Essays on Firm Heterogeneity and International Trade

by

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Abstract

This thesis provides four contributions to the literature on the productivity-internationalization nexus by considering some recent developments in the literature. A well-established stylized fact is reported by this literature, which is that exporters are more productive and larger than non-exporters, and two hypotheses attempt to explain this finding. The first, often referred to as the self-selection hypothesis, suggests that more productive firms select themselves into export markets, while the learning-by-exporting hypothesis highlights the role of learning from exporting.

In this thesis, first, the self-selection hypothesis is revisited, and it is shown that evidence against self-selection exists in some UK industries. Second, it is demonstrated that some UK firms experience rising marginal costs, although both traditional and new trade theories assume constant marginal cost. It is then shown that the evidence against self-selection that we report can be best explained by the existence of increasing, rather than constant, marginal costs.

Third, the learning by exporting hypothesis is tested empirically for UK firms. Highlighting the importance of the scale effect in total factor productivity growth, it is shown that any learning by exporting effects are predominantly attributable to a change in scale efficiency.

Unlike Melitz (2003), some recent studies consider some other strategies to access foreign markets, such as foreign direct investment, and cross-border mergers. Finally, following this new branch of the literature, the productivity-internationalization nexus is examined by utilizing a two-country oligopolistic model. It is shown that more productive firm might prefer greenfield investment over cross-border merger, which contradicts the findings provided by the relevant literature.

Key words: Firm heterogeneity, self-selection, learning by exporting, cross-border mergers, matching, dynamic probit models

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1: Introduction

1.1 Background

Over the last two decades, the availability of new large datasets has allowed economists to examine several economic issues at firm-level.[1] Many empirical studies utilizing these datasets report some interesting findings, in particular that firms are heterogeneous in terms of their productivity and size, and the wage rates they pay.[2] These studies have also discovered that firms' participation behaviour in international trade is not random, and there are quite a few exporting and importing firms relative to the number of domestic producers.[3] More importantly, it is suggested that exporters are more productive and larger than non-exporting firms. Although the majority of the empirical studies in the literature confirm that exporters are more productive than non-exporters, the causality in this relationship is not well-explained. For this reason, the greater part of the related literature mainly focuses on this issue.

Two principal non-exclusive hypotheses attempt to explain this relationship. First, the self-selection hypothesis suggests that more productive firms select themselves into export markets. One possible reason for this is that there is an additional cost of selling goods to foreign countries and only the most productive firms are able to afford these costs.[4] Another explanation for the self-selection mechanism

[1] As Caves (1998) states, researchers were unable to access the firm-level database from the national census bureaux or statistical institutes until the end of the 1990s. Nowadays, in addition to countries' statistical institutes, some commercial databases are another option for researchers who want to use firm-level data.

[2] Following Bernard and Jensen (1999) several empirical studies document similar findings.

[3] Wagner (2007) provides a survey of the recent empirical studies in this literature.

[4] This cost is known as a sunk cost, and it consists of transportation costs, distribution or marketing costs, or the cost of the skilled workers who are needed to deal with foreign networks (Roberts and Tybout, 1997; Melitz, 2003).

is proposed by Aw and Hwang (1995), who suggest that export market entry implies being exposed to fierce product competition, which only more productive firms can deal with. The second hypothesis points to the role of learning-by-exporting which suggests that those firms entering the export market enjoy an improvement in productivity even after the entry has taken place. In theory, firms operating in international markets could benefit from exporting as a result of a technological exchange with their international rivals and clients. Moreover, exporters face pressure to improve their production techniques in order to meet high requirements arising from intense competition in the international markets, and this process, as a consequence, may cause productivity improvements (Aw, Chung and Roberts, 2000). On top of that, exporters could benefit from economies of scale that result from the production capacity improvements determined by the international demand. Thus, in the presence of economies of scales and/or technology transfers, one would expect to observe improvements in the post-entry performance, which verify the learning by exporting hypothesis (LBE) (Clerides, Lach and Tybout, 1998).

The aim of this thesis is to examine the productivity-internationalization nexus by using an empirical approach as well as theoretical modelling. Thus, we revisit both self-selection and the learning-by-exporting hypothesis in the light of some recent developments in the international trade literature. The rest of this introduction proceeds by i) further outlining some relevant themes in the literature, and ii) providing a more detailed summary of each chapter.

1.1.1 Self-Selection, Learning-by-Exporting or Both?

The new findings described above have triggered a growing amount of literature on heterogeneous firms, which is ignored (or not considered) by traditional trade theory.[5] In this sub-section, we provide a quick review of some important studies in order to describe how these new results are handled by the literature.

In the light of the findings mentioned above, the seminal paper of Melitz (2003) provides a theoretical framework of international trade that accounts for firm heterogeneity. Melitz (2003), and the subsequent works (which are called "new" new trade models), extend Krugman's (1980) framework by considering firm heterogeneity where firms differ in terms of their marginal productivity of labour. Melitz (2003) utilizes a monopolistic competition game to show that more efficient firms self-select into the export market, while less efficient firms serve only the domestic market, and the least efficient ones stop producing. Consequently, since the least efficient firms are eliminated, aggregate industry productivity increases as a result of a change in the industry composition, as well as resource allocation towards more productive firms. Following Melitz (2003), many empirical studies using firm-level data from different countries around the world have examined the causality between export and firm productivity, and the majority of them confirm the predictions of Melitz (2003).

The relationship between export and growth, especially export-led growth, is a well-established finding at the macro level (Edwards, 1993). As we mentioned, over the last few years, the focus of international trade studies has shifted from industries and countries to firms and plants.[6] For this reason, at the micro level, the literature on the links between exports and firm-level productivity is new and growing. Following the increasing availability of firm-level data, after the mid-1990s, several studies examined the productivity enhancing effect of export at firm level. Although there are an extensive number of studies on this issue, the evidence on the learning by exporting (LBE) effect is mixed and still unclear. (Wagner, 2007).

[5]Neither the Ricardian and the Heckscher-Ohlin trade models, nor Krugman trade models consider firm heterogeneity.

[6]In fact, this is a consequence of the limited availability of data until mid 1990s.

Despite some substantial studies, the results provided by the literature, in this regard, are far from being consolidated. Therefore, the purpose of this thesis is to revisit the relationship between firm productivity and the foreign market entry mode by addressing some recent developments in the literature that we highlight in the following section. In addition, we utilize some recently available econometric methods that tackle some important problems that previous studies have suffered from.

1.2. Some Recent Developments in the Literature on Heterogeneous Firms and Trade

1.2.1 Constant Marginal Cost Assumption

Although the new generation trade models relax the homogenous firms assumption of the existing trade models, they maintain some restrictive assumptions, such as constant marginal costs. Under the constant marginal costs assumption, firms maximize their profits in domestic and foreign markets independently of each other. This means that in response to a positive export demand shock, firms do not alter their level of domestic sales, since the level of production has no effect on the level of marginal cost. In other words, domestic and export sales are independent for firms experiencing constant marginal costs. On the other hand, for a firm producing with increasing marginal costs, it will be optimal to reduce its domestic sales in order to meet the increased export demand, as the marginal cost of production increases.[7]

Both traditional and new trade models consider the constant marginal cost of production. However, some recent empirical studies have challenged this assumption.

[7] Please see Figures A1.1 and A1.2 in Appendix 1 Section A for a diagrammatic illustration of the effect of a positive demand shock on a firm's output under both constant, and increasing marginal cost assumptions.

Vannoorenberghe (2012), for example, reports a pattern of a negative correlation between the output variation in the domestic and export markets for French firms. Blum, Carlo and Horstmann (2013) also show a robust relationship between export and domestic sales for Chilean firms, and conclude that those firms face increasing marginal costs. Additionally, they suggest that this issue arises from the physical capacity constraints of firms, which prevent them from maximizing profits in domestic and foreign markets independently of each other.

We believe that these new findings cast doubt on the constant marginal cost assumption of the trade models, and we address this issue in Chapter 2, where we revisit the predictions of Melitz (2003) for UK firms.

In the following subsection we address some further developments in the trade literature that seek to incorporate FDI as a mode of foreign market entry into heterogeneous firm models.

1.2.2 Heterogeneous Nature of FDI

Although initially, the literature considered exporting as the only way access to foreign markets (as in Melitz, 2003), Helpman, Melitz, Yeaple (2004) extend this framework by modelling two ways to serve the foreign markets: export, and foreign direct investment (FDI). In their paper, Helpman et al. (2004) show that only the most productive firms within an industry engage in FDI, while the less efficient firms serve the foreign market via exports, and the least productive firms sell only to domestic market or stop producing.

In reality, FDI consists of both greenfield investment and cross-border merger.[8] However, the vast majority of the literature considers FDI as greenfield investment,

[8]Firms internationalize their production process via foreign direct investment, which takes a form of either cross-border merger or greenfield investment. Greenfield investment provides an improvement in the host country's capital stock, while cross-border mergers cause a change in the ownership of an existing firm in the host country (Ferrett, 2005).

and has neglected its heterogeneous nature.[9] Recently, the increasing importance of cross-border mergers has triggered a new and growing body of literature that can be considered as an extension to the existing literature on FDI. Some recent papers, such as those of Ferrett (2005), Bjorvatn (2004), Nocke and Yeaple (2007), Neary (2009), and Stepanok (2015) explicitly model cross-border merger, and greenfield investment as components of FDI.

1.2.3 Motives for Cross-Border Merger

The traditional Industrial Organization (IO) literature provides two motives for mergers: an efficiency motive and a strategic motive. Efficiency gains might arise from transferring technology, cost savings or managerial synergies, while a strategic motive is associated with the competition reducing effect of merger (Neary, 2002). A group of papers in the literature, such as that of Neary (2009), focus on the strategic motive for mergers, while some other groups of studies, such as that of Nocke and Yeaple (2007), consider an efficiency motive as a key factor for mergers. We provide a detailed analysis with regard to this issue in Chapter 4.

In Nocke and Yeaple (2007), firms are heterogeneous in terms of their internationally mobile, and non-mobile capabilities, and they operate in a monopolistically competitive market, where the available strategies for firms to access to a foreign market are: export, greenfield investment, and cross-border merger. They consider that acquiring firms' main motivation for undertaking a cross-border merger is to exploit complementaries when combining firm-specific capabilities, and they confirm the so-called productivity ranking in FDI literature.[10] However, since they consider monopolistic competition in their model, Nocke and Yeaple (2007) fail to take any

[9] Studies, such as that of Head and Riese (2003); Helpman, Melitz, and Yeaple (2004); and Yeaple, (2005), mainly explore the well-known proximity-concentration trade-off between greenfield investment and export.

[10] Helpman, Melitz, Yeaple (2004)

strategic motives in to account for cross-border mergers.

This dissertation is a collection of three essays that focus on the issues mentioned above. Now, I will provide some detailed information about how I investigate these issues in this thesis.

1.3. A Thesis Outline

Chapter 2 provides an empirical analysis of the prediction of Melitz (2003), who suggests that the more productive firms self-select into the export market. Basically, we examine the self-selection hypothesis for UK firms by using a panel dataset covering the period between 2003 and 2011. We test the self-selection hypothesis by using both pooled data where all firms from different industries are included, and industry level data. By doing this, we aim to show that the results for the self-selection hypothesis may differ when we consider industry-specific differences. Furthermore, following the recent developments in the literature, we examine whether UK firms really experience a constant marginal cost of production. To do this, we analyse the relationship between the average growth in sales in domestic and foreign markets for each industry.

As discussed earlier, two principal non-exclusive hypotheses attempt to explain the fact that exporters are more productive than non-exporters. In Chapter 2, existence of a causality running from productivity to export decision is examined, while in Chapter 3 we present an analysis of the effect of exporting on productivity growth. The literature on learning by exporting focuses on three potential sources of learning: technology transfer, competition, and economies of scale. In Chapter 3, we highlight the importance of the scale effect in the learning-by-exporting analysis, which is overlooked by many recent UK studies. In these studies, the effect of scale is ignored, since it is assumed to be zero under the constant returns to scale assumption. Thus, we aim to uncover the potential importance of the scale effect in the learning by exporting analysis by examining whether or not UK firms really experience constant returns to scale. Moreover, in order to be able to single out the scale effect, we examine the different channels through which exporting influences TFP growth, by decomposing it into its components, namely technical change, scale change, and efficiency change.

By following Melitz (2003), in Chapters 2 and 3 we consider that export is the only way to sell abroad. However, in reality, firms have further available strategies to access foreign markets. Helpman, Melitz and Yeaple (2004) take this into account, and extend the work of Melitz (2003) by including foreign direct investment as an alternative way to export. However, this time Helpman et al. (2004) failed to explain the heterogeneous nature of foreign direct investment. More precisely, there are two options for a firm aiming to invest in foreign markets: cross-border mergers, and greenfield investment. However, the heterogeneous composition of foreign direct investment is largely neglected by the relevant literature. Some recent papers, on the other hand, such as that of Ferrett (2005), Bjorvatn (2004), and Nocke and Yeaple (2007) explicitly model the two different components of FDI to examine the internationalization decisions of firms.

By following Nocke and Yeaple (2007), in Chapter 4, we focus on the relationship between firm level productivity, and a firm's decision on foreign market entry. To do this, we utilize a two-country oligopolistic model of differentiated product competition with heterogeneous firms, where firms compete in the home country's market via export, greenfield investment or cross-border merger. Unlike Nocke and Yeaple (2007), in Chapter 4, we consider both an efficiency motive and a strategic motive for cross-border mergers.

Finally, Chapter 5 provides a conclusion and a summary of our findings. It also suggests some potential future research topics that follow on from the thesis.

