Department for International Trade

Analysis

Methods using econometrics to evaluate the impact of trade promotion activities

Lessons learned and options for original analysis

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frontier economics

This is a report of research carried out by Frontier Economics, on behalf of the Department for International Trade.

Frontier Economics is one of Europe's largest economics consultancies, with more than 250 graduate economists working across seven offices. They specialise in providing robust, independent advice to businesses, regulators and government agencies on issues related to competition, commercial strategy, regulation and public policy.

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Executive Summary

This report is part of a project commissioned by the Department for International Trade (DIT) to establish a robust methodology to assess the Value for Money (VfM) of the department's client-facing trade promotion activities. The report aims to assess whether and how the existing evidence base on the impact of trade promotion activities could be strengthened through further robust econometric analysis.

To conduct this assessment, we relied on desk research (consisting of a review of existing literature and sources of data), and interviews with a number of experts, as well as engagement with stakeholders within DIT, the Office for National Statistics (ONS), and Her Majesty's Revenue and Customs (HMRC).

The current evidence base on trade promotion in the UK includes two recent studies, Mion and Muuls (2015, hereinafter 'MM') and Rincon-Aznar et al. (2015, hereinafter 'RR') that have used econometric methods to estimate the impact of UK Trade and Investment (UKTI) export promotion activities. Given the characteristics of UKTI export promotion, and the available sources of data on UK firms, the Propensity Score Matching (PSM) methods used by MM and RR are in line with international best practice in the evaluation of trade promotion and with UK practice in the evaluation of other forms of business support provided by government. Drawing on other studies included in our review, we have identified a number of ways in which future analysis could build on the MM-RR approaches to further strengthen their robustness.

International research shows that the impact of export promotion on the growth rate of exports, employment and turnover is larger for Small and Medium Enterprises (SMEs) than for other firms. A study on Canadian firms (Van Biesebroeck et al., 2015) also showed that types of support involving tailored advice were more effective than pure information provision in promoting exports.

Studies on the UK include relatively little evidence on how the impact of export promotion varies according to the characteristics of the supported firms (such as their size), and of the support provided. This gap is partly due to the limitations of the data used in MM and RR, which under-represent SMEs. Future research aiming to evaluate the impact of DIT export promotion activities could aim to fill these gaps by constructing a new analytical dataset, which would ideally:

- include information on basic firm characteristics (such as industry and location) and key business outcomes (employment, turnover) from the Business Structure Database (BSD) or Longitudinal Interdepartmental Business Register (L-IDBR), two datasets that include administrative and survey information on nearly all UK firms
- include information on exports from HMRC data (chiefly, Customs declarations)
- identify the firms supported by DIT and the type of support they received over a relatively long time period (around five years)

1 Introduction

This report is part of a project commissioned by the Department for International Trade (DIT) to establish a robust methodology to assess the Value for Money (VfM) of the Department's client-facing trade promotion activities.

Assessing the VfM of trade promotion requires robust evidence on the economic impact of these activities, but producing robust impact estimates is challenging because:

- changes in exports and other business outcomes in firms that have used export promotion services may be due to many other factors (exchange rate fluctuations, changes in management or business strategy, wider economic conditions)
- firms that use export promotion services are likely to be different from other organisations. Export promotion users may export more than other firms, but this will be due in part to characteristics of users that make them more likely to export regardless of their interaction with trade promotion agencies

This report aims to establish if and how the existing evidence base on the impact of trade promotion activities could be strengthened through further robust econometric analysis. We considered the impact of export promotion on both export activity and wider economic outcomes (such as turnover and employment). This review consisted of:

- a literature review of existing econometric evidence on the impact of trade promotion, this relied on a systematic review we carried out as a separate strand of this project
- a review of studies evaluating the impact of other business support policies in the UK using econometric methods (including innovation policy, business advice, and transport and local growth interventions specifically aiming to improve business outcomes such as employment, turnover and productivity)
- a review of available data on trade promotion activities, exports, business characteristics, and business outcomes in the UK
- interviews with six experts on trade promotion, business data, and policy evaluation using econometrics

To ensure that the material reviewed would be relevant for the aims of this review, we agreed with DIT the following scope.

Within the trade promotion literature, we considered both effects of trade promotion on its immediate intended outcome (exports) and on further business outcomes, including chiefly employment, sales, productivity (but also extending sometimes to innovation-related outcomes). Moreover, we focused on methods using firm-level data to evaluate impact rather than approaches such as gravity modelling (which rely on time series to provide macroeconomic impact), as these methods are in principle able to identify granular impacts by policy and beneficiary that would best support a wider value for money framework.

Investigating both the trade promotion literature and the wider policy evaluation literature, we have focused on methods above a minimum threshold of robustness.

2 Our Approach

2.1 Literature review

The literature review focused on understanding the relative strengths and weaknesses of econometric methods used to evaluate the impact of publicly funded business support on business outcomes.

The primary focus was on methods used for the evaluation of export promotion services, but we have also considered insights from on the evaluation of business support policies in the following policy areas:

- Inward investment and foreign direct investment (FDI)
- Innovation and Research and development (R&D)
- Transport and infrastructure investment
- Defence
- International development
- Local growth

To identify the relevant literature, we proceeded in three steps:

- one, perform searches on aggregators: we performed Boolean searches from three aggregators (Google Scholar, Jstor, Sciencedirect) on a combination of keywords, focusing on papers written before the year 2000
- two, snowballing, we went through the bibliography of the selected papers to understand whether some of their references could be useful for our purposes
- three, further input from partners, we also relied on the input from the working group, expert partners and interviewees to identify any additional papers

All studies identified through these processes were subject to an abstract sift to assess whether they provided evidence related to the research questions. To ensure that the studies reviewed would provide insights on robust evaluation methods, we focused on publications whose methods would achieve a minimum score of 3/5 on a reasoned Scientific Maryland Scale (SMS).[1]

Figure 1 overleaf describes the key methods that, if appropriately implemented, can achieve this score.

[1] Sherman et al. (1998). In the UK, used in evidence reviewed carried out by the What Works Centre for Local Growth. A ‘reasoned’ SMS takes account not only of the method used but also of the way in which it is implemented – specifically, the extent to which the empirical strategy adopted justifies the assumptions on which the validity of the method rests.

Figure 1 Brief description of key econometric methods used in impact evaluation

Method	Description
Difference-in-Differences (DiD)	Comparison of outcomes in treated group after an intervention, with outcomes in the treated group before the intervention, and a comparison group used to provide a counterfactual.
Difference-in-Differences combined with Propensity Score Matching (PSM-DiD)	As above, but treated and control groups selected so they are close in terms of their propensity to be 'treated'.
Panel data methods	Including, among others, dynamic panel data models and 'fixed effects' models, which control for all fixed characteristics of treated and control observations.
Regression Discontinuity Design (RDD) and Instrumental Variables (IV)	Exploit near-random variation in treatment. IV relies on finding a variable that influences treatment but not the outcomes of interest. RDD relies on finding appropriate thresholds such that groups just above (below) the threshold are (non) treated but equivalent in all other ways to groups just below (above).
Randomised Controlled Trial (RCT)	Participants are split in treatment and control group in a way that ensures there are no significant differences between the two groups, other than the treatment itself.

However, for both trade promotion and other policy areas, we also considered other selected contributions if, based on the abstract sift, they had particularly useful insights into relevant datasets or if they would be particularly informative on wider issues. For instance, Conconi et al. (2016) identified a link between export activity and the likelihood of engaging in FDI, using Belgian data. Although it did not have a specific UK or policy evaluation focus, we reviewed it to improve our knowledge base on the factors affecting the export decision.

