, only the CEO might be observed in one business and a graduate apprentice in another. However, the random nature of the survey means that the average across all those businesses should be representative of the true average wage in each of those businesses.

businesses[25], businesses that only access the free website downloads, and the general ASHE population.

Table 7: Summary statistics of employees of NMS supported businesses

	NMS Supported	Downloads only	ASHE
Real gross weekly pay (logs)	6.3	6.2	5.9
Basic weekly hours	35.0	34.2	31.7
Total weekly hours	36.6	35.7	32.8
Age	41.2	39.8	40.5
Female	33%	35%	53%
Full-time	86%	83%	69%
Total years of work experience	13.1	12.5	11.0
Years out of employment	7.8	7.1	8.2
Length of current employment spell	7.1	7.0	5.5
More than one job	0.6%	0.5%	1.4%
High skilled (SOC 1-3)	42.1%	34.3%	34.1%
Medium skill (SOC 4-8)	43.3%	48.4%	44.4%
Low skill (SOC 9)	6.1%	9.2%	13.4%
Number of observations (all years)	123,814	63,944	1,839,612

It shows that among NMS supported businesses: average earnings are higher, hours are longer, average age and experience is higher, and employees are predominantly male. They are also more skilled with 42% in high-skilled occupations, compared to 34% of employees on ASHE in general. Figure 9 plots a time series of average weekly earnings in businesses that were supported at some point in the period between 2004 and 2016. The gap between average weekly wages paid by NMS supported businesses and the rest of the population on ASHE is roughly £200, which is consistent with the summary statistics in Table 7. However, this cannot be interpreted as an impact of NMS support, as businesses would be classified as “NMS supported” even in the years before they received support. Rather, the summary statistics indicate that supported businesses operate in areas with higher productivity and employ a more skilled workforce than the average UK business.

[25] The definition of supported businesses in the wage premium analysis differs from that of regularly supported businesses in the previous sections. Here, “NMS supported” is equal to 1 for all businesses that ever used NMS services, paid for contract R&D, or participated in a collaboration with NMS. Although Belmana (2019) does not explicitly state the reasons for not performing a wage analysis for regularly supported businesses, we believe sample size could be one of them. Since the analysis here is based on ASHE dataset, which is a 1% random sample of all employees in the HMRC’s PAYE system, it is possible that the sample size of employees from just the regularly supported businesses would have been very small to perform any statistically meaningful analysis. Instead, looking at employees from businesses that ever had an incidence of NMS support could have increased the sample size significantly.

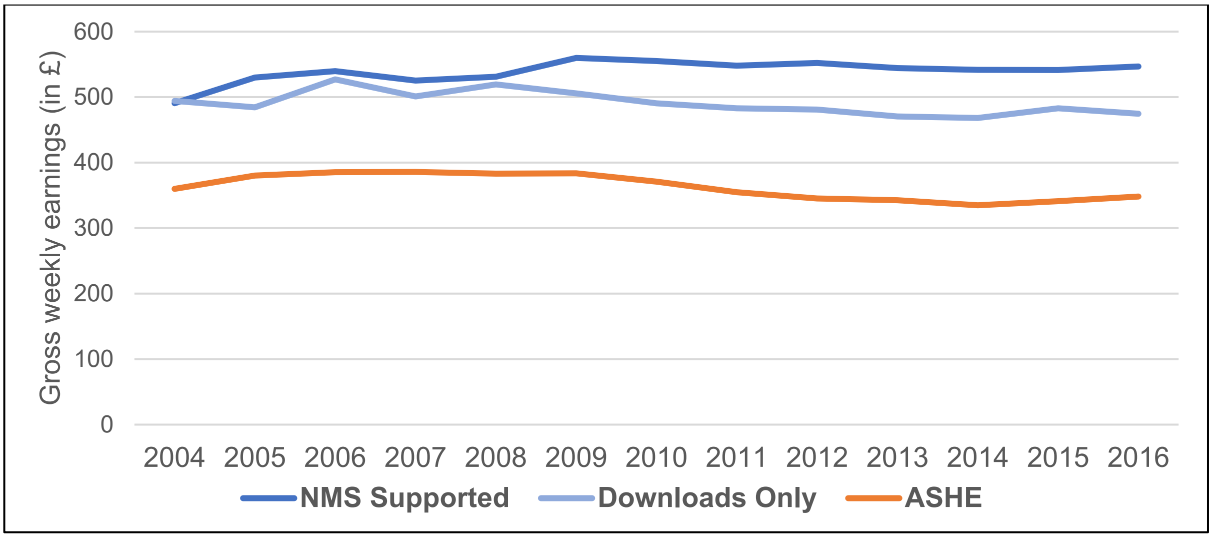


Figure 9: Average earnings in NMS supported businesses

To check if higher wages in supported businesses can be attributed to NMS support, the data can be analysed in several ways.[26] The main approach employed in Belmana (2019) follows D'Costa and Overman (2014) to focus on the wage effects of job-switching to or from a supported business. That is, a treatment effect can be identified from job switchers: If the wage growth of switchers to supported firms is higher than that of switchers to the unsupported firms, it would indicate that support has a positive effect on earnings. Using this approach, it is also possible to control for the fact that some employees may have been specifically hired in response to the support, however the analysis in Belmana (2019) does not do that. Figure 10 compares earnings of job switchers to and from NMS supported businesses to earnings of job switchers between other businesses. Switchers to and from NMS supported businesses are considered if the switch occurred in the first year of support by an NMS laboratory or any year thereafter.

[26] One possible approach involves combining the DiD and PSM. Firstly, average wages per firm can be computed every year. Even when individual workers join and leave a business, average wages can be calculated in a pseudo-panel and changes in workforce characteristics can be accounted for. Comparing wage growth in regularly supported businesses before and after support against wage growth in the matched control group businesses can then provide an estimate of the causal impact of support. However, this method does not account for the fact that changes in the workforce may happen due to the support itself. For example, a business may hire new engineers and scientists to perform R&D on a collaborative project with the NPL. In such cases, the channel through which support generates impact may be less clear: does support lead to higher wages via increased productivity, due to new hires of high-skilled workers, or some combination of the two. It should be noted that hiring can be a channel for impact, as those workers may have never been hired in the first place without support.
Alternatively, wage growth comparisons can be done by limiting the sample to include only the employees who stay with one firm during the whole period, before and after support. This method makes it possible to measure the effect of innovation support on the productivity of workers (assuming wages are a true reflection of their marginal productivity). Worker fixed effects can be used to control for individual characters that are stable over time.

