Department for International Trade

Analysis

Methods review: Economic impacts of large exporters

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London Economics

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Responsibility for the contents of this report remains with London Economics. Recommendations made in Part 3 of the report are made by London Economics.

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Executive Summary

Purpose and structure of this report

This report seeks to undertake a methodological review to examine how to robustly estimate the economic impact of large exporters[1] on the UK economy, at a local and national level.

Developing a better understanding of the impact of large exporters is important as, often, the largest exporters account for a substantial share of an economy's export volume (Freund and Pierola, 2016). For example, in the UK, only one in five firms reported trading activity, but these trading firms accounted for 40% of all employment (Wales et al., 2018). Understanding the effects of large exporters is also important as they generate large economic impacts directly and through supply chains by virtue of their size.

Estimating the local or regional effects is important for understanding the distribution effects of exporting. For instance, at a regional level, there are significant concerns about the distribution of productivity. In the UK there are many candidate explanations of regional productivity disparities, which relate to the mix of firms present in different regions, of which export intensity is an important one. If exporting operations were to be located in regions with lagging productivity, this could contribute to closing regional disparities (and 'levelling up'), bearing in mind where they would generate the largest economic impacts. Therefore, understanding the disparity in the size of exporting effects across different regions could have important policy implications and demonstrates an important research gap to be addressed.

The report differentiates between the direct and indirect effects of large exporters. These are defined as follows:

- Direct effects – refer to the impacts accruing to exporters themselves as a direct result of the decision to export.
- Indirect effects – refer to the impacts accruing to other firms, for instance, through the transmission channels of firms' supply chains, firms in the exporters' region or firms in the exporters industry.

The report further investigates impacts along both the extensive and intensive margin of exporting, whereby the extensive margin refers to the impacts of the decision to enter the export market, and the intensive margin refers to the impacts of varying degrees of exporting.

There are three parts to this report.

Part 1 provides a comprehensive overview of the existing literature that addresses the relationship between exporting, firm-level outcomes and wider economic outcomes beyond the exporting firm.

Part 2 assesses how the economic impacts of exporting are estimated at the firm level and how the wider economic impacts of exporting are assessed in the existing literature. This part of the report provides a detailed discussion of the methodological challenges associated with alternative estimation approaches and investigates how various approaches are applicable to the estimation of the direct impacts of large exporters and regional effects in particular. Moreover, datasets that are available to implement said approaches are explored and the relative merits of different data sources are discussed.

Part 3 of this report provides recommendations on how to estimate the direct and indirect economic impacts of large exporters. These recommendations are based on the detailed review of potential estimation methods and their suitability for estimation of causal impacts for large exporters, and for

[1] Large exporters are defined as UK businesses with more than 250 employees.

regional impact breakdowns; a review of available datasets for the UK; and the insights of various academic and government experts on both the robustness and feasibility of alternative estimation approaches.

Part 1 – What is the relationship between exporting, firm-level economic outcomes (direct effects), and wider economic outcomes beyond the exporting firm (indirect effects)?

There is now a large amount of empirical literature available on the economic impacts of exporting, with estimates varying broadly across outcome measures, countries, sectors and estimation methods.

Evidence on the direct impacts of exporting

Most of the existing empirical literature on the impacts of exporting focuses on the productivity, output and innovation effects of exporting on the exporting firms themselves, that is, the direct effects of exporting. The literature on the direct impacts of exporting investigates both the intensive and extensive margins of exporting, with the intensive margin estimating the effects of varying degrees of exporting and the extensive margin estimating the effects of the decision to start exporting.

The literature in this area is generally concerned with examining and validating the "learning-by-exporting" (LBE) hypothesis, which postulates that exporting increases firms' productivity because it allows the exporting firms to learn from the expertise of foreign contacts (such as foreign buyers, competitors or suppliers) in their export market. Some studies focus on the *outcomes* that might be driven by those hypothesised productivity increases (increases in total factor productivity (TFP), apparent labour productivity (ALP), output or GVA), while other studies directly examine the *sources* or *mechanisms* that drive those effects (increased innovation or R&D activity).

Any meaningful empirical examination of the LBE hypothesis usually involves consideration of the idea of self-selection of firms into the export market. In particular, it is generally acknowledged that the same characteristics that determine whether or not a firm can enter the export market in the first place are also the characteristics that are expected to be improved through LBE. For example, it is generally acknowledged that more productive or larger firms find it easier to be successful in the export market, but at the same time, the learning effects from exporting are expected to result in higher productivity and ultimately an increase in size of the firm.

Overall, the majority of studies find positive and causal direct effects of exporting on productivity. This includes nine studies that provide direct evidence for the UK. This positive relationship is observed by a vast majority of studies for both TFP or ALP measures of productivity, for both productivity levels and growth rates, and for both extensive and intensive export margins.

The existing literature also finds positive impacts of exporting on other dimensions of firm performance such as employment, wages, profitability, and firm survival. The number of studies investigating these impact measures, however, is still relatively small and sometimes only report correlation relationships as opposed to causal effects.

Evidence on the indirect impacts of exporting

The literature on the spillover impacts of exporting on other firms is considerably more limited than the literature investigating the direct effects of exporting. Existing studies focus primarily on the effects of encouraging exporting activity in other firms, and to a lesser extent productivity spillover effects.

Export spillovers are generally categorised into three groups:

- horizontal spillovers are the spillovers from exporters to domestic firms that operate within the same industry;
- vertical spillovers are the spillovers from exporters to domestic firms that are linked to the exporting firm through their supply chain; finally,
- regional spillovers are the spillovers from exporters to domestic firms that operate in the same region.

Overall, the evidence found suggests a weak relationship between exporting firms and the productivity of domestic firms in the same region, industry or supply chain. The evidence is somewhat stronger for spillovers on the probability of other firms becoming exporters.

Evidence gaps

While the relationship between exporting and firm-level outcomes is well established in the literature, less is known about the indirect effects.

Moreover, only few studies investigate how outcomes differ by firm size, and no studies currently exist that focus on large exporters in particular.

In addition, there is a similar need to fill the research gap with respect to estimating the regional effects of exporting. Most studies estimate the impact of exporting at the national level, however, there are likely to be important regional disparities that need to be considered.

Part Two - How are the economic impacts of exporting on large exporters estimated (direct effect); and beyond how are the wider economic impacts (indirect effects) estimated at a local and national level?

The second part of the report provides an overview and discussion of the relative advantages and limitations of methods and datasets that can be used to estimate the impacts large exporters at a national and regional level.

Econometric methods were shortlisted based on the approaches used in the wider literature on the impacts of exporting.

The report provides a discussion of the most common approaches used in the existing literature on the impacts of exporting, including propensity score matching and difference-in-difference estimation (PSM-DiD), instrumental variable approaches, quantile regression, static panel approaches, dynamic panel generalised method of moments estimators, input-output analysis, and approaches relying on spillover proxy variables.

Certain methods are more appropriate for direct impacts, others for indirect impacts. Not all methods are useful to estimate the impacts both at the extensive and the intensive margin. The methods also vary in how well they can estimate large exporters specifically or regional impacts.

With regards to the estimation of direct effects, firm-level panel approaches are considered more appropriate than PSM-DID and a quantile regression approach when estimating impacts for large exporters. A PSM-DiD approach is considered to be less suitable for estimating the impacts of large exporters because of the difficulty of defining an appropriate treatment for large firms that is both credible and relevant from a policy perspective; the challenges associated with defining an appropriate control group for large non-exporters; the limited amount of pre-treatment effects likely to be observable in the data; and the DIT's preference for estimating export impacts along the intensive margin. A quantile regression approach is considered less suitable for the purposes of the present report, because it would be more difficult to account for endogeneity in a quantile framework and because the approach would further reduce the size of the sample that is already limited due to the focus on large exporters only.

Moreover, panel approaches are preferred to instrumental variable approaches because an IV approach is less suited to estimating the impacts of various degrees of exporting across different geographical markets and product types over time.

In terms of the indirect effects estimation, firm-level panel approaches are considered to be more suitable for the purposes of the present report compared to aggregate approaches such as an IO-analysis or sector level panel or time series approach, because they allow for robust causal inference as unobserved firm level heterogeneity can be controlled for. Moreover, a firm-level approach allows to investigate the spillover impacts associated with specifically large exporters; it allows to determine the spillover impacts on specific sub-set of firms (SMEs, or low-/high-productivity firms); and it allows for the estimation of regional impacts. IO tables moreover only provide static snapshots of input-output relations, and assume constant returns to scale and fixed productivity levels. As such, IO analysis cannot be used to investigate productivity impacts.

Part 2 of the report also provides an overview of available UK datasets for estimating the direct and indirect impacts of exporters. Datasets were identified based on existing literature, and published dataset catalogues and meta data by the UK Office for National Statistics and private data providers.

Part Three - What approach is recommended to estimate the relationship between exporting, firm-level economic outcomes (direct effects), and wider economic outcomes beyond the exporting firm (indirect effects) at a local and national level?

Part 3 of the report provides recommendations for how the direct and indirect impacts of large exporters can be estimated, at both the national and regional level, given existing data for the UK. These recommendations are based on the detailed review of potential estimation methods and their suitability for estimation of causal impacts for large exporters, and for regional impact breakdowns; a review of available datasets for the UK; and the insights of various academic and government experts on both the robustness and feasibility of alternative estimation approaches.

Recommended estimation approach for estimating the direct impacts of large exporters

Estimation approach

The overall recommendation is for the DIT to use a mix of static and dynamic panel estimation approaches to asses the direct impacts of large exporters. In particular, the preferred approach would involve building up the analysis starting with simple correlations between firm-level export and outcome measure variables, pooled Ordinary Least Squares (OLS), random effects and fixed effects estimators, before moving on to a more complex dynamic panel approach such as a generalized method of moments estimator (GMM-DPD).

Model

The main model[2] for the estimation of the direct impacts of exporting is as follows:

$$\ln(y_{it}) = \ln(y_{it-1}) + ex_{it-1} + newmarket_{it-1} * (1 + ex_{it-1}) + \ln(newprod_{it-1}) * (1 + \ln(ex_{it-1})) + \ln(X_{it}) + \ln(GVA_{St}) + time_t + \eta_i + \varepsilon_{it} \quad \text{...(A)}$$

whereby:

- *Dependent variable, y_{it}*: economic impact measure for firm i at time t;
- *Independent variables of interest:*
  - ex_{it-1} is the lagged export intensity for firm i at time t-1 and the main independent variable of interest. ex_{it-1}, is defined as an intensity, that is, the ratio of exports to turnover, to test whether the effect of an increase in the £-value of exports is different to the effect of a £-increase in domestic sales.
  - $newmarket_{it-1}$ is a count variable indicating the number of markets firm i exports to at time t-1;
  - $newprod_{it-1}$ is a count variable indicating the number of products firm i exports at time t-1;
- *Control variables*
  - y_{it-1} is the lagged economic impact measure for firm i at time t-1, which is included because of likely serial correlation in the outcome measures of interest;
  - X_{it} is a vector of control variables for firm *i* at time *t*; These are specific to the economic impact measure and listed in Section 4 of Part 3 of the report;

[2] Parameters not included in the equation.

- $time_t$ are time-specific effects (world economy, national economy, trade liberalisation, GVC);
- GVA_{St} is sectoral GVA, and used in addition to time dummies to control for macro-economic shocks that might only affect individual sectors and hence not be captures through the time dummies;
- μ_{it} is a firm-specific fixed effect to control for time-invariant unobservable firm characteristics that may affect both enterprise performance and exports; and

ε_{it} is the error term.

The model investigates the direct impacts of exporting along three different dimensions: ex_{it-1} captures the impact of expanding exports with existing products in existing markets. The interaction between this variable and $newprod_{it-1}$ provides evidence on whether the impacts are different if exports are increased with new products, while the interaction with $newmarket_{it-1}$ provides evidence on whether impacts are different if exports are increased in new markets.

The three export variables are not logged, implying that a one percentage point increase in the export intensity ratio is assumed to have the same effect on the dependent variable irrespective of the level of the ratio. Similarly, the model assumes that the impact of adding one new market is the same regardless of the number of markets already served by the firm.

The model uses lagged export variables to take account of the fact that the learning effects from exporting might take time to materialise. Moreover, some authors argue that including lagged export variables helps control for the issue of reverse causality, because contemporaneous shocks of the outcome measures are less likely to have an influence on export decisions made in the past. The specification assumes that exports are lagged by one year, but the optimal lag structure should be chosen based on information criteria and significance or different lags.

In order to estimate whether the direct impacts of large exporters differ depending on where in the UK the exporter is located, it is proposed that interaction terms between region dummies and ex_{it-1} (and potentially the interactions of ex_{it-1} with the count variables).

Several robustness tests are proposed in the main body of the report.

Sample

The recommendation is that equation (A) will be estimated for the sample of large exporters only. This is in line with the underlying research question of how exporting more will translate into higher direct effects for large exporters (rather than difference between large exporters and large non-exporters).

Estimating the sample for large exporters only further is more appropriate given the interpretation of the export intensity coefficient in the above model, which implies a constant percentage point impact of increased export intensity.

Limitations

While the static panel data methods proposed in this report are intuitive, they cannot be used for causal inference in the context of the present research questions.

The use of a dynamic GMM estimator (GMM-DPD) is therefore recommended to test whether any correlations uncovered through static panel approaches can be interpreted as causal effects.

However, the validity of GMM-DPD estimation relies on the exogeneity of the instruments, that is, the values of the instruments are independently distributed of the error process. Another potential issue with estimating system GMM regressions is the proliferation of instruments.

Arguably the most important limitation of the GMM-DPD estimator is that results are not always transparent, and sometimes sensitive to the assumptions made by the researcher.

Finally, additional issues might arise for the regional effects estimations. For example, the number of large exporters in a certain region might be too small to meet the Office for National Statistics' disclosure requirements. Moreover, the regional impacts estimation might be compromised by the lack of plant-level datasets for the UK, which implies that regional impacts are sometimes estimated based on variables referring to the headquarter rather than the plant location.

Recommended estimation approach for estimating the indirect impacts of large exporters

Estimation approach

The recommended approach for estimating the spillover effects associated with large exporters' export activity is to use a firm-level panel model, whereby firm-level outcome measures are regressed on a set of variables that capture the export activity of large exporters in the same sector (horizontal spillovers), upstream or downstream sectors (vertical spillovers) and the same region (regional spillovers).

The recommended approach relies on the same static and dynamic panel estimators as used for the direct effects estimation (pooled OLS, fixed effects, random effects and GMM-DPD).

Model

The main model[3] for the estimation of the indirect impacts of exporting is as follows:

$$\ln(y_{it}) = \ln(y_{it-1}) + \ln(X_{it}) + \ln(horizontal_{St-1}) + \ln(backward_{St-1}) + \ln(forward_{St-1}) + \ln(regional_{Rt-1}) + \ln(GVA_{St}) + time_t + \eta_i + \varepsilon_{it} \quad \text{(B)},$$

whereby:

- *Dependent variable,* y_{it}: economic impact measure for firm i at time t;
- *Independent variables of interest:*
  - $horizontal_{St-1}$ is a variable capturing the lagged export activity of large exporters operating in the same industry as firm i;
  - $backward_{St-1}$ is a variable capturing the lagged export activity of large exporters in the industries that are being supplied by firm I's industry;
  - $forward_{S-1}$ is a variable capturing the lagged export activity of large exporters in the industries supplying to firm i;
  - $regional_{R-1}$ is a variable capturing the lagged export activity of large exporters in the same region as firm i;
- *Control variables*
  - y_{it-1} is the lagged economic impact measure for firm i at time t-1, which is included because of likely serial correlation in the outcome measures of interest;
  - X_{it} is a vector of control variables for firm *i* at time *t*. These are specific to the economic impact measure, and listed in Section 4 of Part 3 of the report;
  - $time_t$ are time-specific effects (world economy, national economy, trade liberalisation, GVC);
  - GVA_{St} is sectoral GVA, and used in addition to time dummies to control for macro-economic shocks that might only affect individual sectors and hence not be captures through the time dummies;
  - μ_{it} is a firm-specific fixed effect to control for time-invariant unobservable firm characteristics; and

  ε_{it} is the error term.

Careful consideration needs to be given as to how spillover variables are specified. Options are to either define export activity in an industry or region in terms of the number of large exporters, or the value of large exporters' exports. Moreover, it is recommended that the export spillover variables are specified as ratios relative to total turnover of large exporters in the same sector, upstream or downstream sectors, or region. This is to account for the fact that the same £-amount of exports is unlikely to have the same spillover impacts in large compared to small sectors.

Spillover variables ($horizontal_{St-1}$, $backward_{St-1}$, $forward_{St-1}$ and $regional_{Rt-1}$) are lagged by one period, because it is assumed that spillover impacts take time to materialise. As for the direct effects estimation approach, the recommendation is to experiment with alternative lag lengths.

[3] Parameters not included in the equation.

In line with the direct effects model, spillover variables are not logged. This means that a one percentage point increase in the ratio may be assumed to have the same effect on the dependent variable irrespective of the level of the ratio.

Several robustness tests are proposed in the main body of the report.

Sample
The recommendation is to estimate equation (B) for the sample of **non-exporters only.** This is in line with the underlying research question of how increased export activity by large exporters has an impact on ‘other’ firms in the UK. Excluding small (in addition to large) exporters from the sample means that the direct effects of exporting do not have to be controlled for.

If the DIT wishes to explicitly investigate the spillover impacts of large exporters on certain types of businesses, such as SMEs or high- or low-productivity firms, the sample could further be reduced to only those types of firms.

In order to estimate whether the spillover impacts of large exporters vary across regions, re-estimation of equation (B) for sub-samples of firms located in different regions of the UK is proposed. Sub-samples are preferred to interaction terms because adding interaction between region dummies and the four spillover variables would make the model unnecessarily complex.

Limitations
The proposed approach is in line with the literature investigating the impacts of FDI and previous DIT work in this area.

The same limitations to the static panel approaches and the GMM-DPD approach as for the direct effects approach apply.

An additional disadvantage of the proposed model for the indirect effects estimation is that it might run into multi-collinearity issues when including up to four export spillover variables at the same time. This would be the case if sectors are regionally concentrated, for example, as the regional and sectoral export activity variables would then be strongly correlated.

The proposed approach moreover does not always allow to establish the transmission channel for the observed impacts.

As is the case for the direct impacts, regional estimations might moreover be imprecise due to the lack of region-level datasets on the outcome (and control) measures of interest. Again, estimating regional sub-samples to derive regional spillover effects might give rise to issues of disclosure.

Introduction

In 2018 the Department for International Trade (DIT) launched its Export Strategy, setting a Government wide ambition to increase exports as a proportion of UK GDP from 30% to 35% in the long run. This export strategy aims to unlock the potential of UK businesses and access a greater proportion of world trade to drive growth, productivity, and prosperity (DIT, 2018).

Its overarching strategy is to tackle key attitudinal practical barriers preventing businesses from reaching their full export potential by inspiring UK businesses to sell overseas, providing information and practical assistance, connecting UK businesses with overseas buyers, international markets, and each other and offering financial support.

Given the evolving trade patterns, it is important to determine where best to target DIT's resources to deliver the maximum additional impact to the economy - DIT is now evolving its strategy further, to embed a proportional approach to delivering export promotion service by targeting exporters that confer the largest benefit to the UK economy.

The overall aim of this research is to undertake a methodological review to examine how to robustly estimate the direct and indirect economic impact of large exporters on the UK economy at a local and national level. Large exporters are defined as UK businesses with more than 250 employees.

When investigating the economic impact of exporting, it is important to differentiate between the direct and indirect effects. These are defined as follows:

- Direct effects – refer to the impacts accruing to exporters themselves as a direct result of the decision to export.
- Indirect effects – refer to the impacts accruing to other firms, for instance, through the transmission channels of firms' supply chains, firms in the exporters region or firms in the exporters industry.

DIT is also interested in both the extensive and intensive margin of exporting. The extensive margin refers to the impacts of the decision to enter the export market, and the intensive margin refers to the impacts of varying degrees of exporting.

This research will review the literature that addresses the relationship between exporting, firm-level outcomes (direct impacts) and wider economic outcomes beyond the exporting firm (indirect impacts) at the local and national level. The research will identify key findings, as well as address any evidence gaps.

Secondly, the study aims to assess how the economic impacts of exporting at the firm-level and how the wider economic impacts of exporting are estimated in the existing literature; how those approaches are applicable to the estimation of the direct impacts of large exporters and regional effects in particular; and what other approaches could be used to estimate the direct and indirect effects of large exporters. It is vitally important to understand the data and methodological challenges to alternative estimation approaches, as well as the availability and viability of potential data sources.

Finally, the research recommends how best to estimate the economic impacts of exporters. This recommendation will be based on a review of potential estimation methods and their suitability for estimation of causal impacts for large exporters, and for regional impact breakdowns; a review of available datasets for the UK; and the insights of various academic and government experts on both the robustness and feasibility of alternative estimation approaches.

For the export strategy, maximising the indirect effects is especially important because these are not accounted for in firms' decision-making yet have benefits on the wider UK economy. Wider economic outcomes include, but are not limited to, employment, wages, research and development, productivity, growth, and survival.

It is also important to understand the regional dimension to inform the DIT's export promotion strategy and how the effects of exporting are distributed regionally.

A better understanding of the direct and indirect effects of exporting in the UK and the estimation methods and datasets that are used to robustly estimate these effects will help to strengthen the evidence base for the UK's export strategy.

Part One - What is the relationship between exporting, firm-level economic outcomes (direct effects), and wider economic outcomes beyond the exporting firm (indirect effects)?

There is now a large amount of empirical literature available on the economic impacts of exporting, with estimates varying broadly across outcome measures, countries, sectors and estimation methods.

The literature investigates the intensive and extensive margins of exporting, with the intensive margin estimating the effects of varying degrees of exporting and the extensive margin estimating the effects of the decision to start exporting.

Most of the existing empirical literature focuses on the productivity, output and innovation effects of exporting on the exporting firms themselves (direct effects). The literature in this area is generally concerned with examining and validating the “learning-by-exporting” (LBE) hypothesis, which postulates that exporting increases firms’ productivity because it allows the exporting firms to learn from the expertise of foreign contacts (such as foreign buyers, competitors or suppliers) in their export market (see for example Silva et al., 2012; Wagner, 2007). Some studies focus on the *outcomes* that might be driven by those hypothesised productivity increases (increases in total factor productivity (TFP), apparent labour productivity (ALP), output or GVA), while other studies directly examine the *sources* or *mechanisms* that drive those effects (increased innovation or R&D activity). There is also evidence in the literature on other dimensions of firm performance such as employment, wages, profitability, and firm survival. The number of studies investigating these, however, is still relatively small and tend mostly to report correlation relationships as opposed to causal effects (Wagner, 2012).

Any meaningful empirical examination of the LBE hypothesis usually involves consideration of the idea of self-selection of firms into the export market. In particular, it is generally acknowledged that the same characteristics that determine whether or not a firm can enter the export market in the first place are also the characteristics that are expected to be improved through LBE. For example, it is generally acknowledged that more productive or larger firms find it easier to be successful in the export market, but at the same time, the learning effects from exporting are expected to result in higher productivity and ultimately an increase in size of the firm.

The literature on the spillover impacts of exporting on other firms is very limited, and focuses primarily on the effects of encouraging exporting activity in other firms, and to a lesser extent productivity spillover effects.

A related direction of research in the spillover literature has been to estimate the effect of global value chain (GVC) participation on productivity. It is generally hypothesised that the participation of countries or sectors in GVCs facilitates the transmission of knowledge and technology, thus leading to productivity enhancing effects beyond the firms directly participating in GVCs (Banh et al., 2020). However, the GVC literature often does not explicitly control for the direct exporting effects in a country or sector, so that reported effects often need to be interpreted as the combined direct and indirect impacts of exporting. Moreover, the GVC literature slightly deviates from the other research consulted for this report in that the authors do not consider the impact of gross exports and only focus on the export of intermediate inputs to a country that are then re-exported to a third country (forward linkages) and the importing of intermediate inputs from foreign sources that are then used to produce exports (backward linkages) (see Box 2). We therefore treat those papers separately in our report (see Box 2).

In what follows, we present existing evidence on the direct and indirect impacts of exporting that has been observed for exporters located in the United Kingdom (UK) and other developed countries[4]. We focus on the papers that estimate causal effects, with the findings of papers that examine correlations between exporting and impact measures being deferred to Annex 2[5].

[4] In particular, we include any evidence from Member States of the European Union and Member States of the Organisation for Economic Co-operation and Development (OECD).
[5] We include all studies focusing on the UK’s experience in the main text, however, even if the studies only report correlations or if the methods cannot clearly establish causality.

Please refer to Annex 3 for a more comprehensive account of our literature identification and filtering strategy.

1. Evidence on the direct impacts of export market entry

We start with a review of the existing literature on the direct impacts of export market entry, that is, the literature focused on assessing impacts along the extensive export margin This strand of the literature addresses self-selection concerns by comparing the performance of exporters (treatment group) with the performance of non-exporters (control group).

1.1. Level of Productivity

1.1.1 National Impacts

The relationship between exporting and the level of productivity is well documented in the literature[6].

Nine studies provide direct evidence from the UK overall supports the learning-by-exporting hypothesis, in that exporting firms experienced positive productivity effects as a result of the decision to enter the export market (extensive margin). Evidence also shows that the intensive margin is important, with productivity impacts increasing by export intensity. For UK based papers, we include studies that estimate the causal effects and the correlations between exporting and productivity.

Starting with the literature on the extensive margin, most recent evidence is provided by Wales et al. (2018), who conduct a productivity analysis on a newly constructed dataset of British business which declare international trade in goods to HM Revenue and Customs (HMRC). Using OLS regression analysis including industry and firm fixed effects, they find that, when controlling for firm size, ownership, and industry effects, those businesses which declared that they are exporting were 21% more productive than non-exporters. The authors also break down their results on the productivity impacts achieved by UK exporters based on export destination, specifically those who trade with EU and non-EU countries. They find that the productivity premium is lower for firms that trade with the EU in comparison to those trading with non-EU based firms. The increase in labour productivity from exporting is 14.7 percentage points higher for those trading with non-EU firms than those trading with EU firms. One caveat presented in this paper, however, is that these results cannot be interpreted as causal effects.

Harris and Li (2007) examine the effect of exporting on the level of firms' total factor productivity for both the manufacturing and services sectors in the UK. The authors use panel data and apply three different estimation techniques to control for self-selection and endogeneity: matching techniques, an instrumental variable approach, and a Heckman approach. They find that overall, each estimation method yields similar results. They find that learning-by-exporting effects are present but not universal across industries, the estimates of productivity gains from exporting vary in size and significance. On average, across industries, they find an increase in the level of total factor productivity of 34.3% in the period of entry, relative to non-exporters, and this falls to 5% two years post-entry, based on the IV approach. By sector, generally estimates of productivity gains are slightly larger for industries in the services sector relative to the manufacturing sector.

Crespi et al. (2008) further investigate the mechanism through which UK firms seem to be able to increase performance due to exporting. They use firm-level panel data on firm's "knowledge sources" from the UK Community Innovation Survey (CIS). In the CIS, firms are asked to report on any sources of knowledge they have used for innovation purposes and their relative importance, whereby the

[6] Please refer to Silva et al. (2012), Martins and Yang (2009), Wagner (2012) and Ciuriak (2013) for comprehensive comparative analyses of the most recent literature that explores the concept of learning-by-exporting at the firm-level.

sources include knowledge acquired from i) customers, ii) suppliers, iii) competitors or iv) within the firm. The authors find that exporting is associated with a 24% increase in the level of labour productivity relative to non-exporters. To investigate the mechanism by exporting affects productivity, they estimate a two-stage model which first estimates the effect of exporting on the probability that a firm reports learning from one of the stated knowledge sources. Secondly, they estimate whether this learning had significant effects on labour productivity growth. The authors find significant evidence of this relationship whereby exporting firms that report more learning from customers, relative to other forms of learning, are statistically significantly more likely to experience increases in labour productivity two years later. One caveat of the results presented in this paper, however, is that these results cannot be interpreted as causal effects.

Table 1: Summary of Productivity Level Estimates in Evidence from the UK

Reference	**Impact measure**	**Country coverage**	**Dataset used**	**Coefficient (Decision to enter)**
Wales et al. (2018)	ALP	UK	HMRC, IDBR, ABS	0.21***
Harris and Li (2007)	TFP	UK	FAME	0.343***
Crespi et al. (2008)	ALP	UK	CIS	0.024***

Note: TFP = Total factor productivity; ALP = Apparent labour productivity. For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

Extending the analysis beyond the UK, there is also a substantial amount of literature that explores the relationship between exporting and productivity in other developed countries. Overall, the majority of studies find positive direct effects on productivity.

Silva et al. (2012) review and summarise the methodologies and results of empirical studies on the exporting impacts on productivity from over 15 developed countries[7]. They find that, while many studies present some evidence on an existing causal effect between exporting and productivity increases, those effects are generally only observed under limited conditions. For example:

- Fernandes and Isgut (2005) and Harris and Li (2008) find the effect is only present for new entrants into the export market, and the effect dissipates thereafter; and
- Andersson and Lööf (2008) and Castellani (2002) only find significant evidence of a positive effect of exporting on productivity for persistent exporters with a high export intensity.

Turning to individual studies examining the productivity impacts of export market entry in developed countries other than the UK, we start with the most recent evidence from other European countries.

Segarra-Blasco et al. (2020) investigate the learning-by-exporting hypothesis by means of a coarsened exact matching procedure and a generalised structural equation model, using a sample of European manufacturing firms. This methodology allows for controlling potential sample selection and endogeneity issues. The authors decompose the learning-by-exporting effect by considering the temporal and spatial dimensions of LBE and estimating the effects these have on productivity. Temporal LBE refers to past export experience relative to new exporters and spatial LBE refers to the number of markets firms export to. In terms of temporal effects, they estimate that more experienced exporters have a 13.9% higher labour productivity relative to new exporters. In terms of spatial effects, exporting to an additional market is expected to increase labour productivity by 0.45%. The authors also disaggregate their analysis by the innovative capacity of their country of origin by dividing their sample

[7] They further include studies from over 10 developing countries, but we do not report on the results from those studies here.

into ‘Leader’ and ‘Laggard’ countries, as defined by the European Innovation Scoreboard. They find larger labour productivity effects of spatial learning on laggard countries (4.8% relative to 4.6% for leaders), and larger effects of temporal learning on leader countries (14.7% relative to 13.3% for laggards).

Amendolagine, Capolupo and Petragallo (2011) use a sample of Italian manufacturing firms to examine the self-selection and the learning-by-exporting hypotheses. Using matching sampling techniques, the authors estimate the causal effect of exporting on firm level productivity. In the first period post-entry, exporting induces labour productivity and total productivity gains of around 4% and 3%, respectively. However, in contrast, this effect is found to be insignificant in the next period.

Andersson et al. (2008) examine the effect of international trade on productivity by means of GLS random effects and GMM models on a sample of Swedish firms. They find that, on average, exporters have a 5% higher labour productivity compared to non-exporters. They find that productivity increases with the number of markets entered and the number of products traded. A firm that exports at least 9 products is estimated to have a productivity level double that of those firms that export only 1 to 4 products (10.2% relative to 4%). They also find that the export productivity premium for firms exporting to at least 13 destinations is approximately three times as large as those exporting to 1 to 4 destinations (15.3% relative to 4.1%). Additionally, firms that are both exporters and importers are more productive than firms that only export or import. The authors find that firms that both import and export have an 8% labour productivity premium relative to non-exporters, that is 3 percentage points higher than those firms who only export. The authors break down the results by the number of export products and the number of export markets and find productivity premiums increase in both number of markets and number of products traded.

De Loecker (2007) investigates the productivity premium from exporting in a large sample of Slovenian manufacturing firms, using Slovenia’s entry into the EU as a natural experiment. To control for self-selection, the author uses matching techniques and difference-in-differences analysis to estimate a causal effect of entering the export market on firm-level productivity. They find that export entry increases the level of total factor productivity by 8.8% on average and this premium also increases over time to around 13% after 4 years. They estimate this effect by industry and find significant heterogeneity across various manufacturing industries. The industries where an immediate productivity effect was present include chemical producers, publishing and printing, and machinery and equipment. Those that saw no evidence of productivity gains include basic metals and furniture manufacturing. They find the productivity effects they detect for their sample of Slovenian manufacturing firms only holds for those firms that export to developed countries. The destination country of exports seems to be an important factor when it comes to determining whether a firm can achieve productivity gains from exporting. In particular, many studies hypothesise that only exporting to more developed and technologically advanced countries enables the knowledge transfer and competition effects that are thought to underlie an exporting firm’s productivity gains (De Loecker, 2007; Wagner 2012).

Eliasson et al (2009) examine the productivity trajectories of future exporters in a sample of Swedish firms. Their analysis is comparable with Greenaway et al. (2005) who also matching techniques in a sample of Swedish firms. The authors examine the outcome for smaller firms in particular (SMEs) and find the effect differs considerably. They explore the learning-by-exporting hypothesis by isolating the causal effect of export entry on labour productivity post-entry. They find that exporting increases the level of labour productivity by 4.2% in the period of entry relative to non-exporters. The effect is stable across the following 3 years. However, the authors also explore an alternative learning-by-exporting hypothesis whereby the causal effects may precede entry into the export market. They argue that firms make a deliberate effort to invest with the explicit intention to become exporters, so they do not treat productivity exogenously (as with the self-selection hypothesis) but regard it as endogenous with the respect to the decision to enter the export market. Their estimates are based on export entrants and non-entrants that have similar labour productivity and other firm characteristics three periods prior to entry but for which the trajectories of these characteristics may differ thereafter. They find no significant effects prior to entry, but in the period of export entry they find a significant increase in labour productivity by 5.7%.

Benkovskis et al. (2018) investigates the effect of export entry on firm-level productivity in a sample of Latvian and Estonian firms in the context of the global value chain. They hypothesise that for exporting to produce productivity gains post-entry, exporters have to participate in high value-added activities in the upstream of GVCs. They disaggregate their results by export type, that is, the exporting of intermediate goods, final goods, and re-exports. They also estimate the effect of exporting separately for goods and services. Intermediate goods are defined as inputs into the global value chain that will be embodied in exports by a third country. These, as well as the exporting of services, are interpreted as participation in knowledge intensive activities found in the upstream of the GVC. Using propensity score matching, the authors estimate the average effect of export entry on the level productivity (total factor productivity and labour productivity). They find that, on average, export entry increases the level of labour productivity by 23% in Latvian firms in the year of entry, falling to 20% after three years. For Estonian firms, labour productivity is found to increase by 14% in the year of entry but fall to 13.5% three years later. When estimating the effect by export type, positive and significant effects on labour productivity are found for exporters of intermediate goods and re-exports for both Latvia and Estonia (estimates on TFP are also significant for Latvia but insignificant for Estonia). Exporting intermediate goods is found to increase the level of labour productivity by 27% and 12.2% for Latvia and Estonia, respectively. No significant results are found for the effect of exporting final goods for either country. Additionally, in general, stronger effects are found for the exports of services compared to goods. These results support the authors' hypothesis that greater productivity gains can be found in, what they consider to be, more knowledge-intensive areas of the GVC.

Garcia and Voigtländer (2013) use propensity score matching and difference-in-differences analysis to examine the plant-level efficiency gains from entering the export market in a sample of Chilean manufacturing plants. The authors argue that the use of revenue-based total factor productivity (TFPR), which is widely used in literature, can produce small and insignificant estimates due to exerting a downward bias on the results if higher efficiency is associated with lower prices. To demonstrate this, they calculate both revenue-based TFP and a product-plant level marginal cost as an alternative measure of productivity and compare regression results using either of the two measures. They find, as predicted, insignificant effects of exporting on revenue-based TFP, however they find persistent negative effects of exporting on marginal cost and prices. The authors suggest this is indicative of new exporters passing on productivity gains to their customers. They estimate that when plants begin to export, marginal costs fall by 15 to 25% on average. The authors point to the important fact that when a firm produces on the decreasing part of the marginal cost curve, an increase in sales (at unchanged prices) will lead to an increase in the sales or value added per employee simply because the firm produces at a greater scale. This scale effect may drive a number of the results presented in other papers if not properly taken into account in the analysis.

Finally, recent evidence from Asia shows positive productivity impacts of exporting.

Hahn (2013) uses data from Korean plants and estimates the effect of exporting at the plant level. They examine the linkages between trade liberalisation on plant-level growth and productivity. The author uses matching techniques on a micro dataset of Korean plants to estimate the causal effect of exporting on various indicators of performance. They find that export entry increases plant-level total factor productivity by 4.1% and this effect increases to 9.5% three periods later.

Ito (2012) examines the productivity gains through learning-by-exporting in first-time exporters using firm-level panel dataset from Japanese manufacturing firms and also extends their analysis by estimating the effect by export destination. To estimate a causal effect, the author implements propensity score matching technique. They match firms based on a set of observables to control for self-selection. To control for further unobservables, the author uses difference-in-differences estimation. The author finds largely insignificant effects of entering the export market on productivity. The authors extends their analysis of productivity gains achieved by Japanese manufacturing firms by estimating the effect by export destination and find that for firms which decide to start exporting to North America and Europe, total factor productivity growth rate is 1.1 percentage points higher one period post-entry relative to non-exporters. However, exporting to Asia does not have any significant effects.

The capacity to absorb and process knowledge is critical to the learning-by-exporting effect (Ciurik, 2013). Several studies investigate how the extent to which exporters can absorb knowledge affects, their *absorptive capacity,* impacts their productivity gains.

Kang (2019) also uses a sample of Korean manufacturing firms to examines how the absorptive capacity of firms impacts the learning-by-exporting effect, focusing on the extent to which the pay-system a firm adopts impacts the productivity gains from exporting. The author hypothesises that a performance-related pay system would enhance productivity gains because it will motivate employees to upgrade their skills post entry into the exporting market, which increase absorptive capacity. By breaking down their sample by payment-system adopted by the firm pre-entry, they find that those firms who adopted a merit bonus (lump-sum performance related payment) experienced a 6.9% increase in total factor productivity as a result of exporting, whereas for those without, the productivity gains were found to be insignificant.

Lööf and Nabavi (2013) examine the impact of innovation and how knowledge acquisition pre-entry affects the productivity of exporting firms. They hypothesise that innovative and non-innovative exporters have a distinct difference in their productivity and growth rate trajectory and further that variations in local knowledge spillovers influence this gap. Using a dynamic one-step GMM estimator on a sample of Swedish manufacturing firms, the authors empirically test these hypotheses. They find that innovative exporters are more productive than non-innovative exporters and knowledge spillovers strengthens this finding. They estimate that innovative exporters have an up to 10% higher productivity level than non-innovative exporters, and attribute this difference to the knowledge spillover effect from exporting that can only materialise for innovative (rather than innovative exporter). Therefore, the authors find evidence suggesting that the learning-by-exporting effect might depend on innovation strategies and geographical location post-entry.