2.2 Data review

The data review aimed to identify and assess potential sources of data needed for an evaluation of the impact of Department for International Trade (DIT) export promotion. These data would need to include information on which firms use export promotion services (receive 'treatment'), and on the characteristics and outcomes (exports, further business outcomes) of both treated and non-treated firms.

For data on firm outcomes and characteristics, we identified potential sources as follows:

- literature review: we reviewed the data sections of the studies identified within the review described above
- dataset desk review: relying on information provided by the Office for National Statistics (ONS) and the UK Data Service

For treatment data, we engaged a number of stakeholders within DIT to assess the availability and quality of data on service users collected by the department.

2.3 Interviews

The interviews were intended to complement the insights generated by the systematic and data reviews. They were helpful in refining our understanding of key methodological issues which had been identified in the first two strands, but which might not be discussed at length in publicly available sources.

During the process, we interviewed six experts from academia, government and third sector. The interviews were based on a topic guide agreed with DIT. They varied between 15 minutes and one hour, depending on the experts' availability, and they were conducted over the phone.

Figure 2 List of interviews

Expert	Title and organisation
Chiara Criscuolo	Senior Economist, Structural Policy Division
Rafael Mastrangelo	Head of Compilation and Delivery – Trade Statistics, HMRC
Mirabelle Muuls	Assistant Professor in Economics, Imperial College Business School
James Phipps	Principal Researcher, Nesta
Rebecca Riley	Director of Economic Statistics Centre of Excellence, National Institute for Economic and Social Research
Ana Rincón-Aznar	Principal Economist, National Institute for Economic and Social Research

3 Evidence on the Impact of Trade Promotion Activities

A separate report produced as part of this study describes in detail the literature on the impact of trade promotion activities on exports and other business outcomes, including employment and turnover. In this report, we only provide a short overview of the findings from this review to inform our discussion of methods and data in Section 4 and following. Key findings from the impact review are the following:

- impact on exports: evidence from both the UK and other countries shows that export promotion leads to growth in exports the following year. In the UK, this effect is typically an increase of 7 to 10 percentage points. There is limited evidence on longer term effects
- impact on other business outcomes: there is also evidence of impact on further business outcomes (employment, turnover, and productivity) in the short-term. In the UK, evidence is weaker on employment outcomes and stronger on turnover and productivity
- variation in impact:

- in the international literature, trade promotion typically has a stronger impact on smaller firms (employing at most 100 or 250 workers, depending on the case). In the UK, identifying the effect of trade promotion on smaller firms has been challenging, because the data used under-represents this group
- studies from outside the UK have found more intensive promotion services and support that involves different types of promotion to have a greater impact. Again, evidence on variation in impact from the UK is relatively weak

3.1 Evidence from the United Kingdom

In the UK, three recent studies have analysed the impact of trade promotion activities on exports and outcomes.

Mion and Muuls (2015) - hereinafter 'MM' - used a Difference-in-Differences combined with Propensity Score Matching (PSM-DID) methodology to evaluate the impact of UK Trade and Investment (UKTI) services on the intensive margin (amount of exports per firm) and extensive margin (number of exporters, number of countries, number of products) of exports. Their analysis relied on exports data from Her Majesty's Revenue and Customs (HMRC) and firm-level data from the Financial Analysis Made Easy (FAME) database. They found positive impacts on exports, mainly through the extensive margin (expansion of existing exporters into new countries), but no statistically significant differences by policy or firm type.

Using a similar PSM-DID approach, but data on outcomes exclusively from the FAME database, Rincon-Aznar et al. (2015) – hereinafter, 'RR' - analysed the impact of a wide range of UKTI services on employment growth, turnover growth, and asset growth. They identified positive effects on turnover and labour productivity, while the employment effects depend on the specification chosen. They did not find systematic differences in impact by firm size, but they conclude that firms using more than five services experience greater growth in turnover and labour productivity compared to firms using two to five services.

Breinlich et al. (2012) evaluated whether firms holding Intellectual Property (IP) were more likely to export (on the extensive or intensive margin) relative to other firms. They found, using a PSM technique and FAME data, that IP active firms were 4% to 9% more likely to export.

Earlier studies also found positive, statistically significant effects of trade promotion activities, but focused on evaluating more specific issues, relying on less robust approaches. For instance, Rogers and Helmers (2010) assessed the link between two UKTI schemes, Passport to Growth and Export Marketing Research Scheme (EMRS), and the probability of exiting the market. The study aimed to account for observable differences between supported and unsupported firms, but could only rely on a limited number of control variables due to data limitations.

3.2 Evidence from other countries

Numerous studies have evaluated the impact of export promotion services in other countries, relying on similar methodologies, but in some case on more comprehensive data sources. Key findings are the following:

- overall effects: export promotion activities have typically been found to have a positive effect on exports (Gorg et al., 2008, Volpe and Carballo, 2010, Van Biesebroeck et al., 2015, Broocks and Van Biesebroeck, 2017). There is weaker evidence of impact on other business outcomes. A study on Danish firms has identified positive average turnover effects and effects on value added, but no employment effects (Munch and Schaur, 2018)
- variation by policy: Using multiple types of export promotion services has been linked with greater export growth (Van Biesebroeck et al., 2015). More "intensive" services have been found to be more conducive to exports than less intensive services: financial incentives have a greater impact than logistical support (Broocks and Van Biesebroeck, 2017) and troubleshooting (meaning consulting-like support on strategy and events) services have a greater impact than information provision (Van Biesebroeck et al., 2015)
- variation by firm type: The impacts tend to be larger for small and inexperienced firms because these firms tend to have more scope for expanding and learning (Volpe and Carballo, 2010, Munch and Schaur, 2018, Broocks and Van Biesebroeck, 2017). Positive employment and value-added effects have only been identified for small firms, with less than 20 employees (Munch and Schaur, 2018)

4 Methods used in firm-level impact evaluation

The impact evaluation studies we have identified have typically relied on methods that would achieve a robustness rating of 3/5 on the Scientific Maryland Scale (SMS). A majority of studies in the trade promotion literature use a Propensity Score Matching (PSM) methodology, both in the UK and elsewhere. Within the PSM framework, the choice of variables included in propensity score by UK researchers has been constrained by data availability. UK studies stress the importance of including the following information for calculating propensity scores:

- past export activity: all studies control for past export activity but they do it differently. Mion and Muuls (2015, hereinafter 'MM') and Breinlich et al. (2012) use a Heckman selection procedure, whereas Rincon-Aznar et al. (2015, hereinafter 'RR') use overseas turnover as a control variable
- past innovation activity: the UK trade promotion literature since Breinlich et al. (2012) controls for past patent activity given close relation between innovation and exporting

The international literature on trade promotion suggests adjustments to the PSM methodology which could help ensure the comparability of treated and control group, if sufficiently detailed data are available.

The wider impact evaluation literature suggests:

- checking that treated and control groups are equally likely to have received other forms of public support other than trade promotion
- including detailed geographical controls in the propensity score model, taking into account different degrees of economic clustering in the firm's local area
- controlling for past innovation by relying on the sampling frame for the Business Expenditure on Research & Development dataset

4.1 Insights from trade promotion literature

Impact evaluation in the UK –

Figure 3 presents an overview of data and methodologies employed in the three most recent UK studies (RR, MM and Breinlich et al, 2012). All three studies use a Propensity Score Matching (PSM) method, combined with Difference-in-Differences (DiD) in the case of RR and MM. Given the characteristics of UK Trade and Investment (UKTI) support, it is unlikely that methods justifying higher scores on the SMS would have been feasible. For example, a Regression Discontinuity Design would require a fixed threshold over/below which UKTI support was/was not provided.