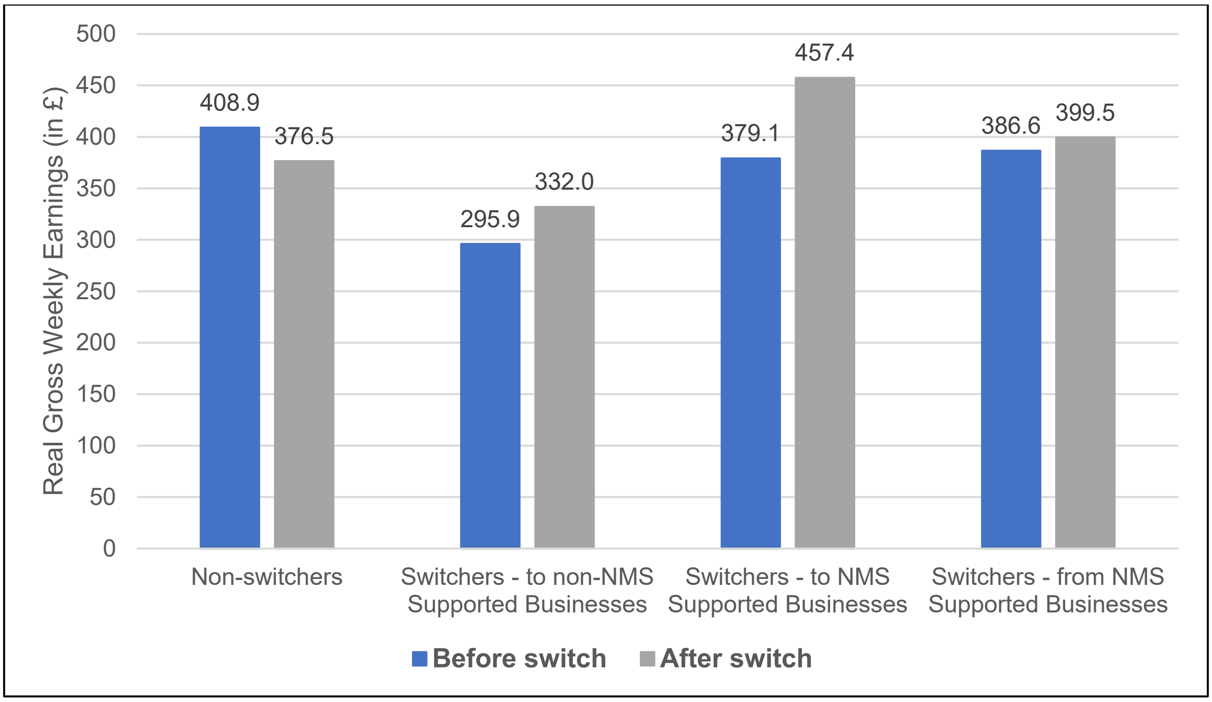


Figure 10: Earnings of job switchers to and from NMS supported businesses

The average weekly wage premium for employees switching to NMS supported businesses is roughly £78.3, which translates into an average annual wage premium of £4,083. Moreover, it is reasonable to assume that this represents a *lower bound* for the wage premium earned by employees switching to NMS regularly supported businesses, since regularly supported businesses can be expected to experience larger productivity shifts and pay their employees higher wages as compared to businesses that are supported sometimes. As discussed in Section 3.4, 5.12 additional jobs are created each year on average at the 175 regularly supported businesses. Since the new employees at these businesses receive an average annual wage premium of at least £4,083, **it follows that the wages ("earning power") increase by *at least* £20,905 (= 5.12*4,083) on average every year for the new employees at each regularly supported business.**

The above analysis of job switchers does not control for worker characteristics. As is evident from Table 7, employees at NMS supported businesses have quite different characteristics from the general population. Belmana also performs a multivariate regression analysis to control for the effects of observable characteristics, such as age and occupation. Table 8 shows the regression results from the multivariate analysis. The dependent variable is the logged gross weekly earnings in constant GBP, and four different model specifications are estimated. The first two specifications use Ordinary Least Squares (OLS) estimation. In the first specification, an employee's skills are accounted for by two dummies – "high-skilled" and "medium-skilled" ("low-skilled" being the baseline) – derived using SOC codes. In the second specification, the dummies are replaced by more detailed O*NET variables.[27]

[27] O*NET is a coding scheme that rates occupations on various physical and cognitive skills as well as the use and importance of different knowledge domains. There are 70 variables, measuring both the level and importance of skills and knowledge. Belmana (2019) uses factor analysis to reduce them into 26 variables. It is based on US survey data but can be mapped to UK Standard Occupation Classification (SOC) codes. Since O*NET variables are only available from 2010 onwards, the specifications using these variables cover a shorter time frame.

Table 8: Multivariate estimation of the effect of NMS support on wages

	OLS (1)	OLS (2)	FE (1)	FE (2)
NMS Supported[28]	0.05***	0.07***	0.03***	0.04***
NMS Downloads Only[29]	0.03***	0.03***	0.01***	0.03***
Labour force experience	0.01***	0.01***	0.01***	0.00***
Age	0.05***	0.04***	0.07***	0.08***
Age-squared	-0.00***	-0.00***	-0.00***	-0.00***
Full-time Employed	0.80***	0.74***	0.62***	0.55***
High-skilled (SOC 1-3)	0.62***		0.16***	
Medium-skilled (SOC 4-8)	0.17***		0.06***	
Low pay	-0.14***	-0.11***	-0.08***	-0.08***
High tech	0.04***	0.01***	0.04***	0.00
Manufacturing	-0.00	0.01***	0.02***	0.04***
Scale up	0.02***	0.03***	0.01***	0.01***
Knowledge Intensive	0.03***	0.06***	-0.00	0.01*
Constant	3.86***	4.30***	3.74***	3.62***
O*NET	No	Yes	No	Yes
Region effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
R-sq.	0.67	0.70	0.40	0.37
adj. R-sq.	0.67	0.70	0.40	0.37
within R-sq.			0.40	0.37
overall R-sq.			0.59	0.60
between R-sq.			0.66	0.65
N	1754948	978771	1754948	978771

Note: Employment and Turnover categories highly significant across models; these and some other variables suppressed for brevity.
Asterisks on coefficients indicate the statistical significance: * for p<.05, ** for p<.01, and *** for p<.001. Selected models also include O*NET variables, region and year effects, where individual coefficients are not displayed, but their presence is indicated at the bottom of the table.

The second set of regression specifications uses fixed effects (FE) estimation, which exploits the panel structure of the data by controlling for unobservable employee characteristics that stay constant over time. By doing so, FE estimation helps in controlling for omitted variable bias due to unobserved heterogeneity that might occur in OLS estimation (assuming that this heterogeneity is time-invariant).[30] In these regressions, the effect of NMS support is identified through changes – either when businesses go from unsupported to supported, or as individuals move to supported businesses. As the dependent variable is expressed in logarithms, the coefficient on the dummy regressor for NMS support can be interpreted as the percentage change in gross weekly earnings due to NMS support. We focus on the fourth specification –

[28] "NMS Supported" is equal to 1 for all businesses that ever used NMS services, paid for contract R&D, or participated in a collaboration with NMS.
[29] "NMS Downloads Only" is equal to 1 for businesses that only accessed downloads from the NMS laboratories. It is not considered as a treatment here since it is a light-touch measure of support. But it could still provide important information on industry affiliation with an interest in measurement services.
[30] One of the caveats is that only individual fixed effects are included here. There may still be considerable selection bias relating to the businesses that opt to work with NMS. On business side, only variables such as turnover, employment, and some industry characteristics have been controlled for. Other factors like innovation and management motivation that might both influence using NMS services as well as wages are not included.

FE estimation with O*NET controls – as this is the most robust specification for the reasons discussed above.

As can be seen in the last column of Table 8, the wage effect of NMS support is estimated to be around 4%. Once again, it is reasonable to assume that this represents a *lower bound* for the wage effect on regularly supported businesses. Figure 10 shows that switchers out of NMS supported businesses earn an average weekly wage of around £386.6, which can be treated as the baseline for these businesses. Given a 4% wage effect of NMS support, the baseline average weekly wage in unsupported businesses is about £371.73 (= £386.6/1.04). In other words, there is a weekly wage premium of roughly £14.87 (= £386.6 - £371.73) at supported businesses, which translates into an annual wage premium of £775. As discussed in Section 3.4, each regularly supported business safeguards an additional 1.20 existing jobs on average compared to a matched control business. Since employees at these businesses receive an average annual wage premium of at least £775, **it follows that each regularly supported business adds a value of *at least* £930 (= £775*1.20) in the form of wages through safeguarded jobs. Combining it with the wage increase for new employees, we obtain that a regularly supported business adds a total value of *at least* £21,835 (= £20,905 + £930) on average every year just in the form of wage renumerations.**

However, wages are only one component of the Gross Value Added (GVA) – the other components are profits and taxes on production. Belmana (2019) mentions the following: *"There is a recognition that only about half of the productivity effect is passed on to workers in the form of higher earnings (Dearden et al., 2005). Firms pass productivity shocks through to employees if employees can use the threat of outside job options to force a renegotiation of their wage (Postel-Vinay and Turon, 2010)."* Dearden et al. (2005) suggest that the increase in the profits of regularly supported businesses would be roughly equal to the increase in wages. Hence, there is an additional £21,835 on average going to each regularly supported business in the form of profits every year, giving a combined increase of £43,670 through wages and profits. Belmana's analysis does not consider the third component – taxes on production – which is needed to obtain a more complete picture of the GVA by NMS business support. For a rough initial estimate, if we assume that there is an equal (one-third) split across the three components, then an additional £21,835 comes in the form of production taxes per regularly supported business every year. Thus, the total GVA per regularly supported business per year comes out to £65,505. Multiplying the number by 175, we obtain that the GVA by NMS business support is roughly £11.46 million every year. In further work, data on taxes published in the UK National Accounts: The Blue Book (2021) can be used to compute the full GVA estimate.