Lööf et al. (2015) re-visits the sample of Swedish manufacturing firms and examines the ‘innovation premium’ of the productivity of exporters. They investigate the differential impact of innovative activities and knowledge spillovers on persistent and temporary exporters by means of a dynamic GMM approach. They find that continuous innovating is positively and significantly associated with higher total factor productivity growth in persistent exporters. Exporters who continuously innovate have a 0.53 percentage point higher total factor productivity growth rate than non-innovating exporters. This effect is insignificant for temporary exporters.

Pre-entry R&D is also considered by some to build a firm’s absorptive capacity and helps firms to learn more from exporting and thus achieve higher productivity gains. Dai and Yu (2013) also postulate that a firm’s absorptive capacity, measured by its pre-export R&D, is crucial to a firm’s post-entry productivity gains from exporting as it increases their learning efficiency. The authors find that exporting positively effects firm’s total factor productivity, however when splitting the sample between those with pre-export R&D and those without, this effect only holds for those that did engage in R&D. Pre-export R&D in exporters is associated with a total factor productivity gain of 16.4%, increasing to 21.6% two-periods post entry.

Similarly, Ito and Lechevalier (2010) explore firm-level heterogeneity in productivity in a sample of Japanese manufacturers. They investigate the effect of exporting and R&D strategies on firm productivity and the complementarities between the two strategies. Using a system GMM approach, they find that a firm’s choices regarding exporting and R&D expenditure, is positively and significantly associated with higher productivity and a higher probability of survival. However, when employing propensity score matching and difference-in-differences analysis, the authors find that only the interaction variable of engaging in both exporting and R&D (in the period prior to entry into the export market) is associated with an increase in the level of total factor productivity of 8.3%. The authors suggest this in indicative that the knowledge accumulated through R&D positively affects the firm’s productivity outcomes post-entry, therefore the two strategies are complementary.

Máñez, Rochina-Barrachina and Sanchis-Llopis (2015) examine the effect of exporting on firm-level productivity in a sample of Spanish manufacturing firms. Using De Loecker (2013) approach, they estimate a dynamic model of exporting in which they allow past export experience to endogenously affect productivity. The authors also include R&D activity in their model and estimate the joint effect of firms who export and engage in R&D on total factor productivity. They find that exporters have a total factor productivity level that is 3.8% higher than that of non-exporters. Firms that undertake both exporting and R&D activities have a total factor productivity level that is 5.1% higher.

Aw, Roberts and Winston (2005) examine the effect of exporting on the level of total factor productivity in a sample of Taiwanese firms. Using maximum likelihood estimation, they find that export entry is associated with a 4.2% increase in total factor productivity relative to non-exporters. They go on to analyse the role of R&D in the process of learning-by-exporting. They focus on the argument that firm's R&D is necessary to assimilate knowledge and thus form an important part of learning-by-exporting. Using maximum likelihood estimation, they find that exporting firms investing in R&D and worker training experience a 7.8% increase in total factor productivity levels relative to non-exporters.

In contrast to the previously referenced international studies that find positive productivity impacts of export market entry for non-UK developed countries, Pisu (2008) and Saxa (2008) do not find any significant results.

Pisu (2008) examines the causal effects of exports and productivity in a sample of Belgian manufacturing firms and finds no evidence of the LBE hypothesis. While initial correlations suggest a positive relationship between exporting and productivity, when using matching techniques and difference-in-differences analysis to estimate a causal effect, the author finds no significant relationship. Pisu (2008) interprets the results as evidence of the initial positive correlations being driven by self-selection of more productive firms into exporting. They do not find that the level of development of the export destination country changes their findings.

Saxa (2008) conducts both matching techniques and instrumental variable analysis to examine the effect of export entry on both total factor productivity and labour productivity in a sample of Czech firms. Using propensity score matching based on a set of firm-specific covariates, they estimate the average effect of entering the export market on labour productivity and total factor productivity and find no significant estimates of starting to export on labour productivity or total factor productivity. The results also remain insignificant for an alternative (instrumental variable) estimation approach.

Du, Lu, Tao and Yu (2012) examine whether the impact of exporting on firm productivity in China differs for domestic firms as compared with foreign affiliates. Using PSM techniques and a method developed by Olley and Pakes (1996) to account for endogeneity, they find that domestic firms display significant productivity gains upon export entry, whereas foreign affiliates show no evident TFP changes. Specifically, the TFP level of domestic export starters increases by 0.8% in the year they begin to export, reaching 3.9% cumulative TFP premium within 5 years after entry. Foreign affiliates display no significant impact on TFP from exporting. The productivity gains for domestic export starters are more pronounced in high-and medium tech industries than low-tech industries.

Aw, Roberts and Xu (2011) estimate a dynamic structural model of producer’s decision to invest in R&D and export, allowing both choices to endogenously affect the future path of productivity. Based on plant-level data for the Taiwanese electronics industry 2000-2004, they find that both R&D and exporting have positive effect on plant’s future productivity, which drives more plants to self-select into both activities. Specifically, past exporters have productivity that is 1.96% higher. R&D and exporting together raise productivity by 5.56%.

Vogel and Wagner (2011) estimate exporter productivity premia of German business service enterprises by looking at labour productivity and using data from 2003-2007. When using a fixed effects regression, they find that exporters have a productivity premium of 3.4%. When leaving out the 1st and 99th percentile of the distribution, the coefficient decreases to 1.4%, but is still statistically significant. To control for all outliers, the authors also apply a method of moments estimation to obtain robust estimates. Under this specification, the productivity premium is no longer statistically significant and different from zero.

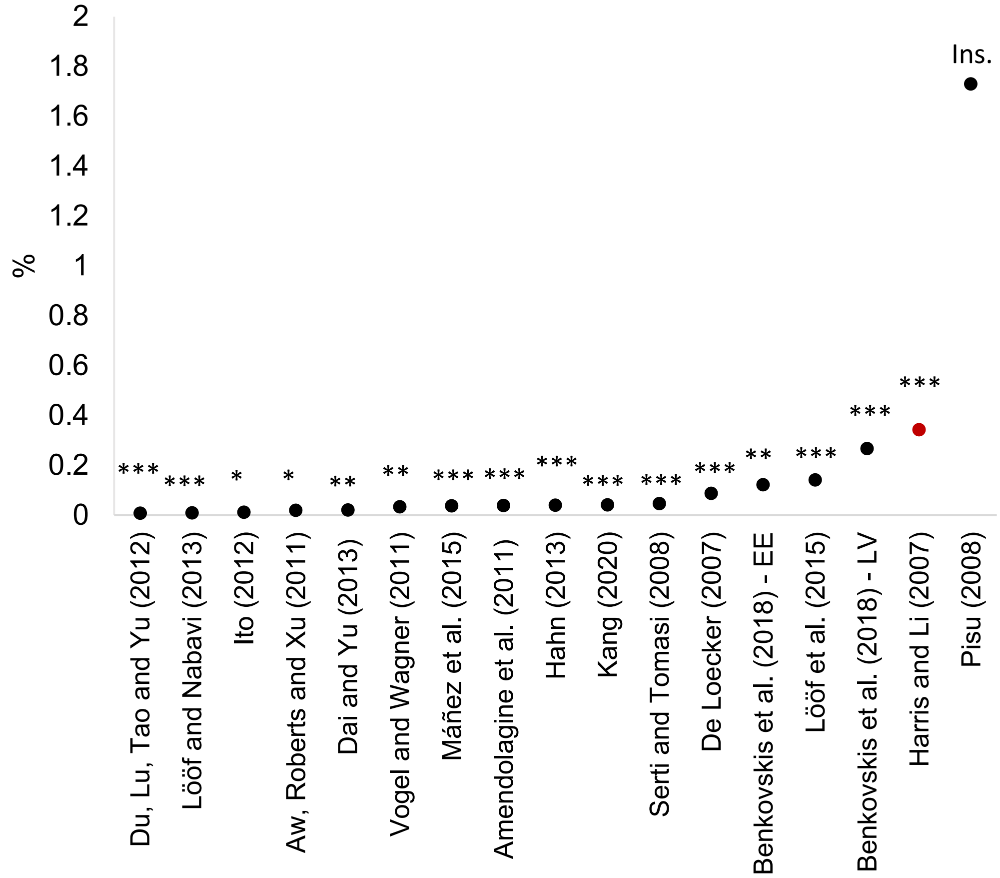
Table 2: Summary of Productivity Estimates in Evidence from Other Developed Countries

Reference	**Impact measure**	**Country coverage**	**Coefficient estimate (Decision to export)**
Segarra-Blasco (2020)	ALP	Europe (Austria, Germany, France, UK, Italy, Spain and Hungary)	Temporal Effect 0.139** (Full sample) 0.147*** (Leader) 0.133*** (Laggard) Spatial Effect 0.045** (Full sample) 0.0046*** (Leader) 0.0048*** (Laggard)
Amendolagine, Capolupo and Petragallo (2011)	TFP ALP	Italy	0.039*** 0.041**
Andersson et al. (2008)	ALP	Sweden	0.049***
De Loecker (2007)	TFP	Slovenia	0.088***
Eliasson et al. (2009)	ALP	Sweden	0.042***
Benkovskis et al. (2018)	ALP TFP	Latvia Estonia	0.232*** (L) 0.141*** (E) 0.268*** (L) -0.027 (E)
Garcia and Voigtländer (2013)	Marginal Cost	Chile	(-)0.203***
Hahn (2013)	TFP	South Korea	0.041***
Ito (2012)	TFP	Japan	-0.006 (Full Sample) 0.0116* (Export to NA/EU) 0.007 (Export to Asia)
Kang (2020)	TFP	Korea	0.042*** (Full sample) 0.069*** (High AC) 0.059 (Low AC)
Pisu (2008)	TFP	Belgium	1.73 (Full sample) 8.94 (High income) 4.84 (Low income)
Saxa (2008)	ALP TFP growth	Czech Republic	(-)1.42 (-)0.04
Lööf and Nabavi (2013)	TFP	Sweden	0.010***
Lööf et al. (2015)	TFP	Sweden	0.142***
Dai and Yu (2013)	TFP premium from exporters engaging in R&D	China	0.021** (Exporting only) 0.164*** (with R&D)
Ito and Lechevalier (2010)	TFP premium from exporters engaging in R&D	Japan	0.0826***
Máñez, Rochina-Barrachina and Sanchis-Llopis (2015)	TFP	Spain	0.038*** (Exporting only) 0.051** (with R&D)
Aw, Roberts and Winston (2005)	TFP premium from exporters engaging in R&D	Taiwan	0.042** (Exporting only) 0.078** (with R&D)
Du, Lu, Tao and Yu (2012)	TFP premium (%)	China	0.008***
Aw, Roberts and Xu (2011)	TFP	Taiwan	0.0196*
Vogel and Wagner (2011)	ALP	Germany	0.034** 0.014** (without outliers) -0.0001 (MM estimation)

Note: TFP = Total factor productivity; ALP = Apparent labour productivity, AC = Absorptive Capacity. For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

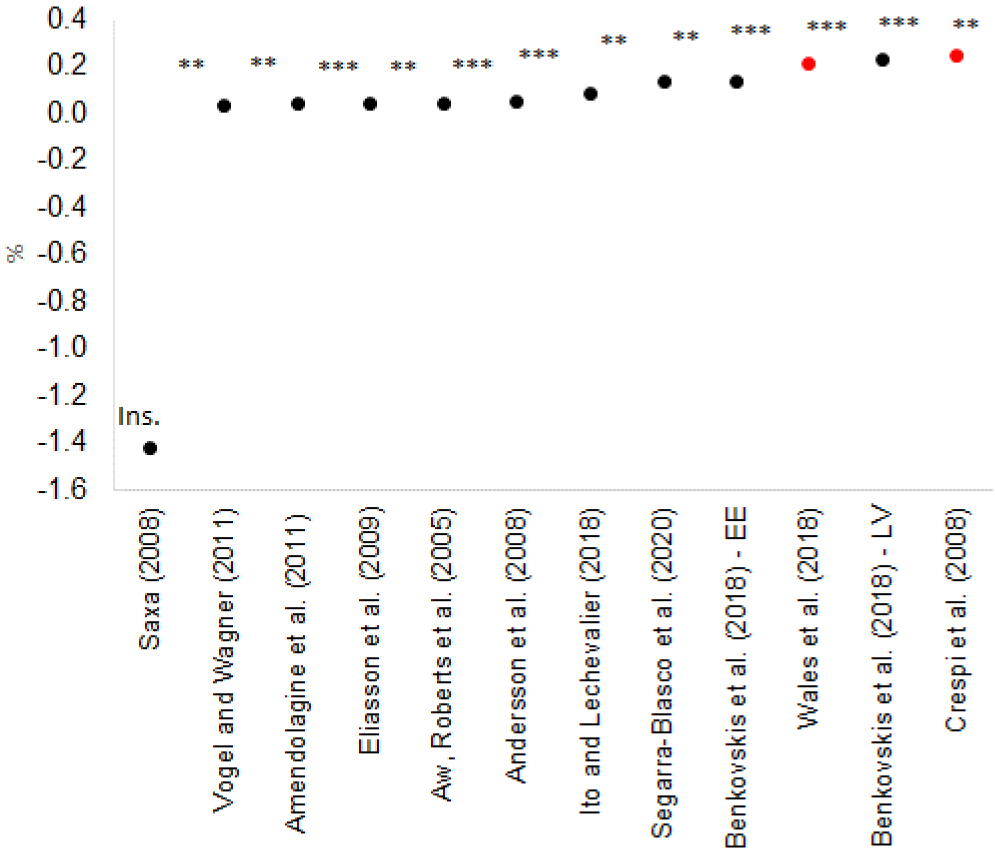
The figures below summarise the observed direct productivity (level) impacts associated with a firm's entry into the export market. They show that estimates are by and large of similar magnitudes across papers.

Figure 1 Direct effects TFP coefficients (extensive margin)



Note: Red points are UK sample, black all others
Source: London Economics

Figure 2 Direct effects ALP coefficients (extensive margin)



Note: Red points are UK sample, black all others
Source: London Economics

1.1.2 Sub-National Impacts

There is currently no applicable evidence found on the effect of export market entry on the level of productivity at the sub-national level.

1.1.3 Impacts by firm type (size)

There is limited evidence of the effect of exporting on the level of productivity by firm size. Eliasson et al (2009) examine the productivity trajectories of future exporters in a sample of Swedish SMEs. They further divide their sample of firms by size: small (1 to 9 employees), medium-sized (10 to 49 employees), and larger firms (at least 50 employees). They find the strongest effects for the smaller sized firms of 7.2% increase in the level of labour productivity in the year of entry. The estimate for the medium-sized firms was slightly smaller at 3.5% and the effect on firms with at least 50 employees was insignificant. When testing their alternative learning-by-exporting hypothesis, they find that the productivity differential between exporters and non-exporters is again driven by small firms. They also find that small firms appear to prepare to enter the export market by improving their productivity in the two years pre-entry. The authors interpret this finding at ‘learning to export’.

1.2 Productivity Growth

i) National Impacts

Martins and Yang (2009) conduct a meta-analysis of over 20 papers that investigate the causal relationship between exporting and firm productivity growth across a wide range of countries in Europe, North America, and Asia. They find that, on average, studies of developed countries report a positive causal effect of exporting on productivity growth, with coefficients ranging between 0.07 and 0.31 on average. Their meta-analysis also shows that the effect of exporting is largest in the first year of entry to the export market.

A further four studies provide direct evidence from the UK overall supports the learning-by-exporting hypothesis, in that exporting firms experienced positive productivity growth effects as a result of entering the export market.

Greenaway and Kneller (2004) investigate whether the export market entry of UK-based manufacturing firms results in productivity increases for the exporting firms. The authors use propensity score matching and difference-in-differences analysis to estimate the causal effect of export market entry on total factor productivity (TFP) growth at the firm level. They find that in the entry year new exporters experience total factor productivity growth that is 3.6% faster for new exporters relative to non-exporters, the effect is insignificant in the following periods.

Girma, Greenaway and Kneller (2004) use a similar methodology to examine exporting and firm performance for a panel of UK manufacturing firms. On entry year, exporting firms experience a TFP growth rate which is higher by about 1.6 percentage points than for non-exporters. In the year of entry into the export market, the estimates for labour productivity are insignificant. They also find that one-year post-entry into the export market, exporting firms experience a labour productivity growth rate which is higher by around 151 percentage points than the treatment group productivity growth rate, but this effect is statistically significant only at the 10% level. They find no significant effects for total factor productivity growth one year post entry.

Greenaway and Kneller (2007) further investigate whether the effect of entry into the export market on productivity in the UK varies by sector, and specifically whether these effects are driven by a sector’s existing exposure to foreign competition. The authors hypothesise that the productivity effect of entry should be lower in industries that already benefit from the competition and knowledge effects of being exposed to foreign firms. Again, using propensity score matching and a difference-in-differences approach, the authors find evidence in support of their hypothesis. They find on average 2.9% faster TFP growth in each of the three years following export market entry compared to non-export firms. However, there exists significant cross-industry differences. For industries that are already exposed to high levels of R&D and high levels of international competition, the effect of entry on TFP is lower. At the industry R&D mean the average effect of export market entry remains positive and productivity growth is around 2.8 per cent per year higher. The effect is non-linear (the squared term is also significant) such that the entry effect is at its minimum in industries with an intensity of around 3.25, the entry effect is just 0.1 of a percentage points per annum in these industries.

Table 3: Summary of Productivity Growth Estimates in Evidence from the UK

Reference	Impact measure	Country coverage	Dataset used	Coefficient estimate (Decision to enter)
Greenaway and Kneller (2004)	TFP growth	UK	OneSource and FAME	0.036***
Girma, Greenaway and Kneller (2004)	ALP growth TFP growth	UK	OneSource	1.518*
Greenaway and Kneller (2007)	TFP growth	UK	OneSource and FAME	0.029***

Note: TFP = Total factor productivity; ALP = Apparent labour productivity, AC = Absorptive Capacity. For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics’ analysis

Extending the analysis beyond the UK, De Loecker (2010, 2013) revisits the Slovenian dataset used by De Loecker (2007) and derives nonparametric estimates of exporting on production by including past exporting experience into the production function itself. The author re-confirms the learning-by-exporting effect found in De Loecker (2007) as they find that exporting produces a significant and permanent productivity growth premium of 4.1% relative to the productivity growth of non-exporters.

Damijan and Kostevc (2005) also investigate the existence of a causal link between exporting and productivity using firm-level data from Slovenia, however, the sample of firms is substantially smaller relative to De Loecker (2007, 2013). In order to isolate a causal effect, the authors again use propensity score matching and difference-in-differences analysis. The results show significant evidence of learning-by-exporting in the period when firms enter the export market, they estimate total factor productivity growth to be 0.61 percentage points higher in exporters relative to non-exporters, but this effect dissipates in the following years. In relation to foreign market competition, they find that entering a foreign market with a high level of competition has a negative effect on total factor productivity, with the result also only being significant for the period of entry.

Manjón et al. (2012) use a GMM framework to estimate productivity and matching techniques to estimate the causal effect of export entry on productivity in a sample of Spanish manufacturing firms. They find insignificant evidence of learning-by-exporting when they allow productivity to evolve exogenously, however they find that exporters obtain an extra yearly average cumulative productivity growth rate of around 3% after entry relative to non-exporters when allowing past export experience to affect productivity. These results are comparable with De Loecker (2013).

Ketterer (2015) investigates the causal effect of single and multi-market export entry on firm level productivity in a sample of Lithuanian manufacturing firms. Using matching techniques, they find firms entering a single export market experience 10% higher total factor productivity growth and 16% higher labour productivity growth in the year of entry into the export market relative to non-entrants. The estimates for the effect of multi-market entry, however, are insignificant for both labour productivity and total factor productivity. They further disaggregate their results by the level of development of export destination countries and find significant productivity effects only for those firms that export to developed countries. The majority of estimates for those exporting to developing countries are insignificant.

Silva et al. (2010) estimate the causal effect of exporting on productivity in a sample of Portuguese firms. Using propensity score matching and difference-in-differences analysis they find that in the period of entry into the export market, total factor productivity growth is 0.8 percentage points higher relative to non-entrants, this gap increases to 4.5 percentage points higher two periods post-entry. Labour productivity growth is found to be 0.3 percentage points higher than that of non-entrants in the period of entry.

Greenaway, Gullstrand and Kneller (2005) analysis the productivity differences between export starters and non-exporters in a sample of Swedish firms. Using matching techniques and difference-in-differences estimation, they estimate the average rate of total factor productivity growth of new exporters and non-exporters to analyse the change in the rate of TFP growth specific to firms entering the export market. They find no significant effects of export market entry on productivity growth in the year of entry or in any years following. They suggest that due to the high degree of openness and international exposure in Sweden means there are smaller difference in firm characteristics, as only a small proportion of firms (approximately 20%) do not export.

Serti and Tomasi (2008) examine the causal effect of exporting on firm-level productivity in a panel of Italian manufacturing firms. They also use propensity score matching and difference-in-differences analysis and find that the average effect of entry into the export market is positive and significant for a range of performance indicators. The authors find the rate of labour productivity growth in exporters is 4.3% higher than that of non-exporters one-period post-entry, with this gap increasing to 13% higher than non-exporters after 5 years. Similarly, they find export starters have a higher total factor productivity rate of growth by 4.7% one-period post-entry compared to non-exporters, with this gap increasing to 17% after 5 years. The authors then disaggregate their results by region and firm size. They find consistent results for productivity in the Northern region, which on exhibits higher export levels as well as a higher GDP; however, the results are generally insignificant for Central and Southern regions, in which exporting levels and income per capita is lower. The authors do not comment on whether they think the regional discrepancies relate to the differing exporting levels or regional disparities in income, or any other factors. In terms of firm size, the results for TFP are relatively similar across firm sizes, however, they find stronger long-term effects for medium to large firms relative to small firms.

Wagner (2002), who examines the causal effects of exports on growth of labour productivity using a matching approach on a sample of German manufacturing firms also finds overall insignificant estimates. While average labour productivity growth differs between exporters and non-exporters by around 1% a year, this difference is not statistically different from zero.

Several studies investigate the effect of exporting on productivity growth in Asian firms.

Kim and Sung (2020) study the dynamic relationship between total factor productivity, exports and knowledge assets for a sample of Korean manufacturing firms. Using a GMM estimator, they find exporting is associated with 2.6% increase in total factor productivity growth, which suggests a learning-by-exporting effect could be present.

Kim (2013) investigates the relationship between productivity performance and exporting activity in a sample of Korean manufacturing firms. The paper evaluates the linkage between exporting and productivity at different quantiles of the conditional productivity distribution using quantile regression. They find significant effects of exporting on productivity at the upper end of the conditional productivity distribution. Annual total factor productivity growth is 2.6% higher for export entrants compared to non-entrants at the 75th quantile and 8.1% higher for those at the 90th quantile.

Dai and Yu (2013) examine the instantaneous and long-run effects of exporting on productivity using a sample of Chinese manufacturing firms. Econometrically, the authors use propensity score matching based on observable firm characteristics and then calculate the average effect. They find that entry into the export market is associated with total factor productivity growth of 2.1% in the period of entry relative to non-exporters, however, as in Kang (2020), this effect is insignificant in the following periods.

Turning to studies from the Americas, Lileeva and Trefler (2010) use a mandatory policy change, in the form of tariff cut, that serves as an instrument for the decision of Canadian plants to begin exporting to the United States, as a natural experiment to isolate a causal effect of exporting of firm productivity. To assess the impact at a plant-level, the authors link the tariff-cut data to a plant's commodity data to compute the average tariff-cut of the specific plant. The authors compute marginal treatment effects, namely the impact of starting to export on the labour productivity for the plants that were induced to start exporting due to the tariff cut. They find that labour productivity growth rate was up to 50% higher post-entry for low productivity firms, but that high-productivity firms experienced almost zero productivity gains.

Table 4: Summary of Productivity Growth Estimates in Evidence from Other Developed Countries

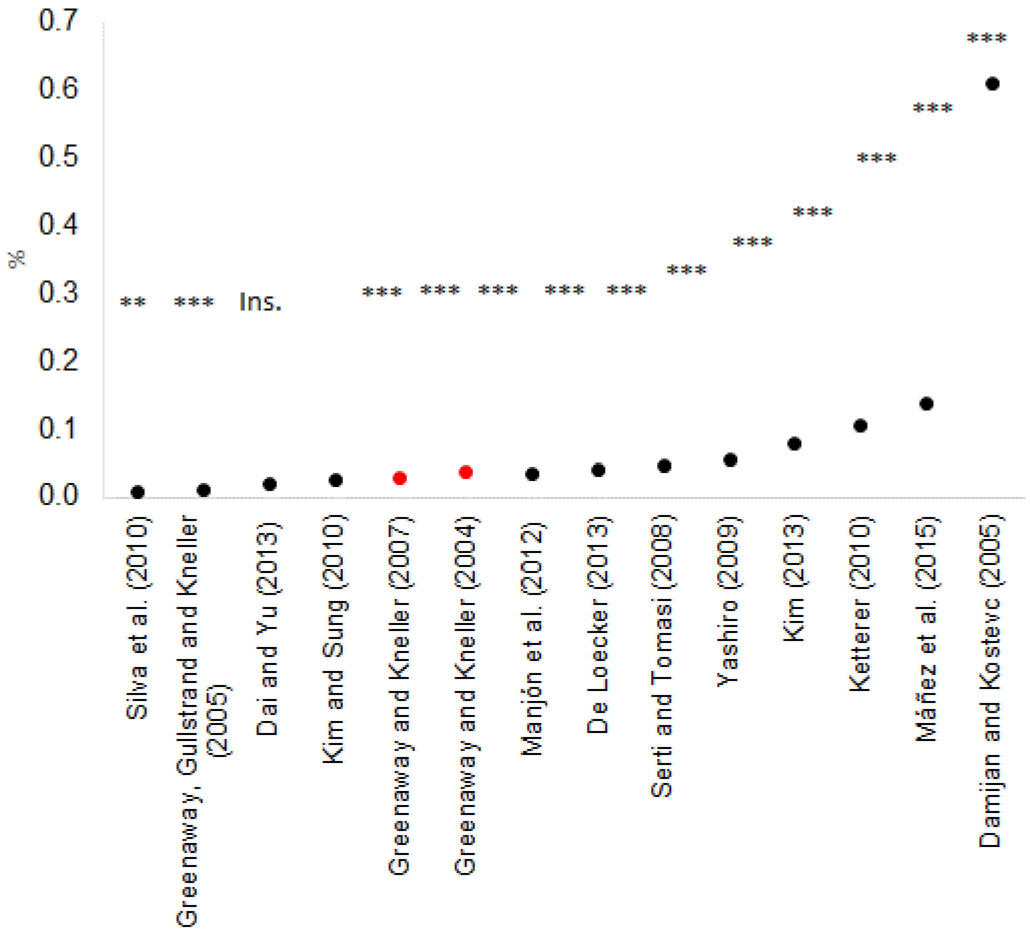
Reference	Impact measure	Country coverage	Coefficient estimate (Decision to export)
De Loecker (2013)	TFP	Slovenia	0.041***
Damijan and Kostevc (2005)	TFP	Slovenia	0.61***
Manjón et al. (2012)	TFP	Spain	0.03***
Ketterer (2015)	TFP ALP	Lithuania	0.105*** 0.134***
Silva et al. (2010)	TFP ALP	Portugal	0.008** 0.003***
Greenaway, Gullstrand and Kneller (2005)	TFP	Sweden	0.011
Serti and Tomasi (2008)	ALP TFP	Italy	0.043*** 0.047***
Manjon et al. (2012)	TFP	Spain	0.036***

Kim and Sung (2010)	TFP	Korea	2.586***
Kim (2013)	TFP	Korea	0.081***
Wagner (2002)	ALP	Germany	3.89
Dai and Yu (2013)	TFP premium from exporters engaging in R&D	China	0.021** (Exporting only) 0.164*** (with R&D)
Lileeva and Trefler (2010)	ALP	Canada	0.40**

Note: TFP = Total factor productivity; ALP = Apparent labour productivity, AC = Absorptive Capacity. For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

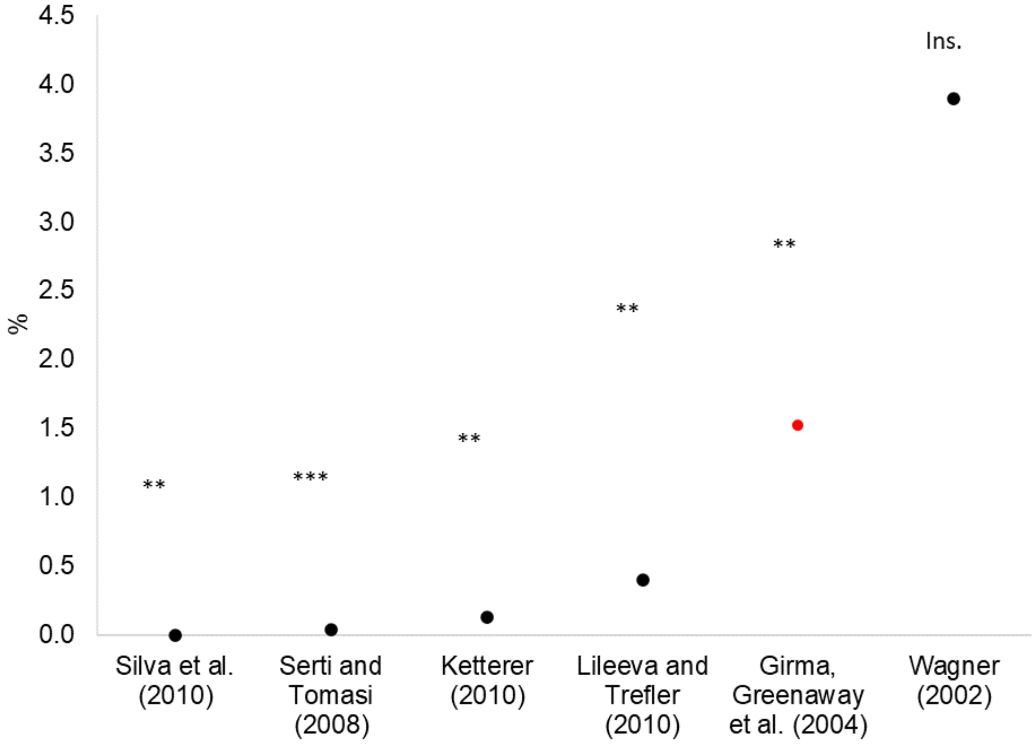
The figure below provide an overview of TFP growth coefficients observed in the literature. Again, UK-based studies are represented by the red dots.

Figure 3 Direct effects TFP growth coefficients



Note: Red points are UK sample, blue measured in percentage points not %, black all others
Source: London Economics

Figure 4 Direct effects ALP growth coefficients



Note: Red points are UK sample, blue measured in percentage points not %, black all others
Source: London Economics

1.2.2. Sub-National Impacts

There is very limited evidence of estimating the effect of exporting at a regional level. Serti and Tomasi (2008) examine the causal effect of exporting at the regional level by dividing their sample into northern, central and southern regions of Italy. Using propensity score matching and difference-in-differences analysis, they find that the effect of exporting on total factor productivity growth is only significant for northern regions. Total factor productivity growth increases by 4.8% in the period of entry relative to the group of non-exporters, increasing to 14.5% five periods post-entry. The effect in central and southern regions is insignificant, indicating substantial heterogeneity of exporting effects within a country.

1.2.3. Impacts by Firm Size

Yashiro (2009) investigates the effect of the export boom in Japan during the 2002-2005 period on firm-level productivity growth as well as the differential effects of exporting by firm size. They define large exporters as those firms with 300 employees or more and small exporters as those with less than 300 employees. Using difference-in-differences analysis, with exporting referring to continuous export participation within this period, they find that large exporters experience significantly higher productivity growth than non-exporters. However, the effect is insignificant for small exporters. On average, exporting firms experienced 5% higher growth of total factor productivity compared to non-exporters. When dividing the sample by firm sizes, they find 4.5% higher TFP growth for large exporters compared to non-exporters, but the effect is absent for small exporters.

Serti and Tomasi (2008) examine the causal effect of exporting on firm-level productivity in a panel of Italian manufacturing firms and disaggregate their results by firm size. They use propensity score matching and difference-in-differences analysis and find that the effect of exporting on firm-level total factor productivity (TFP) is relatively similar across firm sizes. They define small firms as those with less than 50 employees and medium to large firms as those with more than 50 employees. They find slightly stronger long-term effects for medium to large firms relative to small firms. Compared to non-exporters, total factor productivity growth increases by 12.3% two periods-post entry for medium to large firms, increasing the 22.1% five periods post-entry. For small firms, TFP growth increases by 4.6% two periods post-entry, increasing to 18% five periods post-entry.

Silva et al. (2010) in their analysis of Portuguese firms also divided their sample into small and large firms. Small firms are defined as those with less than 50 employees and large firms with at least 50 employees. Using propensity score matching and difference-in-differences analysis, they find that 'large' firms experience significant total factor productivity effects from exporting, but this is not the case for 'small' firms. One period post-entry, exporting increases total factor productivity growth in 'large' firms by 3.5 percentage points, however this effect is insignificant for 'small' firms.

Máñez-Castillejo, Rochina-Barrachina and Sanchis-Llopis (2010) analyse the relationship between exporting and total factor productivity in a sample of Spanish manufacturing firms. They also investigate how the causal effect of exporting differs by firm size. They define small firms as those with 10 to 200 employees and large firms as those with over 200 employees. Using matching techniques, they find for small firms, extra productivity growth (EPG) for export starters varies between 7.2 and 8.6% relative to non-exporters one year post-entry, depending on the matching techniques used. This then decreases in the following years. For large firms they experience EPG of around 14% relative to non-exporters, however this effect is only significant two-years post-entry.

1.3 Innovation and Research and Development (R&D)

1.3.1 National Impacts

Innovation is also widely studied in the learning-by-exporting literature. The general intuition is that learning would likely manifest itself in the form of innovative activity and this would drive productivity growth. Therefore, the learning-to-innovate-by-exporting literature find overall a positive association between exporting and innovation performance at the firm level.

Peters et al. (2018) examine the links between exporting, innovation inputs, innovation outputs, and productivity in service enterprises in the UK, Germany, Ireland by means of a CDM model which is used to link the relationship between innovation and productivity. They find that exporting plays a major role in the context of innovation in services in all three countries, since exporting firms are 15.3%, 16.5% and 9.3% more likely to invest in innovation than non-exporters in Germany, Ireland, and the UK, respectively.

Fassio (2015) investigates the effect of exporting on the innovation strategies of firms using firm-level data from France, Germany, Spain, Italy and the UK. The author analyses two different mechanisms through which exporting can affect innovation activities. Firstly, exporting can foster innovation as firms learn to innovate from foreign clients and competitors when they are active in technologically advanced foreign markets, this is the technological learning effect. Secondly, exporting can encourage innovation through the increase in demand in a firm's output from the foreign market and thus increases the profitability of introducing new products, this is the foreign demand effect. To control for endogeneity, the author employs an instrumental variable approach. They find that, through the technological learning effect, exporting increases the probability to introduce new product innovations. Through the foreign demand effect, exporting is also found to increase the probability to engage in more efficient strategies based on process innovations. They also find that stronger effects for German exporting firms relative to firms from the other European countries included in the sample.

Extending the analysis beyond the UK, Siedschlag and Zhang (2015) also uses data from Irish firms to examine the links between internationalisation of manufacturing and service firms and their innovation and productivity performance, following the methodology of Crepon et al. (1998)[1] and Griffith et al. (2006).[2] They find that relative to firms that serve the domestic markets only, firms with international activities were more likely to invest in innovation, to be successful in terms of innovation output, and experience higher labour productivity. Exporters were 21% more likely to invest in innovation than

[1] Crépon, B., E. Duguet, and J. Mairesse. 1998. "Research, Innovation and Productivity: An Econometric Analysis at the Firm Level." Economics of Innovation and New Technology 7 (2):
115–158.
[2] Griffith, R., E. Huergo, J. Mairesse, and B. Petters. 2006. "Innovation and Productivity across Four
European Countries." Oxford Review of Economic Policy 22 (4): 483–498

domestic firms, and 23% more likely to have product innovations than domestic firms. The impact was the greatest on product innovation, compared to process or organisational innovation.

Salomon and Shaver (2005) examine the relationship between exporting and innovative outcomes on a panel of Spanish manufacturing firms. They hypothesise that exporting firms can access knowledge that is not available to the domestic market, and this knowledge can be used to increase innovation. They measure innovation outcomes using level of product innovation and the number of patent applications submitted in a given year. Using a nonlinear GMM estimator, the authors find strong and persistent effects of exporting on innovation. One-period post-entry into the export market, the number of product innovations increased by 0.6 and 0.9 two periods post-entry. The number of patent applications increased by 1 one-period post-entry and 1.2 two-periods post-entry.

Revisiting the same sample of Spanish manufacturing firms, Salomon and Jin (2008) examine how exporting affects the innovative outcomes of firms in leading and lagging industries. The authors categorise firms as technologically leading or lagging based on their proximity to the global technological frontier, that is whether the industry is operating near to or below the frontier. Using negative binomial regression on a dynamic longitudinal model, the authors find that in both technologically leading and lagging industries, exporters engage in more innovative activity (measured by patent applications), with effects being stronger for firms in leading industries compared to firms in lagging industries. The authors divide their sample further by examining the differential between the first and fourth quartile splits in the industry-level proximity to the global technological frontier. By doing so, the authors find evidence to support their hypothesis that lagging industries learn more from exporting, as proxied by innovative outcomes, than leading industries. The authors find that the technologically weakest laggards have the strongest innovation response to exporting, whereas the results for the strongest leaders are now negative and statistically insignificant.

Similarly, Damijan and Kostevc (2010) also divide their sample of Spanish firms by their proximity to the technological frontier. They explore the learning-by-exporting hypothesis by investigating the causal links between exporting, importing and innovation. The authors study the sequencing of firm’s learning through trade with one such sequence estimating the direct causal effect of exporting on innovation, measured by the introduction of a new product or process. Using propensity score matching to control for selection bias, they find that exporting has a positive and significant effect on product and process innovation. Exporting firms were 3.2 and 2.1 percentage points more likely to engage in product and process innovation, respectively. The authors disaggregate their results by firm size and firm’s proximity to the technological frontier by categorising the firm as a ‘productivity leader’ or ‘productivity laggard’. They define a productivity leader as those firms in the top quantile of the industry’s production distribution, and productivity laggards the bottom quantile. In terms of proximity to the technological frontier, strong, positive effects of exporting are found for product innovation in productivity leaders, but no such effect is found for process innovation or for productivity laggards.

Several studies also use data from Italian manufacturing firms. Bratti and Felice (2012) investigate the learning-by-exporting hypothesis by estimating the effect of a firm’s export status on the likelihood of engaging in product innovation. They use an instrumental variable specification in a linear model and a probit model to isolate a causal relationship in a sample of Italian manufacturing firms. In the authors preferred specification with the most robust controls, the authors find exporting is associated with a 13.3 percentage point increase in the likelihood the firm engaging in product innovation, therefore, providing supporting evidence for learning effects on the firm’s innovative ability.