Figure 3 Overview of methodology for UK-specific studies

Authors	Geo	Methodology	Data	Key lessons
Breinlich et al. (2012)	UK	PSM (nearest neighbour matching), augmented with a Mills ratio as in Mion and Muuls (2015). Matching variables include turnover, age, IP activity, multinational status and foreign ownership	Data from Financial Analysis Made Easy (FAME) for overseas turnover. Small firms are underrepresented as in Rincon-Aznar et al (2015) Data on patent activity from the Oxford Firm Level Intellectual Property (OFLIP) database and the Intellectual Property Office (IPO)	Controlling for past through patents data innovative activity is important
Rincon-Aznar et al. (2015)	UK	PSM (nearest neighbour matching as the baseline) and PSM DiD. Only two periods (before and after promotion). PSM-DiD leads to smaller estimates. Matching variables include size (in terms of	Authors need to string-match FAME and the UKTI contact list, losing information for about 50% of firms. FAME has turnover/employment info for less than 1/3 of	Robustness checks included different matching techniques, changes in control group (only to firms who had never been supported) and timing of

		employment and assets), age, overseas turnover, IP activity, ownership, sector and region (prior to treatment) and matching is done on each year separately.	matched firms, and these are more likely to be large. IP data from UK IPO for IP activity	matching (at the time of treatment) Authors replicate results for firms who receive "multiple treatments" from UKTI
Mion and Muuls (2015)	UK	PSM as a baseline (with only two time periods, t and t+2), with growth variables for previously supported firms and levels for new exporters. Similar variables to RR. The main difference is that authors augment PSM with a Mills ratio based on a firm export status to account for self-selection. Their results depend on this assumption.	The need to string-match FAME and the UKTI contacts list leads to a loss of about half of "treated observations" Authors investigated the possible use of BSD but could not match BSD with export data within the HMRC data lab.	It is important to control for selection into exporting. This could be done by augmenting the PSM model with a Mills Ratio, based on past export activity.

Source: Frontier Economics analysis

In general, the validity of a PSM estimation depends on:

- selection into treatment: the model of selection into treatment (the Propensity Score model) accounts for all factors that explain variation in treatment and in the outcomes of interest (whether the 'conditional independence' assumption holds)
- testing the matching procedure: the matching procedure is successful in finding close matches for a large majority of the treated (whether there is 'common support' between treated and control observations)

We discuss these two conditions in relation to the three studies separately, noting to what extent the authors were able to show that they were fulfilled.

Selection into treatment

Ideally, matching variables should include all the characteristics that influence both whether a firm receives support ('treatment') and outcomes of interest (such as firm turnover). The three studies use a rich set of firm characteristics as matching variables. The authors do not discuss at length the choice of matching variables, which is likely to have been driven at least partly by data availability, but their work suggests that two issues are likely to be particularly important:

- one, using data on patents as a control: Breinlich et al. (2012) show that supported firms are more likely than non-supported to have innovated in the past. They control for this by including a binary indicator for patent ownership in the propensity score model. Later studies also control for past innovation activity using IPO data

- two, controlling for past export activity: firms that have exported in the past are more likely to be supported. All the UK studies considered here control for this, in two different ways which appear equally valid:
  - MM and Breinlich et al. (2012) model the propensity to export first, before modelling the propensity score (selection into treatment). The propensity score model includes an indicator of the propensity to export among the control variables.[2]
  - RR use overseas turnover as a control variable directly in the first stage of the PSM

Moreover, both MM and RR show that the treated group includes a small number of especially large firms. They check that their results are not driven by these firms by excluding the top 5% in the distribution of assets from a set of the estimates.

Testing success of matching procedure

RR and MM show that their matching procedure has been successful:

- balancing tests: They report tests showing that the matching procedure makes the treatment and control groups more comparable in terms of observable characteristics. After matching, there are no statistically significant differences between treated and control firms in terms of these characteristics
- common support: they show that a matched control could be found for a large majority of treated firms, and do not report that any specific groups of treated firms were less likely to be matched
- choice of matching algorithm: estimated treatment effects are not sensitive to the choice of matching algorithm (for example whether each treated is matched only to the 'nearest' control in terms of their propensity score, or rather matched to all controls within a given distance)

Breinlich et al (2012) also report that the choice of matching algorithm did not significantly alter their results. They report limited evidence on balancing tests and common support.

Methodological challenges –

Data

The three studies relied on information from the FAME database, and data on UKTI support from OMB Research, a market research firm which has conducted telephone-based surveys of UKTI users.

The use of these two datasets limited the researchers' ability to investigate variation in effects by firm size. Around half of the 'treated' observations from the UKTI support data could not be used (RR, MM) and the achieved sample significantly

[2] Formally, they estimate a Heckman selection model. Using this model requires finding variables that affect the first selection stage (in this case, selection into exporting) but not the second stage (in this case, selection into treatment). Both studies argue that lagged exports (e.g. exports two years before treatment, say 2012) influence whether the firm has exported in the year before treatment (e.g. 2013), but do not determine whether the firm has received treatment in a given year (in this example, 2014).

under-represented smaller firms. These two issues were determined by some reporting issues in the underlying data:

- missing firm-level identifiers: the UKTI support data did not include a unique firm identifier (such as Companies House Refence Number) that could be used to match across to other datasets. As a consequence, firms from FAME had to be “string-matched” to firms from the UKTI contact list, using company names, telephone numbers and postcodes, leading to significant reduction in sample size
- reporting requirements in FAME: FAME extracts data from the financial reports submitted to Companies House. The reporting requirements in Companies House are less stringent for smaller companies. For instance, Breinlich et al (2012) note that in 2005 firms were legally obliged to disclose turnover information only if this was above £5.6 million. This means that FAME has lower coverage of smaller companies

Estimating variation in effects

Studies of the impact of trade promotion in the UK have been limited in their ability to investigate how the estimated effects vary. This has mainly stemmed from the data limitations mentioned above, which have constrained the available sample size. However, estimating how the impact of trade promotion varies by type of service and over time can be challenging for other reasons, as suggested by the international literature reviewed below:

- variation by service type: supported firms often benefit from several services in the same time period. This makes it challenging to find a sufficient number of firms that receive only one type of service
- variation over time: supported firms often benefit from export promotion services repeatedly over the years. This makes it challenging to understand whether the export growth experienced by a supported firm two years after receiving a service (for example 2016) is linked to the service received in 2014 or to the further services received in 2015

4.2 Impact evaluation studies outside the UK

The literature from other countries has relied on similar techniques to the existing UK studies, generally scoring 3/5 on the SMS. All these studies relied on administrative data, which meant they were better able than UK studies to include small firms in their estimates. The key additional insights were the following:

- use of panel data techniques: A minority of studies reviewed used panel data techniques along with PSM methods (Volpe-Martincus and Carballo 2008; Van Biesebroeck et al, 2015). These techniques allow to separate out the effects in different time periods (one year after support, two years after support) and to control for the historical export performance. This may come at the cost of focusing on older firms with a longer export history.
- restrictions to control group:

  - Broocks and Van Biesebroeck (2017) suggest restricting the group of potential control firms in two distinct ways: i) using only firms that have had at least some contact with the export promotion agency (‘near-treated’); ii) using firms that have particularly high incentives to export. They argue that all Belgian firms over a minimum size threshold would fit under ii), due to the limited size of the domestic market.
  - Munch and Schaur (2018) restrict the control group to firms who have purchased of external consultancy work from other private firms or increased their wage bill on sales workers, drawing on detailed financial data from Danish firms. This should control for the possibility of receiving export promotion support through other media. In a further robustness check, they also restrict the treatment group to firms who have been selected by the council or to firms who have self-selected into the support services.
- control variables in the PSM: Munch and Schaur (2018) benefit from especially detailed data on Danish firms, which allows them to control for factors that are typically not observable:
  - whether there has been an increase in demand for the firm’s product. Firm specific-demand shocks are a potential important driver behind selection into export promotion and improved performance. Munch and Schaur (2018) compute firm specific demand shocks by using information on export sales by product codes by destination countries and information on domestic product sales from the PRODCOM register. They then aggregate these firm-specific pre-treatment sales to the six-digit Harmonised System (HS) level and combine them with product specific changes in demand on international markets from the UN COMTRADE data. They then create dummy variables to control for increases in firm specific demand in years before a firm receives an export promotion service
  - the composition of the firm’s workforce (in terms of age, gender and educational attainment)
- quantile treatment regressions: Using quantile regression can be useful to assess how the impact of export promotion varies by firm size, as in Volpe Martincus and Carballo (2010)

Figure 4 overleaf summarises the methodologies and data sources employed by the most important studies from other countries.

Figure 4 Overview of methodology for other countries

Authors	Geo	Time period	Methodology	Data	Key lessons
Volpe-Martincus and Carballo (2008)	Peru	2001-2005	Authors experiment with several techniques (all for before and after effects): DiD with employment and age as controls, Blundell Bond estimator[3], PSM DiD (matching variables are the lag of exports, treatment, employment, age and location)	Data on Peruvian exporters at the firm-product-market level and firm-level employment data from the National Tax Agency	The Blundell-Bond estimator could be a useful cross check (including an instrumented lagged export variable in the DiD equation) They propose five tests to judge the quality of PSM estimation (stratification test, bias test, difference in means, Hotelling t-squared, comparing pseudo R^2 before and after balancing)
Volpe-Martincus and Carballo (2010)	Chile	2002-2006	Use a quantile treatment effect regression with PSM (before and after), on top of an estimation of the ATE	Use data from Chilean export agency and the Central Bank of Chile, including sales and exports for all exporters	Quantile treatment effect regressions can be used to estimate the variation in the size of the effect with size of the firms
Van Biesebroeck et al. (2015)	Canada	1999-2006	Uses FE, PSM, PSM DiD and the mean difference in growth rates between supported and not supported firms (all before and after)	Data for the full export history of all exporters, merged with Business Register	Several firms in their data receive treatment in multiple years. They estimate the impact on the first instance of treatment and then estimate a separate model for the "intensity of treatment"
Munch and Schaur (2018)	Denmark	2002-2012	Use a PSM DiD technique for two time periods. List of matching variables is comprehensive (industry, lagged	Detailed administrative data for the population of Danish firms.	Estimate impact separately according to size of the firm, but using different thresholds (1-20, 20-50, 50+)

[3] The Blundell-Bond estimator is an example for a GMM Dynamic Panel Data technique. In a panel model, it is not always possible to insert the lag of the dependent variable as a regressor, because it could be correlated with the error term. The Blundell-Bond estimator circumvents this problem by using further lags of the regressor as an instrument.

			sales, VA, employment, workforce composition, capital stock, raw materials, wage bill, export and import intensity and a dummy for firm-specific demand shocks)		Identification of control group: limit only to firms who purchase consulting services or hire extra sales workers. Distinguish between a treatment group for firms contacted by the Trade Council and for self-selected firms Control for firm-specific demand shocks.
Broocks and Van Biesebroeck (2017)	Belgium		Outcome variable is the probability of export market entry (0 or 1). Authors rely on probit regression and a linear probability model with fixed effects, applying different restrictions to the control group.	Detailed administrative firm-level data merged with indicators of export promotion support from Flanders Investment & Trade (FIT)	Restricting the control group could be useful if sufficient data are available. In particular: using only firms that have had at least some contact with the export promotion agency; using firms that have particularly high incentives to export.

Source: Frontier Economics analysis

4.3 Insights from impact evaluation in other policy areas

In addition to our review of studies evaluating the impact of export promotion, we have also looked for methodological insights from impact evaluation in other policy areas (FDI, innovation, local growth, transport, defence, access to finance, other forms of business support). The literature on export promotion services seems to be quite well-developed in terms of techniques used. Therefore, we have focused on the United Kingdom to primarily capture potential gaps in terms of key lessons and data. Key insights from this component of our review include the following:

Dynamic panel data models have been used to evaluate the impact of tax credits for Research and Development (Harris et al., 2009; Fowkes et al., 2015), in a similar way to Volpe Martincus and Carballo (2008) and others that have applied the same approach to trade promotion. Harris et al. (2009) and Fowkes et al.(2015) discuss the application of the approach but do not comment on its advantages or disadvantages compared to alternatives (for example PSM, DiD).

PSM and PSM-DiD approaches are a relatively popular choice. Recent studies suggest ways of modelling the propensity of treatment that could be applied to a study of export promotion:

Frontier Economics (2017) uses a firm's inclusion in the sampling frame of the Business Expenditure on Research and Development (BERD) dataset as a control for past innovation activity, and controls for past receipt of public support (including both the forms of support being evaluated and other forms of support from the Department for Business, Innovation and Skills - BIS). Indeed, internal research conducted by BIS (2014) suggests that there might some overlap in support provided by different government programmes. In particular, 10% of firms who received export support services were also granted finance or business advice.

Vanino et al. (2017) include detailed controls for location and sector-specific factors: agglomeration indices at region and industry level; regional Research and Development (R&D) intensity; proxies for the competitiveness of local markets.

Local interventions have been evaluated using large datasets (such as BSD) and granular information on the location of the treatment. This approach involves comparing areas that differ only slightly in their distance to the intervention site. Gibbons et al. (2017) applies this method to the evaluation of the UK's Single Regeneration Budget. Other studies using the same approach include Einiö and Overman (2016), and Gibbons (2015). However, this method is not well suited to estimating the impact of public policy interventions that are not linked to specific locations.[4]

At times, eligibility to public support is determined by rules that are not related to firm-specific characteristics or to the behaviour the policy aims to encourage. Aguiar and Gagnepain (2017) and Criscuolo et al. (2018) exploit such situations to estimate the impact of funding for R&D provided by the European Union and of investment subsidies provided by the UK Government respectively.

In the UK, BIS performed a Randomised Controlled Trial (RCT) to evaluate the effectiveness of a business support service, the Growth Vouchers programme (IFF, 2016). This could be a good foundation for thinking about the use of RCTs in an export promotion context, something that goes beyond the purpose of this review.

The literature includes evaluations using alternative sources compared to BSD and FAME, the key sources employed in the UK literature on trade promotion. Alternative sources include the Annual Business Survey (ABS) and its predecessor, the Annual Respondents Database, and company information collected by Dun & Bradstreet (D&B). However, using ABS implies a focus on relatively large enterprises (employing 250 workers or more). Advantages and disadvantages of the D&B database compared to FAME and to BSD have not been discussed in the literature, to the best of our knowledge. We report findings from our conversations with D&B in section 5 of this report.

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[4] This approach is also referred to as 'spatial differencing', for example in Department for Business, Energy and Industrial Strategy (2017), "Evaluation of Policies for Local Economic Growth: Scoping Study", BEIS Research Paper No.5.

Figure 5 summarises methods and data used in each of the studies we have reviewed in detail, along with key implications for this report.