Chapter 2: Self-Selection to Export: Understanding the Evidence and Impact of Increasing Marginal Cost

2.1. Introduction

Following Bernard and Jensen (1999) several empirical studies document that in an industry, some firms export, while other firms operate only in the domestic market. Additionally, it is reported that firms are heterogeneous: Exporters are more productive, larger, and they pay higher wages compared to non-exporters. In response to these findings, a new literature has emerged which examines the determinants behind this evidence.

The seminal paper of Melitz (2003) provides a theoretical framework of international trade that accounts for firm heterogeneity. Melitz (2003) is built on Krugman's (1980) framework, considering firm heterogeneity where firms differ in terms of their marginal productivity of labour: he shows that more productive firms self-select to enter the export market. Following this, a large number of empirical studies have examined the findings of Melitz (2003), which is referred to as the self-selection hypothesis, and the vast majority of these studies confirm a causal link between firm productivity and a firm's decision to exporting.

Although Melitz (2003) and subsequent works relax the homogenous firms assumption of the existing trade models, they maintain some restrictive assumptions, such as constant marginal costs which implies that firms maximize profits in domestic and foreign markets independently of each other. On the other hand, for a firm producing with increasing marginal costs, the optimal approach will be to reduce its domestic sales in order to meet the increased export demand, as the marginal cost of production increases. For this reason, we believe that the constant marginal costs assumption plays a key role in the analysis of the self-selection hypothesis.

This chapter focuses on this restrictive assumption of constant marginal costs and revisits the literature on self-selection hypothesis. We report a set of very interesting findings suggesting that firms in some important UK industries produce with rising marginal cost. In relation to this, we also show that the self-selection hypothesis does not hold for the very same UK manufacturing industries, where firms face rising marginal cost.

In this chapter, we firstly revisit the prediction of Melitz (2003) regarding the relationship between firm level productivity and the decision to export for UK manufacturing firms. Like most of the previous literature, we start our analysis with a dataset where all industries are pooled, and show that more productive UK firms self-select themselves into foreign markets.[1] It is a well-known fact that each industry has different characteristics. For instance, as we report in this chapter, firms in some industries produce at constant marginal costs, while some other industries face increasing marginal costs. In order to account for such differences between industries, we test the self-selection hypothesis again, but this time for each industry. Eventually, we show that our findings do not strongly confirm the self-selection hypothesis for some important industries. We find that self-selection occurs in some industries,

[1] However, Nocke and Yeaple (2007) criticize this approach by stating that *"... the common procedure of pooling industries in regression analysis is inappropriate as the mapping from firm characteristics to mode choices differs qualitatively across industries in a systematic fashion."*

such as Textiles/Cloth/Leather, and Other Manufacturing, while we find evidence against it in some others, such as Non-metal Minerals and Motor vehicles/parts.

More importantly, we show that the average rates of sales growth in domestic and foreign markets are negatively correlated in many industries, in a way that is consistent with increasing marginal cost. This negative correlation suggests that optimal output levels in each individual market are not independent of the other market for firms in some important industries, such as Non-metal Minerals and Motor vehicles/parts. We beleive that these findings raise doubts about the constant marginal costs assumption of both the standard and new trade models. Finally, we show a pattern suggesting that self-selection does not occur in the UK industries where firms produce at increasing marginal cost.

In this chapter we also benefit from two recent methodological developments in the literature. First, most of the early examples in this literature, such as Clerides, Lach and Tybout (1998) or Bernard and Jensen (1999) use labour productivity (value-added per worker) as a proxy for firm productivity, although it is admitted that labour productivity is not a true measure of total factor productivity (Clarides et al., 1998). Following recent improvements in econometric techniques, total factor productivity (TFP) became preferable to labour productivity as a measure of efficiency (Harris, 2005). For this reason, to examine the self-selection hypothesis, we compute firm level TFP as residuals from a Cobb-Douglas production function.[2] Second, another important issue with the self-selection analysis is related to the sunk cost effect. As Melitz (2003) suggests, the sunk cost effect is one of the key factors behind the self-selection hypothesis.[3] Surprisingly, many empirical studies ignore this effect when it comes to self-selection analysis. Sunk cost is represented by the previous year's export status in a regression equation. However, including the previ-

[2]See section 2.3.

[3]According to Melitz (2003), the most productive firms self-select themselves to enter the export market, since only such firms can overcome the sunk cost of exporting activity.

ous year's export status (as a lagged dependent variable) causes serious econometric problems that we describe in section 2.5.3. We tackle these problems by employing the dynamic probit model proposed by Wooldridge (2005).

The rest of the paper is organized as follows. Section 2.2 provides a review of related literature, while section 2.3 explains the methodology used for the estimation of total factor productivity (TFP). Section 2.4 describes the data we use in this analysis and shows some descriptive evidence of the difference between exporter and non-exporter firms in terms of some firm characteristics. Section 2.5 describes the framework of the econometric analysis, and Section 2.6 provides our results. In section 2.7 we provide robustness check results, and finally, Section 2.8 provides the conclusion.

2.2. Related Literature

Two principal non-exclusive hypotheses attempt to explain the fact that exporters are more productive than firms that operate only in domestic markets: namely the self-selection hypothesis and learning-by-exporting. In this chapter, we focus mainly on the self-selection hypothesis, while we will examine the learning by exporting hypothesis for UK manufacturing firms in the third chapter of the thesis.

This chapter contributes to the literature on the endogenous selection of heterogeneous firms into the export market. The seminal paper of Melitz (2003), which is a key paper in this literature, followed by many empirical studies which examine the well-established empirical association between export and productivity by using different econometric techniques on different datasets. One can say that the self-selection hypothesis is largely confirmed. However, similar to our study, some recent studies, such as Lu (2010), Lu et al. (2010), and Yang and He (2013) find evidence against self-selection from their data. They report a productivity puzzle suggesting that Chinese exporting firms are overall less productive than non-exporters. Unlike our paper, these studies try to explain this productivity puzzle with local protections, an export spillover effect, and factor endowment heterogeneities between countries.

Many UK studies examining the the self-selection hypothesis, such as Harris and Li (2008), and Girma, Kneller and Pisu (2003), report evidence in favour of self-selection. However, although Melitz (2003) shows the importance of the sunk cost of exporting when it comes to the decision to export, these studies overlook the sunk cost effect. Instead, we take the sunk cost of export into account explicitly by considering the previous year's export status as a measure of the sunk cost of exporting. Doing this, we tackle a very important econometric issue that may harm our estimations.[4] There are other studies that take the previous year's export status into account by utilizing a dynamic panel estimation method, such as Greenaway, Kneller and Zhang (2007), and Temouri, Vogel, and Wagner (2013); they do not confirm the self-selection hypothesis for UK firms. However, these studies use labour productivity as a measure of firm-level productivity, while we use total factor productivity.[5] Greenaway, Guariglia, and Kneller (2007) is the closest to our study. They examine a relationship between some financial factors and export decisions, by using the same database that we use for our study.[6] Employing dynamic GMM to deal with the endogeneity problem, they do not find any evidence for more productive firms self-selecting to enter the export market. Unlike these studies, in this chapter we provide more detailed information regarding self-selection at the industry level, where we even report evidence against the self-selection mechanism. Moreover, unlike the previous UK studies, we also consider the rising marginal cost, and its implications.

[4]See section 2.5 for details.

[5]In Section 2.3 we explain some advantages of TFP as a measure of productivity compared to labour productivity.

[6]They use FAME data for the period 1993-2003, while our data covers the period between 2003-2011.

Our work is also related to a new and growing literature which challenges the constant marginal cost assumption of Krugman (1980) and Melitz (2003) by exploring the relationship between domestic and export sales. Some recent papers such as Nguyen and Schaur (2011), Ahn and McQuoid (2012), and Vannoorenberghe (2012) argue for such a relationship between domestic and export sales at firm level for Danish, Indonesian, Chilean, and French firms. Eventually, these studies conclude that the real world data from different countries do not support the assumption of constant marginal cost which is heavily used in the literature: instead, they suggest that firms in their dataset produce at increasing marginal cost. In contrast to our study, this literature mainly concerns the determinants of rising marginal cost, while we examine the endogenous selection of heterogeneous firms into the export market. One exception is the paper by Blum, Carlo and Horstmann (2013), which examines export entry and exit behaviour of occasional exporters without addressing the self-selection phenomenon.

2.3. Estimation of Total Factor Productivity (TFP)

Most studies that analyze TFP assume that production takes a form of a Cobb-Douglas production function.[7] A standard Cobb-Douglas production function is given by:

$$Y_i = F(A_i, K_i, L_i) = A_i K_i^{\beta_k} L_i^{\beta_l} \tag{2.1}$$

where Y_i, L_i and K_i denote firm i's output, labor input, and physical capital stock respectively. In the literature, labour input is usually measured by the number of employment or the numbers of hours worked, while output is measured as value-added or gross output.[8] A_i is a measure of firm-level efficiency that cannot be

[7]However, as suggested by Ackerberg et al. (2007), the estimation methods that we will analyze in this part of the study are applicable to the other types of production functions.

[8]As Eberhardt and Helmers (2010) highlighted, there is an inconclusive literature on the supe-

observed by the researcher, while Y_i, L_i and K_i are all observable. A_i is commonly known as Total Factor Productivity (TFP) and it is assumed that this term includes all unobserved determinants of output. It is assumed that the effect of A_i on Y_i is Hicks-neutral, which implies that TFP is additively separable from the other production factors in log-linearized form (Eberhardt and Helmers, 2010). Finally, β_l, and β_k denote output elasticities of labour and capital, respectively. Taking natural logs of equation (2.1) we obtain the following equation to estimate:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_0 + \varepsilon_{it} \tag{2.2}$$

where t is time subscript ($t = 1, ..., T$), and lower case letters are log values of the variables introduced above. In equation (2.2), $ln(A_i)$ is represented by the combination of two elements; β_0 and ε_{it}, where β_0 denotes mean efficiency level across firms over time, and ε_{it} represents deviations from that mean for specific firms and times. ε_{it} can be decomposed further to predictable and unobservable components that are ν_{it} and u_{it}, where u_{it} is an i.i.d. error component, and ν_{it} is the productivity term.[9] Eventually, this gives us the following equation:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_0 + \nu_{it} + \mathrm{u}_{it} \tag{2.3}$$

where firm-level TFP (ω_{it}) is represented by the sum of β_0, and ν_{it}. Typically, equation (2.3) is estimated and solved for ω_{it}. Then, estimated TFP can be calculated as:

$$ln\hat{TFP}_{it} = \hat{\omega_{it}} = \hat{v}_{it} + \widehat{\beta}_0 = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \tag{2.4}$$

As we already mentioned, labour productivity is not a preferred productivity measure because of its limitations (Eberhardt and Helmers, 2010). More precisely,

riority of the value-added and gross output-based specifications.

[9] Here, u_{it} represents either measurement error or a non-predictable productivity shock (van Beveren, 2012).

we can show labour productivity growth by subtracting the logarithm of employment from both sides of equation (2.4). If we differentiate equation (2.4) with respect to time we get:

$$\dot{y} - \dot{l} = (\hat{\beta}_l - 1)\dot{l} + \hat{\beta}_l \dot{k} + lnT\dot{F}P$$

where $\dot{y} - \dot{l}$ represents labour productivity. The equation above shows that labour productivity is determined not just by differences in efficiency and technical changes, but also changes in factor inputs themselves. An increase in labour productivity is negatively related to an increase in employment (where $(\hat{\beta}_l - 1) < 0$), and positively related to the capital stock. Thus, TFP is preferred to labour productivity as a proxy for firm productivity, since it does not depend on the production factors (Harris and Li, 2008).

In Appendix 1 Section B, we provide a detailed discussion with regard to some econometric issues arising from estimating equation (2.4). We also review some methods used in the literature to overcome those issues. Based on our review, in this study, we have decided to use a semi-parametric method proposed by Levinsohn and Petrin (2003) to estimate equation (2.4).

2.4. Data and Descriptive Statistics

2.4.1 Data

In this study we use FAME firm-level database, which includes all manufacturing firms operating in the UK that are required to register their accounts at Companies' House.[10] The FAME database contains information on many variables appearing in a firm balance sheet, such as number of employees, intermediate expenditure, total

[10]The Financial Analysis Made Easy (FAME) dataset is a commercially available UK company-level panel data published by Bureau van Dijk. I am very grateful to the University Manchester Main Library for providing me with access to the dataset.

turnover, assets, and overseas sales.[11] In addition to the financial information, FAME also provides information on the geographical location (UK regions) that firms are established, year of incorporation of the company, and 4-digit 2007 SIC industry code.

Since many small firms in the UK are exempt from reporting their annual accounts, the FAME database is biased towards large firms (Du, Gong and Temouri, 2015). However, Ribeiro et al. (2010) suggest that this bias is not now as strong as it was, since more small firms have been included in the database over the last few years. Although FAME has this disadvantage, several contributors to the literature use this data, such as Greenaway, Kneller and Zhang (2007), Harris and Li (2008), and Greenaway, Guariglia, and Kneller (2007).[12]

After omitting firms that lacked the required data, we begin with a dataset with over 110,000 firms, before the data cleaning procedure. We drop observations with missing data for the variables of interest (output, capital, employment and intermediate input) in order to restrict the sample to firms that have at least two consecutive years of data available. Moreover, we also drop firms that are in the top and bottom 1% of ratios for capital-labour and capital-output variables.[13] After the cleaning procedure our final dataset comprises an unbalanced panel, containing 9,752 firms with 54,609 observations for the 2003-2011 period.[14] The dataset contains information on firms from 15 different industries based on their 2-digit 2007 SIC code. Almost 37% of these firms are observed in at least eight years throughout the nine-year period, while most of the firms are observed for some part of 2003-2011.