Vahter (2011) studies the association between exporting and intensity of knowledge flows to the firm which are used for innovation activities from the firm’s customers, relative to other knowledge sources (suppliers, within the enterprise and competitors). Using an instrumental variable approach on a sample of Estonian firms, they find a positive and significant relationship between exporting and increases in the knowledge spillovers from customers that are subsequently used for innovation activities relative to other sources of knowledge, which suggests evidence in support of the learning-by-exporting hypothesis.

Harris and Moffat (2011) examine the determinants of whether UK firms export, undertake R&D and innovate by means of an instrumental variable approach and probit regressions. They find that exporting increases the probability of engaging in R&D by 14% for manufacturers and 13% for non-manufacturers. The probability to innovate did not seem to be affected by exporting.

Damijan, Kostevc and Polanec (2010) examine both directions of the relationship between innovation activity and the decision to export for their sample of Slovenian firms. They test the prediction that a firm's inclination to innovate increases its probability of becoming an exporter, as well as hypothesis that positive learning effects of exporting lead to additional innovations and boost productivity. By means of propensity score matching, they find that the direct impacts of exporting on the probability of product innovation are statistically insignificant but for process innovation significantly positive. Namely, exporting increases the probability that a firm becomes a process innovator by 1.6-4.6% depending on the matching technique. The authors also break down their results by firm size, with no effect of exporting on innovation for small firms. But for medium and large firms, the lagged export status has a statistically significant positive impact on probability that firm will become process innovator (4.6-8.2% for medium sized and 5.7-6.4% for large firms).

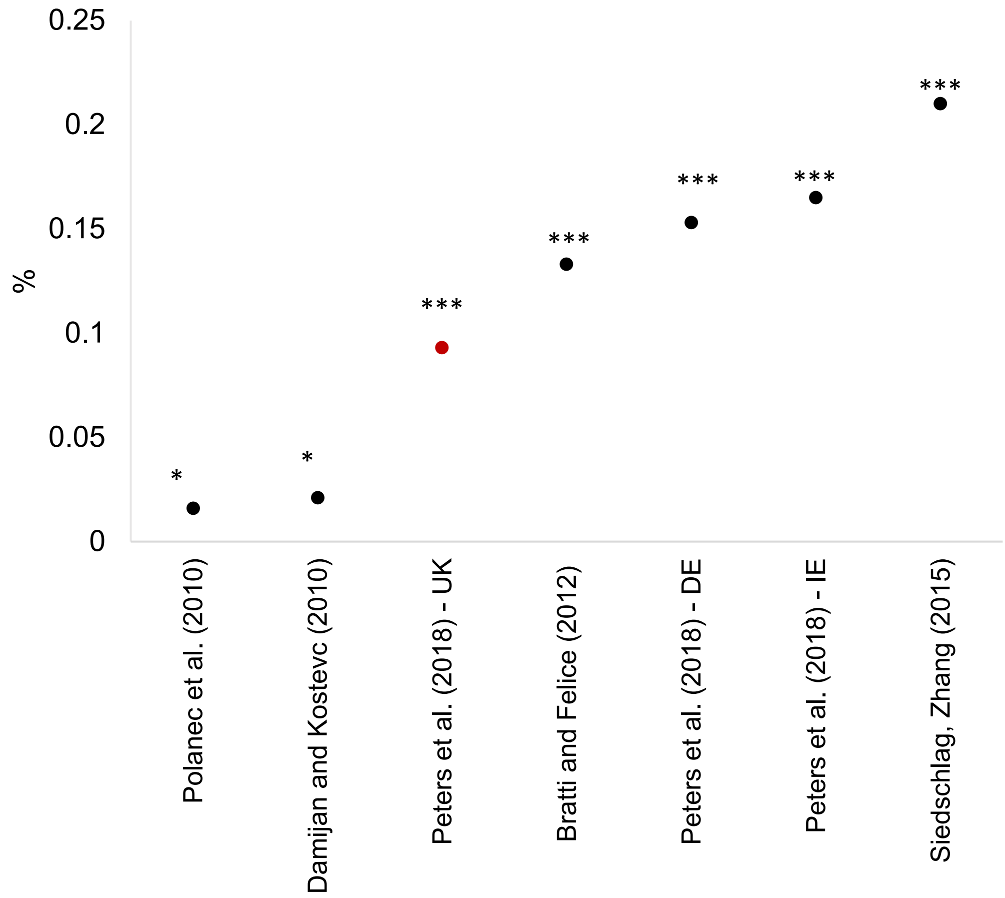
Table 5: Summary of Innovation Estimates in Evidence from Developed Countries

Reference	**Impact Measure**	**Country Coverage**	**Coefficient estimate**
Peters et al. (2018)	Probability of innovation	Germany Ireland UK	0.153*** 0.165*** 0.093***
Fassio (2015)	Probability of product innovation Probability of process innovation		2.066*** 1.327***
Siedschlag and Zhang (2015)	Probability of innovation Product innovations	Ireland	0.21*** 0.23***
Salomon and Shaver (2005)	Product innovations Patent applications	Spain	0.059*** 0.1001***
Salomon and Jin (2008)	Patent applications	Spain	0.834*** (Technological leaders) 0.79*** (Technological laggards)
Damijan and Kostevc (2010)	Probability of innovation	Spain	0.032* (Product innovation) 0.021* (Process innovation)
Bratti and Felice (2012)	Probability of innovation	Italy	0.133***
Harris and Moffat (2011)	Probability of R&D spending	UK	0.14***
Damijan, Kostevc and Polanec (2010)	Probability of process innovation	Slovenia	0.016* (all firms) 0.046* (medium) 0.064*** (large firms)

Note: For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

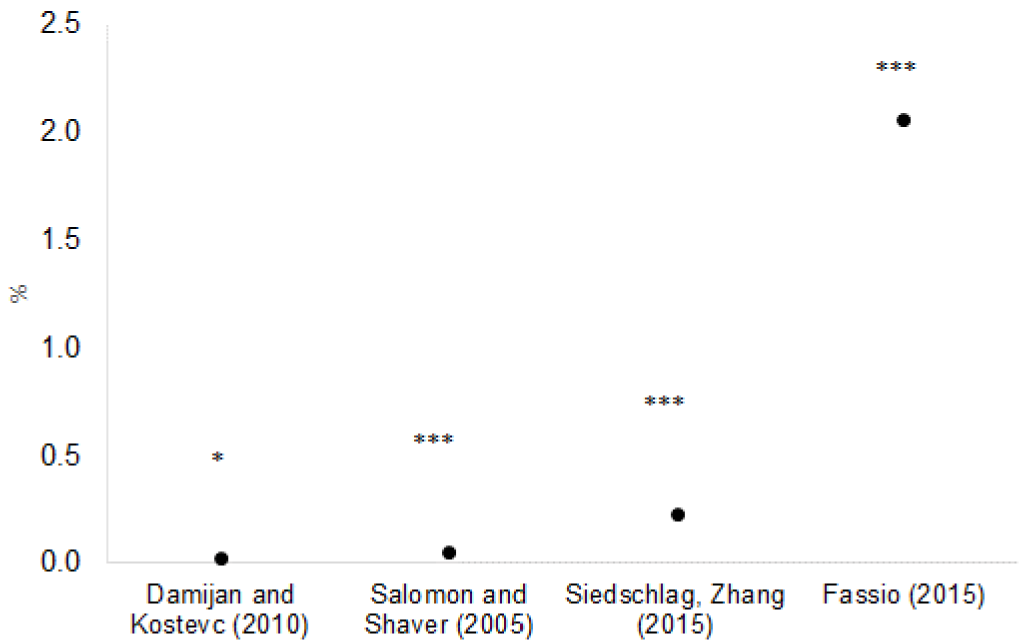
The impacts of exporting on the probability of innovation are further illustrated in the figures below.

Figure 5 Direct effects Probability of innovation coefficients



Note: Red points are UK sample, black all others
Source: London Economics

Figure 6 Direct effects Product innovation coefficients



Note: Red points are UK sample, black all others
Source: London Economics

The research on the direct effect of exporting on R&D is relatively limited. Girma, Görg and Hanley (2007) examine the relationship between exporting and R&D using a sample of British and Irish firms. Using a bivariate probit framework, the authors estimate the model simultaneously using a bivariate probit framework, which estimates a two equation probit model using maximum likelihood techniques. While they find significant evidence of self-selection, that is, those firms that engage in R&D are more likely to be exporters, they find weaker evidence for learning-by-exporting. They find that exporting had no significant association with R&D in the sample of British firms, however, the estimate for Irish firms was positive and significant. Exporting firms in Ireland are found to 28% more likely to engage in R&D than non-exporters.

Table 6: Summary of R&D Estimates in Evidence from Developed Countries

Reference	Impact measure	Country coverage	Coefficient estimate
Girma, Görg and Hanley (2007)	Probability of R&D	Britain Ireland	0.051 0.280***

Note: For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

1.3.2. Sub-National Impacts

There is very limited evidence on the effect of exporting on innovation and R&D at the sub-national level. Kneller (2007) examines whether exporters differ from non-exporters in the knowledge inputs used for R&D at for a region in the UK, particularly whether exporters have an advantage due to their better access to international knowledge. To identify sources of knowledge inputs for R&D, firms were asked to report of any external collaborators involved in the R&D process and their location. Using probit and multinomial logit regression analysis on a small sample of firms from South East England (including London), they find no evidence of a relationship between export status and international knowledge transfer used for R&D. The authors then split their sample by export destination and find that exporting to North America and other non-EU regions is positively associated with international knowledge transfer. This effect turns negative when considering the type of international knowledge transfer.

1.3.3 Impact by firm type (size)

There is also very limited evidence on the direct effect of exporting on innovation and R&D by firm size.

Damijan and Kostevc (2010), in their study of Spanish firms, all estimate the effect of exporting on firm-level innovation by firm size. They divide their sample into three size classes: small firms (less than 50 employees), medium-sized firms (between 50 and 200 employees) and large firms (over 200 employees). They find that for small firms, exporting increases the likelihood of engaging in product innovation by 3.4 percentage points, but the effect for process innovation is insignificant. For large firms, they find that exporting increases the likelihood of engaging in process innovation by 13.4 percentage points, but this effect is insignificant for product innovation. They find no significant effects for medium-sized firms.

Yashiro (2009) investigates the effect of exporting on firm-level R&D intensity by firm size. They define R&D intensity as the ratio of R&D investment to real sales, they use this measure as a proxy for 'innovation efforts'. They find that on average, exporting firms have a 27% higher R&D intensity compared to non-exporters. When dividing their sample by firm size, they find 30% higher R&D intensity for large firms and 19.3% higher R&D intensity for small firms, compared to non-exporters.

1.4 Sales

1.4.1 National Impacts

A number of studies estimate the direct effect of exporting on firm-level sales and find that overall, exporting has positive effects. The majority of studies measure the effect of exporting on a firm's total sales and do differentiate between domestic and international sales.

Ito (2012), in their study of Japanese manufacturing firms, finds that the sales growth rate is 2.45 percentage point higher one-period post-entry, increasing to 4.9 percentage points 4 years later compared to non-exporters. Sales are measured by total firm sales during the period. However, similar to the estimates of productivity, when the author disaggregates the results by export destinations, they find that starting to export to North America and Europe has positive effects on firm's sales growth rate (6.72 percentage points higher in the period of entry relative to non-exporters) but exporting to Asia does not have significant effects.

Serti and Tomasi (2008) also find a positive effect of exporting on firm sales. They find that for their sample of Italian manufacturing firms, entering the export market is associated with a 6.2% sales growth premium relative to non-exporters which increased to 21% in the fourth period post-entry. Sales are measured by total shipments made by the firm. When dividing their sample by region and firm size, they find consistent results by region for sales in the Northern region, but the results are generally insignificant for Central and Southern regions. In terms of firm size, the results for sales are similar across firm sizes, with stronger long-term effects for medium to large firms.

Silva et al. (2010) in their analysis of Portuguese firms also estimated the effect of entering the export market on firm-level sales growth. Measured by the difference in a firm's total sales over a given period. They find that in the year of entry, sales growth is 2.2 percentage points higher relative to non-entrants. This effect is significant only for two years post-entry.

In their study of UK manufacturing firms, Girma, Greenaway and Kneller (2004) find that entry into the export market also positively affects output growth in the year of entry by 3.6 percentage points and one-year post-entry by 2 percentage points.

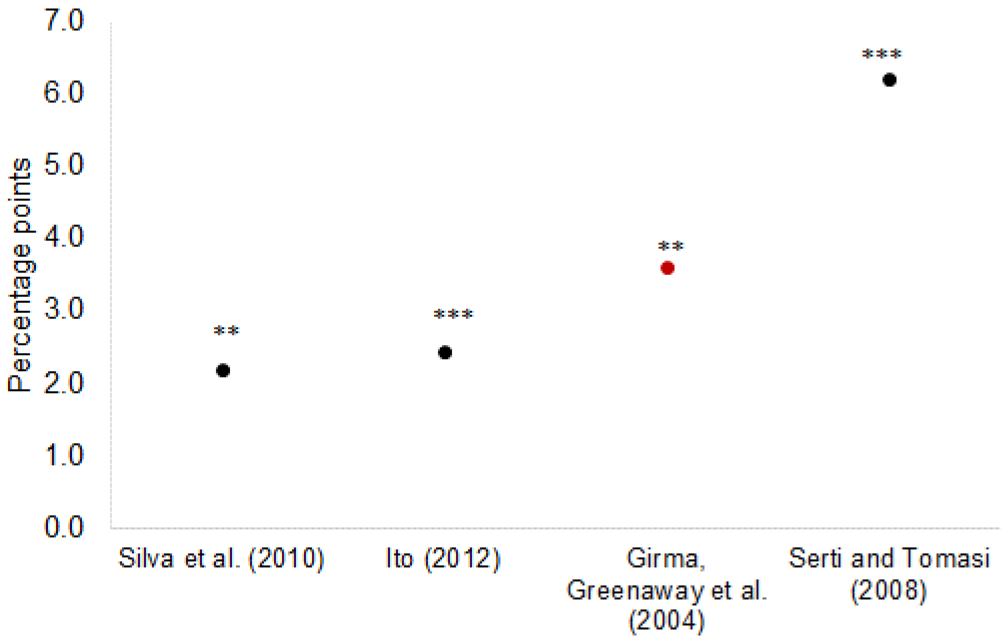
Table 6: Summary of Output Estimates in Evidence from Developed Countries

Reference	Impact Measure	Country Coverage	Coefficient Estimate (Decision to export)
Ito (2012)	Sales growth Capital stock growth	Japan	0.0245*** 0.019***
Serti and Tomasi (2008)	Sales	Italy	0.062***
Silva et al. (2010)	Sales growth	Portugal	0.022**
Girma, Greenaway and Kneller (2004)	Output growth	UK	0.036**

Note: For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

The graphic representation of the studies outlined above us provided below.

Figure 7 Direct effects Sales coefficients



Note: Red points are UK sample, black all others
Source: London Economics

1.4.2 Sub-National Impacts

There is very limited evidence on estimating the effect of exporting on firm-level sales at the regional level. Serti and Tomasi (2008), when dividing their sample by region, find generally consistent estimates for sales growth across regions, with somewhat larger effects for Italy's southern region. They find that exporting increases sales growth by 24.7% two periods post-entry in the southern region, compared to 14.9% and 13.3% for the northern and central region, respectively. However, the effect in the northern region is more persistent over time.

1.4.3 Impacts by firm type (size)

There is also very limited evidence on estimating the effect of exporting on firm-level sales by firm size. Serti and Tomasi (2008) also find that medium to large firms experience greater sales growth from exporting compared to small firms. Two periods post-entry, sales growth increases by 19.4% for medium to large firms and 11.5% for small firms. The effect for medium to large firms remains stronger over time relative to small firms.

1.5 Employment and Employee Compensation

1.5.1 National Impacts

Employment is also a commonly studied performance indicator in the impact of exporting literature. Overall, studies find a positive relationship between exporting and employment, both at a firm level and the level of employment that is supported by the export market nationally.

In their study of UK firms, Girma, Greenaway and Kneller (2004) also include employment in their analysis and find that entry into the export market is associated with a higher employment growth rate of 2.8 percentage points in employment growth in the year of entry and a 1.3 percentage point premium one-year post-entry compared to non-exporters.

Ito (2012) also finds that export entry has positive and significant effects on employment growth rate, and more so for Europe and North America than Asia.

Serti and Tomasi (2008) also find similar patterns hold for the effect of exporting on number of employees in their analysis of Italian firms. Entry into the export market is estimated to increase employment by 2.7% and this increases to 13.6% in the sixth period post-entry for exporting firms compared to non-exporters. This effect remains relatively consistent across region and firm size.
Silva et al. (2010) in their analysis of Portuguese firms also estimated the effect of entering the export market on firm-level employment. In the year of entry, employment is 6% higher in exporters relative to non-exporters. This effect is insignificant in the following periods.

Benkovskis et al. (2018) in their study of Latvian and Estonian firms also investigate the effect of export entry on firm-level employment. They find that entering the export market increases level of employment by 13.7% in Latvia and 5.8% in Estonia. When estimating this effect by export type, they find that exporting of services strongly effects employment, with an increase of 30.9% for Latvia and 11.1% for Estonia. As is the case of their results of the productivity impact of exports, they find exporting intermediate goods and re-exports has a significant effect on employment, but no such effect is found for exporting final goods.

Exporting can also have a positive effect on wages. Wagner (2002) also examines the causal effects of exports on growth of real wages using a matching approach. In contrast to their estimate of productivity effects, they find strong evidence of a positive relationship between the decision to start exporting and real wage growth. Export market entrants are estimated to have an average real wage growth per person of 4.8% compared to 1.91% for non-exporters.

Baumgarten (2010) the role of exporters in increasing wage inequality using linked employer-employee data from German manufacturing firms. The author adopts a simple accounting framework to decompose the changes in the various of wages over time and then employs various regression-based decomposition techniques. They find that the exporter wage gap between exporters and non-exporters increased by 8% in the time period, with also a portion of this effect being attributed to firm characteristics, thus suggesting export participation is contributing to growing wage inequality.

In contrast, Silva et al. (2010), in their analysis of Portuguese firms, also estimated the effect of entering the export market on firm-level wages but find no significant estimates.

Pham, Woodland and Caselli (2018) examine the behaviour of intermediate suppliers facing final producers, comparing suppliers to multinationals and exporting suppliers to purely domestic suppliers. For a sample consisting of firms from 29 European and Central Asian countries, they find that wages are 9.7% higher for exporting firms. These results are found using ex-ante productivity, which provides evidence for the self-selection hypothesis, not causal evidence for the LBE hypothesis.

Bødker, Maibom and Veijlin (2018) look at the exporter wage gap and the sources behind it using Danish employer-employee data. They find a statistically significant unconditional wage gap of 3%. Using an AKM-style wage equation with worker, firm and match fixed effects, they find that workers appear to have skills that are particularly valuable in the exporting sector and thus generate higher wages.

Egger, Egger, Kreickemeier and Moder (2017) examine the exporter wage premium of German manufacturing and service firms between 1996 and 2008. Using a Mincer-type regression they find an average exporter wage premium of 5%. They also apply a general equilibrium model, which yields an average exporter wage premium of 6%, no wage premium for unskilled workers and a premium of 15% for skilled workers. Further, they analyse the effect of exporting and exporter wage premia on labour income inequality and find that exporting increases labour income inequality, particularly for skilled workers.

Table 7: Summary of Employment and Wages Estimates in Evidence from Developed Countries

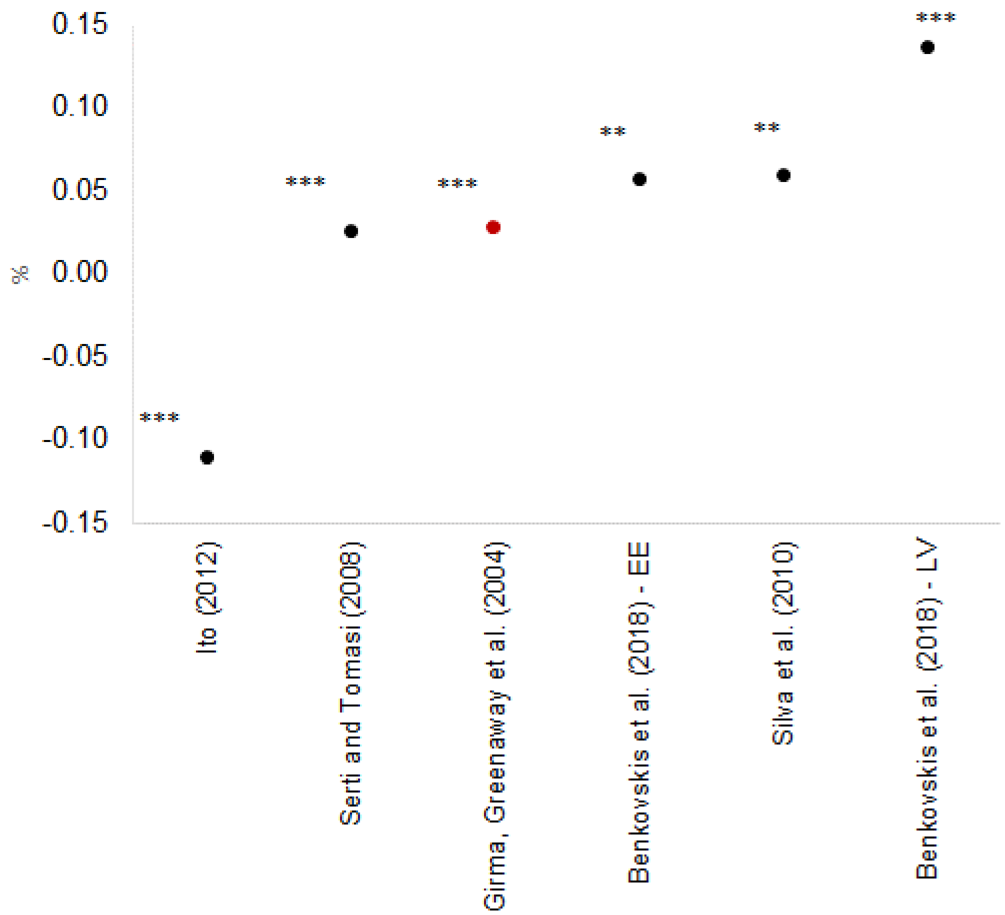
Reference	Impact measure	Country coverage	Coefficient estimate
Wagner (2002)	Wages	Germany	0.0484***

Girma, Greenaway and Kneller (2004)	Employment	UK	0.028***
Ito (2012)	Employment Employment growth rate	Japan	-0.11*** 0.02**
Serti and Tomasi (2008)	Employment	Italy	0.027***
Silva et al. (2010)	Employment Wages	Portugal	0.06** -0.013
Benkovskis et al. (2018)	Employment	Latvia Estonia	0.137*** 0.058**
Baumgarten (2010)	Wages	Germany	0.08***
Pham, Woodland and Caselli (2018)	Wages	Europe and Central Asia	0.097*** (no causality)
Bødker, Maibom and Veijlin (2018)	Wages	Denmark	0.031***
Egger, Egger, Kreickemeier and Moder (2017)	Wages	Germany	0.05** (all workers) 0.15*** (skilled workers)

Note: For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

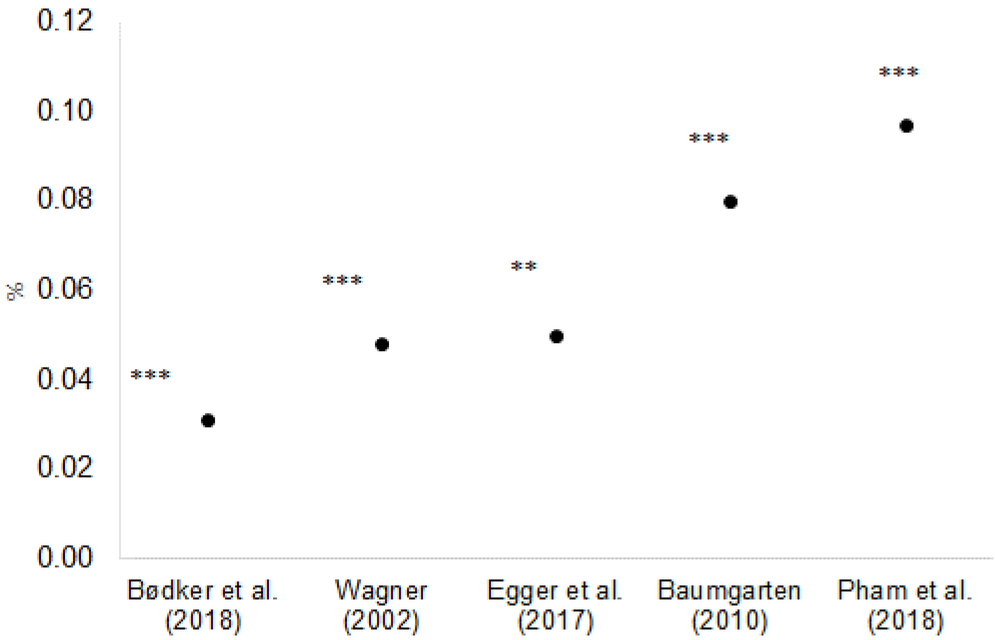
Figures 8 and 9 provide a graphic overview of the observed employment and wages effects of exporting.

Figure 8 Direct effects Employment level



Note: Red points are UK sample, black all others
Source: London Economics

Figure 9 Direct effects Wages



Note: Red points are UK sample, black all others
Source: London Economics

1.5.2 Sub-National Impacts

There is currently no applicable evidence found on the effect of exporting on employment and employee compensation at the sub-national level.

1.5.3 Impacts by firm type (size)

There is currently no applicable evidence found on the effect of exporting on employment and employee compensation by firm size.

1.6 Other – Profits and capital stock

1.6.1 National Impacts

Finally, there are a few limited examples of a few studies that explore the impacts of exporting on other impact measures such as profitability and firm-level capital stock.

Grazzi (2012) examines the relationship between exporting and firm-level profitability in a sample of Italian firms. Using both parametric and non-parametric methods on a sample of Italian manufacturing firms, they find no significant evidence of a positive relationship between exporting and profitability. The author disaggregates their results by industry and finds positive significant effects for a very small number of industries, including food and beverages, wearing apparel, fabricated metal, and non-metal. In these industries, profits were higher by 2.05 and 4.85 percentage points. In some cases, significant and negative estimates are found, for example for petroleum.

Ito (2012), in their study of Japanese manufacturing firms, finds that exporting has positive and significant effects on capital stock growth for the whole sample of 1.9 percentage points in the period of entry relative to non-exporters, increasing to 6.75 percentage points 4 years later.

Pham, Woodland and Caselli examine the behaviour of intermediate suppliers facing final producers, comparing suppliers to multinationals and exporting suppliers to purely domestic suppliers. For a sample consisting of firms from 29 European and Central Asian countries, they find that investment in fixed assets is 63.6% higher for exporting firms. These results are found using ex-ante productivity, which provides evidence for the self-selection hypothesis, not causal evidence for the LBE hypothesis.

1.6.2 Sub-National Impacts

There is currently no applicable evidence found on the effect of exporting on profits and capital stock at the sub-national level.

1.6.3 Impacts by firm type (size)

There is currently no applicable evidence found on the effect of exporting on profits and capital stock by firm size.

2. Evidence on the direct impacts of export intensity

Next, we turn to a review of the literature on the direct impacts of different exporting intensities (intensive margin). Papers in this area are concerned about how the benefits of exporting vary with differing export volumes.

2.1. Level of Productivity

2.1.1 National Impacts

In terms of UK studies on the intensive margin of exporting, Greenaway and Yu (2004) examine the relationship between export intensity and firm-level productivity in UK manufacturing firms in the chemical sector. Using a system generalized method of moments (GMM) approach, they find that higher export intensity in the previous year increases firm-level productivity, as measured by total factor productivity (TFP) and labour productivity. They find that a 10% increase in export intensity in the previous period is associated with a 1% increase in the level of TFP and a 5.6% increase in the level of labour productivity. The authors also break down their results by export experience to investigate whether any learning effects are dependent on previous export experience. They find the strongest learning effects for new entrants and negative effects for established exporters, suggesting learning-by-exporting is a short-term effect that diminishes as export experience increases.

Wales et al. (2018) also analyse the link between the intensive margin of exporting and firm-level productivity using alternative measures including export intensity; the number of products traded; and the number of trading partners. They find that a 10-percentage point increase in the ratio of exports to turnover is associated with a 5% increase in the level of labour productivity. Their findings also suggest that those firms that export a greater number of products and export to more countries are associated with higher labour productivity.

Extending the analysis beyond the UK. A smaller number of international studies estimate the effect of exporting at the intensive margin.

Andersson and Lööf (2009) analyse a sample of Swedish manufacturing firms to investigate the importance of export intensity and the temporal dimension of firms' exporting activity for the learning-by-exporting effect. The authors hypothesise that the LBE is positively associated with the intensity of a firm's exporting activities and greater persistence. Using dynamic generalised method of moments estimation, they find firms that exhibit high export intensity (those with exports-to-sales ratio greater than 50%) and high export persistence is associated with an increase in the level of labour productivity of 9.9%. They find insignificant estimates for firms that have a low export intensity and high export persistence and temporary exporters.

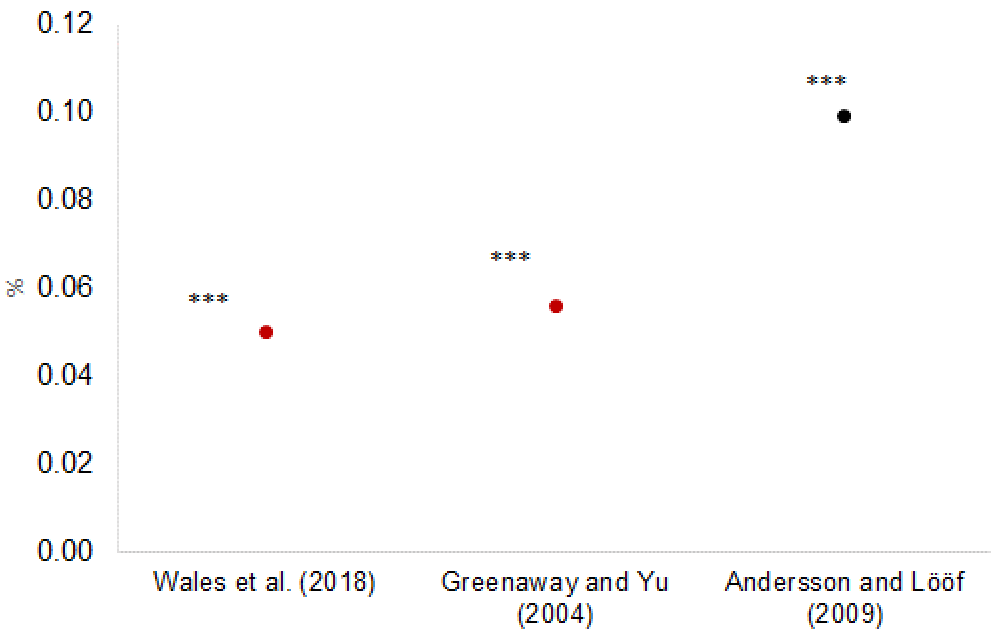
Vacek (2010) examines whether continuous exporters benefit from productivity gains and whether these gains differ by export destination. The author uses primary data from surveying a sample of firms in the Czech Republic. Using a one-step system GMM estimator, they find no significant effect of export share (measured by the ratio of real exports to real output) or export volume on firm-level total factor productivity. When disaggregating their results by export destination, they again find no significant effects.

Table 8: Summary of Productivity Level Estimates in Evidence from Other Developed Countries at the Intensive Export Margin

Reference	Impact measure	Country coverage	Coefficient estimate (export intensity)
Wales et al. (2018)	ALP	UK	0.05***
Greenaway and Yu (2004)	TFP ALP	UK	0.011*** 0.056***
Andersson and Loof (2009)	ALP	Sweden	0.099***
Vacek (2010)	TFP	Czech Republic	0.032 (Export share) 0.0004 (Export volume)

Note: For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

Figure 10 Direct effects ALP (intensive)



Note: Red points are UK sample, black all others
Source: London Economics

2.1.2 Sub-National Impacts

There is currently no applicable evidence found on the effect of export intensity on the level of productivity at the sub-national level.

2.1.3 Impacts by Firm Size

Andersson and Lööf (2009) in their analysis also breakdown their results by firm-size in their sample of Swedish firms. They define small firms as those with between 10 and 25 employees and large firms as those with over 25 employees, thus they use a smaller threshold on the definition of large firms relative to other studies. They find that in small firms that exhibit high export intensity (those with exports-to-sales ratio greater than 50%), high export persistence is associated with an increase in the level of labour productivity of 11.1%. This effect is similar for small firms with low export intensity (those with export-to-sales ratio less than 50%), with an increase of 4.9%. They find in the sub-sample of large firms that exhibit high export intensity and export persistence is associated with an increase in labour productivity of 12.4%, this effect is only significant for those with high export intensity. Therefore, the productivity gains from exporting are found to be greater in large firms.

2.2. Productivity Growth

2.2.1 National Impacts

In terms of exporting at the intensive margin, Girma, Greenaway and Kneller (2004) also investigate the role of export intensity. Export intensity is estimated by the share of exports in total sales. They find that one-year post-entry, firms increasing the export intensity by 10 percentage points experience an additional 2.1 percentage points in total factor productivity growth.

A smaller number of international studies estimate the effect of exporting at the intensive margin.

Masso and Vahter (2011) extend the analysis of entering a new product market and engaging in foreign competition by investigating the productivity premia associated with exporters who enter several foreign markets or with several products against those exporters that enter only single markets. The authors conduct propensity score matching on a detailed dataset of Estonian firms to estimate the average treatment effect of multi-market and multi-product exporters. They find that those that enter several markets see stronger and longer-term total factor productivity growth relative to those entering single foreign or product markets. Firms that entered at least two markets experience TFP growth that is around 12-14 percentage points higher than non-entrants, and 5-7 percentage points higher than those entrants to only one foreign market.

Silva et al. (2010) in their analysis of Portuguese firms also examine the effect of export intensity of total factor productivity growth. They assume that firms with a higher export intensity have a higher degree of commitment to foreign operations and a higher frequency of export sales and this would result in a higher capacity to learn from exporting. They estimate export intensity as the percentage of exports in turnover in new exporters. They split the sample into three groups: export starters with an export intensity less than 5%, export starters with an export intensity between 5 and 35% and starters with an export intensity over 35%, in a period of 3 years. Their findings confirm their hypothesis. Firms with high export intensity (over 35%) experience more immediate and larger total factor productivity gains of 6.4 percentage points one period post-entry. The effect for firms with low export intensity takes a longer time to materialise (becomes significant after 5 years).

Manjón et al (2013) examine whether the productivity gains associated with exporting are dependent on the intensity of the firm’s exporting intensity. Using a sample of Spanish firms, they firstly use matching techniques to estimate the extra yearly cumulative productivity growth (EPG) for export starters relative to non-exporters. Secondly, they use regression analysis to analyse whether the productivity gains depend on the export intensity of the firm. They find generally insignificant estimates of export intensity of the EPG of export starters, which the authors suggest is indicative that the main factor explaining the productivity growth in exporters is the change in export status, not the share of exports in total sales (export intensity). However, they find that the annual growth rate of export intensity over a 5-year period is significantly associated with higher EPG. The authors suggest that productivity gains initially work through the extensive margin, and for those firms that are persistently exporting experience productivity gains through the intensive margin.

Kim (2013) in their study of Korean manufacturing firms also investigates whether the productivity gain from entering the export market is increasing in export intensity. Export intensity is divided into three sub-groups: low export intensity (less than 25% of production is exported), medium export intensity (between 25 and 75% of production is exported), and high export intensity (over 75% of production is exported). They find that higher exporter intensity does have a larger impact on the conditional productivity differential across intensity categories and the effect is large at the upper conditional productivity distribution. Firms with high export intensity have 25% higher total factor productivity growth than non-exporters at the 90th quantile whereas they have only 5% higher productivity growth than non-exporters at the 25th quantile. The effect in the lower intensity category is found to be insignificant across all quantiles.

Fryges and Wagner (2008) examine the causal effect of firms' export intensity on labour productivity growth by means of generalized propensity matching, and dose-response functions in a sample of German manufacturing firms. They find that at an export-sales ratio of 19%, the effect on labour productivity growth is largest, compared to an export intensity of zero (3 percentage points higher labour productivity growth rate). For export-sales ratios between 0 and 52%, the effect on labour productivity growth is smaller but still statistically significant at 5%. Above an export-sales ratio of 52%, there are no benefits on labour productivity growth compared to non-exporting firms.

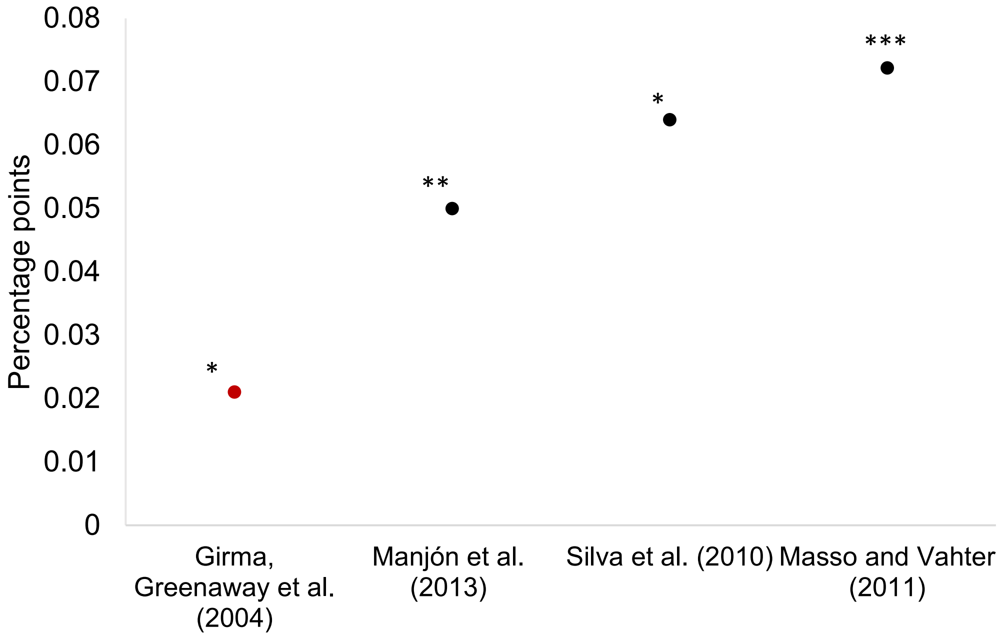
Table 9: Summary of Productivity Growth Estimates in Evidence from Other Developed Countries at the Intensive Export Margin

Reference	Impact measure	Country coverage	Coefficient estimate (Export intensity)
Girma, Greenaway and Kneller (2004)	TFP	UK	0.021*
Masso and Vahter (2011)	TFP	Estonia	7.22*** (Single market entry) 14.3*** (Multi-market entry) 3.8 (Single-product entry) 12.2*** (Multi-product entry)
Silva et al. (2010)	TFP	Portugal	0.064* (High export intensity) 0.107 (Medium export intensity) 0.040 (Low export intensity)
Manjón et al. (2013)	TFP	Spain	0.001 (Export intensity) 0.050** (Export intensity growth)
Kim (2013)	TFP	Korea	0.2573*** (High export intensity, 90^{th} quantile) 0.0767*** (Medium export intensity, 90^{th} quantile) -0.0201 (Low export intensity, 90^{th} quantile)
Fryges and Wagner (2008)	ALP	Germany	0.03***

Note: For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

The plot below summarises the evidence of the impact of export intensity on TFP growth.