3.7. PATENTING AND KNOWLEDGE SPILLOVERS

3.7.1. Patent Impacts

As seen in Table 1, NMS supported businesses tend to be R&D active and operate in more knowledge intensive sectors. Belmana's analysis goes beyond employment and productivity impact measures to determine whether regularly supported businesses invest in innovative ideas that subsequently spread. A comparison of patenting activities of regularly supported businesses with that of the matched control group is presented in Figure 11.[31] It plots the average increase in new patents published per business from the baseline year 2009.

[31] This analysis does not exclude regularly supported businesses whose propensity score lies outside the 25th and 75th percentiles or those that also won Innovate UK grants. While Belmana does not explicitly state the reason(s) for including such business, we believe it might be to increase the sample size to capture enough patenting activity across the two groups of businesses. The reported sample size of each group in Figure 11 is 367 businesses.

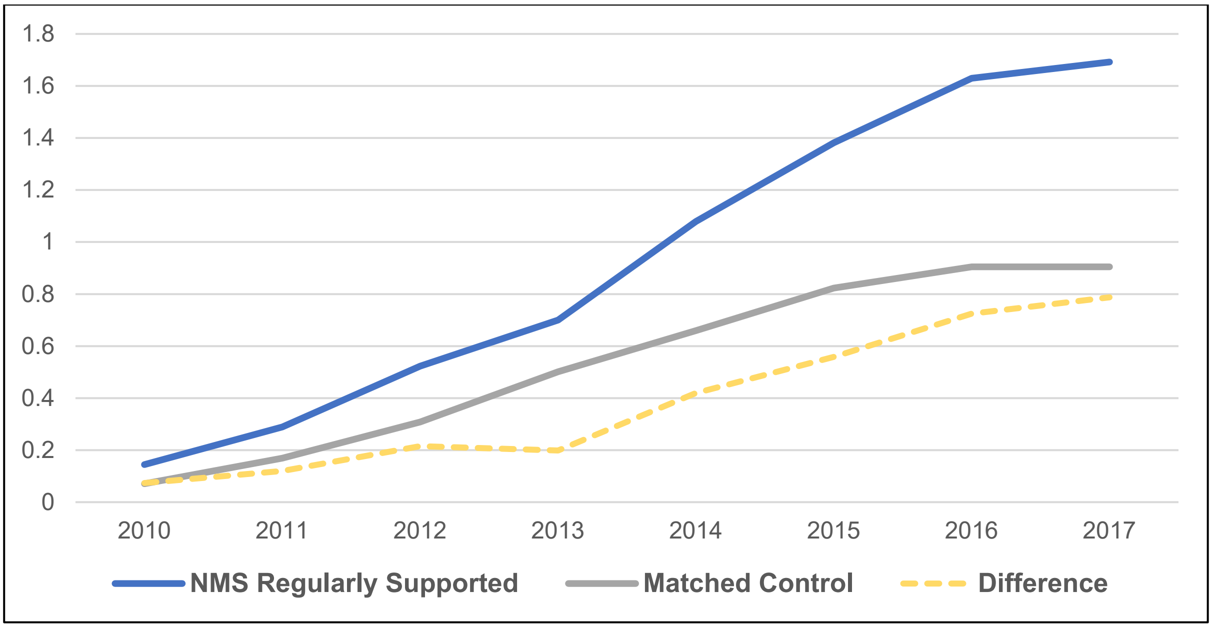


Figure 11: Change in patents for NMS regularly supported and matched control businesses

It is evident that in the years following 2009, a gap emerges between the two groups of businesses in the number of new patents. This gap widens after 2013, such that by 2017, regularly supported businesses have registered nearly twice as many new patents on average as the matched control businesses. Due to large variations in patenting activities, the differences are not statistically significant at standard confidence levels. However, the point estimates still suggest regular NMS support might have a positive impact on businesses' patenting activities.

3.7.2. Knowledge Spillovers

During patenting, innovators cite relevant previous patents that influence their intellectual property, and these citations can be used as a proxy for knowledge spillovers. A simple measure could be how often a patent gets cited, but it might not capture the full influence of the patent because citation counts do not account for the "quality" of the patents that are citing it – a citation from a relatively obscure patent is weighed the same as a citation from a highly cited patent. Thus, it is possible that a patent receives fewer citations than another patent, but the former is cited by more influential, highly cited patents while the latter is cited by more obscure patents. Moreover, ground-breaking patents are sometimes modestly cited due to the small size of an industry at the time of creation, while subsequent patents might be cited more as the field advances. It is possible to consider the number of citations that a patent receives plus the citations received by the patents citing it to get a more comprehensive measure of knowledge spillovers, but even such a measure would encompass only two tiers of citation (i.e., initial citations, and the citations to these citations).

Belmana utilises the whole citation network of patents to get a measure of knowledge spillovers. The citation data used in the analysis, previously prepared by Dechezleprêtre, Martin, & Mohnen (2013, DMM hereafter), develops a sophisticated measure of the importance of an individual patent based on its location in the overall network of citations. It relies on the random surfer PageRank algorithm (Page et al., 1999) that was originally used by Google web search to determine the relevance of a webpage. To do so, it analyses the network of webpage hyperlinks: a webpage is considered important if many other webpages point to it, or if many webpages point to the webpages that point to it (or both), and so on. In a novel approach, DMM (2013) apply this method to rank the importance of patents in clean and dirty technologies. It creates a PatentRank index, which is defined as the weighted sum of PatentRanks of all citing patents. Thus, a patent is assigned a high score if it has more backward citations or if patents citing it have higher scores themselves. The PatentRank index $r(i)$ of a patent i is computed recursively according to the following definition:

$$r(i) = \frac{\beta}{N} + (1-\beta)\sum_{j \in B(i)} \frac{r(j)}{F(j)}$$

Equation 12

where N is the total number of patents, $B(i)$ is the set of patents that cite patent i (i.e., the number of forward citations to patent i), and $F(j)$ is the number of backward citations (i.e, the number of citations made by patent j). The second term of Equation 12 divides the citing patent ranks by the number of citations made, which has two effects. First, it constitutes a fair distribution of rank to all citations. Second, it normalizes the sum of each patent effects and ranks vector to one. β is the damping factor, which is used to avoid patents that are never cited because sink patents will lead to an endless loop.[32]

Belmana matches the patent citation data from DMM (2013) to data for firms in the analysis sample and examines the time trends of knowledge spillovers for NMS supported and unsupported businesses. This part of the analysis considers businesses that ever received NMS support rather than focusing only on regularly supported businesses. Figure 12 plots the mean PatentRank Index scores of patents registered in a given year by NMS supported businesses at some point between 2001-2014 and compares them to the mean scores of patents registered by unsupported businesses. Panel A shows the global PatentRank index, and Panel B shows the PatentRank index when only patents registered in Great Britain are considered. **The time trend highlights an uptick in scores for the supported businesses after 2001, which is the year when NMS laboratories started supporting businesses. Both panels show that in general, businesses supported by NMS laboratories generate patents with higher knowledge spillovers.** It also plots the premium for supported businesses, which is defined as: $\%\ \text{Premium} = \left(\frac{\text{Mean PatentRank Index for Supported Businesses}}{\text{Mean PatentRank Index for UnSupported Businesses}} - 1\right) * 100$. Lastly, to underline the importance of using a measure such as PatentRank Index, Panel C plots a time-series of citations per patents for the two groups of businesses. The downward sloping lines is not surprising since patents registered in the recent years are likely to have fewer citations than patents registered in the earlier years. Patents registered by supported businesses tend to be cited more on average than patents registered by unsupported businesses, but the gap seems to have converged in the recent years. However, as Panels A and B show, the % premium has persisted when we consider a more comprehensive measure of knowledge spillovers.

[32] As explained in DMM (2013): "The mechanism behind the ranking is equivalent to the random-surfer behaviour, a person who surfs the web by randomly clicking links on the visited pages but periodically gets bored and jumps to a random page altogether. Therefore, when a user is on a web page, she will select one output link randomly with probability β or will jump to other webpages with probability $1-\beta$. It can be understood as a Markov process in which the states are web pages, and the transitions are all equally probable and are the links between webpages."