[11] A full list of variable descriptions used in this study can be found in Table A1.1 in Appendix 1 Section A.

[12] Greenaway, Kneller and Zhang (2007) merge the FAME database with data from Onesource to improve its representativeness.

[13] We applied this procedure in order to avoid the impact of outliers on our results, following Eberhardt and Helmers (2010).

[14] The size of the data shrank dramatically after the data cleaning process. The main reason for that is FAME keeps firms that exit the market in the database for 10 years by reporting missing values for their annual accounts. Thus, such firms have to be discarded from our dataset.

Gross output is defined as total turnover in FAME, and it is deflated by using Producer Price Indices for output (2005 prices).[15] Intermediate inputs (cost of sales in FAME) are similarly deflated by using PPI (input) index numbers. And capital (i.e. tangible assets in FAME) is deflated by using an index for fixed investment. With regard to the information on exporting, the overseas turnover variable in FAME is used. This variable is also deflated using PPI (output) figures as we do for the gross output. The age of a firm is calculated using the information about the incorporation year of the firm. Finally, by using the National Statistics Post-code Directory, we convert the firm's post-code information to regional location information, and we obtained the Region variable.

Table 2.1 contains summary statistics for the variables used for the estimation of the production function, such as output, capital, employment and material costs. The statistics suggest a small increase in the average output during the nine years, while the figures for the other variables have not changed that much on average for the observed firms.

Table 2.1: Mean values of some key variables

Year	Output(Value added)	Employment	Capital	Materials
2003	18977	433	20304	52214
2004	20356	429	21352	53849
2005	20261	404	18451	52305
2006	22216	421	18795	53947
2007	23502	423	18694	55130
2008	24884	416	19987	53369
2009	19633	342	15331	41725
2010	20685	349	14772	41734
2011	28389	448	20385	47658

[15] All price indices are available from the Office for National Statistics (ONS) website. The code for PPI index is MM22, and the index for fixed investments price is MM17.

2.4.2. Some Descriptive Statistics

By utilizing the export variable to indicate whether a firm has any overseas turnover, we split firms into two groups, exporters and non-exporters, and we compare these two groups of firms based on a wide range of performance measures, such as productivity, size, output, and capital. We use two different measures for firm-level productivity: labour productivity (LP) and total factor productivity (TFP). We report two different versions of TFP which are TFP_{OLS} and TFP_{LevPet}. TFP_{OLS} is obtained by employing an ordinary least squares method, while TFP_{LevPet} is computed via a semi-parametric estimation technique developed by Levinsohn and Petrin (2003). The size of a firm is measured by the number of employees, while capital is measured as the absolute value of capital stock.

Table 2.2: Proportion of Exporting Firms and Export Intensity

Year	Number of Firms	Exporting Firms (%)	Export Intensity (%)
2003	5659	0.51	33.6
2004	5532	0.49	34.3
2005	5739	0.50	34.8
2006	6013	0.50	35.7
2007	6287	0.51	36.7
2008	6466	0.51	37.4
2009	7962	0.48	37.4
2010	7806	0.51	37.4
2011	3345	0.55	36.0

Table 2.2 illustrates the number of active firms and the percentage of export participation during the nine years period, together with the export intensity, which is calculated as a ratio of overseas turnover to gross turnover. While the number of active firms that we observed increased over the period examined, the export participation rate remained stable for the period 2003-2011.

Table 2.3 presents the average values of some important variables that will be used in the following stages of this work. This table enables us to compare exporter and non-exporter firms with respect to their size, capital stock, and output, in addition to their productivity. Much research confirms the superior performance of exporter firms compared to firms that operate only in the domestic market, and Table 2.3 provides our calculations for the UK manufacturing firms, which are closely aligned with the results from the relevant literature.

Table 2.3: Exporters vs. Non-Exporters

	TFP_{LevPet}	TFP_{OLS}	LP	Capital	N. Emp.	Output
Exporters	6.46	0.05	4.88	21093.3	441.6	79807.9
Non-exporters	6.13	0.01	4.60	15455.8	359.3	62860.9

All differences are statistically significant at 1%

2.4.3. Are Exporters More Productive Than Non-Exporters?

Before analysing the potential causal relationship between productivity and exporting, this subsection first establishes evidence for a positive correlation. The descriptive statistics that we report in the above section suggest the superior performance of exporters, and this is consistent with the previous empirical results. In order to provide additional support to this descriptive evidence, we will basically regress several productivity measures on export status, which is a dummy variable, taking the value of 1 for exporting firms and 0 for non-exporters. The starting point of our empirical estimation approach is based on the procedure employed by Bernard and Jensen (1999), which is used by most of the empirical work in this literature. The regression takes the form:

$$ln(Prod) = \beta_0 + \beta_1 Export_{it} + \beta_2 ln(Size)_{it} + d_t + d_s + u_{it} \tag{2.5}$$

As dependent variable we use different productivity measures which are summarized by $ln(Prod)$. The variables are the natural log of labour productivity (LP) and total factor productivity: TFP_{OLS} and TFP_{LevPet} respectively. $Export$ is represented by a dummy variable, which takes value 1 if a firm has any positive overseas return and zero otherwise, and $lnSize$ is the logarithm of the number of employees. We also add dummy variables for each industry, and year. By adding these dummies, we aimed to control for industry-specific characteristics and business cycles respectively.[16]

The variable of interest is the export dummy, which indicates the average premium of exporting firms. Thus, we report the results for this coefficient. Table 2.4 provides results for the period 2003-2011, and illustrates that export performance is positively related to all productivity measures, as we expected. The coefficients are statistically significant at the 1% level for all cases, and suggest that exporters are around 11-12% more productive than non-exporters, for all productivity measures.[17]

Table 2.4: Export Productivity Premium – OLS (2003-2011)

	(1)	(2)	(3)
	TFP-LEV	TFP-OLS	LP
Export Dummy	0.109	0.105	0.116
	(0.007)*	(0.007)*	(0.006)*
%Export Premium	11.5	11.07	12.2
R^2	0.55	0.20	0.16
N. of Obs.	53900	53900	54607

Note: P-values are in parenthesis (we used robust standard errors). In order to obtain %Export Premium the estimated coefficients for the exporter dummy variable have been transformed by 100(exp(β)−1).
*** indicates significant at the 1% level

[16]Firms in some sectors are bigger and more productive, on average, than firms in other sectors.

[17]We also can consider firm fixed effects in our estimation, and adjust equation (2.5) accordingly. Please see Appendix 1 Section C for the fixed effects model, and the estimation results.

2.5. Self-Selection to Export Markets

2.5.1. The Econometric Model

As we show above, exporters are more productive than non-exporters. In this subsection, the causal relationship between the two will be analyzed. As discussed before, productivity differences between exporters and non-exporters might be a consequence of a self-selection mechanism. It is suggested by the relevant literature that exporting firms face a sunk costs of entry to international markets where they are exposed to higher competition. Thus, it is claimed that only better firms can become exporters, in other words, the initial performance of a firm should be an important factor in the export decision to export (Roberts and Tybout 1997; Melitz 2003).

In this section, we aim to assess the determinants of the decision to export by focusing on the effects of sunk costs and some firm characteristics on the probability of becoming an exporter. We will conduct our analysis by utilizing a binary choice model, since our export participation variable is a binary variable (taking two possible outcomes, 0 or 1).[18] We will use the model below by following Roberts and Tybout (1997). According to their model, firm i exports in period t if the expected gross revenue of the firm exceeds the current cost. Thus, the condition of export decision is:

$$Y_{it} = \begin{cases} 1, if \quad p_{it}q^*_{it} \geq c_{it}(X_t, Z_{it}, q^*_{it-1} \mid q^*_{it}) + S(1 - Y_{it-1}) \\ 0, \qquad otherwise \end{cases}$$

where Y_{it} and Y_{it-1} stand for the export status of firm i at time t, and $t-1$ respectively. S represents the sunk entry costs, p_{it} is the price of goods sold abroad, and c_{it} is the variable cost of producing q^*_{it}. X_t and Z_{it} indicate vectors of exogenous

[18]Models with binary dependent variables are usually tested by using linear probability, probit or logit models.

factors and firm-specific factors that affect the firm's export decision. Based on the equation above we will test self-selection hypothesis by using following the binary-choice model:[19]

$$Y_{it} = \begin{cases} 1 & \text{if } \beta_1 X_t + \beta_2 Z_{it} - S(1 - Y_{it-1}) + u_{it} \geq 0 \\ 0, & otherwise \end{cases}$$

where we basically aim to identify and quantify the factors that affect the probability of being an exporter.

There are some methodological issues worth mentioning. The first is the possibility of unobserved factors that might affect the firm's export decision, such as managerial abilities or strategic management (Syverson, 2011). The unobservable factors can be exogenous as well as firm-specific, or time-variant or time-invariant. In the presence of unobserved firm-specific effects, one needs to control for them carefully in order to be able to obtain consistent estimates.[20]

The second problem arises from including the lagged dependent variable in the model. As we mentioned above, Roberts and Tybout (1997), Bernard and Jensen (2004), and Melitz (2003) suggest that sunk entry cost plays a crucial role in a firm's export decision. Thus, we should consider the effect of sunk entry costs, which are represented by the lagged export status, Y_{it-1}, in our model. Y_{it-1} is equal to 1 if firm i at time $t-1$ is an exporter. This suggests that firm i overcomes the sunk cost at time $t-1$, and it will not incur any sunk cost of export, in case it chooses to export again at time t. For that reason we consider the coefficient of Y_{it-1} as a measure of sunk cost. The problem is that, both dependent variable Y_{it} and lagged dependent variable Y_{it-1}, are a function of the error term, u_{it}. Thus, including the

[19] We follow Roberts and Tybout (1997) and Bernard and Jensen (2004) at this stage.

[20] As Wooldridge (2003) describes, in the presence of unobserved fixed effects, the error term in equation (2.7), u_{it}, can be written as a composite error including both unobserved fixed effects, ε_i, and idiosyncratic error, η_{it} (as in equation 2.6). Researchers usually use random or fixed-effects models to tackle this problem.

lagged dependent variable in the model causes an endogeneity problem. Moreover, if the lagged dependent variable is correlated to other explanatory variables, it might lead to a multicollinearity.[21]

Finally, the possibility of the existence of a two-way relationship between firm characteristics and export decisions may lead to a simultaneity problem. Most of the studies in this literature use lagged explanatory variables to overcome this issue.[22] In this study, we also utilize this approach in order to eliminate the simultaneity problem. The equation we estimate takes the form:

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 TFP_{it-1} + \beta_3 Z_{it-1} + d_t + d_s + d_r + \varepsilon_i + \eta_{it} \tag{2.6}$$

where β_1 and β_2 are vectors of coefficients. Y_{it} represents the export status of firm i at time t, and the lagged dependent variable, Y_{it-1}, is included in order to control for the sunk entry cost. ε_i represents time-invariant firm-specific unobservable characteristics and η_{it} represents idiosyncratic error. Z_{it-1} is a vector of control variables including firm-specific time-variant characteristics, which were lagged one year. Sector dummy, d_s, is included to capture industry-specific effects. Time-specific factors that affect all firms, for instance macroeconomic shocks, are controlled by year dummy, d_t. Finally, in order to capture region-specific factors, we include region dummy, d_r.

We use four different specifications: (1) Linear Probability Model, (2) Pooled-Probit, (3) Random Effects Probit, and (4) Dynamic Probit. First, we estimate the following equation by utilizing a linear probability model, and a pooled-probit model:[23]

[21] For instance, firm-level productivity might be correlated to lagged export status as a result of a potential learning-by-exporting effect.

[22] The use of the simultaneous equation models is preferable in order to tackle the simultaneity problem. However, simultaneous equation models require many instrumental variables, which makes this approach hard to employ in a panel data context (Hiep and Ohta, 2007).

[23] Since logit fails to control for the problem arising from the use of the lagged dependent variable, we prefer to use probit models in this study.

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 TFP_{it-1} + \beta_3 Z_{it-1} + d_t + d_s + d_r + u_{it} \tag{2.7}$$

One of the major limitations of the linear probability models is that they might provide estimations for probability outside the unit interval [0,1], which is unrealistic. Thus, the majority of the studies in this literature prefer logit or probit models to assess the determinants of the firm's export decision. We also are aware that linear probability, and pooled-probit models, have a strong assumption that the error term, u_{it}, is normally distributed and uncorrelated to explanatory variables, where $u_{it} = \varepsilon_i + \eta_{it}$.[24] This is not a very realistic approach in our case, and it might cause biased and inconsistent estimates. However, we will report the results from these specifications, since this will make us able to compare these findings to results from the other specifications.

In specification (3), we a employ random-effects probit model which controls for unobserved effects by assuming that the regressors are independent of the unobservables (Wooldridge, 2002).[25] Finally, in specification (4), we utilize the dynamic random effects probit model that tackles unobserved effects, as well as the endogeneity problem arising from the inclusion of the lagged dependent variable (Wooldridge, 2005).

As we discussed, pooled-probit and random effects probit models face two important theoretical and practical problems: (i) treatment of individual effects, and (ii) treatment of initial observations of export status. On the other hand, the dynamic probit model proposed by Wooldridge (2005) allows for correlation between individual effect and exogenous regressors, and resolves the issue arising from the treatment of individual effects. The dynamic structure of this model also allows us to consider the path dependence of export status, namely the lagged dependent variable Y_{it-1}.