Figure 11 Direct effects TFP growth (intensive)



Note: Red points are UK sample, black all others
Source: London Economics

2.2.2 Sub-National Impacts

There is currently no applicable evidence found on the effect of export intensity on the productivity growth at the sub-national level.

2.2.3 Impacts by Firm Size

There is currently no applicable evidence found on the effect of export intensity on the productivity growth by firm size.

2.3. Sales

2.3.1 National Impacts

Fryges (2009) examines the output effects of the intensive export margin. Using a sample of UK and German technology-orientated firms and a generalised propensity scoring (GPS) and a dose-response function approach, they find a U-shaped relationship between export intensity and the subsequent sales growth rate. Sales are measured by the change in a firm's total number of sales over a given period. The maximum value of expected sales growth (17.7%) is reached at an export-sales ratio of 60%.

2.3.2 Sub-National Impacts

There is currently no applicable evidence found on the effect of export intensity on output at the sub-national level.

2.3.3 Impacts by Firm Size

There is currently no applicable evidence found on the effect of export intensity on output by firm size.

2.4 Employment and Employee Compensation

2.4.1 National Impacts

Munch and Skaksen (2008) examine the link between worker education level, export performance and wages. By means of a job spell fixed effects specification based on a matched worker-firm longitudinal dataset they find that the direct impacts of exporting intensity on wages are weakly negative when including fixed effects and an interaction term between export intensity and skill intensity. Higher exporting intensity lowers wages by 7.5%. Exporting intensity and skill intensity together however raise wages by 31%. Exporting market entry does not appear to affect wages. The authors also break down their results by worker education level (high, middle and low skill), and find, that export intensity lowers wages by 8.8% for low-skilled workers, while export and skill intensity together raise wages of low- and middle-skilled workers by 39.3% and 39.9% respectively. This could suggest that exporting may have negative effects for lower skilled workers, whereas middle and high-skilled workers may benefit from exporting through higher wages.

DIT (2021) estimate both the direct and impacts of exporting on employment and employee compensation based on Input-Output (IO) modelling. They estimate the aggregate and various distributional impacts of UK exports on the labour market across the period 2014 to 2016. They find that UK exports (measured by the total value of UK exports in pounds sterling) directly supported around 3.8 million full-time equivalent (FTE) jobs (13% of total UK FTE jobs) in 2016. DIT also disaggregate their results by sector and find that manufacturing supports the largest number of jobs, while the sectors most dependent on exporting (measured by absolute number of jobs) are professional, scientific, and technical services and admin and support services. They also estimate that median wages on average are higher for those in jobs directly or indirectly embodied in exporting.

OECD (2020) use the 2018 edition of OECD's Inter-Country Input-Output (ICIO) database combined with estimates of employment and employee compensation from official sources to estimate Trade in Employment (TiM) indicators. One indicator is the domestic employment embodied in gross exports, which includes both employment in the exporting industry (direct effects), and employment in upstream domestic industries embodied in intermediate inputs used by the exporting industry (indirect effects). They estimate the effects at the industry level and find significant heterogeneity in the estimates across the industries in the UK. In 2019, on average across industries, the percentage of exporting industry employment used in the production of exports was around 12.5%. The direct effect was largest for the 'basic metals' industry, followed by 'other transport', and smallest for 'construction' and 'real estate'.

OECD (2016) links employment data to Trade in Value Added (TiVA) indicators to estimate the impact of global value chains (GVCs) on employment across OECD countries. They find that trade supports around 10 to 15% of employment in large, advanced economies such as the United States, Brazil and China. The effect for smaller countries such as Luxembourg and Ireland, however, is substantially larger at around 45 to 65%.

2.4.2 Sub-National Impacts

DIT (2021) also estimate the distributional effects of the UK export market on the labour market by region and find that over 25% of the FTE jobs supported by UK exports are concentrated in London.

2.4.3 Impacts by Firm Size

There is currently no applicable evidence found on the effect of export intensity on employment and employee compensation by firm size.

3. Evidence on the indirect impacts of exporting

Several studies examine the indirect impacts of exporting through estimating the effect of export spillovers on wider economic outcomes.

Export spillovers are generally categorised into three groups:

- horizontal spillovers are the spillovers from exporters to domestic firms that operate within the same industry;
- vertical spillovers are the spillovers from exporters to domestic firms that are linked to the exporting firm through their supply chain; finally,
- regional spillovers are the spillovers from exporters to domestic firms that operate in the same region.

3.1 Productivity

There is limited evidence documenting export spillovers to domestic firms. Overall, the evidence found suggests a weak relationship between exporting firms and the productivity of domestic firms in the same region, industry or supply chain. The evidence is stronger for export spillovers on the probability of firms becoming exporters.

3.1.1 National Impacts

Greenaway and Kneller (2008) investigate how regional and horizontal spillovers of exporters affects post-entry productivity of new exporters. Using propensity score matching and difference-in-differences analysis, they find that the presence of existing exporters in the same region (regional spillovers) and industry (horizontal spillovers) has economically significant spillover effects on the decision to enter the export market, but no significant effects are found for post-entry productivity effects. The authors examine spillover effects by estimating the effect of the number of exporters in the same region or industry (or both) on the probability of export market entry of firms and post-entry productivity. They find that an additional exporting firm in the same industry raises the probability of exporting for non-exporters by 0.03 percentage points and 0.02 percentage points if the exporter is in the same region. However, they find no evidence of horizontal or regional spillover effects for post-entry total factor productivity growth in new entrants.

Albornoz and Kugler (2008) investigate whether exporting firms give rise to total factor productivity gains in non-exporting firms through both horizontal and vertical spillovers. They use the presence of exporters within a firm’s sector (horizontal spillovers) and the presence of exporters in a sector that is being supplied to by firms (vertical spillovers) to proxy the extent of knowledge spillovers from exporters. The presence of exporters depends on the number of exporting firms in the sector as well as their overall output. Using a two-step system generalised methods of moments (GMM) analysis, they find that no evidence of horizontal spillovers, from exporters in the same sector as the firm, however they do find evidence of vertical spillover effects. They find total factor productivity growth for firms that supply to exporters increases by 0.5 percentage points. The authors investigate whether these effects differ by firm ownership. They find that positive and significant evidence of vertical spillovers for firms supplying to both domestic and foreign-owned exporters, however the effect is stronger for multinational corporate affiliates.

Masso and Vahter (2016) examine the knowledge spillovers from multinational firms through labour mobility in a sample of Estonian firms. They propose a key mechanism of productivity gains from knowledge transfer functions through the mobility of labour across firms, whereby employees with experience working in or managing multinational enterprises (MNEs) transfer knowledge from their previous (multinational) employer to their new (domestic) employer. They also hypothesise that this knowledge transfer is driven by those employees with export experience in particular. Using fixed effects and an instrumental variable approach, they find firstly that a 10 percentage point increase in the share of managers and high-wage employees from an MNE-experienced workers in a domestic firm is associated with a 24% increase in the level of total factor productivity in a domestically owned firm.

They also find support for their hypothesis in that this effect is mostly driven by employees with export experience as once they include a control for export experience – the effect of MNE experience becomes insignificant, while the effect of those employees with export experience is statistically significant at the 1% level. A 10 percentage point increase in the share of managers and high-wage employees with external export experience is associated with a 2.2% increase in the TFP level of domestic firms.

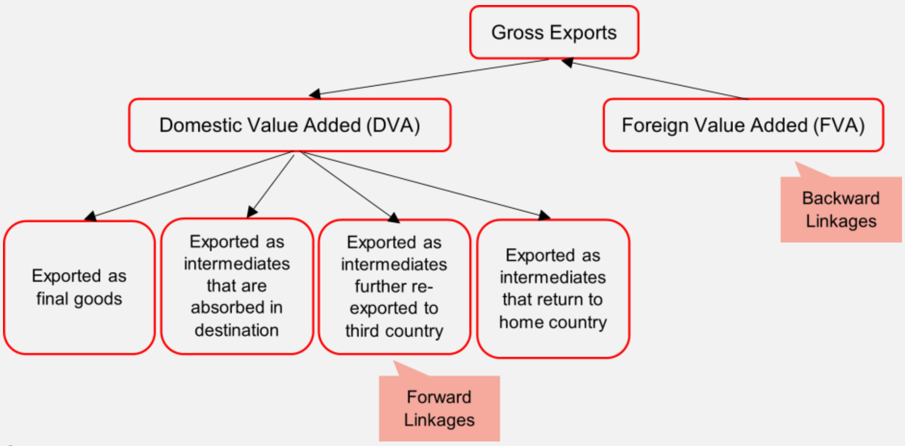
Box 2 – The impact of Global Value Chain (GVC) participation on economic outcomes

Several studies estimate the impact of GVC participation on economic outcomes including Baldwin and Yan, (2014); Gal and Witherdige (2019); Banh et al. (2020); and Ignatenko et al. (2019).

GVC participation is measured by backward and forward participation in GVCs, and is proxied by the trade of intermediate inputs. Intermediate inputs refer to inputs in the GVC that will later be embodied in export goods (Benkovskis et al., 2018). Backward participation refers to the share of foreign value-added in total exports, from the importing of intermediate inputs from foreign sources that are then used to produce exports. Forward participation refers to the domestic value-added embodies in intermediate exports that ae then re-exported to third countries, expressed as a ratio of total exports (Ignatenko et al., 2019).

The GVC literature thus slightly deviates from the other research consulted for this report in that the authors do not consider the impact of gross exports (see Figure below).

Figure 12: Gross exports, forward and backward linkages



Source: (Ignatenko et al., 2019)

Baldwin and Yan (2014) examine whether the integration of Canadian manufacturing firms into a global value chain improves their productivity, by means of propensity score matching and difference-in-difference. They find that the direct impacts of becoming part of a GVC can enhance the level of firms' productivity growth by 5 percentage points in the first year relative to non-GVC firms, and this effect increases to 9 percentage point gap between GVC and non-GVC firms over 4 years. Magnitude and timing vary by industrial sector, internationalisation process, and import-source/export-destination country. Changes in productivity growth were higher for GVC firms that imported intermediates from, and exported products to, high-wage countries.

Gal and Witheridge (2019) assess the link between productivity, innovation and GVC integration at the industry level in OECD countries. They analyse and quantify the role of lower trade intensity in the productivity slowdown, and also explore the channels through which the two phenomena are related, in particular the role of innovation and the nature of GVC integration. They measure GVC integration by backward and forward participation in GVCs. Backward participation is defined the foreign imported value-added content of output, measured by importing of intermediate outputs, and forward participation is defined as the domestic value-added content of exports, both as a share of value added. Using a long difference specification, they find that medium-term multifactor productivity (MFP, equivalent to TFP) growth (log differenced over five years) is positively related to the degree of lagged GVC participation intensity (bound between 0 and 1).

Ignatenko, Raei and Mircheva (2019) also investigate the benefits to participation in global value chains (GVCs) using a data from 189 countries. Using an extensive dataset, the Eora Multi-Regional Input-Output (MRIO) database, the authors compute several measures of GVC participation and regress these on income per capita and productivity at the country-level. Productivity is calculated as the residual of a Cobb-Douglas production function estimate for each country. Using regression analysis, including lags of the dependent variable to control for endogeneity, they find a positive and significant relationship between a country's share of GVC-related trade in GDP and productivity levels, however the effect of the share of conventional trade in GDP on productivity is found to be insignificant. GVC-related trade is defined as exports that either embed foreign value-added or are exports of domestic value-added that are re-exported in other countries' exports. Conventional trade is defined as exports that get directly absorbed in other countries.

Banh, Wingender, and Gueye (2020) estimate the effects of GVC participation on TFP at both the industry level and the firm level by means of OLS and IV regressions. Using Estonian firm level data from ORBIS database, they construct a sample of 27,451 firms for 2002-2016. The data used to construct GVC participation is the Eora Multi-Region Input-Output (MRIO) database. At the industry level, they regress the sectoral median of the log of productivity on lagged GVC participation, controlling for firm, industry, and year fixed effects, and sectoral gross output. At the firm level, they regress the log of TFP of firm i in sector s at time t on lagged industry-level GVC participation, controlling for capital intensity, sector gross output, the Herfindahl-Hirschmann index at industry level, sector fixed effects region fixed effects, and year fixed effects. The authors construct a measure of GVC participation and a measure of upstreamness following Koopman et al. (2010)[8] and estimate firm level productivity using the method proposed by Ackerberg et al. (2015)[9]. Estimating firm-level productivity controls for potential endogeneity problems and relaxes assumption of constant returns to scale. To deal with endogeneity concerns, they instrument GVC participation in Estonia with average GVC participation by industry measured at world level. They find that participation in the GVC has a positive impact on productivity within the same industry. Specifically, an increase of 1 percentage point in the intensity of GVC participation of an industry raises median productivity (level) of that industry by around 0.48%. Again, effects are to be interpreted as the combined direct and indirect effect.

Yashiro et al. (2017) review the literature and the current data from various OECD databases to investigate the effect of GVC participation for Latvia. They find that GVC participation has progressed for Latvia but it still lags behind its Baltic and Central European peers in terms of the domestic value added embodied in foreign final demand, which measures the extent to which Latvia participates in GVCs as a supplier. They also find that the level of employment sustained by foreign final demand falls below the level in other Central European countries. They suggest that participation in GVCs through exports boosts productivity and allows Latvian firms to increase better quality jobs. Yet, only the most productive firms are able to participate in the GVCs and this is not something that is controlled for in this report.

The Global Value Chains Development Report, jointly published by the World Trade Organisation (WTO), the Institute of Developing Economies, the OECD, Research Center of Global Value Chains and the World Bank Group, outlines the development of GVCs and their implication for economic development. They find on average across OECD countries, around 20 to 30% of domestic employment is supported, directly or indirectly, by exports. On reviewing existing studies, they also find that overall trade appears to have small positive labour outcomes at the aggregate level, but these effects can also differ markedly by region. Areas that benefit from export expansion generally experience wage and employment growth whereas those with less access to foreign markets fall behind, which can create significant regional inequalities.

[8] For measure of GVC participation and measure of upstreamness used by Banh, Wingender and Gueye (2020), see: Koopman, Robert, William Powers, Zhi Wang, and Shang-Jin Wei. 2010. "Give Credit Where Credit is Due: Tracing Value Added in Global Production Chains." NBER Working Paper 16426.

[9] For method to estimate TFP at firm-level, see: Ackerberg, A. Daniel, Caves, Kevin and Frazer, Garth. 2015. "Identification Properties of Recent Production Function Estimators." Econometrica 83(6): 2411-2451

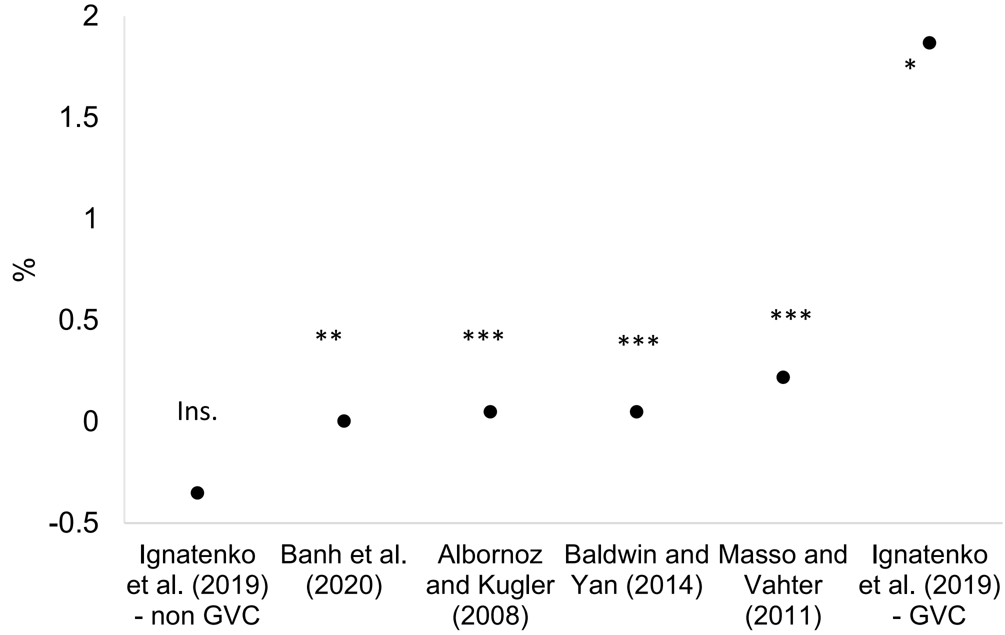
Table 10: Summary of Indirect Productivity Estimates in Evidence from Developed Countries

Reference	Impact measure	Form of Internationalisation	Country coverage	Coefficient estimate
Greenaway and Kneller (2008)	Export Entry TFP growth	Gross exports	UK	0.000 (Regional) -0.000 (Horizontal) 1.554 (Combined)
Albornoz and Kugler (2008)	TFP growth	Gross exports	Argentina	0.005*** (Vertical) 0.001 (Horizontal)
Masso and Vahter (2016)	TFP	Gross exports	Estonia	0.22***
Baldwin and Yan (2014)	TFP	GVC participation	Canada	0.05***
Gal and Witheridge (2019)	Multifactor Productivity growth (MFP)	GVC participation	OECD Countries	0.0995***
Bahn et al. (2020)	TFP	GVC participation	Estonia	0.0048**
Ignatenko, Raei and Mircheva (2019)	TFP	GVC participation	Global	-0.351 (Non-GVC trade) 1.869* (GVC trade)

Note: TFP = Total factor productivity. For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

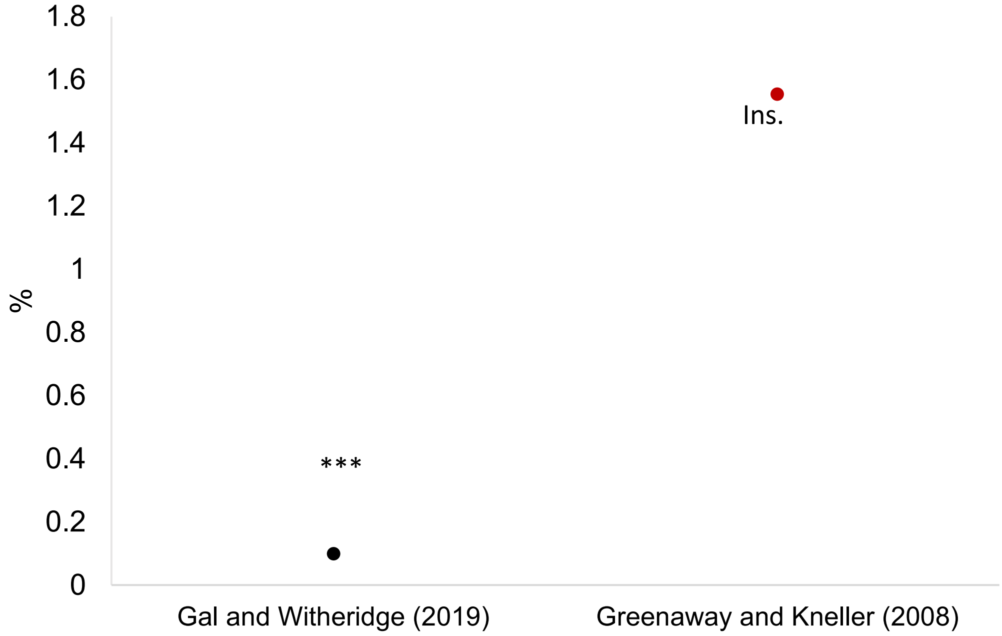
Spillover impact coefficients for productivity impacts (both int terms of levels and growth rates) are presented in the figures below.

Figure 13 Indirect effects TFP coefficients



Source: London Economics
Note: Red points are UK sample, black all others

Figure 14 Indirect effects TFP growth coefficients



Source: London Economics
Note: Red points are UK sample, black all others

3.1.2 Sub-National Impacts

There is currently no applicable evidence found on the indirect effect of exporting on productivity at the sub-national level.

3.1.2 Impacts by firm type (size)

There is currently no applicable evidence found on the indirect effect of exporting on productivity by firm size.

3.2 Innovation and Research and Development (R&D)

3.2.1 National Impacts

The literature on the indirect effects of exporting on R&D is relatively limited.

Piermartini and Rubinova (2014) examine how international production networks affect diffusion of knowledge for a sample of manufacturing sectors in 29 countries in Asia, Central-Eastern Europe and North America. By means of a negative binomial estimator, panel regression and an IV approach, they find that production networks are an important driver of technology transfers and R&D spending increases with intensity of production network links between sender and recipient country. Knowledge spillovers only occur if a country is fully integrated in a GVC network. Mere imports or exports-platform spillovers within production networks do not appear to facilitate knowledge spillovers. This means that a narrower definition of supply chains is more likely to capture a close relationship between consumer and supplier of the intermediate input.

3.2.2 Sub-National Impacts

There is currently no applicable evidence found on the indirect effect of exporting on innovation and R&D at the sub-national level.

3.2.3 Impacts by firm type (size)

There is currently no applicable evidence found on the indirect effect of exporting on innovation and R&D by firm size.

3.3 Employment and Employee Compensation

3.3.1 National Impacts

Cuyvers, Dhyne and Soeng (2010) investigate the relationship between exports and demand for skilled and unskilled labour at the firm level for Belgium, and whether the effects significantly differ depending on the development level of the export destination. Using a dynamic version of a translog cost share equation, they find that a 1 percentage point increase in the share of exports raises demand for production workers by 0.15%, while reducing demand for non-production workers by 0.23%.

Acharya (2017) also examines how trade and technological change affect the employment level and skill structure across Canadian industries, however, does not find statistically significant results. By means of sector-level OLS regression with robust standard errors, they find that exporting has no impact on employment growth. Similarly, they go on to disaggregate their results by export destination and find that Canadian exports to the Chinese market are skill neutral, whereas exports to USA and Mexico have effects of opposing nature: exports to the US increase share of low skill workers and reduce high-skill workers, whereas the opposite is true for exports to Mexico.

DIT (2021), in their study of the aggregate impacts of UK exports on the labour market, find that UK exporters indirectly supported around 2.7 million full-time equivalent (FTE) jobs through UK supply-chain impacts in 2016.

OECD (2020) also estimate the indirect effect of the UK export market on employment. The indirect effect measures employment in other, upstream domestic industries on a country that is embodied in the exports of a certain industry. In 2019, on average across industries, the percentage of employment embodied in the indirect production of exports was around 10%. The indirect effect was largest for ‘coke and petroleum’ and ‘basic metals’ and lowest for ‘other services’ and ‘construction’.

3.3.2 Sub-National Impacts

When estimating the distributional effect of the employment indirectly supported by UK exporters, DIT (2021) find that over 25% of the FTE jobs either directly or indirectly supported by the UK export market are concentrated in London[10].

3.3.3 Impacts by firm type (size)

There is currently no applicable evidence found on the indirect effect of exporting on employment and employee compensation by firm size.

3.4 Likelihood of exporting

3.4.1 National Impacts

[10] DIT (2021) do not provide separate regional breakdowns for direct and spillover impacts of exporting.

Several studies examine the effect of export spillovers on the probability of new entrants into the export market and their subsequent export growth post-entry.

Kneller and Pisu (2007) examine export spillovers from exporting foreign multinationals to domestic firms in the UK and estimate how spillovers affect export entry and subsequent export intensity. They consider horizonal spillovers from foreign firms in the same region and horizontal spillovers from foreign firms located in different regions, and proxy spillover variables as the ratio of exports to total output for foreign firms located in the same industry and same/different region, respectively. The authors estimate an endogenous sample selection model using a two-step approach proposed by Heckman (1979) using a sample of UK manufacturing firms sourced from the OneSource dataset. The combined effect of horizontal and regional spillovers from exporting multinationals in the same industry and region are found to significantly increase a domestic firm's export entry and increase subsequent export intensity. An increase of 1 percentage point in the share of exports in total foreign firm sales in the same region and industry is associated with a rise in the probability of export entry by 0.037 percentage points. This is equivalent to a rise in the probability of exporting by 5.0 percent. Horizontal spillover effects in different regions were found to be significant on subsequent export share post-entry, but not on the probability on entry into the export market. Vertical spillover effects were only calculated in terms of foreign presence, not in terms of exporting activity, and are therefore not reported here.

3.4.2 Sub-National Impacts

There is also evidence of local export spillover effects. Koenig, Mayneris and Poncet (2009) examine the presence of local export spillovers on the decision of firms to start exporting and their subsequent export volume. Using a logit regression analysis on a sample of French manufacturing firms, the authors find significant evidence of local export spillovers. An additional exporting firm in the same area increases the probability to start exporting by 1.07 percentage points (a change to a probability of 31.07% from an average probability to start exporting of 30%). When investigating if export spillovers are product or destination specific, they find that the number of other exporting firms in the area that export the same product, to the same destination, or both, is positively associated with the probability of export entry. What's more, when these variables are included in the model, the effect of general spillovers (the number of other exporting firms in the area) becomes insignificant. However, no spillover effects are found on export intensity post-entry.

Lucio et al. (2019) also examines whether the choice of destinations among new and experienced exporters is impacted by information spillovers at the local level, measured by the number and performance of existing exporters in those destinations. Using data on a sample of Spanish manufacturing firms, they find that the effect of information spillovers is stronger on new exporters than experienced exporters. They also find that a one standard deviation increase in the number of existing exporters in the same region raises the probability that a firm begins to export a new export by 8 percentage points. Higher growth of existing exporters in the same region is also positively and significantly related to a firm entering a new export market. This effect is more pronounced for new exporters.

3.4.3 Impacts by firm type (size)

There is currently no applicable evidence found on the indirect effect of exporting on export growth by firm size.

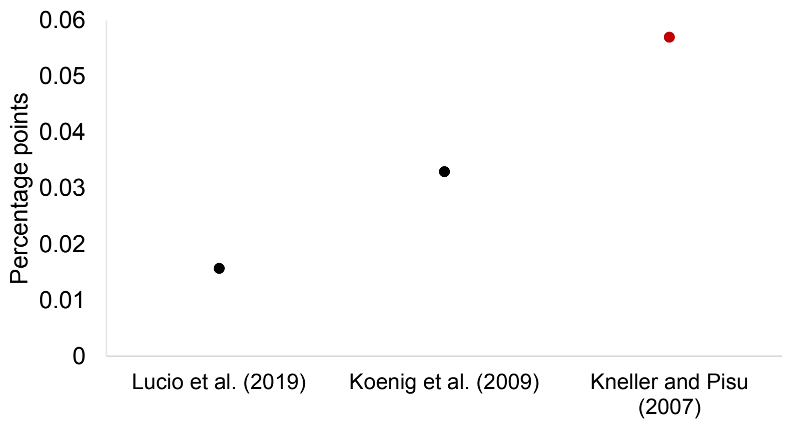
Table 11: Summary of Indirect Output Estimates in Evidence from Developed Countries

Reference	Impact measure	Country coverage	Coefficient estimate	
			Export entry	**Export intensity**

Kneller and Pisu (2007)	Export Spillovers (export growth)	UK (national)	0.453** (Horizontal-regional) 0.705 (Horizontal)	-0.036 (Hor-Ind) 0.156* (Hor)
Koenig, Mayneris and Poncet (2009)	Probability to start exporting	France (sub-national)		0.033***
Lucio et al. (2019)	Probability to start exporting	Spain (subnational)		0.0125***

Note: TFP = Total factor productivity; ALP = Apparent labour productivity. For interpretation of results please refer to the text as each article uses different model specification and outcome variables.
Source: London Economics' analysis

Figure 15 Indirect effects Export spillovers coefficients



Source: London Economics
Note: Red points are UK sample, black all others

4. Evidence gaps

It is considered a stylized fact that larger, more productive firms self-select into the export market, which many suggest is due to the sunk costs associated with exporting (Greenaway and Kneller, 2004; Greenaway and Yu, 2004; Wagner, 2002). This relationship is well established in the literature.

However, less is known about the effect of large exporters on firm-level outcomes, or more generally how outcomes differ by firm size. Developing a better understanding of the impact of large exporters is important as, often, the largest exporters account for a substantial share of an economy's export volume (Freund and Pierola, 2016). For example, in the UK, only one in five firms reported trading activity, but these trading firms accounted for 40% of all employment (Wales et al., 2018). Understanding the effects of large exporters is also important as they generate large economic impacts directly and through supply chains by virtue of their size. Therefore, as the research addressing the impacts of large exporters specifically is very limited, this indicates a critical research gap.

In addition, there is a similar need to fill the research gap with respect to estimating the regional effects of exporting. Most studies estimate the impact of exporting at the national level, however, there are likely to be important regional disparities that need to be considered. Measuring the effect of exporting at the regional level presents more methodological challenges in comparison to estimating national effects. To measure regional impacts, it is necessary to know the location of economic activity (a manufacturing plant) rather than where that activity is accounted for (a registered office).

Estimating the regional effects is important for understanding the distribution effects of exporting. For instance, at a regional level, there are significant concerns about the distribution of productivity. In the

UK there are many candidate explanations of regional productivity disparities, which relate to the mix of firms present in different regions, of which export intensity is an important one. If exporting operations were to be located in regions with lagging productivity, this could contribute to closing regional disparities (and 'levelling up'), bearing in mind where they would generate the largest economic impacts. Therefore, understanding the disparity in the size of exporting effects across different regions could have important policy implications and demonstrates an important research gap to be addressed.

Thus, the following section will focus on the methodologies and data sources that can be used to answer the research questions of how exporting more will translate into higher direct and indirect effects for large exporters, both at the intensive and extensive margin, Additionally, the methodologies will be assessed according to their potential to estimate regional direct and indirect impacts.

Part Two - How are the economic impacts of exporting on large exporters estimated (direct effect); and beyond how are the wider economic impacts (indirect effects) estimated at a local and national level?

This part of the report provides an overview of the methods and datasets that can be used to estimate the impacts large exporters at a national and regional level.

Econometric methods were shortlisted based on the approaches used in the wider literature on the impacts of exporting (see Part One). Certain methods are more appropriate for direct impacts, others for indirect impacts. In previous literature, propensity score matching and difference-in-difference, instrumental variable approaches, quantile regression, or system generalised method of moments have been used to estimate the direct impacts of exporting. For indirect impacts, previous literature used input-output analysis, panel data approaches, or network analysis. Not all methods are useful to estimate the impacts both at the extensive and the intensive margin. The methods also vary in how well they can estimate large exporters specifically or regional impacts.

We also provide an overview of available UK datasets for implementation of shortlisted approaches. Datasets were identified based on existing literature, and published dataset catalogues and meta data by the UK Office for National Statistics and private data providers.

Both shortlisted methods and datasets were tested and discussed with a number of academic and government experts, in order to draw out the advantages and limitations associated with the various approaches and data sources under consideration. We are very grateful for the guidance and advice provided by the following experts (named in alphabetical order): Russell Black, Office for National Statistics; Natalie Chen University of Warwick; Fabrice Defever, City University of London; Hannah Denley, Office for National Statistics; Jun Du, Aston Business School; Robert Elliott University, of Birmingham; Michael Gasiorek, University of Sussex; Ben Graham, Office for National Statistics; Giammario Impullitti, University of Nottingham; Črt Kostevc, University of Ljubljana; Jim Love, University of Leeds; Balazs Murakozy, University of Liverpool; Alejandro Riano, City, University of London; Felix Ritchie, University of the West of England, Bristol; Joachim Wagner, University of Lüneburg; Philip Wales, Office for National Statistics; Zhihong Yu, University of Nottingham; Ben Zissimos, University of Exeter; and George Zorinyants, Office for National Statistics.

The insights from our discussions with those experts directly informed the discussion of the various methods and datasets presented in this Section, as well as the final selection of the preferred method and dataset presented in Part Three of this report.

1. Methods used to estimate the impacts of exporting

1.1 Methods used to estimate the direct impacts

1.1.1 Propensity score matching (PSM) and difference-in-difference estimation

The vast majority of studies investigating the direct impacts of exporting rely on a combination of propensity score matching (PSM) and difference-in-differences analysis (DiD). This combination of propensity score matching, and difference-in-difference method is also called the conditional difference-in-difference method or matching difference-in-difference.

Studies using a PSM-DiD approach include Amendolagine, Capolupo and Petragallo (2011); Baldwin and Yan (2014)[11]; Dai and Yu (2013); Damijan and Kostevc (2005); Damijan and Kostevc (2010); De Loecker (2007); Fryges (2009); Fryges and Wagner (2008); Garcia and Voigtländer (2013); Girma, Greenaway and Kneller (2004); Greenaway and Kneller (2004); Greenaway and Kneller (2007); Hahn (2013); Harris and Li (2007); Harris and Moffat (2016); Ito (2012); Ito and Lechavalier (2010); Kang

[11] Note: the authors look at the direct effects of GVC participation, not exporting.

(2020); Ma, Tang and Zhang (2011); Manjón et al. (2013); Masso and Vahter (2011); Olabisi (2016); Pisu (2008); Serti and Tomasi (2008); Wang et al. (2020) and; Xue and Zhou (2020).These studies focus on the direct impacts of entering the export market, that is, the extensive export margin. Serti and Tomasi (2008) use this approach to estimate the effect of exporting by firm size and by region.

To isolate the definite causal effect of exporting on productivity, researchers aim to compare the productivity outcome of a certain firm post-entry into the export market with the productivity outcome of the same firm had they not entered the export market. The latter, however, is of course unobservable, therefore causal inference relies on the construction of a valid control group which captures the productivity outcomes of firms that remain non-exporters (Girma, Greenaway and Kneller (2004: 859).

To construct a valid control group, researchers use matching techniques based on a set of observable firm characteristics to match exporters and non-exporters that are similar in every way other than their export status (Wagner, 2002: 291). The matching approach has an intuitive appeal but rests on the strong assumption of conditional independence (Conditional Independence Assumption, CIA): the assumption that one can control for observable differences in characteristics between the treated (exporters) and non-treated (non-exporters) group, the outcome that would result in the absence of treatment is the same in both cases. It is this assumption that allows the counterfactual outcome for the treatment group to be inferred, and therefore for any differences between the treated and non-treated to be attributed to the effect of the treatment (here, the decision to export).

The CIA requires that the covariates chosen by the researcher jointly determine (fully) the selection process and outcomes. Hence, the CIA implies that all of the variables affecting both the decision to enter export markets and potential outcomes are observed (Greenaway and Kneller, 2007: 923), meaning that a very rich dataset is required.

To identify appropriate matching variables, researchers use observable firm characteristics that are strongly supported in economic theory and previous literature. In the context of the direct effects of exporting on especially productivity outcomes, commonly used matching variables include firm size, relative skill intensity, research and development expenditure as well as fixed industry and time effects (Greenaway and Kneller, 2007: 923).

Most studies then estimate the probability of entry into the export market (based on these observable firm characteristics) using a probit or logit model, and apply the propensity score matching method of Rosenbaum and Rubin (1983). The propensity score method combines information from a set of variables driving the probability to export into a scalar that is the predicted probability a firm will become an exporter. Each firm is assigned a propensity score that they will become an export firm. Exporters and non-exporters are then matched, most commonly using 'nearest neighbour matching'[12], whereby firms are matched the closest propensity score (Girma, Greenaway and Kneller, 2004: 860).

The PSM approach in itself helps control for selection bias by matching firms with markedly similar characteristics. However, it still leaves the potential for unobservable characteristics that affects both the decision to enter the export market and firm-level outcomes. Therefore, authors combine propensity score matching with difference-in-differences analysis to additionally control for *time-invariant* firm specific characteristics that can determine firm outcomes (Greenaway and Kneller, 2004: 12)[13].

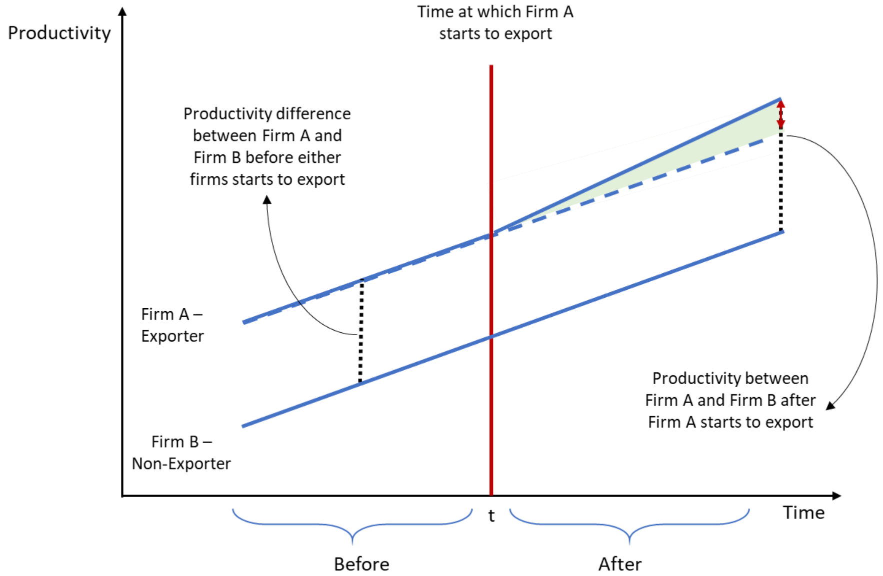
[12] Alternative matching strategies include: caliper and radius matching, which uses nearest neighbour matching but introduces a limit on how different matched observations may be in terms of the value of the propensity score; stratification matching, which relies on the matching of groups of beneficiaries with groups of non-beneficiaries rather than the matching of individual observations; and Kernel matching, which takes all observations in the control group into account by comparing beneficiaries to a weighted average of non-beneficiaries. These matching approaches are less commonly used in the reviewed literature on the impacts of exporting.

[13] Inversely, the difference-in-difference approach in itself allows to control for unobserved differences between control and treatment groups. However, the method has been criticised because it does not control adequately for differences in observable characteristics (see Blundell and Costa Dias, 2008).

The difference-in-differences approach is a two-step procedure. First, authors estimate the difference between average productivity before and after entry in the export market for exporting firms. This difference obtained at the first stage is further differenced with respect to the before and after difference for the control group of non-exporters. When estimating this model, the variable of interest therefore estimates the change in cross-time productivity specific to those firms who entered the export market.

The figure below illustrates the difference-in-difference approach.

Figure 16: illustration of difference-in-difference approach



Source: London Economics

A combination of matching and difference-in-differences approach improves the quality of nonexperimental evaluation studies (Blundell and Costa Dias 2000; Girma, Greenaway and Kneller, 2004). The main advantage of propensity score matching over a random selection of a control group is that matching controls for self-selection bias and thus allows for the construction of a valid counterfactual for causal inference. The advantage of combining matching with difference-in-differences analysis is that is controls for unobservable heterogeneity by removing the effect of covariates that can determine firm outcomes and thus lead to bias in the results (Girma, Greenaway and Kneller, 2004: 861; Damijan and Kostevc, 2005: 15). Therefore, more robust estimates can be obtained using difference-in-differences post PSM analysis.