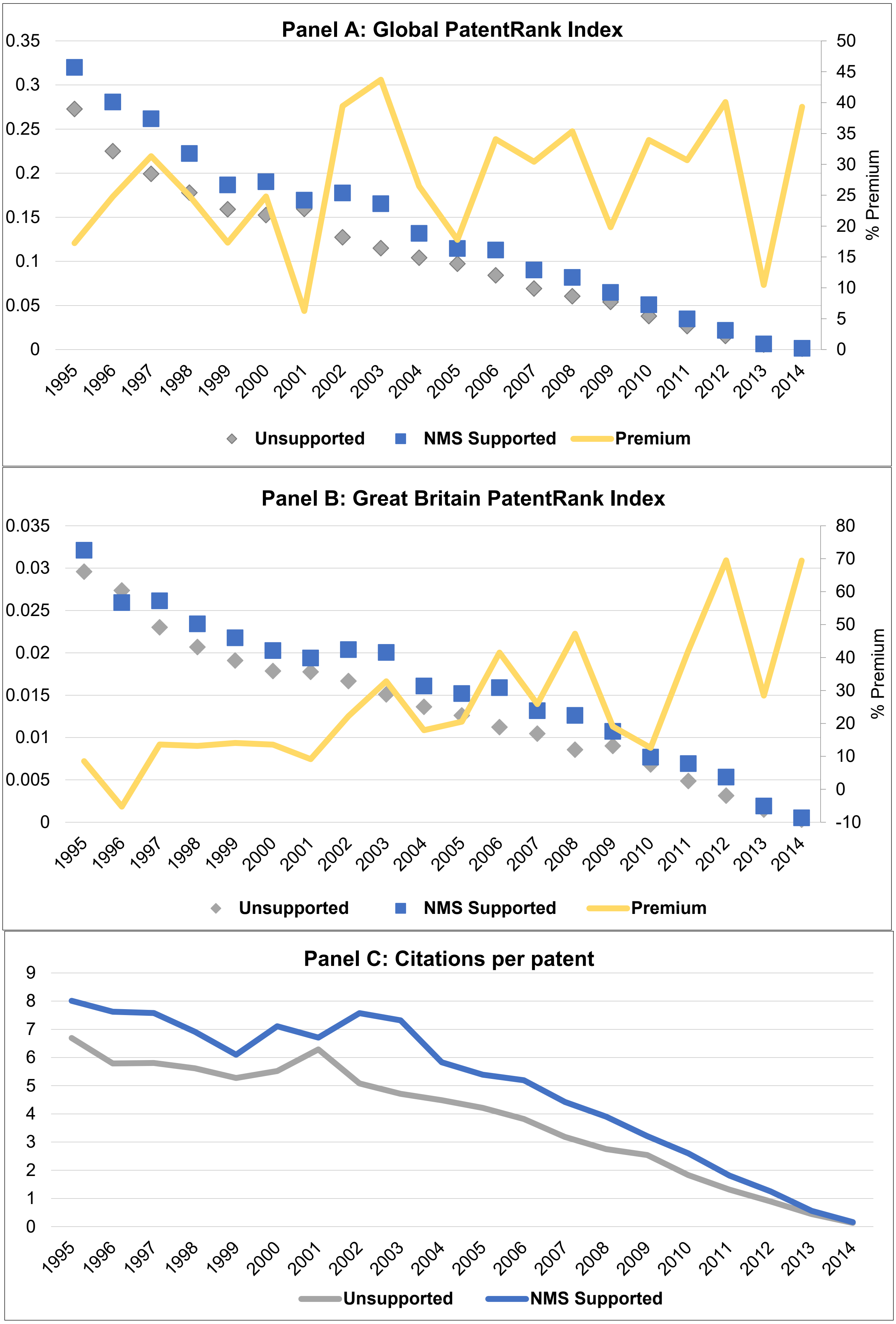


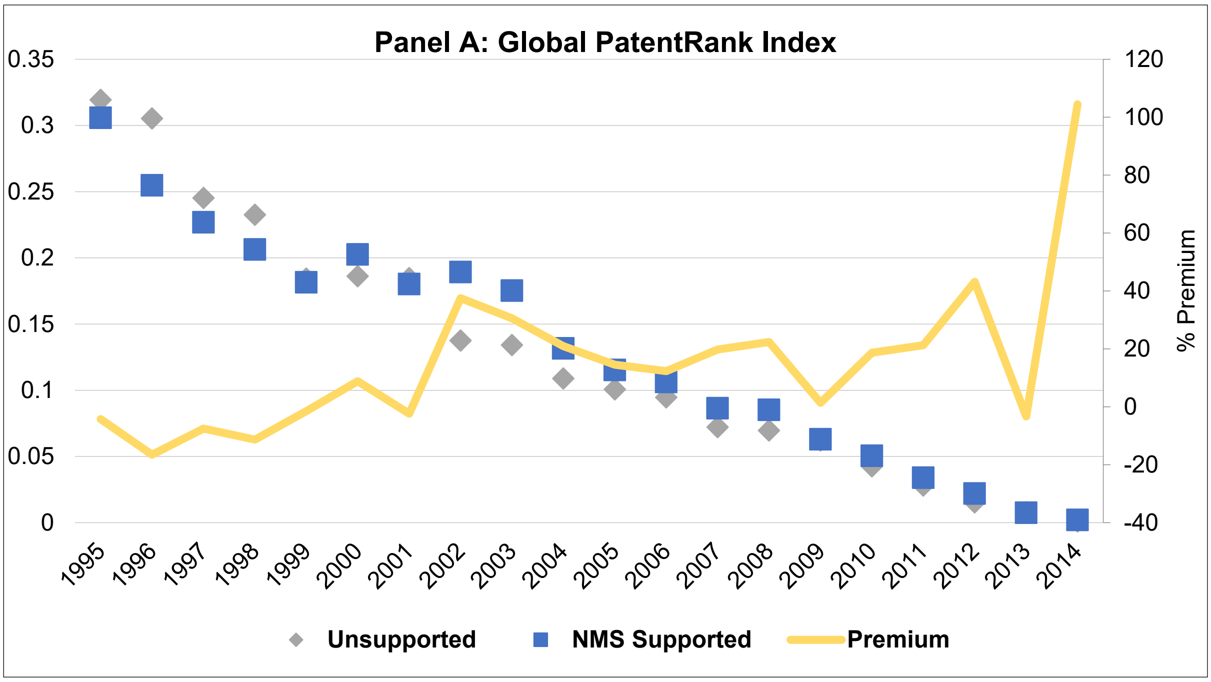
Figure 12: Patent Citation Index for NMS Supported versus Unsupported Businesses

As discussed earlier, NMS support is generally very sector-specific and a major fraction of businesses that work with NMS laboratories operate in the manufacturing sector. This pattern is also reflected in patents, as shown in Table 9 below. Almost two-thirds (=58,088/87,999) of the patents from NMS supported businesses are in the manufacturing sector, of which a little over half (29,625) are within the highly KI manufacturing sector. Less than a tenth of these patents are outside the highly KI or manufacturing sectors.

Table 9: Overall sector split of patents from NMS supported businesses

		Patents
All Industries		87,999
High Tech - Knowledge Intensive Sectors		
	Manufacturing	29,625
	Services	21,625
Manufacturing Sectors		
	Not highly KI	28,463
Other Sectors		8,286

Given the sector-specific nature of NMS support, Figure 13 breaks patents down for businesses within the highly knowledge intensive manufacturing sector. While the patterns observed are very similar to that in Figure 12, the change post 2001 appears more pronounced for this sector. Perhaps, this highlights the effect that NMS support has within the sector in producing more knowledge spillovers.