[24] In other words, these models ignore any unobserved firm fixed effects.

[25] We then relax this assumption and employ a generalized method of moments (GMM) estimation by Arellano and Bond (1991) in Section 2.7 as a robustness check.

Moreover, this approach includes the initial export status, Y_{i0}, in the model as well as the firm-specific time average of the covariates. By doing this, Wooldridge (2005) deals with the initial condition problem, and shows that consistent estimates can be obtained even if the initial condition matters.

For specification (4), we estimate the following dynamic panel probit regression:

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 lnTFP_{it-1} + \beta_3 Z_{it-1} + d_t + d_s + d_r + \varepsilon_i \tag{2.8}$$

where $\varepsilon_i = \alpha_0 + \alpha_1 Y_{i0} + \alpha_2 \overline{lnTFP_i} + \alpha_3 \overline{Z_i} + \eta_i$

In equation (2.8) we again include one year lagged export status, Y_{it-1}, to capture the sunk entry cost effects. ε_i represents the firm-level unobserved fixed effects, while $\overline{lnTFP_i}$, and $\overline{Z_i}$ stand for time average of firm-level productivity, and time average of the remaining control variables.[26] Finally, Y_{i0} is the initial status of export participation for firm i.

As mentioned earlier, the dependent variable is the firm's export status, and our main interest is the relationship between firm-level productivity and the export decision. Following relevant literature, we include some other firm-specific and exogenous characteristics which might affect a firm's export decision in our analysis, such as size, age of a firm, and wages. *Size* is used as a variable in the majority of empirical studies in the relevant literature. It is believed that larger firms might benefit from economies of scale, thus a positive relationship between export status and firm size is expected. In this study, we use number of employees as the size variable. It is believed in the literature that firms' experience, in terms of years, is positively correlated to the decision to export, thus we include a variable for age into our analysis in order to assess the experience effect. We calculate a firm's age by reference to the firm's foundation year. A *capitalintensity* variable is included in order to control for firm's technology. Workforce quality is another important variable that might affect

[26] The remaining error term, η_i, is iid over time and individuals.

the firm's export decision. This variable is usually represented by average wage or the ratio of the number of skilled workers to total employees. Although the latter is preferred, we use average wage as a proxy for labour skill, since our database does not provide information about the structure of workforce of firms.

2.5.2. Results

2.5.2.1. Estimation Results From Pooled Data

Table 2.5a presents our findings from four different specifications: (1) Linear Probability Model; (2) Pooled-Probit; (3) Random Effects Probit; and (4) Dynamic Probit. We use pooled data from all industries and time periods, and all specifications contain sector, region, and time dummy variables. Column (4) reports that firms that exported at time $t-1$ are more likely to export at time t, since we observe a positive, and highly significant coefficient for the lagged dependent variable ($export_{t-1}$). This finding is in line with the results from Roberts and Tybout (1997); Bernard and Jensen (2004); and Arnold and Hussinger (2005) (and many others) who highlight the importance of sunk cost in self-selection analysis.

The estimation results for the first three specifications show that firm productivity is an important determinant of the export decision for the UK manufacturing firms, while the support for the self-selection hypothesis vanishes when we consider the sunk cost effect. The effect of average wage is positive and significant for specifications (1)-(3), implying that firms employing more skilled workers are more likely to export. However, the evidence for a positive relationship between labour skill and export disappears when we include sunk cost in our model. Our results for all specifications suggest that firms with more experience in terms of years are more likely to export, given that we find positive and significant coefficients for the age variable. Finally, firm size, which is represented by the number of employees also seems an important determinant of firms' export status, and the relationship is positive. This finding too is consistent with the literature.

Table 2.5b reports the marginal effects of the right hand side variables on the probability of export, and these findings are comparable with the coefficients from the LPM estimation in Table 2.5a. As can be seen in Table 2.5b column (4), a discrete change from 0 to 1 in lagged export status increases the export probability at time t by 39%. This suggests that firms that exported in the previous year are 39% more likely to export in the following year compared to firms that did not export in the previous year. Moreover, specifications (1), (2), and (3) show that firm-level productivity has a positive and significant effect on firms' export decisions, but not a very big one. A 1% increase in a firm's total factor productivity at time $t-1$ increases the export probability at time t by 2%. However, the size of the marginal effect of firm productivity is around eight times smaller compared to other specifications (.035%). This difference, we believe, arises from the inclusion of the sunk cost effect in specification (4). Since the sunk cost is not considered in specifications (1)-(3), TFP effect is overestimated.

Table 2.5a: Probability of Export (Dependent Variable: $Export_t$)

	(1)	(2)	(3)	(4)
$export_{t-1}$	-	-	-	1.7048
				(.0355)***
$\ln(TFP)_{t-1}$	.0125	.0489	.1175	.0258
	(.0031)***	(.0091)***	(.0297)***	(.0293)
$\ln(empl.)_{t-1}$	.0428	.1101	.4359	.0483
	(.0031)***	(.0066)***	(.0304)***	(.0147)***
$\ln(wage)_{t-1}$	.0307	.1629	.3903	-.0444
	(.0062)***	(.0175)***	(.0631)***	(.0652)
$\ln(cap.int.)_{t-1}$	-.0087	-.2115	-.0673	.0482
	(.0016)	(.0235)***	(.0794)	(.0843)
age_t	.0016	.0028	.0185	.1553
	(.0005)***	(.0008)***	(.0052)***	(.0401)**
constant	-.2194	-2.1888	-7.9296	.0079
	(.0394)***	(.0818)***	(.3852)***	(.0084)
year dummies	yes	yes	yes	yes
region dummies	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
N. of obs.	42283	42283	42283	42283

Robust s.e. in brackets. * indicates significance at the 10%, ** at the 5% and *** at the 1% levels.
(1)LPM, (2) Pooled-Probit, (3) Random Effects Probit, (4) Wooldridge's Dynamic Probit

Table 2.5b: Marginal effects after probit (dy/dx)

	(1)	(2)dy/dx	(3) dy/dx	(4) dy/dx
$export_{t-1}$	-			.3973
$\ln(TFP)_{t-1}$	-	.0177	.0237	.0035
$\ln(empl.)_{t-1}$	-	.0398	.0880	.0067
$\ln(wage)_{t-1}$	-	.0589	.0788	-.0061
$\ln(cap.int.)_{t-1}$	-	-.0764	-.0136	.0066
age_t	-	.0010	.0037	.0021

Result 1: *The well-established self-selection hypothesis is confirmed for the UK manufacturing firms, when we ignore the potential effect of sunk cost of exporting (specifications 1-3). However, when we consider the sunk cost of export, the support for the self-selection hypothesis vanishes.*

2.5.2.2. Estimation Results From Industry-Level Data

Almost all empirical studies in the literature on firm level productivity and export decisions examine the self-selection hypothesis by using pooled data, where all firms from different industries are considered together (as we do in the previous subsection). However, as we show in section 2.6, each industry has different characteristics: firms in some industries operate with rising marginal costs, while in some industries they produce at a constant marginal cost. In order to account for such differences, we test the self-selection hypothesis again, but this time for each industry. Our estimates in the previous subsection show that the export decision at time $t-1$ is an important determinant of the export decision of a firm at year t, which suggests that the sunk cost of entering the export market is an important factor for our analysis. Thus, amongst all four specifications, we decided to use Wooldridge's dynamic probit model for the current analysis, since, as we explained, it is the only one that is able to take the lagged dependent variable (which represents the sunk cost of export) in to account.

First, Table A1.3 in Appendix I Section A shows that the sunk cost effect is positive, and significant for all industries, and the highest effect is observed in the Non-metal Minerals Industry with around 48%. This suggests that being an exporter at time $t-1$, increases the probability of exporting at time t by around 48%, compared to a firm that does not export at $t-1$. We also find that this effect is the smallest, at 9%, in Other Transport Industry, which might imply a low sunk cost of export for this industry.

Second, we show that, our findings for the self-selection hypothesis are mixed. We confirm it for some industries, such as Textile/Cloth/Leather, and Other Manufacturing. In other words, we find that more productive firms in these industries at time $t-1$, are more likely to enter the export market at year t. The probability of export of a firm in Textile/Cloth/Leather industry increases by around 2.5%, if its productivity increases by 1%, while the probability of export increases by around 8.5% for firms operating in Other Manufacturing industry. These findings are consistent with Melitz's results, suggesting that more productive firms self-select to enter the export market.

On the other hand, we observe a negative and significant relationship between TFP and the export decision for some industries, such as Non-metal Minerals and Motor vehicles/parts. This finding is very interesting because it suggests that, in these industries, less productive firms self-select to export, which is the opposite of Melitz's findings.

Finally, we find a positive but not significant relationship between TFP and export decisions for some industries, such as Wood Products and Paper/Printing, while for some other industries, such as Electric Machinery and Coke/Chemicals, this relationship is both negative and insignificant.

Result 2: *We observe findings that are opposite to those proposed by the self-selection hypothesis. Namely, we find that in some industries in the UK, such as Non-metal Minerals and Motor Vehicles/Parts, less productive firms are more likely to export, and these results are robust across different dynamic estimation specifications.*

2.6. Testing the Marginal Cost Assumption

In this section we examine the relationship between export and domestic sales for the UK manufacturing firms. We aim to show whether the independent markets assumption of Melitz (2003) holds for the UK firms. Initially, we group firms in our dataset in terms of their export switching status. We classify a firm as a starter, stopper, or a continuer, where a starter firm is a firm that begins exporting in a given year, and a firm that stops exporting in a given year is classified as a stopper. All other firms (continuing exporters and non-exporters) are considered as continuers. We aim to explore, whether a firm entering the export market reduces its domestic sales compared to export stoppers and continuers, by estimating the following equation:

$$\begin{aligned}\Delta \ln(DomesticSales)_{irt} = \; & \beta_0 + \beta_1 starter_{irt} + \beta_2 stopper_{irt} + X_i \\ & + \beta_3 \Delta \ln(TFP) + d_t + d_s + d_r + u_{irt}\end{aligned} \tag{2.9}$$

In equation (2.9), $\Delta ln(DomesticSales)_{irt}$ stands for domestic sales growth. $starter_{irt} = 1$ if firm i in industry r enters the export market in period t, while $stopper_{irt} = 1$ for firms that stop exporting. Furthermore, d_t , d_s, and d_r are time, 2-digit SIC sector, and region dummy variables respectively, while X_i stands for firm fixed effects.[27] Finally, $\Delta \ln(TFP)$ represents total factor productivity growth of a firm. The coefficient β_1 measures mean variation in domestic sales growth for export starters compared to export stoppers and continuers.

Table 2.6 shows that, relative to continuers and stoppers, starters have a lower domestic sales growth rate, and stoppers have the highest domestic sales growth rate amongst the three categories. These results suggest that firms that begin exporting might face a trade-off between the export market and domestic market in terms of sales, and consequently reduce their domestic sales.

[27] Here, X_i controls for firm-specific differences between starters, stoppers and continuers.

Table 2.6: Export Starters and Stoppers (Dep.Var: Growth Rate of Domestic Sales)

	(1)	(2)	(3)	(4)
Starter	-.5239	-.5309	-.5357	-.5402
	(.0238)***	(.0232)***	(.0254)***	(.0248)***
Stopper	.5964	.6017	.5863	.5931
	(.0299)***	(.0297)***	(.0316)***	(.0314)***
TFP growth		.3772		.3435
		(.0162)***		(.0145)***
year dummies	yes	yes	yes	yes
region dummies	yes	yes		
Sector dummies	yes	yes		
Firm FE	no	no	yes	yes
N. of obs.	44234	43368	44234	43368

Robust s.e. in brackets. * indicates significance at the 10%, ** at the 5% and *** at the 1% levels

The findings we discussed so far provide us with useful information about the firms' domestic growth rates, but they do not give a clear result regarding the relationship between export and domestic sales. In order to test this relationship we use a panel of solely containing continuing exporters, which only includes firms that report positive exports for all observations. We estimate the following equation:

$$\begin{aligned}\Delta\ln(ExportSales)_{irt} = \quad & \beta_0 + \beta_1 \Delta ln(DomesticSales)_{irt} \\ & + \beta_2 X_{irt} + X_i + d_t + d_s + d_r + u_{irt}\end{aligned} \tag{2.10}$$

where $\Delta\ln(ExportSales)_{irt}$ and $\Delta ln(DomesticSales)_{irt}$ represent the growth figures for foreign and domestic sales respectively. Again, d_t , d_s, and d_r are time, 2-digit SIC sector, and region dummy variables. β_1 shows the correlation between the growth rate of domestic sales and export sales, while X_{irt} contains some firm-specific, time varying, characteristics, such as the growth rate of tangible assets, and the growth rate of number of employees.[28] Firm-level productivity growth is another factor that potentially has an effect on both domestic and foreign sales of a firm.

[28]The growth rates of tangible assets are used in all specifications, while the growth rate of employment is considered in specifications 2 and 4.