Figure 5 Overview of key insights from other policy areas in the UK

Authors	Policy Area	Methodology	Data	Key lessons
Fowkes, R.K., et al. (2015)	Innovation	Dynamic Panel Data model using generalised method of moments (GMM) estimator	HMRC data on R&D expenditure combined with FAME	Use of dynamic panel data models; discussion of advantages and disadvantages of Arellano-Bond and Blundell-Bond estimators
Harris et al. (2009)	Local growth/ Innovation	Dynamic Panel Data model with GMM estimator	Business Enterprise R&D and the Annual Respondents Database (ARD)[5]	The Annual Business Survey (ABS) can be matched with external data and could be used in policy evaluations
Mole et al. (2008)	Business Advice	DiD approach	Dun & Bradstreet database used for the control group	Dun & Bradstreet database as alternative to FAME
Gibbons et al. (2017)	Local growth	‘Concentric rings’ approach: comparing areas that differ slightly in distance to intervention area	BSD	Localised interventions can be evaluated (with access to sufficient data) by making comparison between areas at a high level of geographical detail
Frontier Economics (2017)	Innovation	PSM-DiD, modelling separately impact of support on firm survival	BSD, BERD	Highlights importance of survival effects to interpret impacts of support on firm outcomes. Uses presence in BERD as proxy for past R&D activity. Controls for past support.
Vanino et al. (2017)	Innovation	PSM-DiD	BSD, Gateway to Research data on recipients of research funding	Detailed controls or location and sector-specific factors included in propensity score model

[5] Predecessor of Annual Business Survey, collected up to 2008. Source: https://discover.ukdataservice.ac.uk/catalogue?sn=6644

Aguiar and Gagnepain (2017)	Innovation	Uses industry-level availability of funding as an instrument for firm participation in European Union innovation support programme	AMADEUS (international version of FAME)	Possible to use Instrumental Variables (SMS 4) if availability of support at industry/region level varies for reasons not linked to outcome (in this case, firm innovation)
Criscuolo et al. (2018)	Business support	Uses changes in region eligibility as an instrument for firm receipt of investment subsidies	BSD-ARD	Possible to use Instrumental Variables (SMS 4) if availability of support at industry/region level varies for reasons not linked to outcome (in this case, firm investment)

Source: Frontier Economics analysis of selected literature

4.4 Further issues in the implementation of Propensity Score Matching models

A growing body of literature contributes to the evolution and refinement of PSM methods and provides practical guidance for their implementation. A full review of this literature is beyond the scope of this report, but we present here key themes from selected contributions.

Practical guidance for the implementation of PSM, including Caliendo and Kopeinig (2008), Heinrich et al. (2010), and Imbens (2015), provides the following suggestions:

- selecting variables to be included in the propensity score model by relying where possible on theory or practical knowledge about how firms or individuals select into treatment. The literature suggests data-driven methods to further refine the selection (or to select in the absence of strong priors based on theory or previous evidence) but there is no clear consensus in favour of any of these methods
- different matching algorithms (for example nearest neighbour, k nearest neighbours, radius matching) will strike a different balance between strictness of the match, likelihood of finding relevant matches for all the treated, and computational intensity
- estimating standard errors for PSM estimates can be challenging, because the estimated treatment effects depend on the propensity score, which is itself estimated. In practice, simulated ('bootstrapped') standard errors are often used

Heinrich et al. (2010) also discuss recent developments, including the 'Generalised Propensity Score' (GPS) approach, which aims to estimate the effects of changes in treatment levels. In the context of export promotion, treatment levels could be thought of as the length or intensity of engagement with the export promotion agency. GPS is based on the assumption that selection into different treatment levels is random, conditional on control variables. There may be cases where this assumption is more likely to hold compared to what is required for PSM – that is, that selection into treatment (regardless of levels) is random, conditional on control variables.

5 Data

To implement a Difference-in-Differences combined with Propensity Score Matching (PSM-DiD) estimation, we would need the following types of data, at firm level:

- data that identifies firms which used Department for International Trade (DIT) export promotion services ('treatment data')
- information on the characteristics of treated and non-treated firms, to control for any differences other than treatment between the two groups ('control data'). It is also important to note that information on outcomes prior to treatment is effectively used as a control in a Difference-in-Differences strategy
- information on outcomes that may have been affected by treatment ('outcome data'): survival, exports, and further business outcomes (employment, turnover).

These data are included in distinct datasets. Therefore, it will be necessary to match different data sources into a unified analytical dataset. This is easiest when all the data sources to be matched include a unique firm identifier that is consistent across sources. We briefly discuss the available data sources below.

5.1 Available data sources

Treatment data –

Kantar pipeline

Pipeline data provided by Kantar Public ('Kantar pipeline') includes information on around 180,000 unique firm-year combinations (cases of firms supported by DIT) between April 2014 and March 2017, of which around 140,000 supported before April 2016. A Companies House Refence Number (CRN) identifying the supported firm has been recorded in around 28% of the 140,000 cases (just under 40,000 firm-year combinations) prior to April 2016.[6] As explained in section 4, company-level identifiers are very important to ensure that information on a treated company can indeed be used in the econometric work, because they allow to merge information across different datasets.

Data collected by DIT

In parallel to the work undertaken by Kantar, DIT has also carried out internal work to collate, clean and standardise data on service deliveries within the Datahub project. To the best of our knowledge, Datahub should now include data that was recorded in DIT's prior centralised information system, CDMS, which was also the basis for the Performance and Impact Monitoring Survey (PIMS – please see dedicated section below for further detail on this survey).

[6] This proportion is considerably higher – 46% - for April 2016 to March 2017.

DIT has provided us access to pipeline data generated through Datahub ('the Digital pipeline') for calendar years 2014-2017 and have noted the following for years 2014 to 2016:

The number of apparently unique firm-year combinations is higher compared to the Kantar pipeline: 280,796;

The proportion of observations where a CRN has been recorded is higher than in the Kantar pipeline: 63%;

The data appear to be less 'clean':

- it is not clear whether duplicate observations have been removed and whether firms are identified by a unique variable, where there is no CRN
- the way DIT services have been grouped in categories would need a mapping to match categorisation used elsewhere (for example in the PIMS sampling frame). We understand DIT has generated a mapping between the current Datahub categories and the categories that were used in older datasets (including PIMS sampling frame)

PIMS sampling frame

Existing studies, including Rincon-Aznar et al. (2015, hereinafter 'RR') and Mion and Muuls (2015, hereinafter 'MM'), have identified firms treated by DIT through the information used as a sampling frame for PIMS. Specifically, RR used data on firms treated between May 2005 and September 2010, which included a total number of 212,203 records, reflecting treatment of 65,423 unique firms. CRNs were not available in the data received by RR and MM.

Data on exports –

Data on exports held by Her Majesty's Revenue and Customs (HMRC)

HRMC is responsible for three different datasets on firm-level exports. Only the first two can be accessed by external researchers, by submitting an application to the HMRC datalab:

- Non-EU trade panel dataset: covers extra-EU exports in goods at the transaction level from declarations submitted by firms. The data are available for the 1996-2016 period from the HMRC datalab.
- EU trade panel dataset: covers exports in goods conducted by businesses who are on the Intrastat register, but only for transactions over £250,000 (equivalent to 97% of total exports by value). The data are available f for the 2008-2016 period from the HMRC datalab. Earlier data cannot be accessed due to the existing data protection legislation.
- EC Sales list: covers business to business transactions in the EU for goods and services, but cannot be accessed through the HMRC datalab.