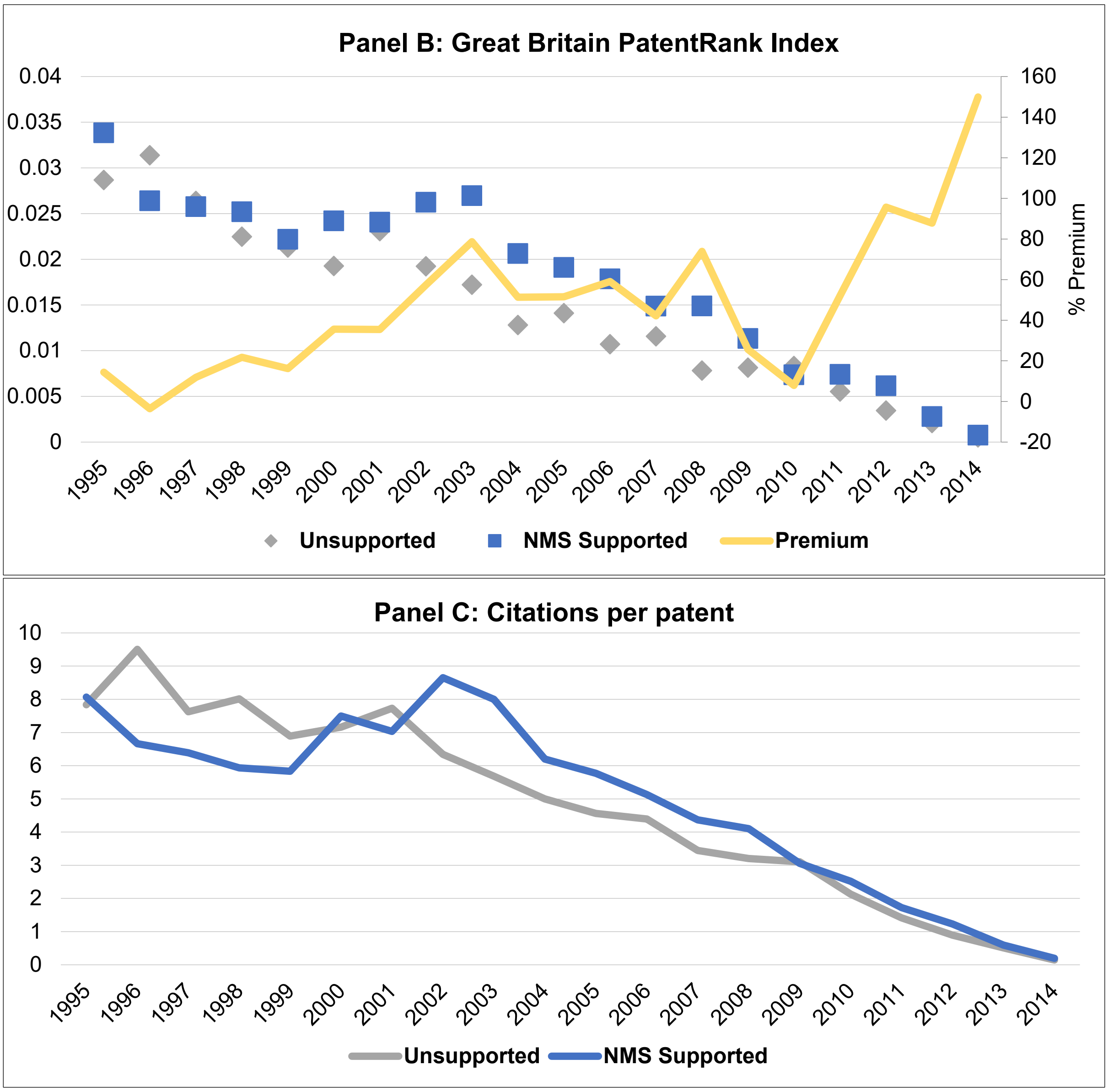


Figure 13: Patent citation index for NMS supported versus unsupported highly KI manufacturing businesses

It is hard to interpret the trends from Figure 12 and Figure 13 as causal impacts of NMS support. However, they strongly suggest that NMS support can lead to businesses engaging in innovation activities with high spillovers. Belmana recognises that patents are only one output of R&D activity, and other measures of R&D activity such as peer-reviewed papers, R&D spend, etc. can be explored more deeply in a future study.

4. GENERALIZED PROPENSITY SCORES AND DOSAGE MODELLING

Up to this point, the analysis of employment impacts considers a binary treatment– the treated group consists of businesses with an incidence of NMS support in more than 85% of the years that they are observed in the ONS data, which is roughly equivalent to being supported for 5 or more years in a 6-year period. And the matched control group only consists of businesses with incidences of support in less than 85% of the years. However, the nature of NMS support is more nuanced than that. For example, businesses that are supported in 60% of the years can still be expected to experience more benefits due to the support compared to businesses that are supported in only 10% of the years. This means that – at a business level – impacts are likely to vary depending on the length of support.

Belmana (2019) performs an exploratory analysis using dosage modelling to study a causal relationship of interest where there is a continuous treatment. It is based on estimating a generalized propensity score (GPS), which is an extension of the propensity score matching (PSM) described for binary treatments. The GPS method is also founded on the Neyman-Rubin causal model of potential outcomes. PSM focuses on the mean outcome of the treated group compared to the mean outcome of the matched control. Whereas the focus in GPS is the pairwise treatment effects along the full domain of potential treatment doses, i.e., the difference in outcomes of businesses that receive a particular dose to a situation in which they receive another dose. The dose refers to the number of years with an incidence of NMS support, normalised so that the least number of years takes the value zero and the maximum number of years has a unit dose.[33] This method allows estimation of a dose response function (DRF) through a generalized linear model, which follows from a two-step procedure. In the first step, selection is modelled by estimating the parameters of the conditional distribution of treatment given the covariates that explain the selection into treatment.[34] In the second step, the conditional expectation for the outcome variable given the conditional distribution of the treatment is modelled.[35] In summary, GPS has the following advantages over PSM:

- It allows for a continuous treatment variable so that different levels of support can be considered rather than a binary treatment.
- It enables estimation across the entire treatment-outcome function rather than focusing on the average level of treatment.
- It also allows an analysis of the optimal dosage of intervention.

Figure 11 considers the dose response for NMS support, where the dose refers to the number of years in which a business records one or more instances of NMS support during the period 2008-2016. The average dose observed in the data is 2.5 years, with many businesses having interacted with an NMS laboratory only in a single year. The left panel plots change in logged employment between 2009 and 2015 against a normalized dose, therefore, the dose response can be interpreted as employment growth. As seen, the dose response function is positive and increasing across the span of levels of support. The lower bound of the 95% confidence interval is also above zero at all levels of support, indicating that the estimates are statistically significant. This suggests that employment growth is positive and does not diminish with more years of NMS support (at least for the number of years observed in the data).

[33] $D = [0,1]$ denotes the interval of all possible treatment levels, and $d_i \in [0,1]$ represents the observed treatment level of an individual business i.

[34] Let $r(d, x)$ be the conditional density of the treatment d given the covariate vector x:

$$r(d, x) = f_{D|X}(d|x)$$

Then, the generalized propensity score is $R = r(D, X)$.

[35] This approach is implemented as follows: First, the conditional expectation of the outcome is estimated as a function of two scalars, the treatment level D and the GPS R, $\beta(d,r) = E[Y(d)|r(d,X) = r] = E[Y|D = d, R = r]$. Then, the dose-response function at a particular level of the treatment is estimated by averaging this conditional expectation over the GPS at that particular level of treatment, $\mu(d) = E[\beta(d, r(d,X))]$. Note that the averaging is not done over the GPS $R = r(D,X)$; but rather over the score evaluated at the treatment level of interest, $r(d,X)$.