Thus, we include it in our analysis in all specifications. X_i represents firm-specific characteristics, which are constant over time. We use Pooled OLS in specifications 1 and 2, while a fixed effect estimation of equation (2.10) is reported in specifications 3 and 4.[29]

Table 2.7: Export-Domestic Sales Trade-off (Dep.Var: Growth Rate of Export Sales)

	(1)	(2)	(3)	(4)
Growt Rate of	-.01003	-.0496	-.0053	-.0662
Domestic Sales	(.0110)	(.0115)***	(.0103)	(.0142)***
Growt Rate of	.3169	-.3106	-.3014	-.2996
Productivity	(.0244)***	(.0240)***	(.0185)***	(.0159)***
Growt Rate of	.02968	.0161	.0282	.0177
Tang. Assets	(.0035)***	(.0032)***	(.0035)***	(.0029)***
Growt Rate of		.5327		.5303
Employment		(.0349)***		(.0305)***
constant	.777	.0723	.0037	.0079
	(.0362)***	(.0297)**	(.0091)	(.0084)
year dummies	yes	yes	yes	yes
region dummies	yes	yes		
Sector dummies	yes	yes		
Firm FE	no	no	yes	yes
N. of obs.	14813	14813	14813	14813

Robust s.e. in brackets. * indicates significance at the 10%, ** at the 5% and *** at the 1% levels

Table 2.7 shows that β_1 is negative for all specifications, and significant in specifications 2 and 4. In other words, both Pooled OLS, and fixed effect estimations suggest that the growth rate of sales in the domestic and export markets for continuing exporters are negatively correlated, which contradict the independent markets assumption of both standard and new trade models.

We also conduct the same analysis for each industry by estimating equation (2.10) based on 2-digit UK SIC codes. Tables A1.5 and A1.6 (in Appendix 1 Section A) provide results for OLS and FE estimations at industry level. All specifications in Tables A1.5 and A1.6 show that for some industries, such as Coke/Chemicals,

[29]As an alternative to Pooled OLS, a fixed effect estimation performs better when it comes to examining within-firm variations.

Basic/Fabricated Metals, Machinery/Equipment, Motor Vehicles/Parts, and Other Transport, β_1 is negative and significant. So, the growth rates of sales in the domestic and export markets are negatively correlated, and this raises doubts about the constant marginal costs assumption of both standard and new trade models.

The observed negative relationship between domestic, and foreign sales for the UK manufacturing firms could be explained via the correlation between domestic, and foreign demand shocks. In other words, if there is a negative correlation between the demand shocks, then it may result in a negative relationship between domestic, and foreign sales even though the firm produces at a constant marginal cost. However, for the UK firms, a negative correlation between domestic and foreign demand shocks seem implausible, given that the UK manufacturing firms have close trade relationships with European countries (BIS, 2010). Hence, we believe this is best explained by the existence of increasing marginal costs. To summarize we state:

Result 3: *We show that in several important UK manufacturing sectors, such as Paper/Printing, Coke/Chemicals, and Basic/Fabricated Metals, firms produce with rising marginal costs.*

2.7. Robustness Check

We now perform a robustness check for the Result 2, which we obtained by using the dynamic random effects probit model. As we already mentioned, a random-effects probit model assumes that the regressors are independent of the unobservables. More precisely, it is assumed that firm fixed effects, such as management and skills, are not correlated with explanatory variables, for instance firm-level productivity, and firm size in our model. If these firm-specific managerial skills or strategic management are correlated with regressors, then the problem of endogeneity occurs. In such a case, the random-effects probit model will provide biased results, since its key assumption is violated.

Some studies in the literature, such as Bernard and Jensen (2004), utilize a linear probability model with fixed effects in order to tackle unobserved firm heterogeneity. However, as we already explained, this model has important limitations. Instead of a linear probability model with fixed effects, Bernard and Jensen (2004) also use a generalized method of moments (GMM) estimator proposed by Arellano and Bond (1991). In this study, we also employ a GMM in order to control for unobserved firm heterogeneity, which may arise from firm fixed effects. Table A1.4 in Appendix 1 Section A shows results from the GMM estimation of equation (2.8). The results for the lagged dependent variable are very similar to those from the dynamic probit model. The coefficients representing the sunk cost of export are positive and significant for all industries. Our findings for the effect of firm productivity on the probability of entering the export market are also very similar to those we obtained by using dynamic probit model. The only difference is that we obtain a negative and insignificant coefficient for the Non-Metal Minerals industry, while we obtain a negative and significant one from the dynamic probit model estimations.

To conclude, we obtain very similar results from two different dynamic specifications. The dynamic random effects probit deals with the unobserved heterogeneity through the independence assumption, while GMM solves the same issue explicitly. Although the key assumptions of these models are very different, the results they produce are very similar. This suggests that the dynamic random effects probit specification that we use in the previous subsection does not suffer from an unobserved heterogeneity effect.

2.8. Conclusion

In this chapter, we have revisited the predictions of Melitz (2003) who suggests that more productive firms self-select to enter the export market. Initially, we used a dataset where all industries are pooled, and showed that more productive UK firms do self-select for the foreign market, if we do not consider the sunk cost of export, as many of the UK based studies do. However, we also showed that, when we consider the sunk cost of export, which is represented by the previous year's export status in the model, our findings do not confirm the self-selection hypothesis.

Then, we ran the same analysis for each industry, showing that self-selection occurs in some industries, Textiles/Cloth/Leather and Other Manufacturing, while we found that less productive firms self-select to enter the export market in some other industries, such as Non-Metal Minerals, and Motor Vehicles/Parts.

Following this, we showed that this evidence against self-selection can be best explained by the existence of increasing, rather than constant, marginal costs. We find that the average levels of sales growth in domestic and foreign markets are negatively correlated in many UK manufacturing industries, and to the best of our knowledge this is the first study examining this for the UK industries. This negative correlation suggests that optimal output levels in each individual market are not independent of the other markets for firms in some industries, and this raises doubts about the constant marginal costs assumption of both the standard and new trade models. Finally we showed that self-selection does not occur in some UK industries where firms produce at increasing marginal cost, such as Non-Metal Minerals, and Motor Vehicles/Parts.

The most serious limitation of this study arises from the data we use. As we highlight in section 4, the FAME dataset is widely utilized in many UK studies, but it is not exempt from criticism. The use of this dataset is criticized by Harris and Li

(2008), who claim that the dataset is biased towards large enterprises, and is therefore unrepresentative of UK firms. On the other hand, Rizov and Walsh (2005) describe the data as one of the most comprehensive databases of UK firms. Eberhardt and Helmers (2010) also address the representativity issue of FAME, and report some other potential problems, such as the lack of investment information in the dataset. Ideally, we would prefer to use a dataset provided by an official statistical institute of a country: however, such data is not very easy to access. As a further research agenda, we are planning to test the predictions of this analysis by using Turkish firm-level data, which will be provided by Turkish Statistical Institute. We believe that it will be interesting to compare our results from this study to findings from an analysis of Turkish firms, providing a good example of an emerging economy.

Appendix 1 - Section A:

Table A1.1: Variable Description

Variables	Definitions
Exporter	Dummy variable coded 1 if firm has positive overseas turnover in any year (2003-2011)
Gross Output	Turnover (in £'000, 2005 prices)
TFP	Total factor productivity
Employment	Number of employees in the firm
Labour Productivity	Gross output per employee
Capital stock	Tangible assets (in £'000, 2005 prices)
Intermediate Inputs	Cost of sales minus remuneration (in £'000, 2005 prices)
Intangible Assets	Non-monetary assets (e.g. innovation, brand, etc.)
Wage	Total labour payment/Number of Employee
Age	Number of years in business
Industry 1	coded 1 if Basic/Fabricated Metals, 0 otherwise
Industry 2	coded 1 if Coke/Chemicals, 0 otherwise
Industry 3	coded 1 if Electrical machinery, 0 otherwise
Industry 4	coded 1 if Food/Beverages/Tobacco, 0 otherwise
Industry 5	coded 1 if Machinery/Equipment, 0 otherwise
Industry 6	coded 1 if Motor vehicles/parts, 0 otherwise
Industry 7	coded 1 if Non-metal Minerals, 0 otherwise
Industry 8	coded 1 if Office Equipment, 0 otherwise
Industry 9	coded 1 if Other manufacturing, 0 otherwise
Industry 10	coded 1 if Other transport, 0 otherwise
Industry 11	coded 1 if Paper/Printing, 0 otherwise
Industry 12	coded 1 if Rubber/Plastic, 0 otherwise
Industry 13	coded 1 if Textiles/Cloth/Leather, 0 otherwise
Industry 14	coded 1 if Wood Products, 0 otherwise
Region 1	coded 1 if East England, 0 otherwise
Region 2	coded 1 if East Midlands, 0 otherwise
Region 3	coded 1 if London, 0 otherwise
Region 4	coded 1 if North East, 0 otherwise
Region 5	coded 1 if North West, 0 otherwise
Region 6	coded 1 if South East, 0 otherwise
Region 7	coded 1 if South West, 0 otherwise
Region 8	coded 1 if Wales, 0 otherwise
Region 9	coded 1 if West Midlands, 0 otherwise
Region 10	coded 1 if Yorkshire&Humberside, 0 otherwise
Region 11	coded 1 if Scotland, 0 otherwise
Region 12	coded 1 if Northen Ireland, 0 otherwise

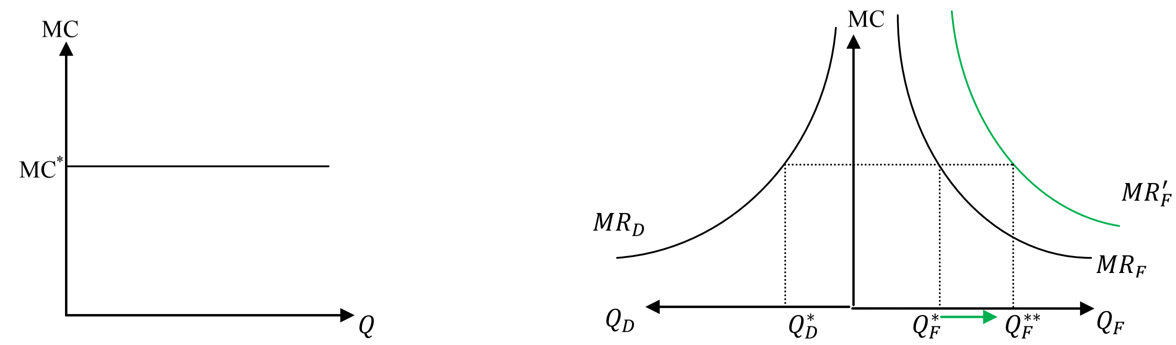

Figure A1.1: Effect of an export market demand shock under constant MC assumption

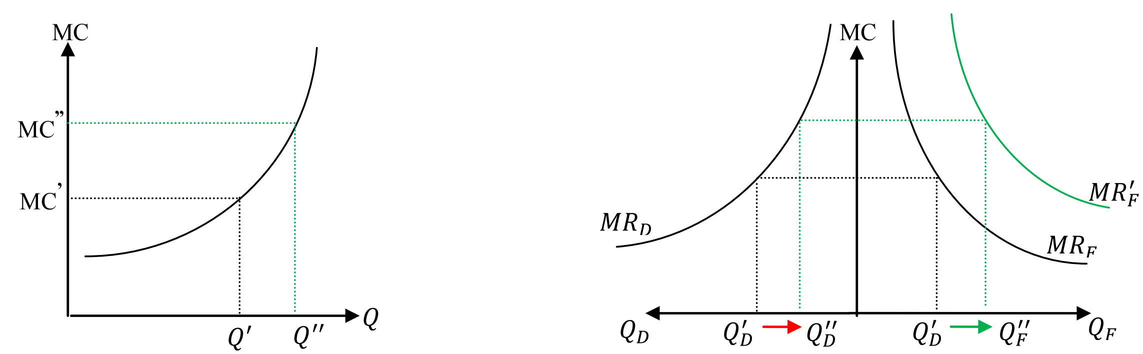

Figure A1.2: Effect of an export market demand shock under rising MC assumption

Table A1.2: Marginal Cost and Self-Selection Findings

Industry	Rising MC	Self-Selection to Export
Food/Beverages/Tobacco	insignificant	insignificant
Textiles/Cloth/Leather	X	✓
Wood Products	insignificant	insignificant
Paper/Printing	insignificant	insignificant
Coke/Chemicals	✓	insignificant
Rubber/Plastic	✓	insignificant
Non-metal Minerals	✓	X
Basic/Fabricated Metals	✓	insignificant
Machinery/Equipment	✓	insignificant
Office Equipment	✓	insignificant
Electrical machinery	insignificant	insignificant
Motor vehicles/parts	✓	X
Other transport	✓	insignificant
Other manufacturing	X	✓

Table A1.3: Probability of Export – Dynamic Random Effects Probit - (Dep.Var: $Export_t$)