We reviewed in depth the EU and Non-EU trade panel datasets. They both display the following characteristics, which could potentially introduce some constraints on the analysis:

- No coverage of services: The datasets only cover exports in goods. In principle, it could be possible to compute a firm's services exports as a residual. Having access to the firm's total export sales, it would be possible then to subtract goods exports from the total to estimate the exports of services. However, this project has not identified a source of information on firms' total export sales. The EC Sales list includes exports of both goods and services to businesses in EU member states, but these data are not available through the HMRC data lab.
- Multiple VAT numbers: The transactions are recorded at the VAT-number level and firms often operate with more than one VAT-number. This means that it might not always be straightforward to assign exports to a particular firm.
- Treatment of large intermediaries: For the Non-UE dataset only, transactions which are managed by large intermediaries (for example logistic companies) are recorded as exports flows conducted by the intermediary, not by the exporting firm. This implies that it might not be possible to monitor exports flows of companies which rely on intermediaries. This issue does not arise for the EU dataset.

Data on exports held by the Office for National Statistics

The Office for National Statistics (ONS) collects and maintains three datasets that report information at firm level on exports. However, this information is only available for firms whose employment is over a minimum threshold. The datasets are:

- Annual Business Survey (ABS): this covers an extensive set of information (including value added) for approximately 62,000 businesses in Great Britain and it is available from the SRS. It contains exports data for firms in services, but not in manufacturing (it only has a yes/no indicator), but they are only available continuously for firms with more than 250 employees.[7]
- International Trade in Services (ITIS): this contains annual data on imports and exports for a total of 14,500 services firms. It is based on the information contained in the Annual Business Survey for export values, but it breaks them down by product type as well.[8]
- Products of the European Community (Prodcom): this contains firm and product level exports for 20,000 firms in manufacturing and it can be accessed through the UK secure access service. For the present purpose, its main limitation lies in the fact that it only has a continuous time series for businesses with more than 100 employees and it only covers goods exports.[9]

FAME information on overseas turnover

The private provider Bureau Van Dijk's manages the FAME (Financial Analysis Made Easy) database. This data source contains some information on annual

[7] https://discover.ukdataservice.ac.uk/catalogue/?sn=7451

[8] https://discover.ukdataservice.ac.uk/catalogue?sn=6711

[9] https://discover.ukdataservice.ac.uk/catalogue/?sn=6729&type=data%20catalogue

overseas turnover, which be used as a proxy for exports. However, there are two limitations:

- difference between exports and FDI: annual overseas turnover also includes turnover from international subsidiaries, so it is not possible to distinguish exports from turnover resulting from FDI
- reporting requirements: reporting annual overseas turnover is voluntary for most firms (especially for smaller firms). This implies that there is a significant incidence of missing values in overseas turnover information

Data on further outcomes and firm characteristics –

The Business Structure Database (BSD)

The BSD is a dataset held by the ONS. The BSD is constructed from an annual snapshot of the Interdepartmental Business Register (IDBR), a live register of data collected by HMRC via VAT and Pay As You Earn (PAYE) records. The IDBR therefore includes information on all businesses in the United Kingdom that are registered to pay Value-Added Tax or Pay As You Earn (PAYE) contributions for their employees. All businesses in the UK are liable to pay VAT if their revenues exceed a minimum threshold.[10] In 2004, it was estimated that the businesses listed on the IDBR accounted for almost 99 per cent of economic activity in the UK. Only very small businesses, such as the self-employed were not found on the IDBR.[11]

The BSD includes data on firms' employment and turnover, as well as on some of their characteristics (industry, location, legal status, information on ownership structure). Information held by HMRC on employment and turnover (from VAT and PAYE records) is complemented by data from ONS business surveys: specifically, the Business Register and Employment Survey (BRES) is used for employment, and the Annual Business Survey (ABS) for turnover. ABS and BRES are essentially annual censuses of large UK businesses (employing 250 or more workers), also including a sample of smaller firms.

A key issue with BSD concerns the exact timing of the data, particularly on employment and turnover. ONS guidance instructs researchers to treat data published in a given year (for example 2017) as representative of the financial period ending in April of the previous year (2015/16). However, the exact timing of the update of VAT and PAYE information provided to HMRC may vary from business to business. This introduces some uncertainty on the exact timing of the information recorded in BSD, which in some cases may be two or even three years old.[12] For nearly all large UK businesses, the employment and turnover information contained in BSD is updated annually, as these data are collected annually through the ABS and BRES. However, for medium and smaller firms, employment and turnover information may be updated

[10] As of April 1st, 2017, this threshold is £85,000. Business can also voluntarily register if their revenues are below the threshold.

[11] https://discover.ukdataservice.ac.uk/catalogue?sn=6697

[12] A data point may be three years old, for example, for a medium-sized business whose information on employment is drawn from BRES. A medium-size business has a 30% chance of being in the BRES sample each year, so its employment information may not be updated for three years if other sources (e.g. PAYE records) are not used.

less frequently or imputed. Figur below summarises our understanding of the available guidance on BSD sources, supported by our conversations with ONS research support staff and interviews carried out as part of this project.

Figure 6 Sources of information on employment and turnover in BSD

Type of business	Included in BSD?	Employment information	Turnover information
Large (250+ employees)	Yes	Updated annually using BRES	Updated annually using ABS
SMEs operating PAYE and VAT scheme	Yes	Updated using recent BRES return or PAYE information	Updated using recent ABS return or VAT information
SMEs operating PAYE scheme but not VAT scheme	Yes	Updated using recent BRES return or PAYE information	Updated using recent ABS return or imputed based on turnover/employee ratio
SMEs operating VAT scheme but no PAYE scheme	Yes	Updated using recent BRES return or imputed based on turnover/employee ratio	Updated using recent ABS return or VAT information
Businesses not operating PAYE or VAT	No	N/A	N/A

Source: BSD User Guide[13]

The IDBR and the BSD provide information on enterprise units or on local units. Information from VAT and PAYE records is only available at enterprise unit level, and the local unit files do not include turnover information. An enterprise unit is defined as 'the smallest combination of legal units (generally based on VAT and/or PAYE records) that is an organisational unit producing goods or services, which benefits from a certain degree of autonomy in decision-making'. A local unit is defined as 'an enterprise or part thereof (such as a workshop, factory, warehouse, office, mine or depot) situated in a geographically identified place'.[14]

Information on how enterprises are combined in groups ('who owns who') is drawn from administrative sources, Companies House, and data from a commercial provider, Dun & Bradstreet.

The IBDR with quality checks (L-IDBR)

The stakeholder engagement exercise has highlighted a project in the Department of Business, Energy and Industrial Strategy (sponsored by the Cabinet Office) aiming to incorporate systematic quality checks in the IBDR. The outcome of the project has been the creation of an augmented IBDR dataset (Longitudinal IDBR, or L-IDBR) for the 2007-2017 period containing:

- financial year variable: A variable specifying the likely financial year covered by the employment or turnover data

[13] Available at: http://doc.ukdataservice.ac.uk/doc/6697/mrdoc/pdf/6697_user_guide.pdf

[14] Source: BSD user guide.