Moreover, the PSM-DiD approach is intuitively simple, transparent and easy to explain. It is a very clean approach which is frequently used for policy evaluation purposes, recommended in HM Treasury's Magenta Book, and rarely criticized.

There are however a small number of disadvantages with conducting conditional DiD analysis, the first being the conditional independence assumption (CIA). The matching procedure relies on this assumption holding, which is strong and cannot be directly tested (Greenaway and Kneller, 2004: 930). There will always be unobservable characteristics of firms, such as firm management, that might have an impact on both the probability to enter an export market and the outcome measure.

Further, the data requirements necessary for a successful matching procedure can present limitations to the methodology. Not only does the dataset at hand need to contain all of the variables that determine entry into the export market, but it is important that the matching is repeated for sub-samples in terms of time periods and/or industries, to test whether the drivers for the decision to export could change each year and be affected by industry-specific factors. It may pose a challenge to identify enough firms for the matching.

Moreover, conditional DiD estimation relies, by construction, on the treatment group and its behaviour relative to the control group to estimate average impacts. Matching as such is restrictive and can omit firms with important information. Related to this, another caveat is the loss of efficiency that comes from restricting the data to a matched sample (Damijan and Kostevc, 2005 25; Greenaway and Kneller, 2004: 11).

There are also multiple options to be considered when constructing the control group, for example, one-to-one vs. one-to-many matching, or the choice of matching strategy discussed above. All of these decisions have to be carefully justified when carrying out the approach.

A final limitation of the PSM-DiD methodology specific to estimating the impact of exporters is that it focuses on the extensive export margin. Therefore, it does not estimate how the extent of exporting affects firm-level outcomes, rather it only estimates the average difference between exporters and non-exporters.

Applicability to estimating the impacts of large exporters and regional impacts

In order to estimate the direct impacts of large exporters using a PSM-DiD approach, one would have to restrict both the sample of the treatment and the control group to large companies[14].

However, there are several challenges associated with implementing such an approach in practice.

First, when defining what the ‘treatment’ under investigation is, defining a credible treatment effect for large companies might prove difficult.

The most obvious option would be to define the binary treatment variable as the decision of a large company to start exporting. However, defining the treatment variable in such a way might not make sense, as large firms that are not yet exporting will not start exporting at random. Estimating the impacts associated with large non-exporters becoming exporters might hence not be relevant from a policy perspective.

Another way of defining a treatment would be to look at the decision of an existing exporter to enter a new geographical market, or to export a new product. While the economic impacts associated with those types of decisions are of relevance to the DIT, the treatment may not be very large in those cases, as exporting to one more country, or exporting one more product, might only constitute an incremental change for large companies. One option here might be to define the treatment as the decision to enter a new region of the world.

Secondly, finding an appropriate control group in the context of large exporters will be challenging. If the treatment is defined as the decision to export, then the control group would have to consist of large non-exporters. However, as large firms tend to be more likely to self-select into the export market, there might not be many large non-exporters that could be considered for the control group. This would imply that control groups are small, and estimations likely top yield imprecise estimates.

More importantly, the limited number of large firms that do not export are likely to be fundamentally different from the sample of large exporters, for either reasons that are observable in the data (such as industry) or unobservable reasons (such as management of the company). The same likely holds if one defines the treatment as the decision to enter a new market, as firms exporting globally are likely very different from firms that only export to Europe. This means that it will likely be difficult to argue that firms in the treatment and control groups are similar.

[14] An alternative approach would be to construct the control and a treatment groups for the full sample of firms (by using size as a matching variable only, but including both small and large firms in both the control and treatment groups), and to add an interaction between firm size and the treatment variable to the DiD model in the second stage. However, given the DIT’s explicit focus on the impacts of large exporters, rather than the difference in impacts between large and small exporters, we focus on the former approach in this Section.

Thirdly, data limitations might prevent DIT from actually observing the pre-treatment effect for large exporters, especially if the treatment is defined as the decision to start to export. This is because most large firms are likely to have been exporting over the entire sample period. If the treatment is defined at a more granular level, for example, the decision to enter a new export market, then this might be less of an issue.

Finally, and regardless of how the treatment is defined, it is important to bear in mind that the average (direct) impact of exporting using a PSM-DiD approach would be estimated based on the sub-samples of large exporters that changed export status (or started exporting to a new market) over the sample period. This means that the approach would require DIT to further limit the sample based on which estimates would be derived from the full sample of large exporters to large exporters that experienced a change in treatment over recent years.

Applicability to estimating regional impacts
Regional impacts could be derived by re-estimating a PSM-DiD approach for regional subsamples, or by adding interaction terms between the treatment variable and a region variable to the regression.

However, any attempt at producing regional estimates will amplify the previously discussed issues of small control and treatment group samples. In particular, it will be difficult to find matches at the regional level, so that sample sizes are likely to be small and therefore estimates likely to be imprecise.

The figure below summarises the advantages and limitations associated with the PSM-DiD approach given the DIT's research questions.

Figure 17: Advantages and limitations of a propensity score matching and difference-in-difference approach

	Pros	Cons
Approach	• **Transparent** and **intuitive** method • Controls for **self-selection bias** through creation of **control group** • Controls for **unobservable, time-invariant firm heterogeneity** through fixed effects • Allows to compare **exporters with non-exporters** • Allows to robustly assess **entry into new market**	• CIA is a **strong assumption and means rich dataset required** • Matching approach implies one might **omit firms with important information -> loss of efficiency** • Only useful to determine the impacts of **market entry or other binary decision (e.g. export of new product)**
Large exporters	• Possible to conduct PSM and DiD for sub-sample of large firms	• Issue of defining a **credible 'treatment'** • Creating the control group will be challenging **(few large non-exporters, and large non-exporters fundamentally different) -> small sample -> imprecise estimates** • Difficult to observe **pre-treatment effect** • Impacts estimated based on sub-sample of large exporters who **changed export status**
Regional impacts	• Possible to add **regional interaction terms** in the conditional DiD regression framework	• Difficulty of matching at the regional level • Further **reduction in sample size** -> imprecise estimates

Source: London Economics

1.1.2 Static panel approaches

Some authors use static panel methods, by which we mean methods used to estimate panel models that do not include a lagged dependent variable, such as pooled OLS, fixed effects, or random effects, to investigate the relationship between exporting and economic outcome measures, such as pooled Ordinary Least Squares (OLS) or fixed effects regression. Authors using static panel methods include Ruane and Sutherland (2005), Grazzi (2012), Grazzi and Tomasi (2015), Karampini (2020), Tavares-Lehmann and Costa (2015), Imbruno (2008) and Garcia et al. (2008). Greenaway and Yu (2004) also start their analysis of export premia using a static panel method to estimate correlations between exporting and firm performance, before going on to develop a dynamic panel instrument approach to control for endogeneity.

Export status in those specifications is usually defined through a continuous variable such as export volume or export intensity (intensive margin). Importantly, the independent variable of interest, exporting, is usually lagged to accommodate the fact that the learning effects from exporting might take time to materialise, and to isolate the learning from the self-selection effect: while contemporary outcome measure values are likely to have an impact on contemporary export levels, contemporaneous shocks of the outcome measures are less likely to have an influence on export decisions made in the past. However, in the context of serially correlated outcome measures, both OLS and fixed effects estimation yield biased results (see also 1.1.5).

The advantage of using these approaches is that they are intuitive and relatively straightforward to implement. The approaches can be used to establish patterns in the date, and to determine at an aggregate level whether there is an association between firm's exporting behaviour and economic outcome measure of interests. Often, static panel approaches are used as a first step in the analysis of impacts of exporting, also to provide further justification for the results of less transparent IV or GMM-DPD approaches (see 1.1.4 and 1.1.5) The obvious drawback of these approaches is that they do not allow to establish a causal link between exporting and the outcome measure.

We nonetheless mention these approaches here because of their popularity as a means for 'preliminary analysis' amongst many of the academic experts that have been advising on this project.

Applicability to estimating the impacts of large exporters and regional impacts
It is technically possible to use static panel approaches to assess the impacts of large exporters, by simply estimating the model for the subsample of large exporters.

Applicability to estimating regional impacts
Regional impacts could be derived by re-estimating an IV model approach for regional subsample, or by adding interaction terms between the treatment variable and a region variable to the regression.
The figure below summarises the advantages and limitations associated with the PSM-DiD approach given the DIT's research questions.

Figure 18: Advantages and limitations of static panel data approaches

	Pros	Cons
Approach	• **Transparent** • **Easy** to implement • **Useful first step** before implementation of more complex approaches • Can add impacts of **entry into new markets** or of exporting **new pr**oducts through dummy variables and interactions	• **No robust causal inference**
Large exporters	• Possible to run panel estimations on **sub-sample of large exporters** • Allows to **include all large UK exporters in sample**	
Regional impacts	• Possible to add **regional interaction terms** in the IV regression framework	• **Reduction in sample size** -> imprecise estimates

Source: London Economics

1.1.3 Quantile regression approach

Some authors use quantile regression in order to refine their results on the direct effects of export market entry. Quantile regression can be combined with any approach that estimates the impacts of market entry, and our review shows that quantile regressions are most often used in the context of estimating the productivity impacts of exporting.

A quantile regression approach allows to investigate how the effect of export status varies along the conditional distribution of the outcome measure.

A weakness of studies that estimate the productivity premium for exporters, conditional on a set of firm level characteristics (that is, a weakness of either of the two previously proposed approaches, PSM-DiD and static panel methods), is that they neglect to consider the form of the productivity distribution and instead focus only on the average difference in productivity between exporters and non-exporters (Ferrante and Freo, 2012; Dobbelaere and Kiyota, 2017). If firms are largely heterogenous in productivity, the relationship between exporting status and productivity is only roughly described by the effect on the productivity average (Ferrante and Freo, 2012).

Quantile regression on the other hand estimates the conditional productivity outcome at various quantiles. Intuitively, it allows the comparison of the exporting premium for those firms whose productivity is lower than expected, conditional on firm characteristics, and higher than expected (Trofimenko, 2008).

The advantage of using a quantile regression approach is firstly that it can reveal effect of exporting across productivity distribution and reveal any underlying heterogeneity. Secondly, quantile regression results are characteristically robust to outliers and heavy-tailed distributions, making them more efficient than standard regression approaches (Dobbelaere and Kiyota, 2017). Finally, quantile regression avoids the restrictive assumption that the error terms are i.i.d at all points of the conditional distribution (Dobbelaere and Kiyota, 2017).

Applicability to estimating the impacts of large exporters and regional impacts

A quantile regression approach would be ideally suited to estimate how the impacts of exporting differ for different size classes of firms, if the dependent variable was defined in terms of size of exporters. If the dependent variable is TFP, a quantile approach could still be used to assess different impacts of exporting for different TFP quantiles. However, given the DIT's focus on large firms only, which already limits the sample size, we do not think further limiting the sample size to estimate quantile regressions is advisable.

Applicability to estimating regional impacts

Regional impacts would be difficult to estimate in a quantile regression context, because the quantile regression would already reduce sample size. Hence, further reducing the sample to estimate impacts for individual reasons might lead to imprecise estimates.

The figure below summarises the advantages and limitations associated with the quantile regression approach given the DIT's research questions.

Figure 19: Advantages and limitations of quantile regression approaches

	Pros	Cons
Approach	• Goes **beyond estimating average effects** of exporting • Allows for **different effects for different groups** of firms	• **Reduction of sample size** might lead to **imprecise estimates**
Large exporters	• Useful if the interest is to **distinguish between the impacts of large and small exporters**	• Of limited use given that **DIT only interested in one particular quantile** • Defining quantiles along other dimensions not recommended as this would further **reduce sample size**
Regional impacts	• Possible to add **regional interaction terms** for each quantile	• Further **reduction in sample size** -> imprecise estimates

Source: London Economics

1.1.4 Instrumental variable methods

A smaller number of studies have estimated the direct impact of exporters using an instrumental variable (IV) approach. Authors using instrumental variable methods in the context of estimating the direct impacts of exporting include Lileeva and Trefler (2010); Bratti and Felice (2012); Vahter (2011); Saxa (2008); Harris and Li (2007) and Saxa (2008). In addition, an IV approach is used in the FDI impacts literature by authors including Crescenzi et al. (2015) and Ascani and Gagliardi (2015).

IV approaches are commonly used when an explanatory variable of interest is correlated with the error term, defined as the remaining variation that is not explained by the model. This could be due to issues of reverse causality – when the dependent variable has a causal effect on one of the independent variables – or omitted variables – when important determinants of the dependent variable are missing from the model. Similar to the previously discussed PSM-DiD approach, IV estimation therefore allows to control for the potential endogeneity bias arising from the self-selection of more productive firms into the export market. Again, therefore, authors using an IV approach commonly focus on the direct impacts of entry into the export market (as opposed to the effects of different export intensities).

Studies relying on an IV approach in the context of estimating the direct impacts of exporting seek to identify an exogenous source of variation in a firm's export status to use as instrument (Bratti and Felice, 2012: 1560). Such an instrument must be (highly) correlated with a firm's export status, but must not have a direct effect on a firm's productivity outcomes (or other outcome measures of interest).

The difficulty in estimating the direct impacts of exporting using an IV approach lies in finding an appropriate instrument (Harris and Li, 2007: 18). The studies use several different instruments for export status including firm's distance to the local industry's productivity frontier (Vahter, 2011), geographical distance to the most likely destination of exports (Bratti and Felice, 2012), and a firm's possession of intangible assets (Harris and Li, 2007). Other commonly accepted instrument variables in the literature on the impacts of exporting are exchange rate shocks, trade agreements, or foreign tariff cuts.

Other authors construct exogenous firm-level measures of export demand shocks, which respond to aggregate conditions in a firm's export destinations but are exogenous to firm-level decisions (Mayer et al., 2016; Aghion et al., 2019; Bartik, 1991; Vannoorenberghe, Wang and Yu, 2016; Chor, Manova and Yu, 2021).

The IV approach is well accepted as a convincing method to address the issue of self-selection, but has its limitations. The main limitation of instrumental variable approach is that the identification of exporting effects relies fully on the quality of the instruments used (Vahter, 2011: 18). However, it is challenging to find an exogenous source of variation in large UK firms' export status (extensive margin), or size of export market (intensive margin) given available data, and justifying instrument choices is often difficult. A standard problem is weak identification of an instrument, whereby an instrument is only weakly correlated with the regressor. A weakly identified instrument can result in imprecise and biased estimates.

Moreover, many of the instruments commonly employed in the literature are specific to a given export market (such as exchange rate fluctuations or free trade agreements). As such, it is difficult to argue that those impacts hold across export destinations, and it would not be possible to disaggregate impacts for different export destination 9even though for other instruments such as distance, this would still be possible).

It would remain, however, very difficult to derive an instrument that can distinguish between the impact of expanding to new markets (extensive margin), impact of expanding with new products in existing markets (intensive margin), and impact of expanding with established products in existing markets (intensive margin).

Applicability to estimating the impacts of large exporters and regional impacts
It is technically possible to use an IV approach to assess the impacts of large exporters, by simply estimating the model for the subsample of large exporters.

Applicability to estimating regional impacts
Regional impacts could be derived by re-estimating an IV model approach for regional subsample, or by adding interaction terms between the treatment variable and a region variable to the regression.
The figure below summarises the advantages and limitations associated with the PSM-DiD approach given the DIT's research questions.

Figure 18: Advantages and limitations of an IV approach

	Pros	Cons
Approach	• **Robust causal inference** if instrument is valid • Controls for **self-selection bias** into the export market	• Difficult to find an **appropriate instrument** • **Weakly identified instrument** can result in imprecise and biased estimates • Commonly employed IVs often **specific to one export market** • Difficulty of **using same instrument for addressing different DIT research questions**
Large exporters	• Possible to estimate IV regressions for **sub-sample of large exporters** • Allows to **include all large UK exporters in sample**	
Regional impacts	• Possible to add **regional interaction terms** in the IV regression framework	• **Reduction in sample size** -> imprecise estimates

Source: London Economics

1.1.4 Generalised method of moments estimators in the context of dynamic panels (GMM-DPD)

Another common way of dealing with the inherent endogeneity issue arising when estimating the direct impacts of exporting is the use of generalised method of moments (GMM) estimators in the context of dynamic panel models. Blundell and Bond refer to this estimator as GMM-DPD, whereby DPD stands for dynamic panel data. We do not consider GMM models outside of a dynamic panel context for the purposes of this report, and therefore all references to GMM made in this report refer to this particular sub-type of a GMM model, which includes lagged dependent variables and different sets of IV in each cross-sectional equation, Authors employing GMM-DPD estimators (or alternative dynamic panel methods) include for example Albornoz and Kugler (2008); Andersson, Lööf and Johansson (2008); Andersson and Lööf (2009); Cuyvers, Dhyne and Soeng (2010); Greenaway and Yu (2004); Ito and Lechevalier (2018); Kim and Sung (2020); Lööf and Nabavi (2013); Lööf et al. (2015); Salomon and Shaver (2005) and Tse, Yu and Zhu (2017). The same technique is often used in the FDI literature: see for example Benfratello and Sembenelli. (2006); Driffield (2006); Liu and Zou (2008) Crespo et al. (2009); Belderbos et al. (2015); Igbinigie et al. (2020), and Benfratello and Sembenelli (2006).

Export status in those specifications is usually defined through a continuous variable such as export volume or export intensity (intensive margin). Some studies estimate the effect of exporting using categorical variables to indicate export intensity at various thresholds; for example, a dummy variable that indicates whether the ratio of exports to sales is above 50% (Andersson and Lööf, 2009). Other studies measure export intensity as a continuous variable (Greenaway and Yu, 2004).

Usually, the GMM-DPD approach involves relating current outcome measure performance to past export levels and past values of the outcome measure (lagged dependent variable, LDV).

As mentioned in the context of static panel methods (1.1.2), the introduction of past values of the export variable in the specification both accommodates the fact that the learning effects from exporting might take time to materialise, and serves to isolate the learning from the self-selection effect: while contemporary outcome measure values are likely to have an impact on contemporary export levels, contemporaneous shocks of the outcome measures are less likely to have an influence on export decisions made in the past.

However, according to Kraay (1999), it is further necessary to include the lagged dependant variable to take account of the fact that outcome measures such as firm productivity are serially correlated over time and is jointly determined with exports. In addition, the model has to include firm-level fixed effects to control for time-invariant unobservable plant characteristics that may affect both enterprise performance and exports, which can lead to a spurious correlation between outcome measures and past exporting status.

The presence of lagged dependent variables and firm-specific effects present problems in the estimation of the dynamic panel data model using OLS and fixed effects estimation[15]. Most authors therefore prefer investigating the direct effects of different levels or intensities of exporting by means of dynamic panel estimation approaches. The most commonly used dynamic panel estimator in the literature is the system GMM estimator. Developed by Blundell and Bond (1998), a system GMM specifies a system of equations in levels and first-difference, using (respectively, lagged levels and difference) instruments for the (respectively, first-difference and level) endogenous variables. The system GMM approach specifically allows for the dynamic nature of the dependent variable, where past realisations determine the current one, the potential for endogenous regressors and firm-specific effects.

The system GMM approach requires authors to classify variables in their dataset are endogenous, pre-determined and weakly and strictly exogenous (Lööf and Nabavi, 2013). In the LBE literature, continuous variables such as export intensity, productivity, human capital, and firm size are usually treated as endogenous (Lööf and Nabavi, 2013: 9). Authors then often consider variables such as firm size and capital stock as pre-determined, whereas other control variables are considered exogenous (such as firm age and dummies).

[15] Past values of productivity for firm i are a function of the firm-specific effects that are time invariant, therefore OLS estimation of equation would yield biased and inconsistent estimates due to endogeneity (Nickell, 1981). While fixed effects estimation removes the firm-specific effects (θi), the estimates remain biased and inconsistent if T is small as lags of the dependent variable are correlated with the average value of the error term, even if it is not serially correlated (Baltagi, 2005).

The system GMM approach again mitigates the issue of estimation bias due to the reverse causality between outcome measures and exporting (Tse, Yu and Zhu, 2017: 2143). The system GMM is well suited to large panels, for which the estimator will be consistent and asymptotically normal, meaning when the sample size is large enough. A further advantage of the dynamic panel methods relative to PSM-DiD is that they can estimate the effect of export intensity to analyse how the extent of exporting affects firm outcomes (Greenaway and Yu, 2004).

When estimating the effect of export intensity as a continuous variable, using a generalized method of moments approach presents a further advantage in that it does not impose any restriction on the distribution of data (Chaussé, 2011). This is beneficial as data for export volumes or the ratio of exports to sales, is not likely to be normally distributed. For example, it is likely that there will be a small number of firms with very high export volumes at the top end of the distribution (Yashiro, 2009; Wales et al., 2018).

A potential limitation of this methodology is that GMM-DPD strictly relies on the assumption of autocorrelation and assumptions on overidentification. Furthermore, the validity of the additional instruments depends on the assumption that changes in the instrumenting variable are orthogonal with the fixed effects (Blundell and Bond, 1998). Another potential issue with estimating system GMM regressions is the proliferation of instruments.

It is further worth noting that running system GMM regressions is technically challenging and computationally intensive, and technical issues might arise when running the regressions.

The academic experts consulted for this project had very mixed views on the value and credibility of system or difference GMM estimators.

On the one hand, most experts agreed that it is a commonly accepted approach to deal with issues of reverse causality.

On the other hand, concerns were raised about the system GMM being very complex, and therefore results not being easy to interpret and not always transparent. Moreover, several experts mentioned that results were known to be sensitive to the assumptions made by the researcher about the lag structure.

Some experts mentioned that while system GMM used to be popular in the past, it has been used less than IV estimations in more recent years.

Overall, it is important to acknowledge that in order to alleviate some of these concerns, a system GMM estimator should only ever be used in conjunction with more transparent approaches (for example static panel approaches).

Applicability to estimating the impacts of large exporters and regional impacts

It is technically possible to use a system GMM approach to estimate the direct effects of different degrees of exporting for large exporters only. Isolating the impacts of large exporters could be achieved by restricting the sample to only include large exporters. Similar to what could be done using an IV approach or a simple panel data approach, the full sample of large exporters could be used, rather than the sample of large exporters that changed treatment status over the sample period (PSM-DiD).

Applicability to estimating regional impacts

Regional impacts could be derived by re-estimating introducing an interaction term between the (lagged) exporting variable and a regional variable, or by re-estimating the model for regional sub-samples.

The figure below summarises the advantages and limitations associated with the (system) GMM approach given the DIT’s research questions.

Figure 18: Advantages and limitations of a GMM-DPD approach

	Pros	Cons
Econometrics	• Controls for **self-selection bias (reverse causality)** through inclusion of **lagged exporting variable** • Controls for **serial correlation** in outcome measure • Controls for **unobservable, time-invariant firm heterogeneity** through fixed effects • Allows to estimate impacts at the **intensive margin** • Can add impacts of **entry into new markets** or of exporting **new pr**oducts	• **Very complex and not always transparent** • **Computationally intensive** • **Weakly identified instruments** can result in imprecise and biased estimates • Autocorrelation and overidentification **assumptions have to be met and tested** • **Results sensitive** to assumptions about lag structure • Proliferation of instruments if many lags included
Large exporters	• Possible to run system GMM on **sample of large exporters** • Allows to **include all large UK exporters in sample**	
Regional impacts	• Possible to add **regional interaction terms** in the system GMM regression framework	• **Reduction in sample size** -> imprecise estimates

Source: London Economics

1.2 Methods used to estimate the indirect impacts

1.2.1 Input-output analysis

Input-output (IO) tables describe the sale and purchase relationships between producers and consumers within an economy. The economics discipline that is concerned with analysis of supply and use tables is known as input-output analysis.

At a national level[16], an IO framework (derived from the supply and use tables) presents the amount of total output that is supplied as intermediate input in each industry, exported to other economies or consumed as final demand by households and government bodies. Simultaneously, the tables present the number of inputs from each sector used in each sector to produce total output, compensation of employees, taxes and subsidies and imports. In combination, the Supply-and-Use table provides an image of the inter-linkages that exist between the sectors in the economy, and therefore offers a way of understanding the relative importance of all sectors to each other.

Based on the IO table, it is possible to calculate the total economic output arising in all sectors from an increase in the amount that is exported to other economies[17]. As such, IO tables can be used to estimate

[16] It is worth noting that while our method review here focuses on national IO tables only, many of the studies introduced in Part 1 of this report rely on global (multi-nation) IO tables. Multi-nation IO tables add a country dimension, showing, for each sector in each country, what is exported to specific sectors in specific other countries. In combination, international IO tables provide an image of the inter-linkages that exist between the countries sectors in the economy, and therefore offer a way of understanding the relative importance of all sectors to each other. While IO tables are required to enable analysis of GVCs (and also for international comparisons of exporting impacts), national IO tables are sufficient for conducting an analysis as suggested in this section. Indeed, DIT (2021) argue that national IO tables are preferable to multi-nation tables as they “require fewer assumptions, are more coherent with National Accounts; can be relatively easily augmented with additional data to examine further indicators of interest; and should provide the most robust results” (DIT, 2021).

[17] It can be shown that transforming the IO framework into a symmetric industry by industry system, normalising by sectoral output (column total), subtracting the resulting use matrix from the identity matrix and inverting the whole expression produces a matrix where each cell can be interpreted as the amount with which each supplying sector (row) would increase its output if the using sector (column) increased

the horizontal and vertical spillover effects of increased export activity in one sector on the economic output of all other sectors.

It is moreover possible to approximate the spillover impacts associated with an increase in exports in one sector in terms of GVA, employment, or employment costs, using the ratio of GVA or employment or employment costs to output in each supplying sector[18].. For example, the Export-Import Bank of the United States (EXIM) uses IO analysis in combination with to model the number of jobs that their exporting financing helps support (for example EXIM, 2018). A similar approach has recently been proposed to estimate the employment impact of UK Export Finance (UKEF) support for UK exporters (UKEF, 2019).

IO tables only provide a static picture, and do not take account of any changes in prices that might result from changes in (export) demand. A key assumption of input-output analysis is that inputs are complements and that there are constant returns to scale in the production function. Put differently, IO tables assume there are no economies of scale. The interpretation of these assumptions is that the prevailing[19] breakdown of inputs from all sectors is a good approximation of the breakdown that would prevail if total demand (and therefore output) were marginally different. The implication is that the spillover impacts calculated based on input-output analysis should be interpreted with caution, especially if the change in exporting that is modelled differs greatly from the data.

The advantage of using IO tables to estimate spillover impacts of exporting is that the approach is relatively simple, and does not require access to firm-level data or complex estimations. Instead, the approach can be implemented quickly with readily available data.

However, the approach is only useful to estimate horizontal and vertical spillover effects of exporting, not agglomeration/regional spillover effects. Moreover, this approach only lends itself to estimating supply chain effects, not any other spillover impacts that might arise from exporting such as knowledge transfer effects.

Furthermore, IO tables only provide static snapshots of input-output relations, and assume fixed productivity levels – they are thus not adequate to investigate productivity spillovers arising from exporting. This is problematic, given that we assume productivity to be one of the main economic outcome measures of interest to the DIT.

A further caveat of using national IO tables for modelling the impacts of exporting is that the modelling relies on sector averages. However, as also highlighted by DIT (2021), firms can vary within sectors according to, for example, trading status, ownership status and size.

Applicability to estimating the impacts of large exporters and regional impacts

The caveat that any IO analysis relies on sectoral averages given present data limitations, makes estimation of the spillover impacts generated by large exporters challenging.

While it is possible to approximate the spillover impacts generated by large firms by combining sector-level IO analysis with insights about the proportion of exports (in a given industry) generated by large firms, it is important to note that this would assume that large exporters behave like the average firm in the industry as far as supplier relations as well as average employment-to-output ratios are concerned (or GVA or wages ratios, depending on the outcome measure of interest).

One the one hand, this is counterintuitive given the evidence on the direct impacts of exporting. We know that large exporters are more productive than the average firm, so that using average employment-to-output ratios might be problematic. Similarly, large firms might be importing more

by 1. This resulting matrix is known as the Leontief Inverse. The column sum of this matrix is therefore equal to the total economic output arising in all sectors from one additional unit of final demand in one sector.

[18] It is possible to transform the Leontief Inverse by the ratio of GVA to output in each supplying sector relative to the sector for which export spillover impacts are calculated. The interpretation of each cell therefore becomes the amount of additional GVA generated in each supplying sector (row) for each additional unit of GVA generated in the sector experiencing a unit increase in GVA.

[19] At the time the input-output table is created.

intermediate inputs from foreign countries, so that the effect of an increase in output by a large exporter actually has less impact on the supplying industry than the increase in output of a small firm would have.

On the other hand, it is worth mentioning that input-output tables report on the total value of output that is supplied as intermediate input in each industry, exported to other economies or consumed as final demand by households and government bodies. This means that IO-tables might actually be more reflective of large firms than of the average UK firm.

Applicability to estimating regional impacts

There are currently no regional IO tables available for England. While there are distinct IO tables for Scotland and Northern Ireland and Wales, combining those tables into a consistent picture of national IO relations would be challenging.

While regional value-added statistics could be used to apportion effects discovered through national IO analysis to individual UK regions, this would assume that large exporters exhibit a similar regional presence than the average UK firm in the same sector.

The figure below summarises the advantages and limitations associated with an IO analysis approach given the DIT’s research questions.

Figure 18: Advantages and limitations of an IO analysis approach

	Pros	Cons
Econometrics	• **Easy to implement** with readily available data • No reliance on firm-level data allows -> **no access restrictions, no matching** requirements • Consistent with **existing DIT, UKEF and EXIM analysis**	• **Static analysis** and no causal inference • Not possible to estimate **productivity spillovers** • Limited to **supply chain (horizontal & vertical) spillovers; no agglomeration/regional or knowledge transfer spillovers** • Assumes exporters do not differ from non-exporters • Cannot distinguish between spillover impacts on **different types of firms**
Large exporters	• Possible to approximate spillover impacts generated by large firms by combining IO analysis outputs with data on **share of large firms in total industry exports** • **IO tables might be more reflective of large firms**	• Assumes large exporters do not differ from non-exporters or small exporters **(“average firm”)** in terms of input-output relations or indirect effects
Regional impacts	• Possible to use **regional GVA statistics** to apportion national effects to regions	• No regional IO tables available • Assumes **large exporters do not differ from average firm** in terms of location

Source: London Economics

1.2.2 Use of firm-level panel data and sectoral or regional spillover proxy variables

Another relatively simple and often used approach to estimating the spillover effects of exporting and other forms of internationalisation is to regress firm- outcome measures on a set of control variables and a set of spillover proxy variables, which capture the presence of exporters, or the export activity, in the same sector (horizontal spillovers), upstream or downstream sectors (vertical spillovers) or the same region (regional spillovers).

Spillover proxy variables are usually defined at either the sector or region level. They are thus constant across a subset of firms that are believed to be impacted by the same spillover impact. In order to include spillover variables that capture interactions in the supply chain (vertical spillovers), many authors make again use of IO tables to derive weighted averages for export activity in upstream or downstream sectors.

In particular, authors usually distinguish between backward (downstream) spillovers – spillovers proxied by the export activity in the industries that are being supplied by a given sector; and forward (upstream) spillovers, defined as the weighted export activity in upstream sectors. The export activity of upstream or downstream sectors is usually weighted by the supply and use shares provided in IO tables.

Sometimes, export spillover variables are defined in terms of the *number* of exporters (Albornoz and Kugler, 2008), and sometimes in terms of gross exports (Cuiyvers, Dhyne and Soeng, 2010). Often, the spillover variables are moreover *normalised* (by output) (see for example Albornoz and Kugler, 2008).

The firm-level models are then usually estimated using appropriate panel data techniques, such as fixed or random effects in the context of static models, and system GMM if lagged dependent variables are included in the model (Albornoz and Kugler, 2008; Cuiyvers, Dhyne and Soeng, 2010).

Studies using firm-level panel approach to capture the impact of exporting include Albornoz and Kugler (2008); Banh, Wingender, and Gueye (2020); Aitken and Harrison (1999), and Blyde, Kugler, and Stein (2004). Studies using this approach to capture the spillover impacts of FDI include Haskel et al., (2002); Smarzynska-Javorcik (2004); Damijan et al. (2013); Konings (2001); and Abegaz and Lahiri (2019). The approach is also widely accepted in the literature on the spillover impacts of exporting.

By using firm-level data, authors can control for observable or unobservable firm-level characteristics that may also determine productivity to improve identification of the spillover impacts. Moreover, this approach allows to explicitly distinguish spillover impacts from the direct effects of exporting, by either including firm-level exporting as a control variable, or by estimating the impacts of the proxy variables on non-exporters only.

The use of firm-level data moreover alleviates endogeneity concerns for horizontal spillover estimation due to self-selection bias, as it is unlikely that many firms are able to influence the export activity of their entire industry – export activity is thus likely to be exogeneous from a firm perspective. However, this might not be fully true in the context of estimations seeking to assess the impacts of large enterprises, as for example a group of highly productive large firms might account for the bulk of export flows across borders. To mitigate this concern, lags of spillover variables (sectoral or regional export activity) are often used rather than contemporaneous spillover variables Banh, Wingender, and Gueye, 2020). Another way of addressing the endogeneity concern is again to exclude exporters from the sample, and to only derive the spillover impacts of exporting on non-exporters.

Using firm-level data moreover allows to investigate whether spillover impacts are different for different types of firms. This will allow the DIT to answer potentially interesting research questions, such as whether the spillover impacts accrue to exporters or non-exporters, large enterprises or SMEs, or more or less productive firms.

A disadvantage of this approach is that the transmission channel for the observed impacts is not always clear. For example, the export activity in a sector might have spillovers on firms in the same sector through either competition or knowledge transfer effects, and judgement will have to be used when interpreting the results. This concern can be alleviated if additional controls for the competition effect are included (Herfindahl Index).

The academic experts consulted for this project were generally in favour of this estimation approach.

Applicability to estimating the impacts of large exporters and regional impacts

It is possible to only capture the exports of large firms in the spillover proxy variable, even though exports of other firms should be added as a control. Some export data is readily available broken down by sector and firm size; however, depending on whether regional spillover variables are to be included as well, and/or further breakdowns (by destination region or product category), it might be necessary to aggregate firm-level export data for large exporters to derive the proxy variables. This latter approach relies on comprehensive export data, so that no arbitrary fluctuations in the proxy variables are introduced by changes in the underlying sample. However, given that export data is based on VAT records rather than surveys, this should not be a big concern.

Applicability to estimating regional impacts
As was the case for most of the approaches for the direct effects estimation, it would be possible to introduce interactions between spillover variables and a regional variable, or to re-estimate the spillover estimations for regional sub-samples, to derive regional spillover effect estimates.

The figure below summarises the advantages and limitations associated with the approach described in this section.

Figure 19: Advantages and limitations of a firm-level panel and spillover proxy variable approach

	Pros	Cons
Econometrics	• **Robust causal inference** possible • Controls for **unobservable, time-invariant firm heterogeneity** • Allows **isolating spillovers from direct impacts** • **Flexible** in terms of what spillovers are included: can test for horizontal, vertical and regional spillovers; extensive and intensive export margin • Can further investigate **what firms benefit** from spillovers	• **Remaining endogeneity** concerns for horizontal spillovers if exporters are included -> remove exporters or estimate GMM • Need to decide on type of spillover and appropriate granularity levels **ex ante** • More **resource and time intensive** than IO analysis • Challenging to distinguish between **transmission mechanisms** (knowledge spillovers or competition or supply chain effects)
Large exporters	• Possible to only capture **exports of large firms** in spillover proxy variable	• Use of IO data to construct spillover backward or forward spillover variables relies on assumption that large firms exhibit the same supply interlinkages as the **"average firm"**
Regional impacts	• Possible to add **regional interaction terms** to assess regional variation in spillover impacts	• **Reduction in sample size** -> imprecise estimates

Source: London Economics

1.2.3 Use of sector-level panel data and sectoral or regional spillover proxy variables

Closely related to the previously introduced approach, some authors also seek to assess the spillovers of exporting or other forms of internationalisation by regressing sector-level outcome measures on control variables and spillover proxy variables. This is a particularly common approach in the literature on the impacts of GVC participation, while less commonly employed by authors estimating the impacts of gross exports. Authors employing such a sector-level panel approach include Banh, Wingender, and Gueye (2020); Gal and Witheridge (2019); and Hagemeier, 2016[20].

In contrast to firm-level panel estimations, sector-level estimations that regress sector-level outcome measures on horizontal sector-level export activity variables do not allow to explicitly distinguish between the direct and the indirect effects of exporting. For example, productivity in a given sector might be positively correlated with the export activity in a sector because of the increased productivity of the exporting firms themselves, or because of spillovers on other firms. This is less of an issue for the estimation of vertical spillover effects.

Causal interpretation of the relationship between the spillover variables and outcome measures at the industry level can moreover be problematic given endogeneity concerns and potential for reverse causality. In particular, it is unclear from correlations whether GVC participation improves firms'

[20] Piermartini and Rubinova (2014) also use sector-level panel estimations and spillover variables; however, they directly focus on cross-country spillovers of R&D expenditure, rather than the within-country spillover impacts.

performance and drives industry productivity growth or higher productivity growth makes it easier for firms and industries to participate in GVCs. This concern can in part be mitigated through the inclusion of lagged spillover variables (which are less likely to be jointly determined with the outcome variable than contemporaneous spillover variables) and/or the use of instruments for the spillover variables (see for example Banh, Wingender, and Gueye, 2020). However, sometimes, authors use cross-sectional approaches that do not lend themselves to establishing causal relationships, however (Hagemeier, 2016).

Applicability to estimating the impacts of large exporters and regional impacts
It is possible to only capture the exports of large firms in the spillover proxy variable, even though exports of other firms should be added as a control. Some export data is readily available broken down by sector and firm size; however, depending on whether regional spillover variables are to be included as well, and/or further breakdowns (by destination region or product category), it might be necessary to aggregate firm-level export data for large exporters to derive the proxy variables. This latter approach relies on comprehensive export data, so that no arbitrary fluctuations in the proxy variables are introduced by changes in the underlying sample. However, given that export data is based on VAT records rather than surveys, this should not be a big concern.
Applicability to estimating regional impacts
It is not possible to estimate regional variations in spillover impacts if sectoral data is used. Theoretically, regional value-added statistics could be used to apportion sectoral output (or productivity) data to regions, so that the panel could be estimated at a sector-region level. However, the firm-level approach discussed in the preceding section lends itself more directly to estimating regional spillover effects.

The figure below summarises the advantages and limitations associated with the approach described in this section.