Industry	$export_{t-1}$	$\ln(TFP)_{t-1}$	$\ln(empl.)_{t-1}$	$\ln(wage)_{t-1}$	$\ln(cap.int.)_{t-1}$	age_t	Number of Obs.
Food/Beverages/Tobacco	1.7355	.0999	-.0344	-.5259	.2389	.0477	5360
	(.1049)***	(.1120)	(.0481)	(.1981)***	(.2446)	(.0467)	
Textiles/Cloth/Leather	1.5818	.3439	.0757	-.5859	.1338	.0151	1155
	(.2054)***	(.2118)*	(.0825)	(.3464)*	(.5615)	(.0797)	
Wood Products	1.9032	.3521	.0376	-.4320	-.4983	.1705	899
	(.2642)***	(.3298)	(.1554)	(.6099)	(.9654)	(.1187)	
Paper/Printing	2.0265	.0931	-.0121	-.0998	.4828	.0825	3620
	(.1418)***	(.1199)	(.0589)	(.2149)	(.3568)	(.0317)*	
Coke/Chemicals	1.5492	-.0638	.0522	-.0284	-.0229	-.0634	6564
	(.0848)***	(.0720)	(.0352)	(.1482)	(.1613)	(.0379)*	
Rubber/Plastic	1.8322	-.0473	.0567	.3597	.5060	-.0813	2738
	(.1488)***	(.1305)	(.0632)	(.3218)	(.4469)	(.0596)	
Non-metal Minerals	2.0008	-.5501	.2460	-.0354	.4909	.0529	1285
	(.2425)***	(.2683)**	(.1170)**	(.4085)	(.5408)	(.1110)	
Basic/Fabricated Metals	1.8271	.0398	.1160	-.0608	.1546	-.0716	6889
	(.0862)***	(.0664)	(.0364)***	(.1665)	(.2299)	(.0354)**	
Machinery/Equipment	1.5495	.1129	.0341	.1075	-.1618	.0364	4030
	(.1104)***	(.0921)	(.0502)	(.2125)	(.2165)	(.0491)	
Office Equipment	1.7185	.0236	-.0041	.0204	.1369	.0465	1441
	(.1691)***	(.1489)	(.0578)	(.3562)	(.7014)	(.0769)	
Electrical machinery	1.7694	-.1589	-.0080	-.0952	-.1241	-.0307	2097
	(.1474)***	(.1410)	(.0674)	(.3100)	(.5694)	(.0685)	
Motor vehicles/parts	1.5206	-.3776	.0924	.7295	.5048	-.0315	1277
	(.1869)***	(.1358)***	(.0830)	(.4655)*	(.8245)	(.0867)	
Other transport	1.4688	.0478	.0277	-.4767	-.0223	.0260	962
	(.2727)***	(.1923)	(.0852)	(.5590)	(.5539)	(.1186)	
Other manufacturing	1.6141	.2857	.0772	.2740	.4609	-.0003	3966
	(.1422)***	(.1119)***	(.0588)	(.2233)	(.4345)	(.0540)	

Robust s.e. in brackets. * indicates significance at the 10%, ** at the 5% and *** at the 1% levels

Table A1.4: Probability of Export – GMM (Arrelano and Bond, 1991) - (Dep.Var: $Export_t$)

Industry	$export_{t-1}$	$\ln(TFP)_{t-1}$	$\ln(empl.)_{t-1}$	$\ln(wage)_{t-1}$	$\ln(cap.int.)_{t-1}$	age_t	Number of Obs.
Food/Beverages/Tobacco	.2686	.0177	.0055	-.0728	.0191	.0102	4049
	(.0347)***	(.0170)	(.0208)	(.0281)***	(.0357)	(.0069)	
Textiles/Cloth/Leather	.2335	.0264	.0480	-.0474	.0301	.0035	828
	(.0696)***	(.0345)	(.0496)	(.0824)	(.1229)	(.0130)	
Wood Products	.1902	.0501	-.0181	-.0403	-.0091	-.0001	638
	(.0698)***	(.0364)	(.0581)	(.0449)	(.0837)	(.0138)	
Paper/Printing	.3769	.0264	-.0392	-.0057	.0552	.0106	2727
	(.0452)***	(.0168)	(.0303)	(.0223)	(.0379)	(.0062)*	
Coke/Chemicals	.3280	-.0208	.0126	.0203	-.0260	.0117	5085
	(.0294)***	(.0136)	(.0235)	(.0249)	(.0308)	(.0068)*	
Rubber/Plastic	.3509	-.0169	-.0183	.0553	-.1317	.0155	2077
	(.0473)***	(.0204)	(.0353)	(.0478)	(.0681)**	(.0117)	
Non-metal Minerals	.4786	-.0152	.1366	.0497	.0401	-.0139	958
	(.0758)***	(.0308)	(.0494)***	(.0546)	(.0549)	(.0137)	
Basic/Fabricated Metals	.3535	-.0013	-.0118	-.0094	-.0861	.0186	5158
	(.0297)***	(.0108)	(.0226)	(.0230)	(.0484)*	(.0058)***	
Machinery/Equipment	.3131	.0137	-.0535	-.0367	-.0866	.0273	3090
	(.0371)***	(.0154)	(.0308)*	(.0371)	(.0418)**	(.0075)***	
Office Equipment	.2859	.0179	-.0421	.0105	.0550	.0209	1109
	(.0579)***	(.0341)	(.0509)	(.0699)	(.1033)	(.0157)	
Electrical machinery	.4078	-.0284	-.0649	-.0365	-.0095	.0498	1596
	(.0561)***	(.0254)	(.0304)*	(.0527)	(.1016)	(.0124)***	
Motor vehicles/parts	.1876	-.0532	.0699	.1261	.0023	.0046	988
	(.0584)***	(.0214)**	(.0602)	(.0683)*	(.1356)	(.0179)	
Other transport	.0981	-.0171	-.0325	-.0918	-.0061	.0412	734
	(.0074)***	(.0235)	(.0590)	(.0816)	(.0453)	(.0148)***	
Other manufacturing	.1180	.0851	-.0323	.0472	.0872	.0034	2895
	(.0370)***	(.0179)***	(.0297)	(.0330)	(.0592)	(.0990)	

Robust s.e. in brackets. * indicates significance at the 10%, ** at the 5% and *** at the 1% levels

Table A1.5: (OLS): Export-Domestic Sales Trade-off - Industries (Dep.Var: Gr. R. of Export Sales)

Industry	Growth of Dom.Sale	Growth of Productivity	Growth of Tang. Assets	Growth of Emply.	Number of Obs.
Food/Beverages/Tobacco	.0208	.6069	.0066	.3699	1089
	(.0242)	(.0816)***	(.0287)	(.0397)***	
Textiles/Cloth/Leather	.2234	.1345	.1741	.9311	440
	(.1345)*	(.1443)***	(.0687)**	(.2368)***	
Wood Products	.0047	.3106	.0731	.4183	77
	(.0137)	(.1001)***	(.0285)***	(.1719)**	
Paper/Printing	-.0231	.3551	.0565	.4434	774
	(.0240)	(.1024)	(.0249)**	(.0849)***	
Coke/Chemicals	-.0822	.3746	.0692	.4029	2685
	(.0338)**	(.0463)***	(.0255)**	(.0743)***	
Rubber/Plastic	-.0286	.3485	.0318	.6515	1120
	(.0184)	(.0478)***	(.0148)**	(.1124)	
Non-metal Minerals	-.0072	.3178	.0495	.4541	322
	(.0372)	(.0938)***	(.0372)	(.1016)***	
Basic/Fabricated Metals	-.0329	.2518	.0340	.6260	2571
	(.0142)**	(.0332)***	(.0244)	(.0547)***	
Machinery/Equipment	-.0875	.3452	.0331	.6501	1779
	(.0261)***	(.0508)***	(.0306)	(0812)***	
Office Equipment	-.0745	.4782	.0121	.6289	507
	(.0367)**	(.1042)***	(.0420)	(.1387)***	
Electrical machinery	-.1160	.3395	.0368	.5029	823
	(.0646)*	(.0862)***	(.0262)	(.1114)***	
Motor vehicles/parts	-.0865	.2292	.0126	1.097	472
	(.0438)**	(.0565)**	(.0451)	(.2757)***	
Other transport	-.1467	.091	-.0285	.8304	424
	(.0503)***	(.0584)***	(.0546)	(.1238)***	
Other manufacturing	.05522	.3235	.0044	.3667	1730
	(.0201)***	(.0562)***	(.0086)	(.0662)***	

Robust s.e. in brackets. * indicates significance at the 10%, ** at the 5% and *** at the 1% levels

Table A1.6: (FE): Export-Domestic Sales Trade-off - Industries (Dep.Var: Gr. R. of Export Sales)

Industry	Growth of Dom.Sale	Growth of Productivity	Growth of Tang. Assets	Growth of Emply.	Number of Obs.
Food/Beverages/Tobacco	.0329	.5828	.0173	.3501	1089
	(.0249)	(.0799)***	(.0285)	(.0378)***	
Textiles/Cloth/Leather	.2254	.2604	.1398	.8866	440
	(.1289)*	(.0775)***	(.0631)**	(.3301)***	
Wood Products	.0112	.3109	.0694	.4840	77
	(.0111)	(.0966)***	(.0254)***	(.1438)**	
Paper/Printing	-.0167	.3483	.0715	.3927	774
	(.0301)	(.1099)***	(.0264)**	(.0901)***	
Coke/Chemicals	-.0737	.3557	.0690	.3204	2685
	(.0349)**	(.0503)***	(.0273)**	(.0790)***	
Rubber/Plastic	-.0257	.3483	.0209	.6698	1120
	(.0205)	(.0503)***	(.0188)**	(.1417)	
Non-metal Minerals	-.0217	.2982	.0355	.5184	322
	(.0357)	(.0854)***	(.0353)	(.1316)***	
Basic/Fabricated Metals	-.0404	.2481	.0244	.6158	2571
	(.0158)**	(.0376)***	(.0302)	(.0665)***	
Machinery/Equipment	-.0823	.3474	.0278	.6525	1779
	(.0285)***	(.0651)***	(.0373)	(.0999)***	
Office Equipment	-.0701	.5041	.0187	.5368	507
	(.0363)*	(.1089)***	(.0410)	(.1507)***	
Electrical machinery	-.1069	.3230	.0401	.4907	823
	(.0648)	(.0818)***	(.0258)	(.1111)***	
Motor vehicles/parts	-.0723	.2223	.0054	1.007	472
	(.0420)*	(.0566)***	(.0390)	(.3322)***	
Other transport	-.1520	.2058	-.0162	1.128	424
	(.0512)***	(.0548)***	(.0569)	(.1372)***	
Other manufacturing	.0427	.3545	.0042	.3934	1730
	(.0174)**	(.0621)***	(.0097)	(.0557)***	

Robust s.e. in brackets. * indicates significance at the 10%, ** at the 5% and *** at the 1% levels

Appendix 1 - Section B:

Methodological Issues and TFP Estimation Methods

Some Methodological Issues

In this subsection, some methodological issues arising from the estimation of TFP will be explained and different estimation methods aiming to tackle these issues will be analyzed. One can estimate equation (2.4) using Ordinary Least Squares (OLS). However, the use of the standard OLS procedure to estimate firm-level TFP provides biased estimates because of endogeneity of input choices (i.e. simultaneity bias) and selection bias (van Beveren, 2012).

As Marschak and Andrews (1944) highlight, characteristics of a firm play an important role in determining production function inputs. In other words, "simultaneity bias" arises from a correlation between unobserved productivity shocks and input choice. Olley and Pakes (1996) suggest that if a firm has prior knowledge of ω_{it} before making an input choice, this causes endogeneity, since input decisions will be affected by the prior knowledge.[30] Although Marschak and Andrews (1944) highlighted the importance of this issue for the estimation of TFP a long time ago, only very recently some new methods have been developed to deal with this problem.[31] Some newly developed techniques amongst them, such as Olley and Pakes (1996), Blundell and Bond (2000), and Levinsohn and Petrin (2003) have replaced the traditional methods over the last fifteen years.

Another issue in the estimation of TFP is a "selection problem" arising from the market entry and exit of firms in any period. Earlier studies in the literature

[30]As De Loecker (2007) describes, a positive productivity shock causes upward bias in input coefficients, since firms tend to increase the use of input quantities under a positive productivity shock.

[31]Until recently, this problem has been addressed by using some traditional methods, such as fixed effects and instrumental variables.

used balanced panels which avoids the market entry and exit behaviours of firms. However, by using a panel for Spanish manufacturing firms, Farinas and Ruano (2005) show that a firm's exit is a function of unobserved productivity. Moreover, they suggested that more productive firms had a lower probability of exit from the market. And if firms have prior knowledge about their productivity levels (ω_{it}), then their decisions on input allocation will depend on its survival probability.[32] Thus, if the selection bias is not taken into account explicitly, it causes TFP estimation to be biased upwards (Eberhardt and Helmers, 2010).

The final methodological issue we will discuss is "omitted price bias", which is associated with the use of industry level price indices in order to deflate input and output variables. In such a case, if firms' decision on input choice depends on firm-level price differences, this would result in biased estimates. Since firm-level prices are rarely available, this problem is common for most of empirical studies conducting firm-level analysis.[33] Recently, some studies tried to overcome this problem, such as De Loecker (2007), who introduces differentiated factor markets and demand conditions for exporters and non-exporters to Olley and Pakes's (1996) estimation procedure.

TFP Estimation Methods

In recent years there has been considerable progress on the measurement of total factor productivity, and there are different methods available for researchers. In this part of the study, we will review some of the methods that were developed in order to tackle problems of simultaneity and sample selection biases.

[32] Selection bias will lead to a negative correlation between ε_{it} and K_{it}. This causes downward bias for the capital coefficient (Eberhardt and Helmers, 2010).

[33] However, this problem can be tackled by using quantities of output rather than deflated sales, where available (van Beveren, 2012).

Fixed Effects Estimator

As we have already discussed, estimation of the production function using OLS provides inconsistent and biased estimates. However, the fixed effects estimator aims to overcome simultaneity bias problem by assuming ω_{it} is plant-specific and time-invariant, ω_i (Levinsohn and Petrin, 2003). Under this assumption, a fixed effects estimator would provide results unaffected by both simultaneity and selection biases. However, Olley and Pakes (1996) show that applying a fixed effects estimator both on balanced and unbalanced panels provides different results. In other words, their results show that this estimator is not successful in eliminating of selection bias caused by endogenous entry and exit. Moreover, Wooldridge (2009) states that the assumption of the fixed effects estimator, which is associated with the strict exogeneity of the outputs, is unreal. He shows that the fixed effects estimator performs inefficiently if this assumption fails.[34]

Standard Instrumental Variables (IV) Regression

These disadvantages of the OLS and the fixed effects approach have led researchers to the instrumental variable method which is another way to tackle simultaneity problem (Levinsohn and Petrin, 2003).[35] This approach uses instruments for the input variables in the production function which cause the problem of endogeneity.[36] Input prices are commonly used as instruments in this literature, although they serve their purpose well only if input markets operate in perfect competition, which is rare (van Beveren, 2012).[37]

[34] This assumption implies that the firm's input decision is independent of a productivity shock.