- flag for data issues: A flag highlighting potential quality issues with employment and turnover (for example were the data imputed?)
- a field for data source: allowing researchers to understand whether a particular data point was imputed or adjusted

Based on our stakeholder engagement, we understand that there are processes in place that will make the L-IDBR available in the SRS. At the moment of writing, the BSD is the only version of IDBR data that can be accessed in the SRS. Using this dataset would lead to two potential improvements compared to the 'standard' version of the BSD data:

- alignment of data sources: It would be possible to improve the alignment between the timing of support and the employment or turnover data. In general, data reported in a given year of BSD (such as 2018) are representative of the previous financial year (2016/17). However, for some firms the data may actually refer to a previous period. In BSD it is not possible to understand where this is the case; conversely, using this version of the IBDR, we would know the likely financial year covered by the employment or turnover data
- improving data quality: It would be possible to exclude from the analysis firms with lower quality employment or turnover data, which could induce measurement error in the treatment effects. Using the BSD, this information would not be available

Bureau Van Dijk's FAME database
The FAME database is managed by the private provider Bureau Van Dijk's. It is available upon subscription and gathers a detailed set of balance sheet items, such as assets, employment, turnover, profits and, as mentioned above, annual overseas turnover. The data are extracted from the annual returns companies have to submit to Companies House, with limited additional manipulation or quality assurance. This implies some potential limitations:

- imperfect coverage: FAME is not a census of economic activity, unlike BSD. Some companies may not be registered on Companies House or they might use ownership structures which partition revenues and turnover across several entities. In a project for BIS, Aston University has estimated that only about two-thirds of 'middle-sized businesses' (defined having a turnover between £25 and £500 million) available from the BSD could be found on FAME. The proportion is lower for smaller firms[15]
- reporting standards: A large majority of firms that are registered with Companies House are not required to submit full accounts, and in particular are not required to submit information on their employment or turnover. The reporting standards are less stringent for smaller firms. Currently, companies fulfilling two of three `size' conditions (a turnover of £10.2 million, £5.1 million or less on its balance sheet, 50 employees or less) can submit a simplified balance sheets and do not need to submit the profit loss account. In fact, in

[15] https://www.gov.uk/government/statistics/msb-growth-performance

previous UK studies on export promotion, the authors were only able to find turnover information for less than a quarter of supported firms, out of those that were found in FAME (RR, 2015)

- unit of analysis: the way in which a company reports data on Companies House will depend on its ownership structure. Unlike in the case of IDBR/BSD, where reporting takes place from standardised statistical units ('reporting units' or 'local units'), it is not always clear whether a company is reporting its total turnover and employment including all of its local establishments. Our stakeholder engagement suggests that many companies report both total turnover and employment across all local establishments under their headquarters, and local turnover and employment under separate units. Therefore, for multi-establishment firms, care should be taken not to double-count employment and turnover

Other sources

- Dun & Bradstreet (D&B): D&B provides balance sheet data on private firms, including those who are not registered on Companies House. Unlike FAME, it also conducts some modelling and market intelligence to complement the publicly available information. However, part of this information is also used in developing the Business Structure Database. D&B has not been previously used by the export promotion literature in the UK.
- UK International Patents Office (IPO): The IPO records information on intellectual property activities of UK companies, which is available upon request. It has data on UK-based intellectual Property (IP), but it also includes international information from the European Patent Office (EPO) patents, Patent Cooperation Treaty (PTC) patents and European Community trademarks and designs. The data are supplied with CRN, which allows for a nearly perfect match with other data sources, such as FAME (RR, 2015).
- Data on other government support: To control for participation in other forms of support, it might be possible to rely on several existing datasets:
    - Data collected by the Department for Business, Energy and Industrial Strategy: stemming from the Star Chambers exercise, BEIS has developed an integrated database bringing together different forms of government support.
    - Innovation support: Innovate UK releases periodically a list of recipients of innovation funding.
    - Incubators and accelerators: A dataset on the location of incubators and accelerators has been made available by BEIS.[16] This might be helpful to control for the presence of technology-oriented advisory services in the local area.
- Annual Inquiry into Foreign Direct Investment (AFDI): Building on Conconi et al. (2016) export activity is strongly linked to outward FDI. This means it might

[16] https://www.gov.uk/government/publications/business-incubators-and-accelerators-the-national-picture

be important to control for engagement in FDI activity and explore the relationship between exports and FDI more generally. The main UK source is the AFDI, which has information on outward investment by UK-based companies to their overseas parents or subsidiary companies. The main limitations are that it only covers a subset of companies (less than 20,000) and that the sample is skewed towards larger firms.

- Data on composition of the local workforce: Information on the local composition of the workforce could provide an additional control variable, as in Munch and Schaur (2018). The data could come from two different sources:
  - ONS: the Labour Force Survey (LFS) has information on the qualification held by employees. It would not be possible to link it directly with the BSD, but it could still provide a proxy for the average level of skills in the local area.
  - Burning Glass (BG): BG provides detailed information on the characteristics of vacancies posted by firms. It would complement LFS by providing data on the number and type of vacancies. This could be valuable to control for a firm's intention to grow and for differences in the types of skills that are sought and employed by different firms. However, these data are not available for firms that do not advertise on-line (in which case there is no on-line advert to match the vacancy) and for firms that advertise through professional recruiters (in which case an on-line advert may exist but is not easily matched to the firm).

5.2 Combining and using data sources

Figure 7 and Figure 8 below represent possible ways of matching treatment, control and outcome data to generate an analytical dataset. There are three sources of uncertainty reflected in the figures:

- first, the process involved in linking HMRC exports in goods data with the BSD or L-IDBR is not completely clear. Our stakeholder engagement suggests that this link is feasible, but this project is in the process of understanding:
  - the specifics of accessing a linked HMRC exports-BSD/L-IDBR dataset. HMRC and ONS data are generally accessed by researchers in separate secure settings (the HMRC datalab and the SRS). Using the linked data requires accessing both datasets in one physical or virtual location
  - the expected success rate in linking firm records between HMRC exports data (where firms are identified by a VAT number) and BSD/L-IDBR. We understand from our stakeholder engagement that this linking is feasible and has been performed before but we were not able to access data on the outcomes of this link – for example, what proportion of records in each dataset is not matched to the other
- second, it is not clear whether it would be possible to access to data on firms treated prior to 2014. The Kantar pipeline would impose some constraints on the sample size available, because it would provide with one full usable year of

treatment data (the financial year 2014/15). Conversely, data held by DIT may cover a longer timer period. In Figure 7, we illustrate potential options for the analytical dataset using treatment information from the Kantar pipeline alone. In Figure 7, we assume options relying on a longer time series of treatment data

- third, it is not clear whether we would be able to secure access to the IBDR with quality checks, within the current project. For this reason, we focus on BSD in the figures and the sample size analysis below. In any case, we note that the main change introduced by the IBDR with quality checks would be a small decrease in the total sample size, caused by the potential loss of low quality observations

All arrows in the figures represent feasible matches across datasets. However, not all matches could be made based on a consistent identifier such as the Companies House Reference Number (CRN). Dashed lines represent 'fuzzy' matches, cases where the match is not based on CRN but on other information (such as firm name, location, industry). In Figure 7, the first two lines on the left are solid, as the Kantar pipeline includes CRNs for a majority (though not all) supported firms. In Figure 8, the two lines are dashed, to account for the fact that older treatment data may not include CRNs (although the three most recent years of treatment data from Datahub include a proportion of CRNs similar to the Kantar pipeline).