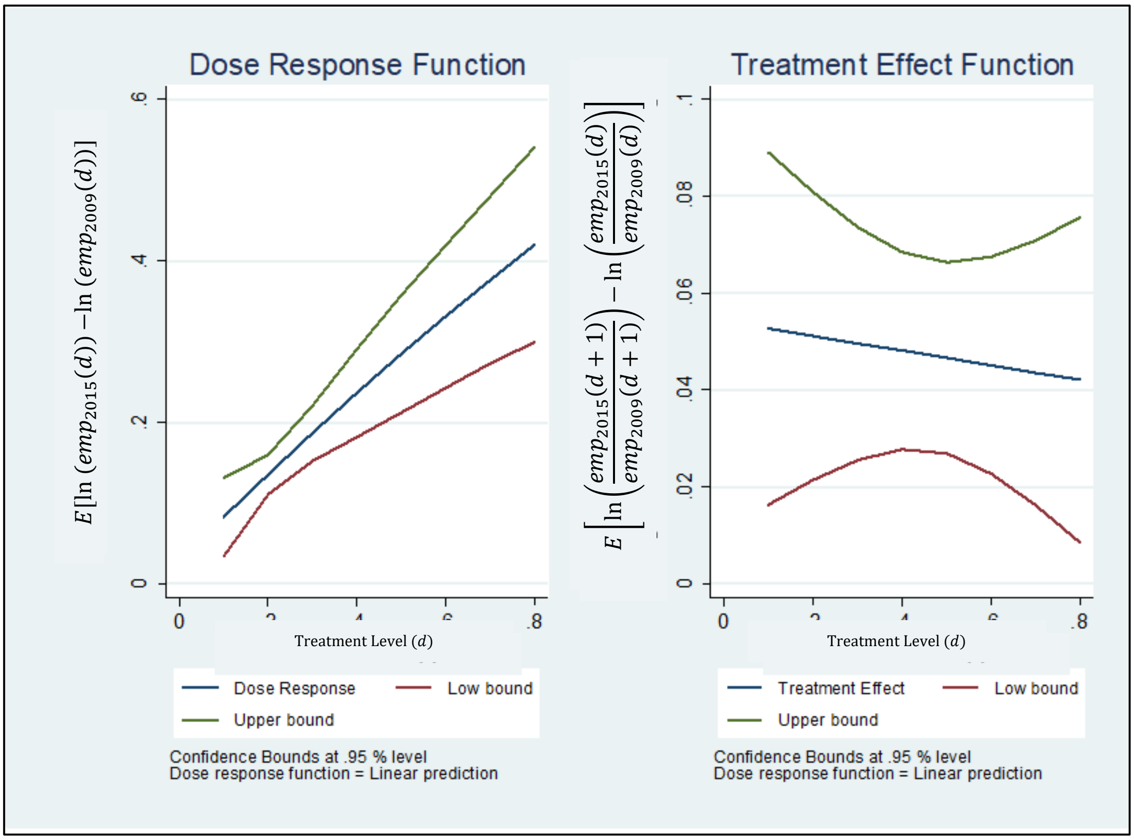


Figure 14: Treatment impact by dose size (number of years) of NMS support, 2008-2016

The right panel plots the treatment effect function, which corresponds to the slope of the dose response function.[36] The treatment effect is statistically significant and positive; however, it is slightly downward sloping, which suggests the dose response function is slightly concave (even though it looks linear). A concave dose response function means that there is an optimal level of dose, beyond which the marginal effect of increasing the level of support on employment would start being negative. However, a very slight concavity suggests that this optimal dosage could be very high.

Figure 12 considers the dose response for NMS support, where the dose refers to the value of services purchased from the NMS laboratories during the period 2008-2016. The results are statistically insignificant since the 95% confidence intervals for both the dose response function as well as the treatment effect function include zero impact. Belmana (2019) mentions that a statistical difficulty with using the value of purchased services as the treatment variable is that value measures are often a poor proxy for the number of incidences of support, primarily because value of services strongly correlates with the size of the businesses. Even controlling for business size in the regressions does not mitigate the issue.

[36] The treatment effect function captures the change in outcome upon varying the treatment from one level to another.

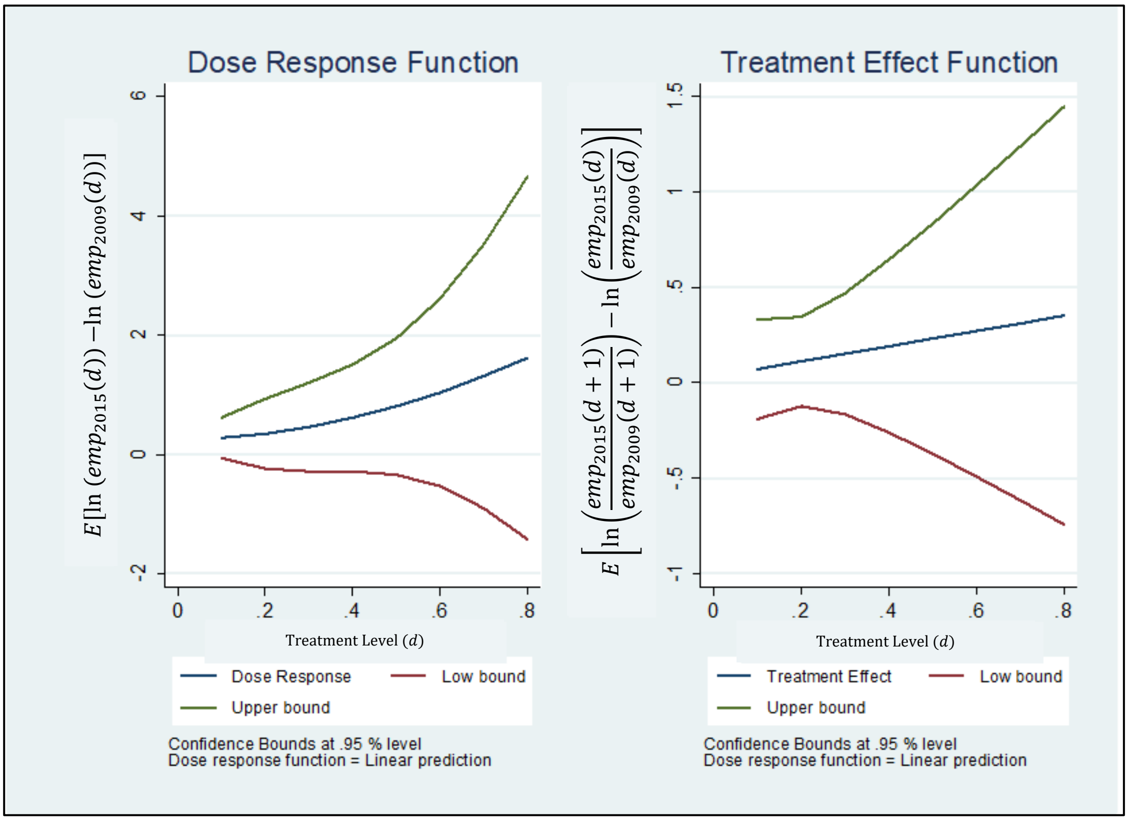


Figure 15: Treatment impact by dose size (value of services) of NMS support, 2008-2016

Beyond the two figures presented here, Belmana (2019) does not contain other results pertaining to dosage modelling for the impacts of NMS support. This analysis should be treated as an exploratory work that can potentially be developed into a more detailed econometric analysis in future work.

5. CAVEATS AND IDEAS FOR FURTHER WORK

This section summarises a few caveats of the existing analysis and proposes ideas for future work where some of these caveats can be addressed.

First, a natural question to ask following the evidence presented in Belmana's analysis is: *If NMS regularly supported businesses experience better outcomes than unsupported businesses, then why do some businesses opt for NMS support while others do not?* In other words, PSM creates a control group of businesses that have very similar characteristics to regularly supported businesses, as seen in Figure 5. Then what might explain the decision of these businesses to not work with the NMS laboratories despite the evidence of better outcomes resulting from regular support? We believe that one of the plausible explanations is hidden in Belmana's analysis. Recall from Section 2.3 that PSM controls for firm characteristics including the sectors in which they operate (like manufacturing versus non-manufacturing, service versus non-service, etc.). But the analysis does not include 2-digit SIC code dummies that reflect the industry in which the businesses operate. So, it is possible for two large, high knowledge intensive, manufacturing businesses to be operating in vastly different industries (based on SIC codes), only one of which is an area where NMS laboratories provide specialist services. Consider the following example consisting of two firms: *Company 1* is a high KI firm that manufactures state-of-the-art engineering-related goods / technologies (for e.g., Rolls Royce or other such firms that operate in the aerospace and defence industries). *Company 2* is also a high KI firm, very similar in characteristics to *Company 1* but operating an industry where NMS laboratories do not have a large footprint (for e.g., hedge funds, pharmaceutical manufacturing, etc.). Both companies would have very similar characteristics (size, location, turnover, etc.), and they might even employ from the same pool of scientists, engineers, and other high-skilled technical workers (i.e., they would compete in the labour market). However, despite these similarities, only *Company 1* would have an incentive to engage with NMS laboratories, which might eventually end up driving their outcomes differently. In summary, drivers of selection into NMS support have been left relatively unexplored in the existing analysis and it is a question that warrants a standalone study in the future.