[35] As Wooldridge (2009) states, unlike fixed-effects estimator, the instrumental variables (IV) approach does not require strict exogeneity of the independent variables, which makes this method preferable to the fixed-effects estimator.

[36] Instruments, in our case, are the variables that are correlated with the inputs in the production function but uncorrelated with unobserved productivity.

[37] If some firms have market power they are likely to affect input prices. This might cause a correlation between unobserved productivity and instruments. In such a case, input prices lose

Other instruments that are commonly used in the literature are the lagged levels of the inputs. However, as Blundell and Bond (2000) highlight, this approach also has some drawbacks.[38] According to them the lagged levels of the inputs are usually highly persistent, thus they might be weakly correlated with input changes, and therefore they may not be good instruments. In addition, one should be aware that even if the selected instruments are valid, this method can only overcome the simultaneity problem. The problem of selection bias arising from the firms' endogenous exits from the market cannot be controlled by using this approach.[39]

Olley-Pakes (OP) and Levinsohn-Petrin (LEV) Estimation Algorithms

As discussed above, finding a valid instrument is not an easy task. Recently, some researchers have tried to develop methods that do not require instruments to estimate the production function. Olley and Pakes (1996) (henceforth OP) is the first study following this approach to tackle both problems of simultaneity and selection. OP developed a semi-parametric estimator by using a firm's investment decision to control for correlation between inputs in the production function and an unobserved productivity shock. They also take the firm's exit decision into account explicitly in order to overcome selection bias.

The OP method has several advantages over the methods we have reviewed so far, and it is widely used by researchers who conduct analysis related to firm-level productivity.[40] However, Levinsohn and Petrin (2003) (henceforth LevPet) show that the OP approach might not always work well, and they have developed an

their validity as an instrument.

[38]Blundell and Bond (2000) also provide a dynamic panel approach, an extended GMM estimator. Since they believe that the weak instruments are the reason for the bad performance of IV estimators, they use lagged first differences of production function variables and obtain better results.

[39]Moreover, if there is a correlation between firm exit and the selected instruments, the instruments would lose their validity (Ackerberg et al., 2007).

[40]Griliches and Mairesse report the advantages of this method over OLS, fixed effects, and traditional instrumental variables estimators (Griliches and Mairesse, 1995, p. 17)

improved version of it. They highlight some technical issues with the OP approach arising from the use of investment as a proxy for unobserved productivity shocks, and they propose to use intermediate input demand instead. According to LevPet, the main disadvantage of the OP method arises from the monotonicity condition, which only permits the use of observations that report positive investment. And this requirement causes significant data loss. LevPet claim that they overcome this issue by using intermediate input demand as a proxy instead of the firm's investment decision, since firms usually report positive use of intermediate input in each year.

These two methods deal with selection bias in different ways. Unlike the OP method, the LevPet technique does not take the firm's exit into account, since they claim that such an approach does not improve their results a lot. Apart from omitting the firm's exit decision and using intermediate input demand as a proxy instead, these two methods are fully analogous (van Beveren, 2012).

Appendix 1 - Section C:

Different Estimation Techniques

Now we will consider firm fixed effects in our estimations, by using the panel structure of our data. Given the result of the Hausman test, we include firm fixed effects in equation (6), in order to control for potential unobserved firm heterogeneity explicitly. The model takes the form:[41]

$$ln(Prod) = \beta_0 + \beta_1 Export_{it} + \beta_2 ln(Size)_{it} + Z_i + d_t + d_s + u_{it}$$

where Z_i is firm fixed effects. Table A1.7 provides our results for the fixed effects model which shows that export status coefficient is still positive and statically significant at 1% level, however, the magnitude of estimated coefficients becomes smaller.

[41] We also used random effects estimator. However, the result of Hausman test suggests that fixed effects model is preferable over the random effects model.

Export productivity premium for total factor productivity measures are around 3%, while it decreases to 1.6% for labour productivity.

Table A1.7: Export Productivity Premia – Fixed Effects (2003-2011)

	(1) TFP-LEV	(2) TFP-OLS	(3) LP
Export Dummy	0.032	0.031	0.016
	0.007*	0.007*	0.004*
%Export Premium	3.2	3.1	1.6
R^2-within	0.12	0.12	0.12
R^2-between	0.54	0.01	0.03
R^2-overall	0.49	0.02	0.05
N. of obs.	53900	53900	54607
N. of groups	9818	9818	9849

Note: P-values are in parenthesis (we used robust standard errors).
To obtain %Export Premium, the estimated coefficients for the exporter dummy variable have been transformed by $100(\exp(\beta)-1)$.
*** indicates significant at the 1% level.

CH 3: Do Firms Learn From Exporting if Returns to Scale are Variable?

3.1. Introduction

The relationship between export and growth, especially export-led growth, is well-established at the macro-level (Edwards, 1993). However, at the micro-level, the literature on the links between exports and firm-level productivity is new and growing. In theory, firms operating in international markets could benefit from exporting as a result of technological exchange with their international rivals and clients. Moreover, exporters face pressure to improve their production techniques in order to meet high requirements arising from intense competition in the international markets, and this process, may cause productivity improvements (Aw, Chung and Roberts, 2000). On top of that, exporters could benefit from the economies of scale which result from the production capacity improvements determined by international demand. Following an increasing availability of firm-level data, since the mid-1990s, several studies have examined the productivity-enhancing effect of export at the firm level. Although there are a number of studies on this issue, the evidence on the learning by exporting (LBE) effect is mixed and still unclear (Wagner, 2007).

The literature on learning by exporting (LBE) focuses on three potential sources of learning: technology transfer, competition, and economies of scale. Although the literature suggests that economies of scale may play an important role in productivity, many empirical UK studies examining the relationship between export and productivity ignore scale effects.[42] It is rather surprising that some of these studies assume constant returns to scale (CRTS) when it comes to total factor productivity

[42] We include those studies in the review of literature in Section 3.2

(TFP) computation. In these studies, the effect of scale is overlooked as a result of the assumption of CRTS. More precisely, TFP growth is assumed to be equivalent to technical change only, since scale effects are assumed to be zero.[43] However, if returns to scale were not constant, productivity improvements from exporting could be due not only to technical change, but may also reflect scale efficiency change (Biesebroeck, 2005). For this reason, those studies employing conventional TFP estimation methods, such as the index method, or assuming a restrictive functional form of a production function, such as Cobb-Douglas, are likely to provide biased results for the export-productivity link.

This chapter has two main contributions. First, showing that some firms in the UK experience non-constant returns to scale, we construct a TFP measure that accounts for scale effect.[44] To do this, we compute firm-level TFP by employing a translog production function which allows for variable returns to scale (VRTS).[45] Second, we show the effect of exporting on the three components of TFP: technical change, scale change, and technological progress (efficiency) change. To our knowledge, this is the first UK study to provide a decomposition of the causal effects of exporting on firm-level productivity improvement. This analysis allows us to examine the different channels through which exporting influences TFP growth, namely technical change, scale change, and efficiency change.

We conduct our analysis by using an unbalanced panel of UK manufacturing firms covering the period 2003-11.[46] In the first part of our analysis, we calculate returns to scale for each firm, and show that some of the UK firms experience variable returns to scale in a way that contradicts any assumption of CRTS.[47]

[43] Please see Coelli (2005) for a detailed discussion on this.

[44] Biesebroeck (2005) suggests that new exporters enjoy scale economies as they expand. Thus, one should control for variable returns to scale to estimate TFP correctly.

[45] As De Loecker and Warzynski (2012) show, a translog production function perform better than a Cobb-Douglas when it comes to TFP estimation.

[46] In this chapter, we use the dataset that we utilized in Chapter 2.

[47] Our findings are consistent with recent UK studies such as Girma and Gorg (2007) and Harris

Following this, we estimate firm-level TFP by controlling for VRTS, and decompose TFP growth into three components by utilizing Stochastic Frontier Analysis (SFA). Then we examine the post-entry effects of export on TFP growth, and its components by comparing export starters (treatment group) with never-exporters (control group). However, we cannot observe what would have happened to a firm if it had not entered the export market. In other words, we can observe a firm in only one situation, since it is either an exporter or a non-exporter in the observation year. For this reason the results from a basic comparison between export starters and never-exporters in terms of LBE effect may suffer from a selection bias. In this paper we try to overcome this problem by employing a combined propensity score matching and difference-in-differences methodology (PSM-DID). This approach allows us to construct a control group from never-exporters where the distribution of the observed covariates for both groups are very similar.

We observe some interesting patterns from our results. First, we find evidence in favour of an LBE effect when we consider the TFP measure which we obtain from a Cobb-Douglas production function. However, the evidence of LBE largely disappears when we consider the TFP measure which accounts for scale effects. Second, and more importantly, we show that any productivity growth effects of exporting are predominantly attributable to change in scale efficiency. More precisely, the main source of TFP growth is not technical improvements, but scale efficiency improvements.

The rest of the paper is organized as follows. Section 3.2 provides a review of the related research, while section 3.3 explains the methodology used for the estimation of total factor productivity (TFP) and provides some estimation results for the production function. Section 3.4 describes the framework of the econometric analysis that we employ in order to assess the relationship between export activity

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and Li (2008), who find increasing returns to scale for some industries. On the other hand, Saal et al. (2007) report decreasing returns to scale for the water and sewerage industry.

and firm productivity. Finally, Section 3.5 provides results, and Section 3.6 offers some concluding remarks.

3.2. Literature Review

We have already highlighted that economies of scale may play a crucial role in LBE analysis, if firms produce with VRTS. This implies that the choice of an estimation methodology for TFP matters when it comes to LBE analysis. The literature on productivity analysis provides several methods that account for scale effects, from non-parametric to fully parametric methods.[48] However, some UK studies, such as Girma, Kneller and Pisu (2007), use an estimation method for TFP which overlooks scale effects. They calculate TFP, under the CRTS assumption, by using a non-parametric approach (index number) proposed by Caves, Christiensen, and Diewert (1982). Some other studies, such as Kneller and Pisu (2010), and Silvente (2005) use a proxy for TFP that cannot take scale effects in to account. While Kneller and Pisu (2010) use R&D level as proxy for TFP, Silvente (2005) use labour productivity. Since such studies do not use TFP as a measure of productivity, their results are not comparable to ours.[49]

Several other studies examine LBE effect for the UK firms. Girma, Greenaway, and Kneller (2004), for instance, examine exporting and firm performance, for the first time, for the UK manufacturing firms, and they report evidence in favour of the LBE hypothesis. In their paper, they calculate TFP as residuals from a Cobb-Douglas production function, where they report firm-level TFP relative to the industry average. Like Girma et al. (2004), Greenaway and Yu (2004) find evidence for LBE. However, they conduct an industry specific analysis for the UK chemical industry, where they also compute firm-level TFP as residuals from Cobb-Douglas

[48]See Heshmati (2003) for a survey.
[49]Thus, these studies are excluded from the review.

production function estimations by assuming CRTS, and they report that the LBE effect is bigger for new export starters compared to more experienced exporters. Unlike our analysis, both Girma et al. (2004), Greenaway and Yu (2004) ignore any scale effects which may arise from VRTS.

As we highlight in Section 3.4.1, selection bias is an important issue for LBE analysis. Girma, Greenaway and Kneller (2003) employ a matching with difference in differences (DID) method in order to reduce selection bias, and this is the first UK study to combine these techniques. They investigate the effect of export market exit on TFP, and they find a negative relationship between the two, while the other studies examine export market entry effect. Based on these results, they conclude that an LBE effect exists. Following this study, Greenaway and Kneller (2004) use a matching method, and they also find evidence of LBE from non-matched data.[50] However, this finding disappears when they consider matched data. Hence, when they control for selection bias, they fail to confirm any learning by exporting effect. It is important to note that Greenaway and Kneller (2004) calculate TFP, under the CRTS assumption, by using the index number approach. Unlike our study, both Girma, Greenaway and Kneller (2003) and Greenaway and Kneller (2004) overlook VRTS when it comes to TFP computation.

The only UK study reporting variable returns to scale for UK firms in this literature is Harris and Li (2008), which employs a Cobb-Douglas production function to compute firm-level TFP. Unlike Greenaway and Yu (2004), they do not impose any constraint on the production function in terms of returns to scale.[51] They estimate a Cobb-Douglas production function by using the generalized methods of

[50]Similar to Greenaway and Kneller (2004), Greenaway and Kneller (2008) also use a matching with difference and differences method, where they construct firm-level TFP from a Cobb-Douglas production function. However, they examine the post-entry effect of export by focusing on export market exposure of firms, and report findings in favour of LBE for firms more exposed to the export market only.

[51]They use an augmented production function with three inputs: capital, employment, and intermediate inputs, and they allow variable returns to scale.

moments (GMM) approach proposed by Arellano and Bond (1991), which corrects for the simultaneity of input choices. They confirm the LBE hypothesis for the UK manufacturing and service firms, and report that LBE effect is higher for continuing exporters compared to new exporters.[52] Although Harris and Li (2008) explicitly account for scale effects, they estimate TFP by employing a Cobb-Douglas production function, which has certain limitations.[53] Unlike our study, they report an exporting effect only on TFP growth, and do not examine any effects on the components of TFP change.