Figure 6 Data matching patterns: only Kantar pipeline treatment data

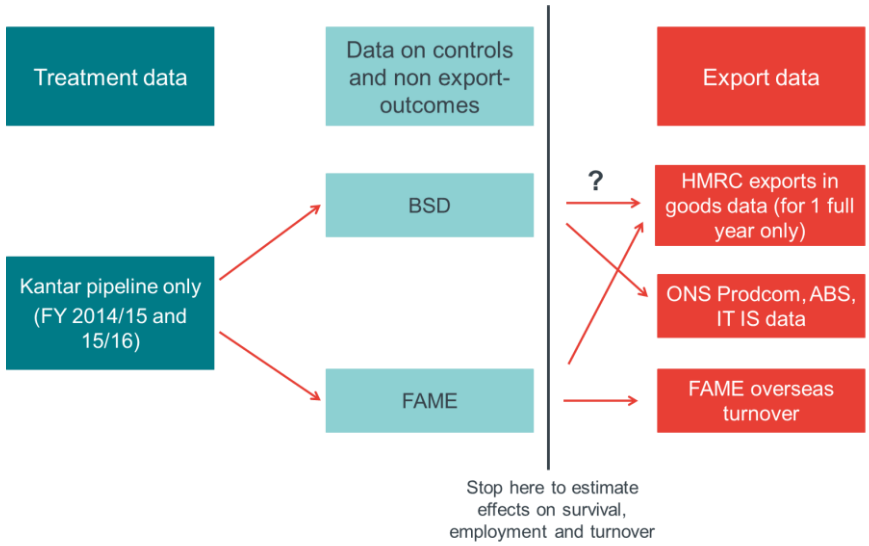
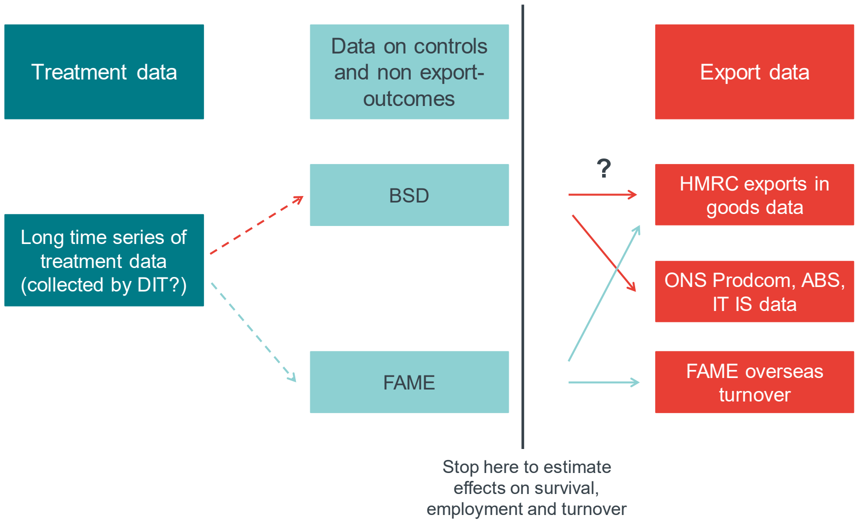


Figure 7 Data matching patterns: treatment data including older service deliveries



Sample size analysis –

Each data matching pattern is likely to yield a different sample of treated firms. This has implications for the types of analysis feasible: specifically, investigating variation in impact requires larger sample sizes. Figure 9 shows likely sample sizes per year of available data. Due to matching problems and missing data, using FAME would lead to the lowest sample size, both with and without CRN. Conversely, using BSD (but with no data on exports) would enable to rely on essentially all the observations. Another important feature to consider is that FAME would make it challenging to compute effects for small and medium firms, due to the problems mentioned in earlier in Section 5.

Figure 8 Overview of available sample sizes from different datasets

Dataset	Estimated % of treated firms available after matching	Treated firms matched per year	Notes on assumptions to derive estimates
FAME (without CRN)	12% (50% lost because of matching problems, then 75% due to missing data from FAME)	6,000	RR report that only 50% of UKTI supported firms can be string-matched and that 24% of supported FAME businesses have info on turnover
FAME (with CRN)	16% (33% lost because of matching problems, then 75% due to missing data from FAME)	8,000	Anyadike-Danes (2011) reports that 2/3 of BSD firms can be matched onto FAME. We then make the same assumption on missing data as in row above.
BSD (with no exports data)	90%	45,000	10% attrition is a conservative assumption

	(assuming a 10% attrition)		
HMRC exports data matched with BSD	27% (30% who are likely to export goods, plus 10% attrition)	14,000	MM report that 30% of supported firms are in manufacturing. These are likely to be most representative group of goods exporters.

Source: Frontier Economics analysis, using statistics from MM, RR, and Anyadike-Danes (2011).

We then conduct some power analysis. We derive the likely number of treated firms that will likely be necessary to derive a statistically significant effect at the 5% level for turnover, labour productivity and exports growth. We provide a range to reflect uncertainty in the size and variance of the effects to be detected. The results are in Figure 10 below. Due to the size of the effect, computing statistically significant effects on exports requires a lower sample size.

Figure 9 Approximate sample size calculations

Data field	Turnover	Labour Productivity	Exports (from HMRC)
Expected Proportional Effect size	1.5% (but up to 1.1%)	1.9% (but up to 1.3%)	8.8% (but up to 6.2%)
Variance	~60%	~100%	~860%
Minimum treatment group size required for 95% significance	5,000 to 10,500 firm observations	5,500 to 11,000 firm observations	2,100 to 4,500 firm observations

Source: Frontier Economics, using data from the 2016 Pipeline from Kantar, RR and MM.

Note: The upper bound of the expected effect and the variance of the effect are taken from the PSM-DID estimates in RR for turnover and labour productivity, and from the exports estimates in MM. The lower bound is just a stress test we introduce to verify what happens if the true effect happens to be 30% lower.

From here, understanding how many breakdowns will be feasible (for example 3 or 4 policy types) is not a straightforward exercise. Generally speaking, the larger the number of the years, the greater the number of feasible breakdowns will be. However, the results will also depend on the following factors, which are difficult to predict:

- distribution of firms across groups: if some policy types were to account for a relatively small proportion of treatment interactions (for example less than 10%), it would be more difficult to have a sufficient sample size to compute separate effects for that policy or combinations of policies
- size of effect and variance for each group: if the effect proved to be smaller (or the variance higher) for a particular group of treated firms, it would be more challenging to obtain statistically significant effects for that group

As we are unsure about the availability of older treatment data, we report below some indication of what might be feasible with the Kantar pipeline for the three options considered above and data from HMRC and BSD combined. In line with Figure 9 above, we assume that the study would rely on 14,000 observations:

- Turnover and Labour Productivity: in a best case scenario, it would be possible to estimate statistically significant effects for two groups separately. As we require at least 5,000 observations for a statistically significant effect at the 5% level, cutting the sample in three groups would likely be challenging.
- Exports: it should be possible to estimate statistically significant effects for two groups and potentially up to four or five. For instance, in a baseline but potentially unrealistic case with 5 services with a similar effect, each covering 20% of firms, it would likely be possible to compute effect separately for five groups.

6 Conclusions

The existing literature has used robust methods to estimate the impact of trade promotion on the exports, turnover and employment of supported firms. It may be possible to further strengthen the robustness of the estimates by controlling for additional ways in which supported firms may differ from the non-supported. These controls are suggested by the international literature on export promotion and the wider impact evaluation literature in the UK. However, the core PSM-DiD method used by the two most recent UK evaluations of trade promotion (MM and RR) would be retained, and we do not expect additional controls to change radically the existing estimates of impact.

The main gaps in the UK literature arise from a lack of evidence on how the impact of trade promotion varies by service type and firm type. It would be possible to fill these gaps with access to appropriate data. Specifically, the ideal dataset would:

- include a long time series of information on supported firms, with CRNs for each supported firm, and it would not under-represent smaller treated firms (an issue with both MM and RR)
- use administrative data collected by HMRC, which are the best source of information on exports at firm-level. However, the data accessible to research do not include exports of services, as the data are sourced from customs declarations

Annex A – References

Studies on the evaluation of trade promotion activities

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