Figure 20: Advantages and limitations of a sector-level panel and spillover proxy variable approach

	Pros	Cons
Econometrics	• **Robust causal inference** possible if IV or GMM estimators used • Can investigate **horizontal or vertical spillover effects** • Data readily available, no firm-level data access required	• Cannot control for **unobservable, time-invariant firm heterogeneity** • Cannot isolate **spillovers from direct impacts** • Need to decide on type of spillover **ex ante** • Challenging to distinguish between **transmission mechanisms** • Cannot investigate **regional spillovers** • Cannot distinguish between spillover impacts on **different types of firms**
Large exporters	• Possible to only capture **exports of large firms** in spillover proxy variable	• Use of IO data to construct spillover backward or forward spillover variables relies on assumption that large firms exhibit the same supply interlinkages as the **"average firm"**
Regional impacts	• Possible to use **regional GVA statistics** to apportion national effects to regions or to create sector-region panel data	• Apportioning of macro-data to regions likely to lead to **measurement error** • **Firm-level panel more appropriate** if regional spillover effects are to be estimated

Source: London Economics

2. Dataset review

2.1 Summary of available data sources for the UK

This section provides details on the most relevant and comprehensive datasets that are available to estimate the direct and indirect economic impacts of large exporters on the UK economy.

Estimating the direct effects of large exporters, that is, the effect exporting has on exporting firms itself, relies on firm-level data regardless of the chosen approach, as it has to be assessed at (at least) the firm level by definition. In order to determine regional effects, even more granular data (plant-level) would ideally be used.

Our discussion of the most important datasets in this section therefore focuses on firm-level datasets mostly. In line with the methods discussed for spillover estimations in the previous section, we further consider UK IO tables as well as existing as well sector-level export datasets below.

In what follows, we provide brief introductions to the subset of datasets which we believe to be most useful for implementation of the approaches discussed in the previous section. A full review of all potentially available datasets is provided in a separate Annex report, which can be made available by DIT upon request.

2.1.1 Firm-level export datasets

HMRC Overseas Trade Statistics (OTS)
HMRC custom records feed into a detailed dataset containing transaction level data of the UKs trade in goods. The HMRC holds information on the value of exports, enabling users to measure the extent to which firms export. Based on the customs records, HMRC publishes the Overseas trade Statistics (OTS) on a monthly basis for the UK, and quarterly basis for individual regions.

HMRC custom records cover at least 93% of the UKs value of trade for imports, and at least 97% of the UK's value of trade for exports, through the compilation of data from several different sources.

Non-EU trade data is collected from UK Customs import and export entries, predominantly via the Customs Handling of Import and Export Freight (CHIEF) system. Trade activity to and from the EU is collected via a statistical survey known as Intrastat. Intrastat only covers transactions over £250,000, which is equivalent to 97% of total exports by value (see above). Information is supplemented by the Ancillary Costs Survey (ACS) which allows HMRC to publish EU (Intrastat) trade figures on the same common valuation basis as all the other EU Member States. The valuation of exports (dispatches) is on a Free on Board (FOB) delivery terms basis, that is, the cost of goods to the purchaser abroad, including: Packaging; Inland and coastal transport in the UK; Dock dues; Loading charges; and all other costs such as profits, charges and expenses (insurance) accruing up to the point where the goods are deposited on board the exporting vessel or aircraft or at the land boundary of Northern Ireland. The valuation of imports (arrivals) is on a Cost, Insurance and Freight (CIF) delivery terms basis including, this includes the cost of the goods; charges for freight and insurance; and all other related expenses in moving the goods to the point of entry into the UK (but excluding any duty or tax chargeable in the UK).

HMRC trade data is available from 1996 to 2020 for trade outside the EU and 2008 to 2020 for trade inside the EU[21]. Earlier data for the EU cannot be accessed due to the existing data protection legislation.

HMRC's OTS data is the most comprehensive firm-level trade in goods data available to researchers. It is more up to date compared to data from the Office for National Statistics (ONS), and given that it is based on official tax records, it has much better and more consistent coverage compared to survey-based data (Annual Business Survey or International Trade in Services, see below) or data derived from company financial accounts (FAME).

The main disadvantage of the HMRC OTS data is that it is recorded on a different basis than ONS data, and therefore not easily linkable. We discuss those issues further in subsequent sections.

Another limitation isthat it excludes trade in services and intangibles.

The other limitation is that matching HMRC data to other firm-level datasets containing information required to derive economic outcome measures (independent variable) or control variables is a complex undertaking that relies on a number of assumptions. Depending on the assumptions made to match

21 https://www.gov.uk/guidance/imports-and-exports-datasets

HMRC and ONS data, the linking process might turn out to be relatively resource intensive. We discuss those issues further in Section 2.2.

Another limitation of the HMRC trade data, which is common to all firm-level datasets discussed in this Section, is that trade flows are recorded at the VAT unit level. For some enterprises, where multiple plants associated with one VAT unit might exist and might be located in different regions, this makes a thorough investigation of regional impacts difficult. We further discuss these issues in Section 2.3.

Additional challenges might arise due to changes in HMRC's data collection system as a result of Brexit, which might lead to breaks in the data collected post 2021.

A final limitation is that (non-EU) transactions which are managed by large intermediaries (logistic companies) are recorded as exports conducted by the intermediary, not by the exporting firm. This reduces the ability to monitor exports of companies which rely on intermediaries for trade outside the EU.

For further details on the HMRC trade data please refer to Wales et al. (2018).

ONS' Trade in Goods-IDBR data (TiG/IDBR)

The Economic Statistics Centre of Excellence in association with the Office for National Statistics have made a pre-matched dataset that links HMRC OTS data to the Inter-Departmental Business Register (IDBR) reporting units available to other researchers. This pre-linked dataset hence contains reporting-unit level exports and imports of goods for 2005-2016. Trade data is given by partner country and 4-digit commodity code for each reporting unit.

Given that the TiG/IDBR data is also based on HMRC tax records, it has the same benefits as the HMRC OTS data in terms of reliability and consistency of coverage. Trade data is moreover broken down by partner country and products. While HMRC data is available for even more granular product categories, the 4-digit breakdown provided in the TiG/IDBR is more than sufficient for DIT's purposes.

The main advantage of using this dataset over the underlying HMRC trade data is that the matching of VAT-level data to reporting units has already been undertaken by researchers at the ONS. While this means that the DIT will not be able to make their own assumptions for allocating exports in cases where one VAT reference number is associated with multiple enterprises (see also Section 2.2), using the matched dataset will allow significant resource and time savings. Moreover, Wales et al. (2018) provide a very detailed description of the matching assumptions underlying this dataset. Finally, the ONS team responsible for matching the HMRC and IDBR data to create the TiG/IDBR confirmed[22] that the final matched dataset relies on what the ONS believes to be the best possible matching strategies given available data, after testing several competing allocation mechanisms (see Wales et al., 2018). Finally, the dataset provides different units of aggregation (reporting unit, enterprise unit, enterprise group). This means that several units of analysis can be tested (See 2.3).

The obvious drawback of using the pre-linked dataset is that panel data has only been linked for years 2005-2016 at the time of writing, and it is not yet clear whether and when the dataset will be updated.

The ONS' export data allocation to reporting units was moreover based on employment data (in addition to product/industry tables), where allocation between multiple reporting units was necessary. If the outcome measure of interest is employment, or labour productivity, then we might artificially introduce some correlation between the right-hand-side variable, total exports weighted by some employment share, and the left-hand-side variable, the same employment level used to create this allocation share. However, if the DIT were undertaking the matching themselves, they would have to rely on the same allocation variable.

For further details on the TiG/IDBR data, including assumptions made by ONS to allocate exports to reporting units in cases where there were several reporting units per VAT number, please refer to Wales et al. (2018).

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[22] We are grateful for the advice provided by Philip Wales and Russel Black in support of this project.

ONS' International Trade in Services (ITIS)

The International Trade in Services (ITIS) survey collects data from UK companies with regards the value of international transactions in respect of imports and exports of services. It is the only UK database which includes product level detail for UK services exports.

The dataset, which spans from 1996 to 2019, records the type of service which was traded and also the country to which the service/s were either imported from or exported to. The ITIS Survey is supplemented by information collected via the Annual Business Survey (ABS) in relation to amounts paid or received for the imports or exports of services.

IT IS data is based on a survey of firms. Data might hence be less reliable, or less consistent over time compared to HMRC-derived trade data (for example, if different persons fill out the survey over different years). Moreover, not all firms are covered in all years. While reporting units with more than 250 employees will be covered in all years, there might still be instances of missing services export data for large enterprises. For example, a large enterprise might be split into two reporting units with 125 employees each, and therefore not be captured in all IT IS survey waves.

The ITIS is not representative of the whole services economy, as travel, transport and some banking sectors are excluded.

Similar to the other datasets discussed here, ITIS data is collected at the reporting unit, not the plant level.

ONS' Annual Business Survey (ABS)

ONS' Annual Business Survey is the main structural business survey conducted by the ONS, covering 2008-2018. Waves from 2011 onwards include information about whether surveyed firms were engaged in international trade during the past year.

The relevant questions are Q15 and WQ163 from the ABS: 'Q15 - Did your business export goods to individuals, enterprises or other organisations based outside the UK in the last 12 months?', which is asked to businesses producing goods; and 'WQ163 - Amounts receivable from individual, enterprises or other organisation based outside the UK', which is asked to businesses in services sectors. As such, the ABS only includes a dummy variable for trade in goods, which indicates whether a given firm has been trading goods in the last year but not the volume of trade. For trade in services, the ABS details information about the value of the exported services.

The trade in goods variable is reasonably well populated (<10% missing for the most recent years, and <25% missing for initial years), while the trade in services variable is almost perfectly populated. However, in contrast to the HMRC OTS and TiG/IDBR data, ABS data, much like ITIS data,is ultimately based a business survey. This means that not all firms are covered in all years. Again, while large reporting units with more than 250 employees are covered each year, some reporting units associated with large enterprises but that are reporting on less than 250 employees would not be covered in each survey wave.

The ABS does not release information on the insurance and reinsurance parts of the financial sector as data for this industry has remained experimental due to ongoing volatility. Additionally, the dataset also excludes public administration and defence; public provision of education and health; unregistered businesses (businesses which are not registered for PAYE or VAT will not be listed in IDBR and therefore not covered by the ABS) and only covers a small part of the agriculture sector (hunting, forestry, fishing and the support activities).

Similar to the other datasets discussed here, ABS data is collected at the reporting unit, not the plant level.

Bureau van Dijk's FAME database

Bureau van Dijk's FAME database covers more than 11 million companies located in the UK and Ireland. The database covers identification and contact information, business descriptions, and financial data, the latter of which incudes detailed turnover data by source (overseas vs. UK). FAME is based on official filings content from the UK's Companies House. Additional information comes from sources including official registers, annual reports, company websites, newswires, telephone research and direct correspondence with the companies.

Variables such as employment, capital expenditure, turnover and age can be extracted from FAME for use as outcome measures, control variables and variables useful for the identification of treatment groups. While FAME has been used in the literature, a major drawback of the database is due to foreign turnover including subsidiary sales, limiting its usefulness in measuring export activity for companies with foreign subsidiaries.

FAME contains information on overseas turnover, which can be used as a proxy for exporting. However, overseas turnover also includes the revenues from subsidiaries that might be located abroad, and as such, export data derived based on FAME would have to be interpreted with caution. FAME exports should be ok for domestic firms, however. Moreover, using ownership information on FAME in conjunction with the overseas turnover variable would allow to derive exports of local firms.

FAME data will have to be matched to other datasets from the ONS via the IDBR, and the matching would have to be undertaken by the ONS rather than researchers at the DIT. As such, it is a lot more complex to combine FAME data with ONS datasets.

Another drawback of the FAME database is that different reporting standards amongst firms can be a drawback of using fame, that is, accounting reporting standards are less stringent for smaller firms. In particular, reporting annual overseas turnover is voluntary for most firms (especially for smaller firms). For a large company analysis, this will be less of an issue.

Summary
The figure below summarises the various advantages and limitations associated with the use of the firm-level export datasets discussed in this section.

Figure 20: Advantages and limitations of a sector-level panel and spillover proxy variable approach

	Pros	Cons
HMRC overseas trade in goods statistics (OTS)	• Information on the **value** of exported goods • Good **coverage:** 97% of UK good exports value • **Data based on tax records** -> most reliable, most balanced coverage • Breakdowns by **destination country** and **product** available • **Monthly** data	• Excludes **trade in services** and intangibles • **Matching** potentially problematic and time-intensive and has to be done based on employment • **Cannot make use of monthly frequency** given lack of monthly data for economic impact measures • Non-EU exports managed by **large intermediaries** • Data at **VAT unit** level, but not plant level
ONS linked TiG/IDBR	• Information on the **value** of exported goods • **Data based on tax records** -> most reliable, most balanced coverage • Breakdowns by **destination country** and **product** available • **ONS doing the apportioning** of export values for complex enterprises -> no matching by DIT required	• Excludes **trade in services** and intangibles • Limited year **coverage: 2005-2016** • Non-EU exports managed by **large intermediaries** • Data at **reporting unit,** but not plant level • Data **allocated based on size**
ONS International Trade in Services (ITIS)	• Information on the **value** of services exports • Breakdowns by **destination country** and **service type** available • Supplemented by information from the ABS	• Excludes **trade in goods** • Excludes trade in certain services sectors **(travel, transport, banking)** • Data at **reporting unit,** but not plant level • **Survey-based data** -> less precise and less coverage
ONS Annual Business Survey (ABS)	• Information on both goods and services exports • Information on the value of services exports	• Exports of goods captured in **binary variable** • Excludes parts of the **financial sector** • Data at **reporting unit,** but not local unit (plant) level • **Survey-based data** -> less precise and less coverage
Bureau van Dijk's FAME database	• Can be used to derive a **proxy** for firm-level exports	• **Overseas turnover** variable includes revenue from foreign subsidiaries • **Matching** to ONS datasets is complicated • Different **reporting standards** for different firms

Source: London Economics

2.1.1 Firm-level datasets for economic impact measures, control variables and spillover estimation

Data on outcome measures and control variables are available through the aforementioned ABS and FAME, as well as additional datasets containing information on employment, R&D or innovation. Export datasets such as HMRC's OTS, TiG/IDBR and ITIS are limited to information on plant identifier variables, export variables, employment and turnover, and as such are not likely to contain all the information required to estimate the direct (and potentially indirect) impacts of exporting using either of the previously discussed approaches.

Outcome variables of interest consist of aspects of the firm that are expected to be affected by a firm's choice to export (direct effects) or exporting choices made by other firms (indirect impacts). The most commonly used impact variable in the literature is productivity, but other performance measures that are potentially of interest are employment, wages, investment (R&D and capital), growth, survival and potentially others.

Endogeneity is likely to be a key issue when estimating the relationship between exporting activity and key performance outcomes. As such, when assessing the direct impacts of exporting on productivity, factor inputs (labour and capital) will be important control variables.

We discuss the firm-level datasets that can be used to measure economic impact and control variables below.

ONS' Annual Business Survey (ABS)
As previously mentioned, the ABS is the main structural business survey conducted by the ONS. It is an annual survey of businesses covering the production, construction, distribution and service industries, which represents about two-thirds of the UK economy in terms of Gross Value Added (GVA). The ABS is the largest business survey conducted by the ONS in terms of the combined number of respondents and variables it covers (62,000 questionnaires despatched in Great Britain, with around 600 different questions asked).

ABS covers 2008-2018. It does not cover the financial sector; public administration and defence; public provision of education and health; unregistered businesses, and only covers a small part of the agriculture sector (hunting, forestry, fishing and the support activities).

ABS includes detailed information on the firm level characteristics and financial performance of UK businesses, including information on the total value of sales and work completed by businesses, the value of purchases of goods, materials and services, and total employment costs. The ABS, however, does not directly ask firms about employment. However, employment data from the IDBR is included in the ONS ABS files.

ONS' Annual Respondents Database X (ARDx)
The ARDx provides the longest comprehensive panel database at reporting unit level available on Great Britain covering the years from 1998 to 2014. The database is based on two ONS surveys, the annual business inquiry (ABI) and the ABS. Since the ABI and ABS are similar in sampling method, structure and questions, they can be treated as one long survey with a break.

As the ABS only collects financial data, employment data is extracted from BRES for years from 2008. Again, IDBR employment data is moreover included in the ARDx files by the ONS.

The ARDx, as the ABS, does not cover the financial sector; public administration and defence; public provision of education and health; unregistered businesses, and only covers a small part of the agriculture sector (hunting, forestry, fishing and the support activities).

The ONS no longer updates the ARDx database, and as such the database ends in 2014.

*Business Register Employment Survey (BRES) and alternative employment data sources*The Business Register and Employment Survey (BRES) publishes employee and employment estimates at detailed geographical and industrial levels. The data is available annually for 2009-2019. It is regarded as the definitive source of official government employee statistics by industry.

Employment is calculated by adding the number of working owners to the number of employees employed by a business, where working owners include sole traders, sole proprietors and partners who receive drawings and/or a share of the profits, but are not paid via pay-as-you-earn (PAYE).

A complementary source for employment data is the IDBR, which complements BRES employment data by using alternative data sources and/or imputations for businesses that are not regularly covered by the BRES. For large businesses, IDBR employment data is updated annually from BRES. For medium-size businesses and smaller businesses with a PAYE scheme, the IDBR keep their BRES employment figure for up to 4 years. After 4 years, if the unit is not re-selected for BRES, businesses with PAYE will revert to the latest PAYE figure. Those without a PAYE will revert to an imputed employment value, based on the turnover per head ratios. Small businesses, not in BRES and not operating a PAYE scheme will have employment updated by an annual imputation, based on turnover per head ratios (calculated by averages from other smaller businesses).

As such, IDBR employment data has better coverage compared to BRES data. However, the problem with using IDBR data (for businesses not covered by BRES) is that both the source and quality of the information and the year the information on employment refers to are unclear.

A third alternative to BRES data is the Longitudinal IDBR (LIDBR) created by the Data Science team at the Department for Business Energy and Industrial Strategy (BEIS). Compared to the IDBR, the LIDBR attaches information on the likely year the employment (and turnover) variable refers to; the quality of the information on employment (information sourced from BRES is from a high quality source); and the number of employees and working proprietors.

The ABS data files available to researchers in the ONS SRS environment report BRES employment for when it is available, and IDBR employment for businesses not covered by BRES. Given the DIT's research focus on large firms, up-to-date employment data from the BRES is likely available for most firms of relevance. We therefore consider the combined BRES/IDBR employment information that is available in the ABS file to be sufficient for the DIT's research purposes.

ONS' Annual Survey of Hours and Earnings (ASHE)
The Annual Survey of Hours and Earnings (ASHE) is the most comprehensive source of information of the structure and distribution of earning in the UK covering the years 2004 to 2018. ASHE provides information about the levels, distribution and make-up of earnings and paid hours worked for employees in all industries and occupations. The ASHE tables contain estimates of earnings for employees by sex and full-time or part-time status. Further breakdowns include by region, occupation, industry, age group and public or private sector. ASHE is based on a 1% sample of employee jobs taken from HM Revenue and Customs (HMRC) Pay As You Earn (PAYE) records. ASHE does not cover the self-employed nor does it cover employees not paid during the reference period.

ASHE replaced the New Earnings Survey (NES) as ONS's main source of information on earnings in 2004 and brought improvements to the coverage of employees, imputation for item non-response and the weighting of earnings estimates.

If the DIT wishes to consider different earnings as an outcome measure, the ASHE could be used to provide more details and breakdowns. However, the ABS and ARDx also contain average earnings data which would be sufficient for the purposes of an earnings control variable. Moreover, regardless of which dataset is used, to our knowledge no dataset exists that explicitly identifies export-related jobs.

Business Enterprise Research and Development
The purpose of the Business Enterprise Research and Development (BERD) Survey is to provide estimates of businesses' expenditure and employment relating to research and development (R&D)

performed in the UK. It uniquely provides information on expenditure on R&D performed by UK businesses, the source of funding for this R&D work, and the employment of people working on R&D.

BERD covers 1998-2018.

The BERD would be the most appropriate dataset if the economic outcome measure of interest was a measure of R&D outcomes.

UK Innovation Survey

The Community Innovation Survey (CIS) covers 1997-2019. The survey covers product, process and wider innovation including expenditure on different kinds of innovative activity, effects of innovation, sources of information and cooperation, barriers to innovation, protection methods for innovation, and public support for innovation.

The CIS would be the most appropriate dataset if the economic outcome measure of interest was a measure of innovation outcomes.

However, the CIS is a voluntary survey, and therefore might not be representative. Moreover, effects of innovation are self-reported, and hence potentially biased.

Annual Purchase Survey (APS)

The Annual Purchases Survey aims to collect information about business' expenditure on energy, services, goods and materials that are used up or transformed by the business activity.

The survey includes raw materials, power and fuel, rental on buildings and business services such as advertising, recruitment consultancy and cleaning. It specifically excludes fixed assets or capital investment, staff costs, and goods and services bought for resale without further processing.

The information supplied helps identify the purchasing patterns of businesses. Information is only available for 2015-2017 currently.

APS data could be used to calculate firm-specific purchases weights when creating backward and forward variables to capture export activity in the down- and upstream sectors. However, it is important to note that this survey-based dataset is very limited in terms of time coverage, and it will have limited coverage of small firms only. As it is small firms mainly for which the DIT wishes to calculate spillover impacts, using IO tables to create those particular export spillover proxy variables might be preferable.

Products of the European Community (ProdCom)

The UK manufacturers' sales by product (ProdCom) database presents annual statistics on the value and volume of products manufactured in the UK. The datasets provide estimates of value, volume and unit values (value per unit of volume) for each product heading (where possible). Other data available by industry include total turnover, merchanted goods, work done, sales of waste products and all other income.

In pre-2014 releases, estimates of intra and extra EU imports and exports, were also reported alongside ProdCom estimates, however this was discontinued from December 2013 onwards.

ProdCom statistics would still be useful, however, to normalise export activity in terms of total production activity. For example, we would expect exports to have less of an impact on productivity of a firm if export activity is small relative to total or domestic production activity. ProdCom would be better suited relative to other datasets as it is the only dataset providing production estimates at the product (and not just company) level.

2.1.2 Sector-level datasets

ONS Input-Output tables

One possibility of estimating the impacts of exporting based on sector-level data is to conduct an input-output analysis.

There is currently only a single industry by industry IO table available for the UK. This table was constructed based on the input-output relations prevailing in 2016, and covers 105 sectors across the UK.

The UK IO table is derived based on data from multiple UK data sources, and consistent with the UK national accounts. There are currently no regional tables available. Additionally, there is no regular production schedule for ONS IO tables (DIT, 2021).

Please refer to DIT (2021) for a more detailed overview of IO tables.

ONS Trade in Goods (TIG) and Trade in Services (TIS)
ONS Trade in Goods (TIG) and Trade in Services (TIS) are two detailed annual datasets containing information on industry level exports. The datasets provide information on goods and services exported to the UK broken down by destination country and sector. The datasets include 176 export destinations and 84 sectors. The TIG
dataset covers the years 2008 to 2019 and the TIS dataset covers the years 2016 to 2018.

The TIG dataset uses information from the IDBR and HMRC data on trade in goods. The TIS dataset combines information from the ITIS survey, the International Passenger Survey (IPS), IDBR, the Annual Survey of Goods and Services and the APS. Data is reported in current prices.

The ONS US TIG and TIS datasets are experimental as their methodology is still under development. It is moreover important to note that the data from the ONS trade by industry series is not entirely consistent with the ONS IO data, as described further in DIT (2021). Moreover, no regional breakdowns of trade by industry data are currently available (see also DIT, 2021).

The TIG and TIS data can be used in combination with IO tables to implement the IO analysis approach described above. The datasets could moreover be used to derive sector-level spillover proxy variables. However, the series would only be useful to calculate spillovers of exporting more generally, as the TIG and TIS datasets are not broken down by firm size.

The ONS *UK trade in goods by business characteristics* data series, which exists for 2016-2018, further includes breakdowns by business size that would allow the direct calculation of sectoral spillover proxy variables that only capture large firms.

2.2 Complexities involved in dataset matching

We have shown in the previous section that there is no single dataset for the UK that contains all the relevant variables to estimate the direct effects of large exporters on the UK economy for the vast majority of the proposed estimation approaches.

This is because the preferable firm-level export datasets do not contain sufficiently rich information on firm performance and financial variables to allow to specify models with the outcome variables of interest and/or control variables required to address endogeneity concerns.

While the ABS and FAME databases contain information on both exporting (or proxies thereof) and economic outcome and control variables, those datasets are less preferable for deriving firm-level export variables for the reasons outlined previously:

- Even though the ABS also contains export information, the export of goods is recorded as a discrete (yes/no) variable rather than a continuous variable. Additionally, unlike the ITIS, export data on services recorded in the ABS is not broken down by product type.
- FAME holds firm level information on overseas turnover; however, this is an imperfect proxy for the value of exports, as it includes turnover from international subsidiaries.

While ABS and FAME have incomplete export information, they do contain detailed information on firm outcomes (such as GVA, gross output) and firm level characteristics that can be used to derive controls (such as capital stock) which HMRC and ITIS are lacking.

For these reasons, a linking of several datasets will be required.

2.2.1 Matching ONS datasets

Unique firm identification numbers in theory will allow DIT to unambiguously match various ONS firm-level datasets, using the common Inter-departmental business register (IDBR) reference numbers:

- enterprise group, which the ONS defines as a group of legal units under common ownership;
- enterprises (entref) are defined in ONS data 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;
- reporting units (ruref) are generally the same as an enterprise (which is the legal entity of the business), but larger enterprises can be split into a number of reporting units based on divisional structure, geographical considerations, type of activity, or other agreed reporting structures. Reporting units return total values that represent one or many local units of that business. Reporting units mostly comprise collections of local units which undertake similar activities.
- local units (luref) closely approximate the establishments of businesses. Local units are individual sites or plants that belong to an enterprise. Each reporting unit has at least one local unit attached to it. The only data that is currently available at the local unit level is data from the IDBR or Business Structure Database (BSD), and limited to information on the sector, location, employment and (although with worse coverage) turnover.

Most UK enterprises are comprised of one single reporting unit, which reports on a limited number of local units. Adopting the same terminology used in Wales et al. (2018), we refer to those businesses with a one-to-one match between enterprise and reporting unit as ‘simple’ enterprises. Multi-reporting unit enterprises will be referred to as ‘complex’ enterprises. Finally, we further distinguish ‘highly complex enterprises’, which are ‘complex enterprises’ (multi-reporting unit) which form part of a larger enterprise group within which they are linked to other enterprises.

ONS data is collected from businesses at the reporting unit level. For example, the TiG/IDBR, IT IS, ABS, ARDx, BRES, BERD, CIS, and APS datasets are all available at the ruref level. Linking those datasets should hence be possibleusing a one-to-one match based on the reporting unit reference number and reference year, even though additional complexities are likely to arise during the implementation phase. The linked datasets could then be aggregated to the enterprise or enterprise group level, depending on the desired unit of analysis (see Part Three).

2.2.2 Matching HMRC trade data to ONS datasets

The matching of HMRC OTS to ONS datasets is more challenging.

HMRC customs records record export in goods data at the level of a “consignment”, a record of exporting a single commodity in a given month. Each of these consignments is listed with a ‘trader ID’, which is defined as a ‘VAT unit or branch of a VAT unit that is exporting goods’.

In order to match the trader IDs from the HMRC to the ONS identifiers (entref) they belong to, one has to match both HMRC trader IDs and ONS entrefs to VAT IDs. For over 99% of entrefs, there is a one-to-one match between VAT IDs and entrefs (Wales et al., 2018).

However, a subset of firms (entrefs) operate with more than one VAT-number. Similarly, enterprise groups with complex business structures may share a VAT-number across subsidiaries, but these subsidiaries may report as separate enterprises under the ONS definition.

While these cases account for very few enterprises, they also account for a large proportion of trade in goods (Wales et al., 2018). Given that we are primarily interested in the linking of export data for large firms, such issues are therefore likely to be important.

Where an enterprise is linked to several VAT numbers, HMRC trade data can simply be aggregated at the enterprise level. Where a VAT ID is linked to several enterprises, the trade recorded against the VAT ID has to be allocated across the enterprises connected with that VAT ID.

This allocation process necessarily relies on a variety of assumptions.

The linked TiG/IDBR dataset, which was created in support of a discussion paper by Wales et al. (2018) published alongside the ONS' publication on 'UK trade in goods and productivity' (ONS, 2018), was constructed based on a two-stage approach.

First, the authors aggregated exports recorded at VAT number level at the highest level of the corporate hierarchy that applies – enterprise group if several enterprises are linked to the same enterprise group ('highly complex' enterprises), and enterprise ('simple' and 'complex' enterprises) otherwise. It is worth noting that they aggregate exports from multiple VAT units at the group level, regardless of whether the VAT IDs are specific to a given enterprise or the same across multiple enterprises in the group. This is because some complex businesses may report all their trade through a single VAT unit – regardless of whether the trade originates from a reporting unit in one enterprise or another.

In a second stage, the authors apportion enterprise group level exports to the reporting units within each complex enterprise group. Exports are allocated across rurefs based on (a) employment in each reporting unit, weighted by (b) the mean exports per head (in simple firms) by ruref industry[23]. In particular, the authors first calculate mean exports per head of employment on an industry by product basis, in order to construct weights for reporting unit employment which give a sense of the intensity with which different industries trade different products. They then assign assigning exports proportionally across reporting units in an enterprise group in accordance with their employee count, except that each employee is assigned a weight for each consignment, based on the product category of the consignment and the industry category of the employee.

While the TiG/IDBR dataset was constructed based on what was considered to be the most robust approach given available data, it is important to highlight that allocating export data to reporting units by means of employment or any other variable could lead to two potential problems. First, the allocation of export values to reporting units likely leads to measurement error in the export variable. Secondly, if the outcome variable of interest is in some way correlated with employment (the allocation variable), we might artificially introduce correlation between the independent variable of interest and the dependent variable. This would be problematic if the outcome measure of interest was, for example, employment.

There are several alternatives to the TiG/IDBR approach that can be considered if the DIT chooses to do the matching of OTS data to ONS data themselves.

First, one alternative would be not to apportion exports to lower units of analysis, and to instead conduct the analysis at the enterprise group or enterprise level. Ongoing work carried out at the University of Sussex relies on such an approach, where the unit of observation is a 'pseudo-enterprise', which captures enterprise group level exports if a VAT ID is matched to multiple enterprises, and enterprise level exports if there is a one-to-one VAT-ID-to-entref match[24]. Such an approach avoids introducing measurement error in the export variable or introducing artificial correlation between exporting and outcome measure variables. However, whether such an approach is appropriate depends on the desired level of analysis (see Part Three). Moreover, using different units of observations for different enterprises might make interpretation difficult. Moreover, exports should always be aggregated at the enterprise group level regardless of whether the VAT ID is specific to an enterprise or not, given that some complex businesses may report all their trade through a single VAT unit.
Secondly, a different allocation mechanism for allocating exports to reporting units might be employed. For example, a slightly different approach is currently being used in ongoing work by the DIT, whereby exports are being allocated to enterprises (not reporting units) directly proportional to employment (without constructing industry weights). Moreover, Wales et al. (2018) experimented with using median exports per head by ruref industry rather than the average.

Finally, other allocation variables than employment might be considered. For example, turnover might be more highly correlated with exporting than employment. However, our conversations with the

[23] The authors test two alternative approaches, and show that those apportionment approaches provide similar results. The alternative apportionment mechanisms are to not use industry weights and simply assign exports proportionally to ruref employment. As a second alternative, they use median rather than mean exports per head by ruref industry for the weight creation.
[24] Information was obtained based on a conversation with the academic lead on the project, Professor Michael Gasiorek.

authors[25] of the Wales et al. (2018) paper confirmed that employment tends to be the best populated and most comprehensively surveyed data, hence why the authors of said paper chose that allocation variable. In particular, we were informed that IDBR or BSD turnover data is less populated than employment data, and in addition turnover value often being derived based on employment figures in the first place.

2.2.3 Matching proprietary data to ONS datasets

To match external datasets such as FAME data to ONS datasets, non-ONS data will first have to be linked to snapshots of the IDBR. For records where the company registration number (CRN) is known, the matching to the IDBR will be relatively straightforward, as there is a direct key between enterprises and CRNs. If the company registration number is not known, fuzzy matching techniques based on company names, postcode and address will have to be applied.

The ONS Secure Research Service (SRS) team is currently responsible for undertaking any matching for datasets that are later to be explored in the ONS SRS environment. Any matching request for external datasets would therefore have to be processed by the ONS SRS team. This would come at a (small) cost to the DIT, and might require several weeks to months of processing time.

Moreover, the ONS currently only provides matching at the enterprise level – hence, the ONS datasets to which external data would be matched also would have to be aggregated to the enterprise level.

2.3 Dataset gaps

In addition to the aforementioned issues related to the lack of a comprehensive pre-linked dataset that combines detailed export information for goods and services exporters with firm-level data on economic outcome measures and control variables, there are three other gaps in the data currently available for the UK that make addressing some of the DIT's research questions somewhat challenging.

2.3.1 Lack of more granular IO tables and lack of IO time series data

As discussed previously, the ONS' local units (luref) closely approximate the establishments of businesses, such as individual sites or plants. However, there is currently no comprehensive luref-level dataset available for the UK with the exception of the IDBR (and the longitudinal version thereof) and the BSD. As such, the only information that is collected at the plant level by the ONS are identifiers such as information on the sector or the location of the plant, as well as employment and (even though with worse coverage) turnover.

However, information on productivity, or R&D outcomes, or financial variables, are all collected at the reporting unit level.

This is potentially problematic for purposes of the DIT's research project for the following reasons. First, estimating the direct impacts of exporting at the plant level would be preferable if we assume that the direct effects of exporting are limited to the exporting plant, not the wider enterprise. If this is the case, estimation of direct effects at the enterprise level would likely mean an under-estimation of effects.

Lack of plant-level data could also hinder the estimation of indirect effects, especially if regional spillover impacts are investigated. This is because for reporting units that cover multiple local units, we only can observe the location of the reporting unit (headquarter) in reporting unit-level ONS datasets, rather than the location of the plants.

Most importantly, and related to the previous point, any estimation of regional impacts based on reporting unit location information might bias results if local units are in effect located in different regions. This holds regardless of whether DIT looks at regional direct or indirect effects.

While performing the analysis at the plant-level would be conceptually preferable because of the above reasons, such an undertaking would require apportioning economic impact, trade and control variables

[25] We are grateful by the advice received from both Philip Wales and Russell Black at the ONS.

across plants (lurefs). This could again be done by using an 'apportionment variable' that is are available at the plant level – most likely employment, which is provided at the plant level in the BSD.

As with the allocation of trade data to reporting units discussed previously, the creation of a plant-level dataset would hence require DIT to make the assumption that the distribution of economics/financial variables within an enterprise (or reporting unit) can be explained by plant-level employment (or industry-weighted plant-level employment). While this assumption may be relatively benign for some variables – the ONS apportions variables across lurefs to derive the ABS's published regional results, after all – apportioning both outcome and export data across plants could prove problematic.

2.3.2 Lack of more granular IO tables and lack of IO time series data

Existing IO tables for the UK (and most other countries) do not provide any detail on supply-chain relationships for different types of firms. We have already discussed how the lack of IO data for specifically large firms poses a problem for our proposed IO approach. Similarly, while there are separate regional IO tables, there currently does not exist a UK-wide IO table with regional breakdowns.

The development of the ONS of more granular IO tables by the ONS, which would split out IO relations for different types of firms (exporters vs. non-exporters, large vs. small firms, or regional breakdowns) would increase the usefulness of any approach relying on such data for the purposes of the present study. The same point has also been made by DIT (2021) in the context of estimating the labour market impacts of exporting.

Another point worth noting here is that the ONS does not currently provide annual updated of IO tables, so that the last (and only) available IO table for the UK is based on 2017 supplier-buyer relationships. More regular (annual) updates of IO tables by the ONS would help improve any estimations reliant on the IO approach discussed in Section 1.2.1 of Part 2 of this approach.

2.4.3 Lack of firm-to-firm trade data

As an alternative to more granular IO tables, additional firm level data on domestic buyer-supplier relationships would be very beneficial for the estimation of spillovers of a particular sub-set of exporters (large firms) on other firms (including SMEs).

An example of the availability of such data in a different country is the B2B Transactions Dataset administered by the National Bank of Belgium (NBB). This data documents both the extensive and the intensive margins of domestic buyer-supplier relationships in Belgium enabling users to observe the complete domestic production network. Transactions valued at over 250 euro between VAT-liable enterprises across all economic activities are documented. Bernard et al (2019) use the database to document stylized facts about a complete production network and using a two-way fixed effects model, present an extensive analysis of how upstream, downstream and final demand (sales to final customers) heterogeneity translate into firm size heterogeneity.

If such information were available for the UK, it could be used for the estimation of spillovers from exporting for particular firm types. Combining such information with HMRC and ITIS data, an analysis could moreover be constructed so as to identify the gains to (particular) suppliers based upon the.

We note that the relatively new APS dataset, which breaks down inputs consumed by surveyed firms for different product types, goes a first step into that direction. However, this dataset is only available for 2015-2017 at this stage.

Part Three - What approach is recommended to estimate the relationship between exporting, firm-level economic outcomes (direct effects), and wider economic outcomes beyond the exporting firm (indirect effects) at a local and national level?

This part of the report presents our preferred approaches for estimating the direct and indirect impacts of large exporters, respectively.

The selection of the preferred approaches follows directly from the discussion of the relative advantages and limitations of various econometric approaches and datasets, as well as the advice provided by the academic and government experts who have kindly shared their views throughout April 2021.

1. Selecting the appropriate unit of analysis

As discussed in the previous section, ONS uses four different identifiers to describe enterprises at various levels:
enterprise group, enterprises (entref), reporting units (ruref) and local units (luref).

While most ONS datasets are made available to researchers at the reporting unit level, in theory, datasets could be aggregated to enterprise or enterprise group level relatively easily, by summing across all reporting units associated with a given enterprise or enterprise group[26]. Similarly, through further apportioning, a luref-level dataset could be created (see Part Two, section 2.3.1).

As such, an important first step when deciding how to estimate the direct and indirect impacts of exporting consists of selecting the most appropriate unit of analysis.

1.1 Reporting unit level

Wales et al. (2018) carry out their analysis of the relationship between trade and productivity at the reporting unit level. The authors transparently lay out why they consider the reporting unit to be the most preferable unit of analysis.

The main advantage of carrying out the analysis at the reporting unit level is that all ONS data is collected and made available to researchers at the reporting unit level. This means that running the analysis at reporting unit level requires the least amount of data preparation, and matching various datasets at reporting unit level is also easier compared to other levels.

While aggregation of those datasets to higher levels is possible based on available ruref-entref-enterprise group tables, aggregation is potentially complicated in cases where not all of the reporting units attached to an enterprise (or group) are sampled in a given survey year. In those cases, DIT would have to either drop the enterprises that do not have data for all reporting units, or make some assumptions to interpolate missing reporting unit data. While all reporting units with 250+ employees are surveyed every year in the ABS and ITIS, there might still be large enterprises with unbalanced survey coverage (for example, if one reporting unit is associated with 50 employees, and the other with 200 employees).