Second, there is a slight limitation of the wage analysis presented in Belmana. The existing evidence only considers wage-based renumeration. But there are other forms of compensation, such as equity/stocks, mixed-income, self-employment income, etc. that are not considered. It would be interesting to see if these follow a similar pattern as wages across supported and unsupported businesses. Also, it is important to note that even though Belmana does not observe statistically significant results for turnover impacts, that could be driven by the noise in turnover figures. We believe that the wage impacts of NMS support that are presented in the analysis point towards underlying positive turnover impacts, and a future analysis can try to uncover these in a more meaningful way.

Third, the exploratory work using Generalised Propensity Scores and dosage modelling has the potential to be developed into a more robust econometric analysis. Concavity of dose response function for NMS support suggests that there is an optimal level of intervention, beyond which the marginal effect of increasing the level of support on employment would start being negative. However, the result seems less reliable at higher levels of treatment. Hence, the reason for the divergence of 95% confidence interval bounds in Figure 14 and Figure 15. In dosage modelling, the specified distribution of outcome variable determines reliability of the results. For example, gamma distribution assumes a continuous probability distribution of the outcome variable, whereas other distributions such as such as binomial, inverse gaussian and negative binomial assume a discrete distribution. The outcome variable under consideration here is employment growth, which could be continuous because it can take any value. But the treatment variable, dose size (number of years of NMS support), is discrete. Paying attention to the assumed distributions of the treatment variable and its functional relationship with the explanatory variables is also essential in dosage modelling. In its current form, Belmana's report does not explicitly state the distributional assumptions and other important details underlying the dose response analysis.

Lastly, as mentioned before, a missing component in Belmana's work is a theoretical model that underpins the empirical results. While we make an initial attempt to bridge that gap by introducing a stylised model in Annex 2, it presents a very simplified picture that does not capture all the nuances of the real world. Therefore, some caveats with the theoretical model and possible approaches to address them in a future paper are also discussed at the end of Annex 2.

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ANNEX 1 – FORMAL DERIVATION OF THE ATE

$$
\begin{aligned}
& E_X\{E(y_i \,|\, Treat_i = 1, \boldsymbol{X_i}) - E(y_i \,|\, Treat_i = 0, \boldsymbol{X_i})\} \\
& = E_X\{E(y_i^1 \,|\, Treat_i = 1, \boldsymbol{X_i}) - E(y_i^0 \,|\, Treat_i = 0, \boldsymbol{X_i})\} \\
& = E_X\{E(y_i^1 | Treat_i = 1, \boldsymbol{X_i}) - E(y_i^0 | Treat_i = 1, \boldsymbol{X_i}) + E(y_i^0 | Treat_i = 1, \boldsymbol{X_i}) - E(y_i^0 \,|\, Treat_i \\
& \qquad = 0, \boldsymbol{X_i})\} \\
& = E_X\{E(y_i^1 | Treat_i = 1, \boldsymbol{X_i}) - E(y_i^0 | Treat_i = 1, \boldsymbol{X_i})\} \\
& \qquad + E_X\{E(y_i^0 | Treat_i = 1, \boldsymbol{X_i}) - E(y_i^0 | Treat_i = 0, \boldsymbol{X_i})\} \\
& = E_X\{E(y_i^1 | \boldsymbol{X_i}) - E(y_i^0 | \boldsymbol{X_i})\} + E_X \underbrace{\{E(y_i^0 | \boldsymbol{X_i}) - E(y_i^0 | \boldsymbol{X_i})\}}_{=0} \\
& = E_X\{E(y_i^1 | \boldsymbol{X_i}) - E(y_i^0 | \boldsymbol{X_i})\} \\
& = E_X\{E(y_i^1 - y_i^0 | \boldsymbol{X_i})\} \\
& = E(y_i^1 - y_i^0) \\
& = \hat{\alpha} = \mathbf{ATE}
\end{aligned}
$$

where the first equality follows from the definition of observed outcome (Equation 4); the second equality follows from subtracting and adding $E(y_i^0 | Treat_i = 1)$; the third equality follows is straightforward; the fourth equality follows from the conditional independence assumption (Assumption 1); the fifth equality is straightforward; the sixth equality follows from collecting terms; the seventh equality follows again from the law of total expectation, and the final equality follows from the definition of the average treatment effect (Equation 3).

ANNEX 2 – SKETCH OF A MICROECONOMIC MODEL

Firm's Production Function

To connect NMS support with business outcomes, assume a constant returns to scale Cobb-Douglas production function, in which Firm i's output at time t $(Q_{i,t})$, is a function of Total Factor Productivity $(A_{i,t})$, physical capital $(K_{i,t})$, and labour $(L_{i,t})$:

$$
Q_{i,t} = A_{i,t} K_{i,t}^{\alpha} L_{i,t}^{1-\alpha} \qquad 0 < \alpha < 1,
$$

Equation 13

where α and $1 - \alpha$ denote the share of physical capital $K_{i,t}$ and labour $L_{i,t}$ in the firm's output, respectively. $A_{i,t}$ – Total Factor Productivity (TFP) – captures the portion of firm output that is not explained by the amount of physical capital and labour used in production. As such, the level of $A_{i,t}$ is determined by how efficiently the inputs are utilized in the production process, which is assumed to depend on R&D investment (private and R&D support) and other firm characteristics. As discussed in Section 1.5, we assume that regular support from NMS laboratories generates business impact through an increase in total factor productivity.

Since the key interest is on connecting NMS support to firm's productivity in the resources it employs, we can rewrite Equation 13 in per labour terms:

$$
\frac{Q_{i,t}}{L_{i,t}} = A_{i,t} \left(\frac{K_{i,t}}{L_{i,t}} \right)^{\alpha} \equiv q_{i,t} = A_{i,t} {k_{i,t}}^{\alpha},
$$

Equation 14

where $q_{i,t}$ is the output per labour, and $k_{i,t}$ is capital per labour.

Firm's Behaviour

Economic theory dictates that profit-maximizing firms would employ labour at a level where the marginal revenue generated by an increment to the output produced by the last labourer employed balances the cost of employing that labourer. The cost of employing a labourer is given by the wage $w_{i,t}$. Let $MPL_{i,t}$ denote the marginal product of labour – change in output when an additional unit of labour is employed, and $MR_{i,t}$ denote the marginal revenue generated by selling the incremental output. Then, demand for labour can be represented as:

$$w_{i,t} = MPL_{i,t} * MR_{i,t}$$

Equation 15

Using Equation 13 & Equation 14, the marginal product of labour MPL_{it} can be written as:

$$\frac{\partial Q_{i,t}}{\partial L_{i,t}} = (1-\alpha)A_{i,t}K_{i,t}^{\alpha}L_{i,t}^{-\alpha} = (1-\alpha)A_{i,t}\left(\frac{K_{i,t}}{L_{i,t}}\right)^{\alpha} = (1-\alpha)A_{i,t}k_{i,t}^{\alpha} = (1-\alpha)q_{i,t}$$

Equation 16

Equation 16 implies that marginal product of labour depends on TFP $A_{i,t}$, capital per labour $k_{i,t}$, and the share of labour in firm's output. Hence, NMS support that drives up TFP will increase the marginal product of labour, which in turn affects the wages paid by the supported firms through the relationship in Equation 15.

Impact of NMS Support on Wage Premium and Labour Switch: Hotelling Model
Consider two firms: i and j. Both firms are unsupported by the NMS laboratories at baseline time t. Assuming both firms have similar production functions, their respective labour demand equations can be written using Equation 15 as:

$$w_{i,t} = MPL_{i,t} * MR_{i,t} = (1-\alpha)A_{i,t}k_{i,t}^{\alpha} * MR_{i,t}$$

$$w_{j,t} = MPL_{j,t} * MR_{j,t} = (1-\alpha)A_{j,t}k_{j,t}^{\alpha} * MR_{j,t}$$

For simplicity, we assume a Hotelling-style model for labour: There is a "linear city" that is represented by the interval $[0,1]$. Labour is uniformly distributed along this interval. The two firms i and j are located at each extreme and they employ labour from this linear city. The unique difference among both firms is their location and the wages they pay, as discussed above. The model is represented in Figure 16.