Even more, aggregation is difficult for binary and categorical variables. The issue is most pronounced for enterprises where different reporting units are associated with different regions or industries. For example, if one enterprise is active in two different regions, there is no straightforward way of deciding which region to attribute to the overall enterprise. This concern is especially important in the context of regional estimations, where random allocation of multi-region enterprises to just one location might bias results. The same holds for all categorical variables. Similarly, binary dummy variables, such as a

[26] Most ONS dataset, including the TiG/IDBR, do contain ruref, entref and enterprise group identifiers as separate variables. Otherwise, ONS datasets can easily merged to existing ruref-entref-group matching tables.

variable indicating whether a reporting unit has undertaken any R&D activities in the last year, areare difficult to aggregate. For example, we might have cases where one reporting unit is undertaking R&D, but five other reporting units belonging to the same enterprise are not undertaking R&D, so again whether or not to set the R&D dummy to 1 at the enterprise level is a somewhat arbitrary decision.

Next, and related to the previous point, the ONS' motivation for the reporting unit structure is to collect data for distinct types of economic activity. Aggregation would therefore lead to some loss of information. Moreover, it might be expected that the direct impacts of exporting only accrue to the business units and plants of a given enterprise that operate in the same sector as the exporting business segment; but there might be no direct impacts on business units with unrelated economic activities.

The disadvantages of using reporting level data are as follows.

First, the reporting unit has not the most straightforward economic interpretation. As mentioned above, the ONS' motivation for the reporting unit structure is to collect data for distinct types of economic activity. As such, the reporting unit is the unit for which data is collected by the ONS; sometimes, the reporting unit captures a plant and sometimes multiple plants; moreover, sometimes the reporting unit captures an enterprise, but sometimes an enterprise consists of multiple reporting units. However, it is common for researchers to conduct analysis at the reporting unit level and interpret findings as firm-level effects, also because most enterprises only have a single reporting unit.

– it is simply the unit for which data is collected, but it is not necessarily neither the plant nor the enterprise.
Secondly, as discussed in Part Two, strong assumptions have to be made to allocate export data to reporting units. Those assumptions are likely to introduce some measurement error in the independent variable of interest. Moreover, if the economic impact measure under consideration is employment, or some variable closely correlated with employment (such as apparent labour productivity), the apportionment might further distort estimation results.

1.2 Enterprise level

The main advantage of using an enterprise level approach is that trade data would not have to be apportioned to reporting units for 'complex' enterprises. For 'highly complex' enterprises, however, group-level exports still would have to be allocated to individual enterprises based on some allocation method[27]. As such, estimations at the enterprise level would alleviate some of the previously raised concerns about measurement error, but not all.

Moreover, the enterprise is much more reflective of the actual economic unit than the reporting unit, and decisions are made at an enterprise, not a reporting unit, level. Hence, one might expect that any learning effects from exporting would accrue to the entire enterprise, not just the reporting unit.

The disadvantage of using enterprise level data closely mirror the advantages of using reporting level data listed in the previous section. Aggregation of, for example, ABS data at the enterprise level will require DIT to drop certain data points, if other reporting units belonging to the same enterprise are not surveyed in a given year. Moreover, DIT would have to either drop enterprises where different reporting units are associated with different locations or industries, or make an arbitrary decision of what industry/location to use. Arbitrary allocation to one region is particularly problematic for regional estimations. If multiple ONS datasets are required, the loss of information from dropping those enterprises might be considerable, as reporting unit coverage depends on the survey.

1.3 Enterprise group level

Another alternative would be to estimate impacts of exporting at the enterprise group level. This approach would fully negate the need to apportion trade in goods data, but we might lose more

[27] At least for enterprises sharing a common VAT ID; buy preferably also for enterprises with distinct VAT IDs, given the insight from Wales et al. (2018) that many highly complex enterprises arbitrarily report all exports under one VAT ID.

observations for firms with missing reporting unit data in certain years. Aggregation of information at the enterprise group level is expected to result in even more loss of information especially with regards to regional or sectoral information, as it is very likely that multiple enterprises of the same group are based in different regions of the UK and operating in different sectors.

Other questions arising here are whether we expect export decisions to be made at the enterprise or the group level, and whether we expect the direct impacts of exporting to materialise across all enterprises under common ownership or not.

1.4 Local unit level

As outlined in Part Two of this report, carrying out the estimations at the plant level would be preferable especially in the context of regional effects estimation. In addition, plant-level estimations might be conceptually preferable if we expect direct exporting effects to materialise at the plant level, or if we expect spillover impacts to be regionally contained.

However, DIT would have to create the plant-level data themselves, based on some allocation rules. Given that the same allocation mechanism would likely have to be applied to all dependent and independent variables, the concern of introducing some artificial correlation through apportioning is even higher compared to the apportioning of export-data to reporting units.

1.5 Summary

Selecting the appropriate level of analysis for the purposes of the present report is particularly challenging, given that the DIT wishes to investigate *regional* impacts of *large* exporters.

For large exporters, which are likely to be mostly ‘highly complex businesses’, estimations at the group or enterprise level would be the most cautious approach, especially if one of the outcome measures of interest is employment.

For regional impacts estimation, however, the most disaggregate unit of analysis would be preferable.

Given this trade-off between the DIT’s research questions, we propose that the DIT start by carrying out the analysis at the reporting unit level. Ruref-level analysis requires the least amount of data manipulations by the DIT, and minimises the loss of information. No additional allocation or aggregation assumptions will have to be made and justified by the DIT, as even trade data is available at the reporting unit level in the TiG/IDBR dataset.

However, we recommend that the DIT re-estimates the main model at both the enterprise and enterprise group level (or, alternatively, at a pseudo-enterprise level, using a combination of enterprises and enterprise groups, in line with the current project carried out by the University of Sussex[28]).

We do not at this stage recommend that the DIT creates a plant-level dataset, because we believe that simultaneous apportioning of all variables based on one allocation mechanism might artificially increase correlation between the dependent and independent variables. There are simpler ways to test whether the regional estimations might be distorted by the lack of plant level data, which we introduce in Sections 2 and 3 of this Part of the report.

2. Recommended estimation approach for estimating the direct impacts of large exporters

2.1 Selecting an appropriate estimation approach

We recommend that the DIT use a mix of static and dynamic panel estimation approaches to asses the direct impacts of exporting.

[28] Further information can be obtained from the academic lead on the project, Professor Michael Gasiorek.

Given the DIT's focus on the impacts of *large* exporters, we favour panel and IV estimation approaches over both a PSM-DID and a quantile regression approach.

A PSM-DiD approach is considered to be less suitable for estimating the impacts of large exporters because of the difficulty of defining an appropriate treatment for large firms that is both credible and relevant from a policy perspective; the challenges associated with defining an appropriate control group for large non-exporters; the limited amount of pre-treatment effects likely to be observable in the data; and the DIT's preference for estimating export impacts along the intensive margin.

Similarly, we reject a quantile regression approach for the purposes of the present report, because it would be more difficult to account for endogeneity in a quantile framework and because the approach would further reduce the size of the sample that is already limited due to the focus on large exporters only.

We take on board the advice given by most academic experts in favour of more simple static panel approaches, and propose that the DIT builds up its analysis starting with simple correlations, pooled OLS, and static panel approaches, before moving on to more complex approaches.

We acknowledge that the academic experts consulted for this report had mixed views on the relative merits and robustness of an IV approach compared to GMM-DPD approaches, and that an IV approach might be less open to criticism compared to a system GMM approach in academic circles. However, we propose that the DIT proceed with a system GMM estimator in this case, because it allows for addressing all of the DIT's research questions in one and the same model, and with the same data, that can also be estimated using more transparent static panel estimation approaches.

Moreover, while there are a number of instrumental variables accepted in the literature, we believe that the DIT might still find it challenging to develop a credible narrative to defend an IV approach given the breadth of its research questions. Since the DIT wishes to examine the impact of expanding exports with established products in existing markets (intensive margin) vis-à-vis the impacts of expanding with new products in existing markets (intensive margin) and expanding to new markets (extensive margin), several instrumental variables would have to be drawn upon. Moreover, the instruments commonly used in the literature are limiting the examination of the research question to a particular point in time, such as the time of an exchange rate shock or the time a new trade agreement is reached. As such, an IV approach is less suited to estimating the impacts of various degrees of exporting across different geographical markets and product types over time. That said, if time permits, DIT could further test the robustness of their results with an IV approach.

A system GMM approach, while having its limitations, is more adaptable to address the nuances of the DITs research questions, and can be more directly compared to the results from more simple correlations and static panel regressions. The use of the static panel methods in conjunction with the system GMM approach should help alleviate concerns about the transparency of GMM-DPD estimators.

Please refer to Part Two of this report for a more detailed discussed of the advantages and limitations of various estimation approaches.

2.2 Setting up the model

Below, we propose our main model for the estimation of the direct impacts of exporting, whereby we remove parameters that are to be estimated for ease of interpretation:

$$\ln(y_{it}) = \ln(y_{it-1}) + ex_{it-1} + newmarket_{it-1} * (1 + ex_{it-1}) + \ln(newprod_{it-1}) * (1 + \ln(ex_{it-1})) + \ln(X_{it}) + \ln(GVA_{St}) + time_t + \eta_i + \varepsilon_{it}$$

whereby:

- *Dependent variable, y_{it}*: economic impact measure for firm i at time t;
- *Independent variables of interest:*
    - ex_{it-1} is the lagged export intensity for firm i at time t-1;
    - $newmarket_{it-1}$ is a count variable indicating the number of markets firm i exports to at time t-1;

- $newprod_{it-1}$ is a count variable indicating the number of products firm i exports at time t-1;
- *Control variables*
  - y_{it-1} is the lagged economic impact measure for firm i at time t-1;
  - X_{it} is a vector of control variables for firm *i* at time *t*; These are listed in Section 4 of this Part of the report;
  - $time_t$ are time-specific effects (world economy, national economy, trade liberalisation, GVC);
  - GVA_{St} is sectoral GVA, and used in addition to time dummies to control for macro-economic shocks that might only affect individual sectors and hence not be captures through the time dummies;
  - μ_{it} is a firm-specific fixed effect; and

ε_{it} is the error term.

Several things are worth noting here.

First, our model uses lagged export variables to takeaccount of the fact that the learning effects from exporting might take time to materialise. Moreover, some authors argue that including lagged export variables helps control for the issue of reverse causality, because contemporaneous shocks of the outcome measures are less likely to have an influence on export decisions made in the past. However, our main method for addressing the issue of reverse causality is through the system GMM set-up, whereby past values of the dependent and explanatory variables are used as IVs. We propose that the DIT use one lag, following the existing literature. However, we also recommend for the DIT to experiment with the lag structure as a robustness test (adding lags 2 and 3), and to select the ultimate lag structure based on the results (significance of additional lags) and information criteria values (Bayesian information criterion and Akaike information criterion) for the alternative specifications.

Secondly, given concerns about serial correlation in the outcome measures likely of interest (productivity, output, and even employment), we introduce a lagged dependent variable in the model which may be jointly determined with (lagged) exports. We recommend removing the lagged dependent variable from equation (1) for the preliminary estimations relying on static panel data methods, given the known problems in the estimation of the dynamic panel data model using OLS and fixed effects estimation[29].

Thirdly, the model includes firm-level fixed effects to control for time-invariant unobservable firm characteristics that may affect both enterprise performance and exports. We therefore do not include either region or industry dummies, which should be subsumed in firm-level fixed effects.

Fourth, we investigate the direct impacts of exporting along three different dimensions, all in the same model. ex_{it-1} captures the impact of expanding exports with existing products in existing markets. The interaction between this variable and $newprod_{it-1}$ provides evidence on whether the impacts are different if the exporters expand with new products in existing markets, while the interaction between ex_{it-1} and $newmarket_{it-1}$ investigates whether the exporting impact is different for firms expanding to new markets. Note that while $newmarket_{it-1}$ and $newprod_{it-1}$ are specified as count variables, the use of firm-fixed effects means that we need to interpret those variables as the effect of a change in the number of markets or products on the change in y. An extension of the above model would be to disaggregate the export intensity variable into the sales in existing markets with existing products, sales in new markets with existing products, sales in existing markets with new products, and sale in new markets with new products. We propose the DIT run this extension as a robustness test initially.

Fifth, our main independent variable of interest, ex_{it-1}, is defined as the ratio of exports to turnover. We prefer export intensity to an estimation with (gross) export levels because any £ increase in sales is likely to increase the economic outcome measure of interest. By using the ratio, we are testing whether the effect of an increase in the £-value of exports is different to the effect of a £-increase in domestic

[29] Past values of productivity for firm i are a function of the firm-specific effects that are time invariant, therefore OLS estimation of equation would yield biased and inconsistent estimates due to endogeneity (Nickell, 1981). While fixed effects estimation removes the firm-specific effects (θi), the estimates remain biased and inconsistent if T is small as lags of the dependent variable are correlated with the average value of the error term, even if it is not serially correlated (Baltagi, 2005).

sales. Also, the impacts of an increase in exports is likely to be more important for firms that export a high share of their total production, so using an intensity measure again makes sense Moreover, expressing exports relative to turnover means DIT will not have to deflate the export variable. Finally, the export intensity measure is easy to interpret and a relatively widely accepted measure. Note that if the DIT intends to investigate whether impacts differ for different product categories, normalising exports by domestic production of the same product would be conceptually preferable to using turnover. However, this would require the DIT to further match their dataset to the ProdCom database (see also Section 4).Sixth, and related to the previous point, it is important to acknowledge that movements in the export intensity variable reflect changes in both exports and total turnover. If, hypothetically, domestic sales increase but export sales do not increase, or increase by less than domestic sales, the ratio will go down even though exports have not fallen. Therefore, we propose to add logged firm-level turnover as an additional explanatory variable to the model as a robustness test. If multicollinearity is an issue, logged domestic turnover could be used instead. Moreover, in addition to adding logged turnover to the above specification, we also propose to run a robustness test whereby logged exports (in levels) and logged turnover (or logged domestic turnover) enter the specification instead of the export intensity variable. The reason we propose to do this as a robustness test only is that export intensity and turnover will be correlated, and collinearity might lead to imprecise estimates.

Seventh, we do not log the export variable (ex_{it-1}) here. This means that a one percentage point increase in the ratio may be assumed to have the same effect on the dependent variable irrespective of the level of the ratio. For example, an increase in the export intensity from 2% to 3% is assumed to have the same effect than an increase in the export intensity from 50% to 51%. Similarly, we assume that the impact of adding one new market is the same regardless of whether a firm changes from 2 to 3 markets or from 50 to 51 markets. Under the alternative specification (logged export intensity ratio), one would instead assume a constant elasticity of the impact measure with respect to the ratio, so that an increase in the export intensity from 2% to 2% (50% increase) would be assumed to be the same as an increase from 50% to 75% (also 50% increase). We prefer not logging in this case, as unlogged export intensity is a widely accepted measure, and because the interpretation of one added product/market is more convenient than the interpretation of a %-increase in the number of products. The constant percentage point change moreover makes sense if the sample is limited to large exporters, which are assumed to have relatively comparable export intensity ratios. Similarly, constant impacts of added markets makes sense if markets are defined in terms of, for example, world regions or continents rather than individual countries. However, we note that the theory is not prescriptive in this case, and our recommendation would be for the DIT to investigate the relationship between export intensity and the outcome measure in the data to examine whether a linear (not logged) or non-linear (logged) relationship seems more appropriate.

Eighth, control variables (vector X_{it}) are specific to the impact measures and all continuous control variables are logged. We specify the model above in its most general form, given that the DIT did not wish to focus on a particular economic outcome measure at the time of writing. However, we believe that the learning-by-exporting hypothesis best be explored by investigating the impacts of exporting on productivity, which is in line with the vast majority of the literature. We therefore provide an overview of how to measure productivity, and what control variables to include in a regression of productivity on (lagged) export intensity, in Section 4, when discussing recommended datasets.

2.3 Defining the sample

We recommend that the DIT estimates equation (1) for large exporters only. This is in line with the underlying research question of how exporting more will translate into higher direct effects for large exporters (rather than difference between large exporters and large non-exporters).
Estimating the sample for large exporters only further is more appropriate given the interpretation of the export intensity coefficient in the above model, which implies a constant percentage point impact of increased export intensity. We believe that this assumption is more appropriate for the sample of existing large exporters, as there might be level effects from starting to export.

Finally, limiting the estimation to the sample of large exporters means we do not have to make any additional assumptions about the export value for firms that could not be matched between the various datasets. In particular, if we only look at large matched firms for which we have export data, we do not have to assume that non-matched firms have an export value of zero.

It is worth clarifying here that large exporters in the context of the present report are defined as large firms that also export (rather than firms with high export values, or firms for which exports account for a high share of their total sales). From an estimation perspective, it is not particularly important of how ‘large’ exporters are defined, apart from potential implications for the sample size (the higher the threshold, the smaller our sample size). In the existing literature, the thresholds are not set uniformly. Yashiro (2009) measures large and medium firms as firms with more than 300 employees, small firms as firms with less than 300 employees. Damijan, Kostevc and Polanec (2010) define small firms as firms with 10-50 employees, medium with 50-200 employees, large firms are defined as firms with over 200 employees.

Given this flexibility, we propose that the DIT use the official definition of large companies (250+ employees) as a starting point.

It is worth mentioning that many of the academics consulted for this project expressed a preference for not giving up the opportunity to compare the effect for large firms and small firms by running estimations on the full sample and for different firm size samples. If the DIT’s research focus changes in line with those recommendations, and if the Department has the resources available, we would therefore recommend to estimate the model for different samples, for example, for different turnover brackets.

2.4 Implementing the estimation approaches

As discussed above, we propose that the DIT initially estimate the model presented in equation (1), but excluding the lagged dependent variable, using static panel data techniques.

We recommend that the DIT start by estimating the equation using pooled OLS, random effects and fixed effects estimators, using cluster robust standard errors at the firm level. The Stata commends for implementing those estimators are *‘reg’, ‘xtreg, re’,* and *‘xtreg, fe’,* respectively. Next, we propose that the DIT run the Breusch and Pagan LM test and Sargan-Hansen test to decide with what estimator to proceed.

Next, it would be advisable to determine the optimal lag structure for the exporting variable in the static model. The optimal lag structure should be chosen based on information criteria and significance or different lags.

Finally, the full dynamic model (that is, the model including all the relevant variables, including lagged variables) should be estimated, with the preferred static panel estimator and then the preferred GMM-DPD estimator. The most commonly used GMM-DPD estimator in the literature is the system GMM estimator. System GMM estimation is generally preferred to the difference GMM procedure because it addresses the problem of weak instruments that may arise in the difference GMM approach due to a lack of correlation between the instrumental variables and the regressors in the first-difference model[30]. The most commonly used Stata code for implementing the system GMM estimator is ‘*xtabond2’.* An alternative command available in more recent Stata versions is *xtdpd.*

System GMM estimations are quite complex, and involve a series of choices.

One has to specify what the endogenous variables are that need to be instrumented, and how many lags of a given instrument will be used. In the LBE literature, continuous variables such as export intensity, productivity, human capital, and firm size are usually treated as endogenous (Lööf and Nabavi, 2013: 9). One important consideration when specifying the instruments is that the number of instruments does not exceed the number of panels. However, the cost of having fewer instruments is that the model has less explanatory power.

Other choices that need to be made is whether to estimate the differenced both a differenced and levels equation; whether to use robust standard errors or not; and at what level to cluster observations.

[30] The problem of weak instruments arises using the difference GMM approach if the dependent variable shows a high level of persistence over time. The difference GMM approach regresses the differenced dependent variable on lagged levels of variables that serve as instruments. However, if the dependent variable is highly persistent in levels, the instruments in levels contain little information about the future values of the differenced dependent variable.

Post-estimation, one should check whether the number of panels exceeds the number of instruments; whether there is second-order auto-correlation (AR test); and whether the variables are exogenous (difference-in-Hansen test).

We note that the Stata helpfile for *xtabond2* is an excellent resource. Further details can moreover be obtained from the authors of this report.

2.5 Regional impacts

In order to estimate whether the direct impacts of large exporters differ depending on where in the UK the exporter is located, we propose to add interaction terms between region dummies and ex_{it-1} (and potentially the interactions of ex_{it-1} with the dummy variables).

As previously noted, the lack of official plant-level data on productivity measures means that we sometimes only observe the headquarter location of a reporting unit in the data. While we minimise this issue by estimating the equation at the lowest level at which data is available, we propose to re-run the estimations for the sample of single-location (single-luref) reporting units as a robustness test. This might prove difficult in practice, given that we investigate large firms only.

Moreover, the DIT might run into issues if the number of large exporters in a certain region is too small to meet the ONS' disclosure requirements. In particular, the DIT might not be allowed to use their estimates if the underlying sample sizes are too small.

2.6 Robustness tests

In addition to using both common static panel estimators in addition to a system GMM approach, we proposed several robustness tests throughout this part of the report. In summary, we propose that DIT:

- re-estimate the main model at both the enterprise and enterprise group level (or, alternatively, at a pseudo-enterprise level, using a combination of enterprises and enterprise groups, in line with the current project carried out by the University of Sussex);
- re-estimate using different lag lengths to address concerns of endogeneity and conceptual uncertainty about how long impacts take to materialise;
- re-estimate using logged exports and logged turnover, or logged exports and logged domestic turnover, instead of export intensity;
- re-estimate for different lag lengths for the instruments used in the system GMM approach;
- re-estimate (regional) specifications for single-location reporting units;
- re-estimate separately for exporters of goods and exporters of services;
- re-estimate for alternative product category or destination market sub-samples;
- re-estimate for different firm-sizes or different definitions of 'large' exporters; and
- re-estimate using an IV approach (for example by constructing firm-level export demand shocks using the approach proposed in Aghion et al., 2019).

2.7 Limitations

The static panel data methods proposed in this section are relatively straightforward to implement, however, they cannot be used for causal inference in the context of the present research questions.

We therefore propose to use a system GMM estimator to test whether any correlations uncovered through static panel approaches can be interpreted as causal effects.

However, the validity of GMM-DPD estimation relies on the exogeneity of the instruments, that is, the values of the instruments are independently distributed of the error process. This can be checked using the Sargan-Hansen test, which tests the null hypothesis that the joint validity of the moment conditions is equal to zero.

Another potential issue with estimating system GMM regressions is the proliferation of instruments. In particular, Roodman (2009) reports the issues faced when too many instruments are used in a system GMM framework. Specifically, instrument proliferation can lead to over-fitting instrumented variables and imprecise estimates of the optimal weighting matrix, which leads to biased standard errors and weakens the Hansen specification test. These issues will be overcome by using principal components analysis to limit the instrument set. Additionally, the Windmeijer (2005) finite-sample correction in the two-step estimation is used to correct the downward biased standard errors due to the use of too many instruments.

Arguably the most important limitation of the system GMM estimator is that system GMM results are not always transparent, with results sometimes being sensitive to the assumptions made by the researcher about the lag structure.

Finally, the regional impacts estimation might be compromised by the fact that we do not always have the physical location of a given reporting unit.

3. Recommended estimation approach for estimating the indirect impacts of large exporters

3.1 Selecting an appropriate estimation approach

We propose that the DIT estimates the spillover effects associated with large exporters' export activity based on a firm-level panel approach, whereby firm-level outcome measures are regressed on a set of variables that capture the export activity of large exporters in the same sector (horizontal spillovers), upstream or downstream sectors (vertical spillovers) and the same region (regional spillovers).

This approach is preferred to an IO-analysis approach, because it allows for robust causal inference and because it allows to investigate the main impact measure of interest, productivity. It is further better adaptable to the DIT's specific research questions and as such is preferred to both an IO-analysis approach and sector-level panel estimations. In contrast to both alternatives, it allows to investigate the spillover impacts associated with specifically large exporters; it allows to determine the spillover impacts on specific sub-set of firms (SMEs, or low-/high-productivity firms); and it allows for the estimation of regional impacts.

Another advantage of using our preferred approach is that the DIT can use the same datasets that are used to estimate the direct impacts. Hence, even though the firm-level panel approach is more demanding in terms of data requirements compared to the alternative approaches, not much additional data access, cleaning and linking work will have to be undertaken if both direct and indirect effects of large exporters are investigated at the same time.

3.2 Setting up the model

Below, we propose our main model for the estimation of the direct impacts of exporting. We again abstract from the parameters.

$$\ln(y_{it}) = \ln(y_{it-1}) + \ln(X_{it}) + \ln(horizontal_{St-1}) + \ln(backward_{St-1}) + \ln(forward_{St-1}) \\ + \ln(regional_{Rt-1}) + \ln(GVA_{St}) + time_t + \eta_i + \varepsilon_{it}$$

…………………………………………………………………………………………(2),

whereby:

- *Dependent variable, y_{it}*: economic impact measure for firm i at time t;
- *Independent variables of interest:*
    - o *$horizontal_{St-1}$* is a variable capturing the lagged export activity of large exporters operating in the same industry as firm i;
    - o *$backward_{St-1}$* is a variable capturing the lagged export activity of large exporters in the industries that are being supplied by firm I's industry;
    - o *$forward_{S-1}$* is a variable capturing the lagged export activity of large exporters in the industries supplying to firm i;
    - o *$regional_{R-1}$* is a variable capturing the lagged export activity of large exporters in the same region as firm i;

- *Control variables*
  - y_{it-1} is the lagged economic impact measure for firm i at time t-1;
  - X_{it} is a vector of control variables for firm *i* at time *t*. These are listed in Section 4 of this Part of the report;
  - $time_t$ are time-specific effects (world economy, national economy, trade liberalisation, GVC);
  - GVA_{St} is sectoral GVA, and used in addition to time dummies to control for macro-economic shocks that might only affect individual sectors and hence not be captures through the time dummies;
  - μ_{it} is a firm-specific fixed effect; and

  ε_{it} is the error term.

Several things are worth noting here.

First, careful consideration needs to be given as to how spillover variables are specified. Options are to either define export activity in an industry or region in terms of the number of large exporters, or the value of large exporters' exports. Given that the DIT is interested in the spillover impacts of existing large exporters in the first instance, assessing the spillover effects associated with a change in the export value by large exporters is more appropriate.

Secondly, spillover variables ($horizontal_{St-1}$, $backward_{St-1}$, $forward_{St-1}$ and $regional_{Rt-1}$) are again lagged by one period. This is because we assume that spillover impacts take time to materialise. As before, we propose that the DIT experiment with alternative lag lengths.

Third, in line of our approach to specifying ex_{it-1} in equation (1), we again specify the export spillover variables as ratios relative to total turnover of large exporters in the same sector, upstream or downstream sectors, or region. This is to account for the fact that the same £-amount of exports is unlikely to have the same spillover impacts in large compared to small sectors. Moreover, expressing exports relative to turnover means DIT will not have to deflate the export spillover variables.

Fourth, and again in line with the direct effects model, we do not log the spillover variables. This means that a one percentage point increase in the ratio may be assumed to have the same effect on the dependent variable irrespective of the level of the ratio.

Fifth, we investigate the indirect impacts of exporting along four dimensions, all in the same model. In particular, we have separate spillover proxy variables for horizontal, vertical, and regional spillovers. The advantage of estimating spillover impacts along the four different dimensions simultaneously is that spillover impacts are assessed while controlling for the impacts of other spillover transmission channels. However, if the spillover variables are highly collinear, estimating the model with all four spillover variables included may lead to some problems. We therefore propose that the DIT examine the correlation of the four spillover variables, and if necessary, estimate equation (2) separately for the different spillover types.

Sixth, careful consideration needs to be given as to the level of sector disaggregation. At high levels of sector-aggregation, the framework may conflate inter- and intra-sectoral spillovers, hence more granular sector definitions are preferred. At too granular levels of sector-aggregation, we might not have enough observations and estimates might pick up random noise rather than actual spillover impacts. We propose that the DIT defines spillover variables at the 2-digit SIC level (for example C.10 – Production of food products).

Seventh, we control for both observable and unobservable firm-level characteristics that may also determine productivity to improve identification of the spillover impacts. Control variables (vector X_{it}) are specific to the impact measures and all continuous control variables are logged. We do not include either region or industry dummies, because those should be subsumed in firm-level fixed effects.

Eight, it is worth noting that we do not control for the direct effects of exporting by adding firm-level exports in equation (2), because we propose to estimate the model for the sample of (small and medium) non-exporters only (see also below). This more directly addresses the DIT's research question, and helps simplify the model.

3.3 Defining the sample

We recommend that the DIT estimates equation (2) for **non-exporters only.** This is in line with the underlying research question of how increased export activity by large exporters has an impact on ‘other’ firms in the UK. If the DIT wishes to explicitly investigate the spillover impacts of large exporters on certain types of businesses, such as SMEs or high- or low-productivity firms, the sample could further be reduced to only those types of firms.

Moreover, excluding small (in addition to large) exporters from the sample means that we do not have to control for the direct effects of exporting by adding firm-level exports to equation (2). Estimating for the sample of non-exporters only thus means issues of reverse causality can safely be ignored when estimating the model.

Again, we note that the sample definition depends on the research question and policy goals. For example, one might be interested in comparing spillover effects on exporters vs. non exporters, in which case the sample would have to be redefined accordingly.

3.4 Implementing the estimation approaches

The model presented in equation (2) will be estimated using the same static and dynamic panel estimators as used for the direct effects estimation. In line with the approach to estimating direct impacts, we recommend that the DIT start by estimating the equation using pooled OLS, random effects and fixed effects estimators, using cluster robust standard errors at the firm level. Next, we propose that the DIT run the Breusch and Pagan LM test and Sargan-Hansen test to decide with what estimator to proceed. As a final step, we propose that the DIT use a system GMM approach.

3.5 Regional impacts

In order to estimate whether the spillover impacts of large exporters vary across regions, we propose to re-estimate equation (2) for sub-samples of firms located in different regions of the UK. Sub-samples are preferred here because adding interaction between region dummies and the four spillover variables would make the model unnecessarily complex.

As previously noted, the lack of official plant-level data on productivity measures means that we sometimes only observe the headquarter location of a reporting unit in the data. While we minimise this issue by estimating the equation at the lowest level at which data is available, we propose to re-run the estimations for the sample of single-location (single-luref) reporting units as a robustness test. In contrast to the regional effects estimation for the direct effects, we do not expect this to be problematic, as the sample of non-exporting SMEs is likely to include many single-plant enterprises.

Finally, as mentioned before, the DIT might run into issues if the number of large exporters in a certain region is too small to meet the ONS’ disclosure requirements. In particular, the DIT might not be allowed to use their estimates if the underlying sample sizes are too small.

3.6 Robustness tests

We propose the DIT carry out the following robustness tests for the estimation of indirect effects:

- re-estimate using different lag lengths, because spillover impacts might take longer than one year to materialise;
- re-estimate for different types of firms, as spillover impacts might only accrue to firms with sufficiently high absorptive capacity (high productivity firms);
- re-estimate controlling for ‘other’ export activity, from non-large firms, at the sectoral and regional level;
- re-estimate regional specifications for single-location reporting units;
- re-estimate separately for spillover impacts from goods and services exports; and
- re-estimate spillovers for specific product categories or export destinations.

3.7 Limitations

Our proposed approach is in line with the literature investigating the impacts of FDI and previous DIT work in this area (DIT 2018, 2021).

The same limitations to the static panel approaches and GMM-DPD approach as discussed in the previous section apply.

A disadvantage of our proposed model is that DIT might run into issues of multi-collinearity when including up to four export spillover variables at the same time. This would be the case if sectors are regionally concentrated, for example, as the regional and sectoral export activity variables would then be strongly correlated.

The proposed approach moreover does not always allow to establish the transmission channel for the observed impacts. For example, the export activity in a sector might have spillovers on firms in the same sector through either competition or knowledge transfer effects, and judgement will have to be used when interpreting the results.

As previously discussed, the regional estimations might moreover be imprecise due to the lack of region-level datasets on the outcome (and control) measures of interest.

4. Recommended datasets

4.1 Selecting the appropriate datasets

We recommend that the DIT carry out the econometric analysis of the direct and indirect impacts of large exporters based on three ONS datasets: TiG/IDBR, ITIS, and ABS. If firm-level R&D activity is of interest as an outcome measure, or to be included as a control variable, matching the dataset to the BERD would further be required.

Given that the TiG/IDBR dataset represents ONS researchers' attempt to match HMRC OTS and ONS data in the best possible way, and in light of the various robustness tests conducted by the authors of the Wales et al. (2018) paper to test the robustness of their dataset to the allocation assumptions made, our recommendation is for the DIT to use the existing TiG/IDBR dataset rather than the underlying HMRC OTS data. While this choice implies that the modelling period covers 2007[31]-2016 only, we believe that the use of the TiG/IDBR both represents both the most robust and the most pragmatic solution. However, going forward, we recommend that this choice be reviewed (for example, if the analysis is repeated by the DIT in subsequent years, but the ONS does not update the dataset, setting up an internal HMRC to ONS data matching code within DIT might be preferable.

If services are to be covered, the TiG/IDBR has to be matched to the ITIS as the only dataset available for the UK that covers exports of services at the product and destination country level.

Finally, we prefer the Annual Business Survey to alternatives such as the ARDx because this allows to cover at least 2015 and 2016 in the modelling period.

TiG/IDBR, ITIS and ABS are all reporting-unit level datasets, and as such, matching the three datasets based on reporting unit identifiers and year should be possible. In order to carry out robustness tests at the enterprise and/or enterprise group level, we would propose that the DIT *collapse* those datasets at the entref and/or group level, removing any enterprises/groups where not all reporting units are surveyed in a given year.

For the estimation of spillover impacts, we propose that the DIT aggregate the firm-level export data from the TiG/IDBR and ITIS datasets to create variables that capture the export activity of large exporters in a given (same, upstream or downstream) sector or region. This is preferred to the use of readily available macroeconomic data series, which are not broken down by firm size for services (TIS), and not broken down by both firm size and region for goods. Moreover, the DIT likely wishes to test whether impacts are different for different product categories or destination markets, and a bottom-up approach to defining those variables allows for more flexibility.

We further recommend that the ONS make use of national input-output tables to create the weights for creating the backward and forward spillover variables. For example, if Sector A sources 20% of inputs

[31] TiG/IDBR is available from 2005, but ABS is only available from 2007.

from Sector B, and 80% from Sector C, then in order to create the forward spillover variable, DIT would create a weighted average of 20% of Sector B's and 80% of Sector C's normalised export activity.

We note that we think IO tables are preferable to the APS data for the purposes of deriving those variables, because we are interested in the supply-chain relations of (and spillover impacts on) small and medium-sized firms. These firms are unlikely to be covered regularly in the APS, so that the latter is less appropriate for creating the weights.

4.1 Selecting the appropriate variables

While the DIT has not committed to a particular economic impact measure at the time of writing, we recommend that they start by examining the productivity impacts of large exporters.

The learning-by-exporting hypothesis can most directly be assessed by looking at productivity impacts, and the majority of the existing literature finds that productivity impacts are important.

Firm-level productivity measures can be obtained from the ABS. One option would be to look at apparent labour productivity, which is defined as GVA per employee, and which can easily be calculated based on two ABS variables. A slightly more complex undertaking would be to estimate TFP as a residual of a production function estimation, using ABS variables on gross output, employment, capital[32], and input materials. We propose that the DIT start by estimating impacts on apparent labour productivity.

The table below provides an overview of the firm-level control variables that should be included when investigating the direct and indirect impacts of exporting on productivity. These are to be considered in addition to the control variables introduced in the model specifications in Sections 2 and 3 of this part of the report.

Table 18: Control variables for estimation of direct and indirect impacts of exporting

Variable	Why required	Used by	How measured	Dataset
Lagged productivity	Eliminate the effect of serial dependence on productivity.	Greenaway and Yu (2004)	TFP or GVA per worker	ABS
Number of employees	Differences in firm size may have an impact on productivity	Lööf and Nabavi (2013);	Number of employees	ABS or BRES
Quality of employees	Firm level labour characteristics will directly affect productivity and must be controlled in order to isolate the effect of exporting.	Andersson and Lööf, (2009)	Average wages	ABS
Knowledge employees	This is a proxy used to control for R&D efforts, as a firms knowledge stock should be positively related to its ability to absorb knowledge capital and returns to productivity	Andersson and Lööf, (2009); Andersson, Lööf and Johansson (2008); Lööf and Nabavi (2013);	Number of employees working in R&D	BERD

[32] The ABS only covers capital expenditure, not capital stocks, so stocks would have to be created based on flows in order to derive a TFP measure at the firm level.

	enhancing investment.			
Capital	Firm investment in machinery and capital may directly affect productivity and must be controlled in order to isolate the effect of exporting.	Andersson and Lööf, (2009); Lööf and Nabavi (2013);	Annual investment in machinery and capital	ABS + public GFCF data for deflation
Capital structure	It is assumed that higher interest expenditures, due to increased leverage, will leave less room for investment expenditure having a negative effect on productivity.	Andersson and Lööf, (2009)	Total debt over total equity	ABS
Imports	When export status is being considered it is necessary to include imports as a control in order to identify the effect a foreign market has on productivity due to a particular export strategy.	Andersson and Lööf, (2009)	Value of imports, normalised by turnover	TiG/IDBR
Foreign ownership dummy	Corporate ownership structure may have an impact on the productivity levels of employees. MNEs may also have greater knowledge diffusion through intra-group networks	Andersson, Lööf and Johansson (2008); Lööf and Nabavi (2013);	Dummy variables based on country of global ultimate owner	ABS

4.3 Limitations

There are several limitations on the data side.

First of all, the microdata used for the purposes of the present analysis is limited in terms of temporal, sectoral and geographical coverage.

In terms of firm-level export data, the existing TiG/IDBR dataset only covers years from 2005 up to 2016, and it is not clear at the time of writing whether and when this dataset will be updated. ABS coverage is limited to 2007-2019.

In terms of sectors, the ITIS excludes the travel, transport and banking sectors, while the ABS only has limited coverage of the financial services sector.

Finally, the ABS and ITIS is accessible to researchers through the ONS SRS environment is limited to Great Britain, rather than the UK, due to the lack of comparable data for Northern Ireland.

More broadly speaking, our recommendation is for the DIT to combine multiple datasets, or use datasets that have been derived based on multiple sources. It is important to note that the various dataset differ in terms of underlying methodologies and definitions, and inconsistencies might potentially bias results. For example, we propose to estimate impacts based on the ITIS, which relies on self-reported trade, and HMRC data that is derived based on VAT records.

As discussed at multiple points throughout this report, the matching of HMRC export data to ONS datasets moreover relies on some important allocation and matching assumptions, which might to some extent introduce spurious correlation between the exporting and economic impact variables.

Finally, obtaining meaningful estimates at the sub-national level will be particularly challenging. Estimating the regional impacts of large exporters would benefit from plant-level information on exports and performance measures, because of a potential discrepancy between headquarter and plant location that remains unobservable in the data. However, there currently is no plant-level data available for the UK. Moreover, the DIT will have to consider potential issues of confidentiality and disclosure when producing regional estimates, as the ONS currently does not allow researchers to produce estimates for small samples.

ANNEXES

Annex 1 References

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Annex 2 Further evidence on the impacts of exporting

In addition to the studies discussed in the main body of this report, there exist a number of studies estimate the relationship between exporting and firm-level productivity using OLS regression or simple correlation analysis. Given that those studies to not manage to establish causality, we report their findings only as an Annex to the main report. Overall, however, it is worth noting that the findings reported here to align with the findings presented in the main report.

Direct Effects

Correlations Between Exporting and Productivity

A number of studies estimate the relationship between exporting and firm-level productivity using OLS regression analysis.

Hagemejer and Kolasa (2008) examine the performance of internationalised firms using data from Polish firms. They investigate internationalisation with respect to FDI, exporting and importing of capital goods. They find positive and significant association between exporting and labour productivity, as measured by value added per worker, and total factor productivity.

Karampini (2020) conducts OLS on a fixed effects model using a sample of Greek firms to estimate the direct impact of exporting on labour productivity. the author conducts OLS regression analysis on a fixed effects model. They find a positive productivity premium associated with participation in the export market of 23.6%.

Tavares-Lehmann & Costa (2015) report similar results in their analysis of Portuguese firms.

Hahn (2004) examines the relationship in Korean manufacturing plants they find that exporting is significantly and positively associated with total factor productivity in the medium term but is insignificant in the short or long term.

Imbruno (2008) analyses both the learning-by-exporting hypothesis and the self-selection hypothesis in a sample of Italian firms. Using OLS regression analysis, they find no evidence of a post-entry exporting premium on labour productivity. However, they do find evidence of positive labour productivity effects on exporting pre-entry, therefore supporting the self-selection hypothesis.

Garcia et al. (2012) analyses the productivity effects of exporting and whether a firm's technological capabilities affect its ability to learn from exporting. Using OLS regression analysis, they find that exporting is associated with higher labour productivity and total factor productivity. They also find that the effects of stronger for firms that invest more heavily in R&D.

A small number of studies examine the effect more broadly by investigating the relationship between modes of internationalisation and productivity. Dobbelaere and Kiyota (2017) examine the effect of internationalisation on firm performance by means of OLS regression and quantile regression. Using a sample of Japanese manufacturing firms, they find that exporting is associated with a 13% labour productivity premium, measured by value added per employee, and 2% TFP premium. The authors also break down their results by industry, showing that the TFP premium for exporting firms varies between 0.5% for transport and 5.1% for electrical machinery.

Similarly, Ferrante and Freo (2012) also examine the total factor productivity gap between international and domestic firms by means of quantile regression in a sample of Italian firms. They estimate the productivity premium for different modes of internationalisation (exporting, commercial penetration, and FDI or offshoring) and find that exporting firms are associated with a positive productivity premium of around 4% on average, but this figure is smaller in comparison to the premium associated with the remaining modes of internationalisation.

Mataloni (2011) examines the relationship between US multinationals' global engagement and their productivity, while controlling for a variety of factors associated with high productivity US business establishments. They attempt to isolate size of the productivity advantage associated with each degree of global engagement, varying from having no exports or foreign affiliates, to exporting, to having a highly developed network of foreign affiliates. By means of OLS regression, they find that higher productivity is associated with firms with greater global engagement. Establishments of non-multinationals that exported were between 9.2-34.7% more productive than establishments that did not export, this result was especially pronounced for service industries.

Giordano and Lopez-Garcia (2019) examines cross-country differences in learning-by-exporting effects from trade in EU countries. Using OLS regression analysis, they find exporting firms are larger and more productive than non-exporting firms. Additionally, opening to trade boosts individual firms' productivity growth via a number of channels, and enhances allocative efficiency across firms, in turn increasing aggregate productivity growth. Looking at the differences between continuous exporters (old EU states) and new exporters (new EU member states), they are significant and range from 0.07 percentage points in additional annual TFP growth in old EU members (0.16 percentage points in new members) to 0.16 percentage points of additional labour productivity growth (0.1 percentage points in new members).

Ruane and Sutherland (2005) investigates the relationship between exporting labour productivity in a sample of Irish manufacturing firms. By estimating a random effects model using OLS regression analysis, they find no significant evidence that exporting effects firm's labour productivity post-entry. The authors go on to hypothesise that exporting to destinations outside of the UK will present significantly greater learning effects. They do find positive and significant estimates on a variety of performance indicators including labour productivity and average wages; however, these were largely driven by self-selection.

Similarly, Li, Warzinksi and Smeets (2019) also demonstrate that revenue-based total factor productivity results in insignificant evidence of exporting effects due to the bias caused by prices in a sample of Chinese manufacturing firms. Using OLS regression, they find a strong positive export premium when considering the physical productivity measure. The size of export premium is larger when using more sophisticated methods dealing with endogeneity. There is no positive export premium when considering the revenue-based productivity measure because exporters charge lower prices on average. The authors also break down the results for firms involved in processed trade and ordinary trade. They find that when looking at revenue-based productivity, firms involved in ordinary trade are less productive, followed by firms only doing processed trade, and both have lower revenue productivity than non-exporters. For the quantity-based productivity measure, the reverse is true.

Pham, Woodland and Caselli (2018) examine the behaviour of intermediate suppliers facing final producers, comparing suppliers to multinationals and exporting suppliers to purely domestic suppliers.

For a sample consisting of firms from 29 European and Central Asian countries, they apply a Seemingly Unrelated Regression (SUR) estimator via Maximum Likelihood estimation for five various outcome measures. They find that labour productivity is 23.4% higher for exporting firms than non-exporting firms. These results are found using ex-ante productivity, which provides evidence for the self-selection hypothesis, not causal evidence for the LBE hypothesis.

Correlations Between Exporting and Output

A number of studies also estimate the correlation between exporting and other firm-level performance outcomes such as output using OLS regression analysis.

Hagemejer and Kolasa (2008) also include sales and capital in their analysis on Polish firms and find positive and significant association between exporting and sales and capital.

Correlations Between Exporting and Innovation

Love and Ganotakis (2013) examine the learning-by-exporting hypothesis by investigating the effect of export activity on innovation in a sample of UK high-technology SMEs. Using regression analysis, they find at exporting firms have a 15% greater probability of engaging in innovation in the next 3 years than non-exporting firms. However, this effect is not found to be significant for the impact on innovation intensity. The authors breakdown their results by considering whether the effect is different for manufacturing and services sector firms. They find that exporting is positively associated with innovation in both sectors, however service sector firms learn from exporting earlier than manufacturing sector firms, to exhibit learning gains from exporting, manufacturing firms require persistence.

Wang et al. (2020) examines the effect of exporting on innovation by estimating the learning-by-exporting (LBE) and the learning-by-technology-importing (LBTI) effects in Chinese emerging market firms. Using OLS regression analysis, they find export status is positively associated with a higher level of both product and process innovation.

Xue and Zhou (2020) similarly conducts both OLS regression analysis and propensity score matching to examine the effect of exporting on corporate innovation for Chinese listed firms. They estimate the effect of export intensity, measured by international sales, on number of patent applications. A 1 percentage point increase in foreign sales ratio results in 0.23-0.32 additional filed patent output. They find that the direct impacts of exporting are more pronounced amongst firms with high financial constraints and located in places where talents, technological resources, institutional environment are more favourable.

Correlations Between Exporting and R&D

A number of studies estimate the correlation between exporting and R&D. Onkelinx and Sleuwaegen (2010), Hahn (2013) and Patterson (2004) use OLS regression analysis to examine the effect of exporting on R&D spending and find an overall positive relationship, however in Hahn (2013) this effect was only significant for one period.

Correlations Between Exporting and Employment & Wages

Guannan et al. (2020) investigate global value chains and the distributional effects of trade in Finland in a report published by the OECD and Statistics Finland. Using a range of data sources including linked microdata, international trade statistics and Finish Supply and Use tables, the report offers a granular view of the impacts of globalisation and trade on business and employment outcomes. They find that globalisation has had an overall mixed effect on Finish employment. In particular, the growth in jobs in exporting firms in the services industries appears to have mitigated job losses in exporters in the manufacturing industry. This has meant the share of jobs supported by exports has remained relatively steady at around 1 in 5 jobs.

Mayer and Ottaviano (2008) examine firm-level datasets to analyse how exporting and FDI-making firms differ from domestic ones based on data from the EFIM Report 2007. They find that there are few ‘superstars’ firms accounting for the majority of exports, suggesting that the extensive margin matters more than the intensive margin. Comparing exporters with non-exporters, they find that exporters display premia for employment, value added, wage, capital intensity and skill intensity in all countries of interest (Germany, UK, Italy, France, Belgium, Hungary, Norway). Generally, exporters perform better than non-exporters, and FDI-makers perform better than exporters.

Sala-Rios et al. (2020) examines how exporting cooperatives perform relative to non-exporters using a sample of cooperatives in Spain. Using pooled OLS and fixed effects models, they find largely no significant effects of exporting on post-entry performance. The estimates were found only to be significant for employment, which indicated that employment growth was 4% faster in exporting cooperatives than non-exporters. However, these estimates cannot be interpreted causally.

Several papers that studied the impact of exporting on productivity also including data on firm-level wages in their analysis. The majority report correlation relationships, with only Wager (2002) investigating a causal effect. Wagner (2002) finds strong evidence in support of a wage premium for exporting firms.

Using OLS regression analysis, Hagemejer and Kolasa (2008) find positive and significant association between exporting and wages. Karampini (2020) finds a positive wage premium associated with participation in the export market of 38.6%.

Hahn (2004) also find a positive relationship between exporting and employment growth that is significant across the estimation time period.

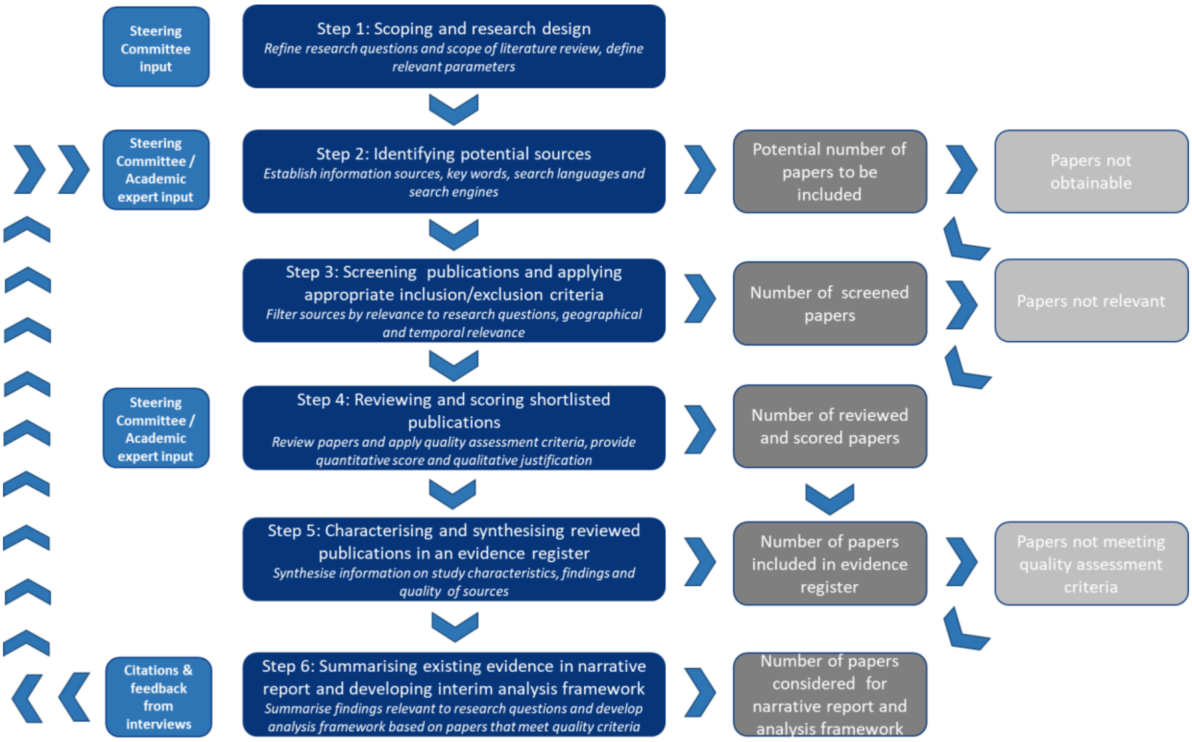
Dobbelaere and Kiyota (2017) examine if the type and degree of labour market imperfections vary across firms that differ in terms of internationalisation by means of OLS regression and quantile regression. They find that wages are on average 9% higher for exporting firms. Regarding market imperfection, differences in product and labour market imperfections between exporters and non-exporters vary across firms. Exporters are more likely to share rents based on the bargaining power of workers relative to non-exporters, but less likely to share rents based on elasticity of labour supply curve facing an individual employer. This suggests that workers' bargaining power, rather than search frictions, seem to be important in generating wage dispersion across firms.

Annex 3 Literature review approach

This section outlines our approach to assessing the existing literature on the direct and indirect effects of (large) exporters on the wider economy.

Our approach can be broken down into six key phases, which are outlined in the figure below and further discussed in subsequent sections.

Literature review flow chart



Source: London Economics

Step 1: Scoping and research design

The literature review serves a dual purpose.
On the one hand, the literature review will allow us to summarise existing evidence on the relationship between exporting, firm-level economic outcomes (direct effects), and wider economic outcomes beyond the exporting firm (indirect effects) at a local and national level.
On the other hand, the literature review will reveal what estimation methods and datasets have been used by other authors to robustly estimate the direct and indirect economic impacts of exporting, again at the local and national level.
More precisely, the literature review serves to answer the following research questions:

1. What is the relationship between exporting, firm-level economic outcomes (direct effects), and wider economic outcomes beyond the exporting firm (indirect effects)?
    a. What are the key findings and evidence gaps?
    b. What transmission mechanisms explain these links, how long do they take to materialise and how long do the effects persist?
    c. What are the effects at the national vs. local level?
    d. How do these effects vary by regional disaggregation and/or region?
    e. How do these effects vary by firm characteristic (size, sector, location, export market, export experience)?
    f. What are the economic outcomes (positive or negative) important to consider when assessing the impact of exports on the economy?
2. How are the economic impacts of exporting on large exporters estimated (direct effect); and beyond to how are the wider economic impacts (indirect effects) estimated at a local and national level?
    a. What are the data and methodological challenges to consider what are the potential data sources available?
    b. What are the strengths and weaknesses of these datasets?
    c. What are the potential estimation approaches that have been used or can be used?
    d. What are their strengths and weaknesses?

In order to focus the literature review and define appropriate search terms and inclusion/exclusion criteria for later stages, the first phase in the review will involve a clear description of the research questions and definition of relevant parameters, including a discussion of:

- Whether the review is to focus on existing evidence on large exporters or evidence on the impacts of exporters (small as well as large) more generally;
- Whether the review is to focus on the impacts of exporting, or consider impact assessments in related policy areas;
- How we define large exporters;
- What the impacts of interest are (direct vs. indirect vs. induced), and how those impacts are defined;
- Whether the variable of interest is the extensive or the intensive margin of export (whether we are interested in the impact of the decision to initiate exporting, or the impact of various degrees of exporting);
- What the economic impacts of interest are; and
- Whether and how we further want to distinguish impacts by the nature of the exported product (good vs. service, new vs. existing product, final vs. intermediate good, sector, etc.), firm characteristics (size and others), and geographic markets

Our initial suggestion is to:

- Consider literature on the impacts of exporting more generally, as there is likely only limited evidence available on the impacts of large exporters;
- Consider including methods used for the assessment of direct and indirect impacts in other policy areas, and in particular include the wider literature on the impacts of different forms of internationalisation (not just exports but also imports, foreign direct investment) and the literature on the impacts of export shocks if methods are relevant and transferrable;
- Define 'large' exporters as UK businesses with more than 250 employees that also export, but add a further distinction between systematic and opportunistic exporters;
- Include both direct and indirect effects in the analysis, but exclude induced effects;
  - Define the direct effects of exporting as the impacts accruing to the exporters themselves as a direct result of the decision to export;
  - Define the indirect effects of exporting as the spillover impacts accruing to other firms, without being prescriptive in terms of the transmission channel so as to include indirect on i) firms in the exporters' supply chain, ii) firms in the exporters' region or iii) firms in the exporters' industry.
- Look at both the intensive and the extensive margin of exporting. While we would assume that larger export volumes will yield different impacts from smaller export volumes, and that the former is particularly useful for large firms which may be exporters already, we do not want to exclude potentially relevant papers by focusing on the former only. Including studies on the extensive margin may moreover allow us to draw parallels for large exporters, for example for when large exporters start to export to new geographic areas or new products;
- Consider any impact measures that may be of relevance, including but not limited to employment, wages, capital investment, R&D investment, productivity, growth and survival; and
- Distinguish between exporters of goods and exporters of services, but do not exclude either and refrain from providing further disaggregations unless clear patterns emerge in the literature.

Step 2: Identifying potential sources

The next step of the literature review will involve identifying potential papers to be considered for review. We will identify papers by means of two different approaches: on the one hand, we will employ a formalised keyword search so as to identify any papers of relevance to either of the two main research questions.

On the other hand, we will engage with experts in the field, including DIT project team members, Steering Group members and academic project team members, to identify any papers that might be of relevance to this project in particular as it relates to potential methods that can be employed to *estimate* the direct and indirect impacts of exporting.

Formalised search

First, the data sources to be trawled for research material will be established. Given the research objectives, we propose to consider both the academic and 'grey' literature, covering:

- Academic journal and textbook articles and working papers;
- unpublished academic sources that might be available either as work in progress or presented as part of university or research discussion paper series;
- Research commissioned and published by international organisations, including the United Nations Conference on Trade and Development (UNCTAD), World Trade Organisation (WTO), Organisation for Economic Cooperation and Development (OECD), and International Monetary Fund (IMF) as and if applicable;
- Research commissioned and published by European institutions (the European Commission or European Parliament);
- Research commissioned and published by UK government departments (DIT itself, and other departments such as the Department for Business, Energy and Industrial Strategy (BEIS), Office for National Statistics (ONS) or HM Revenue and Customs (HMRC);
- Research commissioned and published by government departments in comparable countries (export promotion agencies in other European or OECD countries);
- Research published by research centres and platforms in the UK and abroad (the International Study Group on Exports and Productivity (ISGEP), the Institute for Fiscal Studies (IFS), or the National Institute of Economic and Social Research (NIESR));
- Research published by relevant think tanks (the Economic Research Council (ECR)); and,
- Research commissioned and published by representative organisations or associations (the British Exporters Association (BExA)).

We will perform keyword searches on relevant source databases, using keywords relating to the direct or spillover impacts of exporting.

Given that the literature review is to include any existing evidence on the economic impacts of exporting, without making any judgement about the likely economic outcome measures ex ante, we refrain from combining the keywords outlined above with secondary keywords related to potential outcome measures.

Similarly, we do not use any secondary keywords related to the firm characteristics of interest ('large' exporters), as the literature on the impacts of large exporters on SMEs is likely to be very limited.

Finally, we refrain from using words related to "impacts" in our keyword search when searching for literature on exporters or exporting in particular, as there are many synonyms that could potentially have been used by authors ("effects", "influence", "link", "relation", etc.) when describing their research question in the title and/or abstract. However, when consulting the literature on trade or internationalisation more generally, that is, when broadening the keyword search in such a manner that might identify a considerable number of papers in only somewhat relevant research fields, we do add those secondary keywords related to "impacts" and "effects" to make the amount of literature identified more manageable.

Our keyword search approach hence allows us to identify a relatively large number of papers, which are then filtered for relevance to the research questions and other criteria in a second stage only (see below). While this approach implies that the reviewers are tasked with applying their own judgement to filter out potentially irrelevant papers in a second step, we prefer this approach to a narrower keyword search as we deem the risk of excluding papers of potential relevance by means of a combination of several keywords (such as "exporting" and "impacts") too risky.

Given that the keywords are identifying several hundreds of papers, we are moreover pragmatic in our approach and suggest filtering through the first 100 papers identified by each key word/through each search engine.

We provide the final list of keywords to be used in the Box below.

Box 7: Key words

- Learning-by-exporting
- Export spillovers
- Exporters[33]

[33] Includes literature on 'indirect exporters'

- Exporting
- Superstars
- Multinationals
- Trade impacts/effects
- Internationalisation impacts/effects
- Supply chains[34]
- Global value chains

We used Google Scholar for searching for published and unpublished academic articles. Google Scholar is a freely accessible web search engine that indexes the full text or metadata of scholarly literature across an array of publishing formats and disciplines, and it covers, inter alia, other search databases such as JSTOR and ScienceDirect. London Economics as an organisation has subscriptions to many of the journals that will be identified through the Google Scholar search, and the academic project team members are also likely to have access to most relevant journals.

We will further search for the same key terms using the RePEc (Research Papers in Economics) and SSRN databases to identify working papers and other grey material. REPEC is a database of working papers, journal articles, books, books chapters and software components, while SSRN is a platform for the dissemination of early-stage research. In our experience, Google Scholar does not always identify papers covered in those two databases.

We will further apply the same search terms using the search engines on the websites of the previously identified international organisations, European institutions, UK and overseas government departments, public bodies, research centres, think tanks and representative associations.
The keywords will be translated into German, French, Italian, Spanish, Danish, Polish and Swedish, so as undertake a multi-lingual search of existing literature on Google Scholar, RePEc and SSRN (first 20 papers by keyword).

Alternative search approach
In addition to the identification of papers through a pre-specified keyword search, we will ask both the academic experts on the team as well as the DIT project team and the Steering Group members to identify any additional papers of relevance. This in particular relates to literature in related or unrelated policy areas, which might be considered for the purposes of the present study if the methods applied could potentially be used to assess the study's research questions.
Moreover, we propose to further identify sources in an iterative process to as to:

a. Add any 'keywords' that might have been used by authors of either formally or ad-hoc identified authors in their pre-specified key word list, as far as considered relevant;
b. Identify additional sources through the citations of papers making it to Stage 6 of the review (papers that have not been excluded for relevance or quality concerns); and
c. Ask the academic and government experts during the stakeholder consultations for additional papers.

Step 3: Screening potential sources and applying appropriate inclusion/exclusion criteria

When identifying research papers base on the formalised keyword search, the project team will assess the appropriateness of the shortlisted papers in terms of their relevance for the research questions introduced previously. Only studies related the impacts of exporting will be considered and shortlisted in the evidence register, while research papers related to international competition law will be disregarded.

In addition, after completion of the initial trawl for literature, the project team will apply inclusion/exclusion criteria and screen the documents to assess the geographic and temporal coverage. This helps ensure that only the most pertinent research work relating to the impacts of exporting proceeds to the full in-depth review that will form the basis of the recommendation of an estimation approach.

- Geographic coverage: The review will primarily focus on the United Kingdom and its four constituent nations, and international evidence from other European and OECD countries. The impacts of exporting observed in developing countries is less relevant.
- Temporal coverage: We propose to consider a relatively long time period for an exclusion criterion, 2000-present, to start with. Older studies will still provide useful evidence on transmission channels and methods, and they can later be discounted due to age if necessary.

We will include both theoretical and empirical papers in the full review, to the extent that they fulfil the other three inclusion/exclusion criteria.

Note that we will not apply those inclusion/exclusion criteria to any studies identified by i) the DIT project team, ii) the academic project team members or iii) the Steering Group members.

Step 4: Reviewing, characterising and scoring shortlisted publications

The fourth step of the literature involves the full-scale review of the filtered sources.

To ensure that the literature is sifted for quality and validity and that only high-quality research is considered when providing a narrative report of existing findings and developing an estimation approach (Step 6), a scoreboard will be developed to summarise the quality of each source. We propose the following evaluation criteria for the scoreboard: measurement validity, internal validity, external validity and stability and analytical reliability.

In order to standardise the scoring and justification across different reviewers, we propose that a specific set of ‘sub-questions’ be answered/scored for each criterion.

- Measurement validity is concerned with the extent to which variables used in empirical analysis capture the concept of interest. In the context of the present study, for example, an important consideration will be how to measure productivity as one of the key outcome measures, and alternative approaches (such as total factor productivity estimates based on a production function approach or value added per employee) will need to be compared. Measurement validity will be assessed by answering the following sub-questions:
  - *What is the indicator chosen to measure export activity, and is it well suited to measuring it?*
  - *What is the indicator chosen to measure the outcome variable (for example, productivity), and is it well suited to measuring it?*
- Internal validity concerns whether inferences can be drawn from the empirical analysis carried out, within the context of a study. It will be scored vis-à-vis the estimation assumptions and techniques used (we score related sample and data issues, which also might affect internal validity, separately, when assessing external validity and data reliability). For example, one of the main issues with estimating the direct effects of exporting is reverse causality, whereby firms that are more productive choose to export. Failing to account for selection bias through techniques such as propensity score matching, or instrumental variables will lead to upward biased estimates of the economic impacts of exporting. Internal validity will be assessed by answering the following sub-questions:
  - Assumptions
    - *Are the key identification assumptions discussed and defended credibly?*
    - *Are the results sensitive to assumptions?*
  - Causation
    - *Is the estimation method suitable in the context of reverse causality and self-selection?*
    - *What are the control variables used and are they appropriate?*
    - *Are there any biases that are not addressed?*
    - *Scientific Maryland Scale System score*
- External validity concerns whether the findings of one source can be applied more generally. It will be scored by evaluating the sample data used in a single source (is the data nationally representative?) and, more broadly, be judged by whether multiple sources produce similar estimates over different geographies and time periods. External validity will be assessed by answering the following sub-questions:
  - *Is the sample drawn for analysis representative of the wider population?*

Is the sample large enough?

Are there sample selection bias issues (such as failure to account for drivers of selection into treatment, or issues of self-selection bias)?

Data reliability is concerned with the quality of the data used. In the present context, HMRC returns would be the most reliable source, along with company accounts and ONS surveys followed by other survey data. Stability will be scored according to the quality of the data source and any data cleaning techniques described. Data reliability will be assessed by answering the following sub-questions:

What is the reliability of the source (along the lines of the description above)?

Might survey responses be biased?

Is there any evidence of measurement error in the variables used?

Analytical reliability concerns whether the results of a study are robust to different specifications over the same data. It will be scored based on the width of the range of estimates presented. Analytical reliability will be assessed by answering the following sub-questions:

Is the analysis re-produced for alternative specifications (over same sample), with comparable results? (researchers might have to do some calculations to check that alternative estimates are within the confidence interval of the main result)

Is the analysis re-produced using alternative estimation techniques (over same sample), with comparable results?

We will provide both a quantitative score (ranging from 1 to 3) for each source against the sub-questions and a qualitative justification (1-2 sentences) per sub-question. Headline validity/reliability scores will be computed as a simple (non-weighted) average.

The scoring will follow the Department for International Development's (DFID) guidelines as outlined in the table below. Studies with an average score of less than 2 in any of the headline criteria will be excluded from the final analysis.

Table 1 Quantitative scores for quality assessment as per DFID guidelines

Quantitative score	Study quality	Definition
3	High	Comprehensively addresses multiple principles of quality
2	Moderate	Some deficiencies in attention to principles of quality
1	Low	Major deficiencies in attention to principles of quality

Source: London Economics, based on DFID (2014). Assessing the Strength of Evidence.

In addition, we will score papers according to the Scientific Maryland Scale system, which has been used by the DIT in scoreboards developed for other studies. We note, however, that the Maryland Scale System favours particular types of designs and methods over others (such as randomised control trials) that are unlikely to be of relevance in the present study context.

Step 5: Synthesising findings in an evidence register

The fifth step of the literature review is to provide a comprehensive synthesis of existing evidence in the form of an evidence register.

In a first sheet, we will provide a comprehensive list of all screened and shortlisted sources that are of relevance to the research questions. For those, we will indicate:

- Author
- Publication year
- Publication title
- Citation
- URL
- Paper obtained (Y/N)
- Study type
- Relevance to research question – direct impacts of exporting (Y/N)
- Relevance to research question – indirect impacts of exporting (Y/N)
- Geographic coverage
- Temporal coverage
- Paper shortlisted for full review (Y/N)

In a second sheet of the evidence register, we will provide a full account of relevant study characteristics, information related to each of the detailed research questions and information concerning the quality of the sources for all sources considered in the full-scale review:

- Author
- Publication year
- Publication title
- Key findings for each outcome measure

- Citation
- URL
- Study type
- Geographic coverage
- Temporal coverage
- Sectoral coverage
- Research question / scope /goal (impacts studies and relevant disaggregations)
- Relevance to research question – direct impacts of exporting (Y/N)
- Relevance to research question – indirect impacts of exporting (Y/N)
- Relevance to research question – estimation method (Y/N)
- Extensive/intensive export margin
- National/local/both effects (N/L/B)
- further disaggregations of results (by firm characteristics/destination country/product)?
- Transmission mechanisms (if there is an explicit assumption described in the paper)
- Short- (<=1 year) or long-run (>1 year) estimates
- Outcome measure(s) covered
    - Direct effects (national) headline results (coefficient estimates & significance level)
    - Direct effects (national) effect variation
    - Indirect effects (national) headline results
    - Indirect effects (national) variation
    - Direct effects (local) headline results (coefficient estimates & significance level)
    - Direct effects (local) effect variation
    - Indirect effects (local) headline results
    - Indirect effects (local) variation
- Estimation methods used
- Estimation issues and limitations
- Measurement validity score/justification (by sub-question)
- Internal validity score/justification (by sub-question)
- External validity score/ justification (by sub-question)
- Data reliability score/justification (by sub-question)
- Analytical reliability score /justification (by sub-question)
- Papers cited
- Further comments

The evidence register will be delivered in spreadsheet format. As an annex to the evidence register, we will provide DIT with PDF versions of the abstracts of all screened (as opposed to reviewed) studies that are of relevance to the research questions.

Step 6: Summarising existing evidence in narrative report and developing analysis framework

In addition to the evidence register, we will deliver a narrative report which will summarise the findings of papers that passed the quality assessment criteria and answer the main research questions.

The main challenge of synthesising the evidence is the large number of dimensions relating to the quality and other aspects of the studies involved. We will start by splitting the evidence register into groups of studies that consider direct effects and indirect effects, and then further into studies that relate to the particular outcomes of interest.

Focusing on parts of the evidence register will allow us to identify patterns in the results. We may find larger effects among studies for which data samples relate to particular geographies, sectors and time periods. We may find larger effects for studies that estimate effects for a single year than over longer time periods, showing a short- but not long-run effect. We may also find larger effects for studies with lower internal validity scores, and there are some reasons to expect this to be the case (for example, due to selection bias, as described above), etc.

The narrative report, along with the findings from the review of available datasets, will feed into the development of an interim analysis framework (estimation method), which will then be tested with government and academic experts during the interview phase.

Annex 4 Overview of papers consulted

Direct Effects

Countries

Estimation methods

Outcome measures

UK
- Crespi et al. (2008)
- Fryges (2009)
- Girma, Greenaway and Kneller (2004)
- Girma, Görg and Hanley (2007)
- Greenaway and Kneller (2004, 2007)
- Greenaway and Yu (2004)
- Harris and Li (2007)
- Harris and Moffat (2016)
- Wales et al. (2018)
- Peters et al. (2018)

Asia
- Aw, Roberts and Winston (2005)
- Dai and Yu (2013)
- Hahn (2013)
- Ito (2012)
- Ito and Lechevalue (2010)
- Kang (2020)
- Kim and Sung (2020)
- Ma, Tang and Zhang (2011)
- Olabisi (2016)
- Tse, Yu and Zhu (2017)
- Wang et al. (2020)
- Xue and Zhou (2020)
- Yashiro (2009)
- Park et al. (2010)

Europe
- Amendolagine, Capolupo and Petragallo (2011)
- Andersson and Lööf (2009)
- Andersson et al. (2008)
- Banh et al. (2020)
- Baumgarten (2010)
- Bratti and Felice (2012)
- Damijan and Kostevc (2005, 2010)
- De Loecker (2007, 2010, 2013)
- Fryges and Wagner (2008)
- Grazzi (2012)
- Lööf and Nabavi (2013)
- Lööf et al. (2015)
- Manjón et al. (2012)
- Masso and Vahter (2011)
- Munch and Skaksen (2008)
- Pisu (2008)
- Salomon and Jin (2008)
- Salomon and Shaver (2005)
- Saxa (2008)
- Segarra-Blasco et al. (2020)
- Serti and Tomasi (2008)
- Siedschlag and Zhang (2015)
- Vahter (2011)
- Wagner (2002)
- Davidson et al. (2017)

North America
- Lileeva and Trefler (2010)

South America
- Garcia and Voigtländer (2013)

Global
- Martins and Yang (2009)
- Silva et al. (2012)

Productivity
- Amendolagine, Capolupo and Petragallo (2011)
- Andersson and Lööf (2009)
- Andersson et al. (2008)
- Aw, Roberts and Winston (2005)
- Banh et al. (2020)
- Crespi et al. (2008)
- Dai and Yu (2013)
- Damijan and Kostevc (2005)
- De Loecker (2007, 2010, 2013)
- Fryges and Wagner (2008)
- Garcia and Voigtländer (2013)
- Girma, Greenaway and Kneller (2004)
- Greenaway and Kneller (2004, 2007)
- Greenaway and Yu (2004)
- Hahn (2013)
- Harris and Li (2007)
- Harris and Moffat (2016)
- Ito (2012)
- Ito and Lechevalue (2010)
- Kang (2020)
- Kim and Sung (2020)
- Lileeva and Trefler (2010)
- Lööf and Nabavi (2013)
- Lööf et al. (2015)
- Ma, Tang and Zhang (2011)
- Manjón et al. (2012)
- Martins and Yang (2009)
- Masso and Vahter (2011)
- Pisu (2008)
- Saxa (2008)
- Segarra-Blasco et al. (2020)
- Serti and Tomasi (2008)
- Vahter (2011)
- Wagner (2002)
- Wales et al. (2018)
- Yashiro (2009)

Employment
- Baumgarten (2010)
- Girma, Greenaway and Kneller (2004)
- Ito (2012)
- Munch and Skaksen (2008)
- Serti and Tomasi (2008)
- Wagner (2002)

Innovation
- Bratti and Felice (2012)
- Damijan and Kostevc (2010)
- Girma, Görg and Hanley (2007)
- Olabisi (2016)
- Peters et al. (2018)
- Salomon and Jin (2008)
- Salomon and Shaver (2005)
- Siedschlag and Zhang (2015)
- Tse, Yu and Zhu (2017)
- Wang et al. (2020)
- Xue and Zhou (2020)

Sales
- Girma, Greenaway and Kneller (2004)
- Fryges (2009)
- Ito (2012)
- Serti and Tomasi (2008)

Other
- Grazzi (2012)
- Ito (2012)

PSM and DiD

- Amendolagine, Capolupo and Petragallo (2011)
- Dai and Yu (2013)
- Damijan and Kostevc (2005, 2010)
- De Loecker (2007, 2010, 2013)
- Girma, Greenaway and Kneller (2004)
- Greenawar and Kneller (2004, 2007)
- Hahn (2013)
- Harris and Li (2007)
- Harris and Moffat (2016)
- Ito (2012)
- Kang (2020)
- Ma, Tang and Zhang (2011)
- Masso and Vahter (2011)
- Olabisi (2016)
- Pisu (2008)
- Saxa (2008)
- Serti and Tomasi (2008)
- Wagner (2002)
- Wang et al. (2020)
- Xue and Zhou (2020)

GMM-DPD

- Andersson et al. (2008)
- Andersson and Lööf (2009)
- Fryges (2009)
- Fryges and Wagner (2008)
- Greenaway and Yu (2004)
- Ito and Lechevalue (2010)
- Kim and Sung (2020)
- Lööf and Nabavi (2013)
- Lööf et al. (2015)
- Manjón et al. (2012)
- Salomon and Shaver (2005)
- Segarra-Blasco et al. (2020)
- Tse, Yu and Zhu (2017)

IV

- Bratti and Felice (2012)
- Harris and Li (2007)
- Lileeva and Trefler (2010)
- Vahter (2011)
- Saxa (2008)

Other

- Aw, Roberts and Winston(2005)
- Baumgarten (2010)
- Girma, Görg and Hanley (2007)
- Grazzy (2012)
- Munch and Skaksen (2008)
- Peters et al. (2018)
- Salomon and Jin (2008)
- Wagner (2002)
- Wales et al. (2018)
- Yashiro (2009)

Indirect Effects

Countries

Estimation methods

Outcome measures

UK
- Greenaway and Kneller (2008)
- Kneller and Pisu (2007)
- UKEF (2019)
- Cuyvers, Dhyne and Soeng (2010)
- Department for Business Innovation Skills (2014)

Asia
- Fernandes and Tang (2014)

Europe
- Banh et al. (2020)
- Hagemejer (2016)
- Koenig, Mayneris and Poncet (2009)
- Lucio et al. (2019)
- Raskovic, Udovic and Žnidarsic (2015)
- Ruede-Cantuche and Sousa (2016)
- Statistics Denmark (2017)
- Békés and Harasztosi (2011)

North America
- Acharya (2017)
- Baldwin and Yan (2014)
- Gomez, Garcia, Rajtmajer et al. (2020)

South America
- Albornoz and Kugler (2008)

Africa
- Abegaz and Lahiri (2020)

Global
- Caldarelli et al. (2012)
- De Benedictis, Nenci, Santoni et al. (2013)
- Gal and Witheridge (2019)
- Girma, Görg and Pisu (2004)

Productivity
- Albornoz and Kugler (2008)
- Baldwin and Yan (2014)
- Banh et al. (2020)
- Gal and Witheridge (2019)
- Greenaway and Kneller (2008)

Employment
- Acharya (2017)
- Cuyvers, Dhyne and Soeng (2010)
- Ruede-Cantuche and Sousa (2016)
- UKEF (2019)

Innovation
- Piermartinin and Rubinova (2014)

Export spillovers
- Fernandes and Tang (2014)
- Kneller and Pisu (2007)
- Koenig, Mayneris and Poncet (2009)
- Lucio et al. (2019)

Other
- Hagemejer (2016)
- Caldarelli et al. (2012)
- De Benedictis, Nenci, Santoni et al. (2013)
- Department for Business Innovation Skills (2014)
- Girma, Görg and Pisu (2004)
- Jouanjean, Gourdon and Korinek (2017)
- Korniyenko, Pinat, Dew (2017)
- Raskovic, Udovic and Žnidarsic (2015)
- Statistics Denmark (2017)

Input-output analysis
- Banh et al. (2020)
- Department for Business Innovation Skills (2014)
- Gal and Witheridge (2019)
- Girma, Görg and Pisu (2004)
- Gomez, Garcia, Rajtmajer et al. (2020)
- Ruede-Cantuche and Sousa (2016)
- Statistics Denmark (2017)
- UKEF (2019)

GMM-DPD
- Albornoz and Kugler (2008)
- Cuyvers, Dhyne and Soeng (2010)

Network Analysis
- Caldarelli et al. (2012)
- De Benedictis, Nenci, Santoni et al. (2013)
- Gomez, Garcia, Rajtmajer et al. (2020)
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Department for International Trade

Analysis

The UK’s Department for International Trade (DIT) has overall responsibility for promoting UK trade across the world and attracting foreign investment to our economy. We are a specialised government body with responsibility for negotiating international trade policy, supporting business, as well as developing an outward looking trade diplomacy strategy.

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