Labourers incur a travel cost to work (e.g., cost of gasoline, value of time spent traveling to work, etc.) that is directly proportional to the distance between their home and the firm they work at. Let τ denote the travel cost per unit distance. Therefore, the payoff for a worker living at point ℓ in the interval $[0,1]$ and working at firm i will be equal to $w_{i,t} - \tau\ell$. And the payoff for the same worker if they worked at firm j will be equal to $w_{j,t} - \tau(1-\ell)$. Let ℓ_t^* denote the location of the worker who is indifferent between travelling to either firm. Then ℓ_t^* can be obtained by equating the two payoffs:

$$w_{i,t} - \tau\ell_t^* = w_{j,t} - \tau(1-\ell_t^*) \Rightarrow \ell_t^* = \frac{w_{i,t} - w_{j,t} + \tau}{2\tau}$$

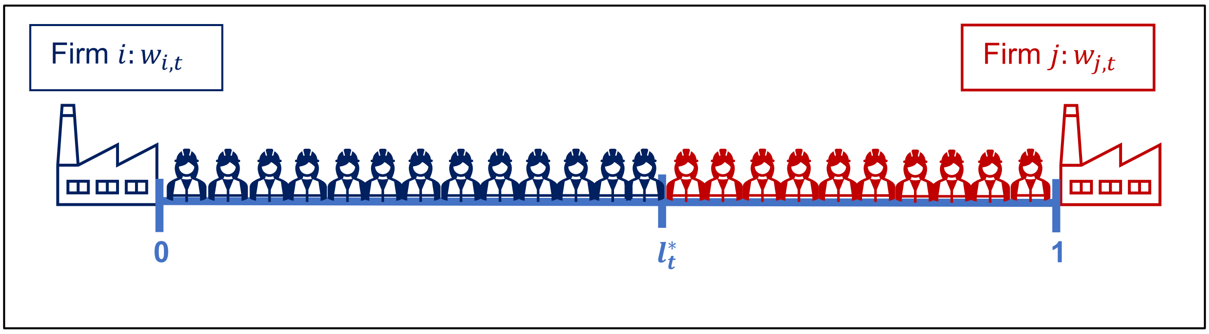

Figure 16: Hotelling model at baseline time t

In equilibrium, all workers located to the left of ℓ_t^* are employed at Firm i, and all workers to the right of ℓ_t^* are employed at Firm j. In other words, ℓ_t^* can be thought of as the proportion of labour force that is employed by Firm i at baseline.

Now assume that at time $t+1$, Firm i becomes a regularly supported firm as it starts working with an NMS laboratory. As a result of receiving NMS support, the total factor productivity of Firm i goes up. That is, $A_{i,t+1} > A_{i,t} \Rightarrow MPL_{i,t+1} > MPL_{i,t} \Rightarrow w_{i,t+1} > w_{i,t}$ (using Equation 15 and Equation 16). Firm j still does not receive NMS support and does not experience any productivity gains. That is, $A_{j,t+1} = A_{j,t} \Rightarrow w_{j,t+1} = w_{j,t}$. Let ℓ_{t+1}^* denote the location of the worker who is indifferent between travelling to either firm at time $t+1$. Then ℓ_{t+1}^* solves the following equation:

$$w_{i,t+1} - \tau\ell_{t+1}^* = w_{j,t+1} - \tau(1-\ell_{t+1}^*) \Rightarrow \ell_{t+1}^* = \frac{w_{i,t+1} - w_{j,t+1} + \tau}{2\tau} > \ell_t^*$$

That is, Firm i experiences employment growth as a result of receiving regular NMS support and the proportion of labour force that it employs goes up from ℓ_t^* at baseline to ℓ_{t+1}^* in the post-support period. The workers who switch to the regularly supported firm are represented by the light blue colour in Figure 17, and the wage premium earned by these switchers in this simple model is given by $w_{i,t+1} - w_{j,t}$.

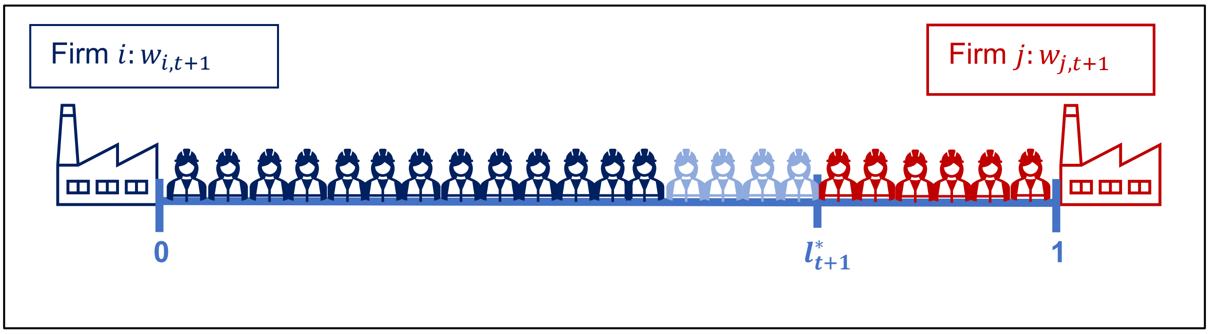

Figure 17: Hotelling model at time $t+1$

Caveats of the Hotelling Model

It is important to keep in mind that the Hotelling model is a simplified representation of the real world and does not capture all its nuances. For instance, wages are exogenous to the model (i.e., they are determined outside the model), and the labour demand is calculated by treating the wages as given. In a future paper, there is the possibility to develop a more complex model where wages and labour levels in equilibrium are simultaneously determined.

Additionally, as outlined in Section 1.5, we assume each firm to be operating as a temporary monopolist in the product market. The rationale behind this assumption is that if the firms were operating in a perfectly competitive market instead, it would be impossible for them to make any supernormal profits.[37] Therefore, they would have any incentives innovate and work with NMS laboratories as that would increase the firms' costs without generating any new revenue. The fact that we observe firms working regularly with NMS laboratories suggests that they probably do not operate perfectly competitive product markets. While it is possible to consider a duopolistic or oligopolistic setup, that makes analytically solving the model significantly more complex. Therefore, the monopolistic market assumption offers a good starting point for the model without losing general insights. It is worth noting that while we assume firms are monopolies in the product market, we do not impose such an assumption on the factor market. In fact, the firms are competing with other firms from the same pool of labour supply as discussed in the Hotelling model.

As discussed, receiving regular support from an NMS laboratory improves TFP, which increases the marginal product of labour. This encourages supported firms to hire more labour and pay them a wage premium. However, Equation 15 suggests that wages paid by a firm depends on the marginal product of labour times the marginal revenue. A monopolistic firm will also internalise that when it increases output by hiring more labour, that will drive down price in the goods market.[38] That is, the marginal revenue falls as output goes up. Thus, in theory, marginal product of labour and marginal revenue can go in opposite directions, and depending on which effect is more dominant, wages can go up or down. However, in practice, wages rarely tend to go down. Which is why in the simplified Hotelling model, we ignore the impact due to marginal revenue and assume that the increase in labour productivity increases wages. In a future study, it would be interesting to explore in detail the conditions on model parameters that will ensure that the effect of labour productivity dominates.

Despite the above caveats, the simple framework presented here outlines how regular support from NMS laboratories increases labour productivity and leads to a wage premium being paid by regularly supported firms. This creates a situation whereby labour exit from the unsupported firms to supported firms because of the ability of the latter to pay higher wages.

[37] In economics, supernormal profit, also called excess profit or pure profit, refers to the excess money that a firm makes above the minimum return necessary to keep it in business (i.e., to pay for its production and operational costs). A perfectly competitive market is characterised by firms that act as price takers rather than price setters. Therefore, supernormal profits are unsustainable because they stimulate entry of new firms in the market, which pushes supply up and forces down prices until the point where supernormal profits are eliminated.
[38] In a perfectly competitive market, individual firms have no control over prices. That is, marginal revenue is independent of the quantity sold by a firm and equal to the market price of the good.