It is clear that results on LBE from the UK studies are mixed. As we report, some studies compute TFP by using a non-parametric method, while some others use regressions by employing a Cobb-Douglas production function. Moreover, some studies compare all export-starters to all non-exporters to find an LBE effect, while some others employ a matching method, and construct a new dataset that includes only those export-starters and non-exporters that have similar characteristics. One may say that different methodologies used to evaluate the LBE effect might be the reason for the mixed results provided by the literature. We also aim to address this issue in the remaining part of this study.

3.3. Decomposing Productivity Growth and Measuring Returns to Scale

In this section, we aim to obtain estimates of firm level total factor productivity by considering potential scale effects, and to decompose TFP growth in order to show the effect of exporting on each component of productivity. In this study, we

[52] We described econometric problems arising from the simultaneity of input choices in Chapter 2.

[53] We highlight these issues in Section 3.3.

employ stochastic frontier analysis (SFA), which is a widely-used method in several areas as a way to measure performance.[54] A production frontier relates to the maximum achievable output level for a firm by using existing production technology and inputs. There are other methods available which can be used in order to decompose TFP, such as data envelopment analysis, or the Malmquist index. However, as Coelli (2005) highlights, SFA offers several advantages with regard to dealing with measurement errors, outliers in data, and random shocks.

We obtain firm-level total factor productivity by using a firm-level transcendental logarithmic (translog) production function, which is a second-order logarithmic approximation of the production that allows for variable returns to scale.[55] We follow Kumbhakar and Lovell (2000) at this stage, and estimate the following translog production function:

$$\begin{aligned} ln(Y_{it}) = \quad & \beta_0 + \beta_1 lnK_{it} + \beta_2 lnL_{it} + \beta_3 t + \tfrac{1}{2}\left(\beta_4 (lnK_{it})^2 + \beta_5 (lnL_{it})^2 + \beta_6 t^2\right) \\ & +\beta_7 (lnK_{it} * lnL_{it}) + \beta_8 (lnK_{it} * t) + \beta_9 (lnL_{it} * t) + v_{it} + u_{it} \end{aligned} \tag{3.1}$$

where Y_{it} stands for output, K_{it} and L_{it} represent the input factors, respectively capital and labour. Finally, t is time trend, and v_{it} is a random error term. Table A2.1 reports point estimates of production function.

Kumbhakar and Lovell (2000), and Sharma et al. (2007) suggest that estimated total factor productivity growth can be decomposed into three components by utilizing equation (3.1): technological process change, technical efficiency, and scale efficiency.

- Technological process change (TP) represents technological improvements that cause an upward shift in production frontier and it is calculated as:

[54] SFA is developed by Aigner, Lovell and Schmidt (1977) and Meeusen and Broeck (1977).

[55] Note that the translog production function is a generalized version of a Cobb-Douglas production function.

$$\Delta(TP)_{it} = \frac{\partial ln(Y_{it})}{\partial t} = \beta_3 + \beta_6 t + \beta_8 lnK_{it} + \beta_9 lnL_{it}$$

We highlighted that, under the CRTS assumption, scale effects are overlooked and assumed to be equal to zero. However, if returns to scale were not constant, scale change could affect TFP growth. For this reason, we aim to examine whether all UK firms produce with constant returns to scale, as assumed by some of the UK studies. From equation (3.1) returns to scale for each firm can be calculated as:

$$\varepsilon_l = (\partial ln(Y_{it}))/(\partial ln(L_{it})) = \beta_2 + \beta_5 lnL_{it} + \beta_7 lnK_{it} + \beta_9 t$$

$$\varepsilon_k = (\partial ln(Y_{it}))/(\partial ln(K_{it})) = \beta_1 + \beta_4 lnK_{it} + \beta_7 lnL_{it} + \beta_8 t$$

where ε_k, and ε_l are output elasticities. Returns to scale (RTS) can then be calculated as:

$$RTS = \varepsilon = \varepsilon_l + \varepsilon_k$$

- Scale efficiency (SE) is related to the scale at which a firm achieves maximum efficiency. As can be seen easily from equation (3.2) below, if there are constant returns to scale, i.e. $\varepsilon = 1$, then scale effects disappear and TFP growth is due to technical change only, when scale effects equal to zero. However, if returns to scale are variable, then scale effects become an important component of TFP growth. Scale efficiency chance can be formulated as:

$$\Delta(SE)_{it} = (\varepsilon - 1)[(\tfrac{\varepsilon_k}{\varepsilon})\dot{K} + (\tfrac{\varepsilon_l}{\varepsilon})\dot{L}] \tag{3.2}$$

where $\dot{K}$ and $\dot{L}$ stand for changes in capital and labour with respect to time.

Table 3.1: Returns to scale and number of firms

$RTS = \epsilon$					
Years	2005	2006	2007	2008	2009
$\epsilon < 0.8$	0	1	1	1	1
$0.8 < \epsilon < 0.85$	4	9	11	18	21
$0.85 < \epsilon < 0.9$	79	95	146	163	214
$0.9 < \epsilon < 0.95$	1099	1336	1742	2002	2686
$0.95 < \epsilon < 1.05$	4469	4493	4320	4233	4986
$\epsilon > 1.05$	88	79	67	49	54

Table 3.1 above shows that many UK firms produce with variable returns to scale. For this reason, we believe that scale effects should be taken into account for UK firms in this analysis.[56]

- Technical efficiency (TE) shows whether a firm utilizes its technology in such a way as to produce an optimum level of output.[57] The change in technical efficiency is calculated as:

$$\Delta(TE)_{it} = \frac{(TE)_{it}}{(TE)_{it-1}}$$

- Finally, total factor productivity growth is calculated as:

$$\Delta(TFP)_{it} = \Delta(TP)_{it} + \Delta(TE)_{it} + \Delta(SE)_{it}$$

Table 3.2 below reports some summary statistics for TFP growth, and its components. We observe negative productivity growth for export starters in 2005, 2006, and 2009, while the average growth is positive in 2007 and 2008. Additionally, we find that scale effects are key component of TFP growth for both export starters and

[56] Appendix 2 Section B provides a description of scale effects.

[57] As Koopmans (1951) highlights a producer is considered as technically efficient, if it cannot produce more without using more of some input.

newer exporters. In the following section we highlight some methodological issues in LBE analysis, and review some potential solutions to these issues.

Table 3.2: TFP growth, Technical Change, Scale Change and Efficiency Change

Years	2005		2006		2007		2008		2009	
Variables	Export Starters	Never Exporters	Export Starters	Never Exporters	Export Starters	Never Exporters	Export Starters	Never Exporters	Export Starters	Never Exporters
TFP_{LevPet} growth	.167	.108	.052	.079	.053	.033	.081	.060	.023	-.055
TFP_{SFA} growth	-.017	-.020	-.002	.061	.099	.024	.029	.039	-.102	-.134
Technical Change	.040	.042	.028	.030	.018	.018	.005	.006	-.006	-.004
Scale Change	-.057	-.062	-.031	.031	.081	.005	.023	.032	-.096	-.129
Efficiency Change	.000	.000	.000	-.000	.000	.000	.000	-.000	.000	-.000

3.4. The Effect of Exporting on TFP Growth and Its Components

3.4.1. Methodological Issues

Although the effects of exporting on firm productivity have been examined via several different methods so far, two core approaches can be distinguished in the literature.[58] The first one is a panel regressions approach, introduced by Bernard and Jensen (1999). However, this method is criticized by some researchers, who claim that a basic comparison of exporting firms to all non-exporting firms provides results suffering from selection bias, a point which we explain below. The second approach used by most of the recent studies on this literature is treatment models, which compare potential outcomes for an individual/firm under treatment, and without treatment. This method is adapted to the literature on LBE by considering export entry as a treatment. However, the main problem with this method is that one cannot observe what would have happened to a firm if it had not entered the export market. In other words, we can observe a firm in only one situation, because it is either an exporter or a non-exporter at time t. We can illustrate this problem by following Heckman et al. (1997) and Heckman and Navarro-Lozano (2004). Let's assume that the difference between the performance of exporters (treated firms), and non-exporters (non-treated firms) Δ_i is the following:

$$\Delta_i = E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0]$$

where Y_i is the outcome of the treatment effect on a firm in terms of whether they receive the treatment D_i, or not, and Δ_i shows how successful the treatment

[58]Some of the other estimation methods are also used in the literature to test the learning by exporting hypothesis, such as the Granger causality test, random effects and fixed effects panel estimation methods.

program is.[59]

However, there is a serious problem with this approach. As we mentioned, we only have information for a specific individual/firm in one situation. In other words, we cannot observe $Y_i \mid D_i = 1$, and $Y_i \mid D_i = 0$ at the same time. In order to tackle this problem, the population average of treatment effect (ATE) is considered as the measurement of the program effect:

$$\Delta_{ATE} = E[Y_i(1) \mid D_i = 1] - E[Y_i(0) \mid D_i = 0] \tag{3.3}$$

which gives the difference between the outcome of the treated participants, $Y_i(1)$, and the outcome of non-treated participants, $Y_i(0)$. However, Heckman et al. (1997) highlight that ATE might not be a relevant measurement, since it considers individuals/firms who actually are not targeted by the treatment program, namely $Y_i(0)$. They propose that one should focus only on the individuals who participated in the program in order to calculate an unbiased treatment effect. According to Heckman et al. (1997), a treatment effect is measured by the difference between the expected outcomes of an individual/firm with and without treatment. So, the average treatment effect on the treated (ATT) is:

$$\Delta_{ATT} = E[Y_i(1) - Y_i(0) \mid D_i = 1] = E[Y_i(1) \mid D_i = 1] - E[Y_i(0) \mid D_i = 1]$$

which gives the difference between the outcome of a treated firm which obtains after exporting and the potential outcome that would have obtained if it had never exported.

This approach enables us to verify what an export starter would have had if it had never exported by using a hypothetical counterfactual. Obviously, we are not able to observe both outcomes for the same firm. We can only observe $E[Y_i(1) \mid D_i = 1]$, while $E[Y_i(0) \mid D_i = 1]$ (outcome of the export starter if they had not exported)

[59] As mentioned above, the treatment is export entry, so, $D_i = 1$ for export starters.

is unknown. Based on this fact, Heckman et al. (1997) define the selection bias problem by rearranging equation (3.3). If we add and subtract $E[Y_i(0) \mid D_i = 1]$, equation (3.3) can be written as:

$$\underbrace{E[Y_i(1) \mid D_i = 1] - E[Y_i(0) \mid D_i = 0]}_{ATE} + E[Y_i(0) \mid D_i = 1] - E[Y_i(0) \mid D_i = 1]$$

which can be written as:

$$\underbrace{E[Y_i(1) - Y_i(0) \mid D_i = 1]}_{ATT} + \underbrace{E[Y_i(0) \mid D_i = 1] - E[Y_i(0) \mid D_i = 0]}_{bias\ \ term} \tag{3.4}$$

Equation (3.4) represents the average treatment effect on the treated (ATT) plus a bias term.[60] Thus, Heckman et al. (1997) conclude that a basic comparison between treated individuals (export starters in our case) and all non-treated individuals (never-exporters) will provide biased results.

It is a straightforward conclusion that the bias would be zero if the treated firms were randomly selected. In other words, if the treated and control groups have the same observable and non-observable characteristics, the bias will be zero, where $E[Y_i(0) \mid D_i = 1] = E[Y_i(0) \mid D_i = 0]$. However, the random selection is generally observed in experimental data, where there is no self-selection. In social sciences, researchers normally deal with non-experimental data, where a self-selection problem exists. In fact, in Chapter 2, we have already verified that better (or larger) firms tend to self-select as exporters in some industries. Thus, we know that our data on the export market are not randomly selected. This suggests that a direct comparison between exporters and all never-exporters will not provide reliable results in terms of the direction of the causality. In other words, selection bias is an important problem to deal with in this study. There are several methods that can be utilized to overcome the selection bias problem, and we review most of these methods in Appendix 2 Section C.

[60] The selection bias can be written as $B(ATT_t) = E[Y_i(0) \mid D_i = 1] - E[Y(0) \mid D_i = 0]$

3.4.2. Propensity Score Matching (PSM)

Considering the benefits and drawbacks of all the methods that we review in Appendix 2 Section C, we have decided to employ a combination of the propensity score matching and difference-in-difference strategy (PSM-DID) to take the selection bias issue into account. One of the main advantages of the use of PSM-DID with respect to the traditional difference-in-difference method (DID) is that this method reduces the bias component which was illustrated in Equation (3.4). Additionally, according to Blundell and Costa Dias (2000), combining a PSM estimator with the DID approach improves the quality of matching significantly, since it removes possible unobserved, time-invariant and firm-specific effects.[61] Because of these advantages of the PSM-DID approach, we prefer to employ this method in order to evaluate the impact of exports on productivity.[62]

3.4.2.1. Combining PSM with the DID Estimator

As we describe in Appendix 2 Section C, Rosenbaum and Rubin (1983) introduce an approach based on a computation of a probability of receiving treatment (propensity score), and show that a matching can be performed based only on this single variable. Obtaining a matched sample, a propensity matching estimator can easily compute sample averages of the two groups and calculate the difference which gives treatment effect on treated. A matching estimator takes the form:

$$M_{(ATT_t)}) = \frac{1}{n_i} \sum_{i \in \{D_i^* = 1\}} \left[Y_{it} - \sum_{j \in \{D_j^* = 0\}} w(i,j)(Y_{jt}) \right]$$

where $w(i,j)$ is the weight given to the j^{th} observation of controls in constructing the counterfactual to the i^{th} treated firm, and n_i is the number of treated observa-

[61]This method controls for the selection bias by comparing changes in the outcome, before and after the exporting, for export starter firm and similar firms from the control group.

[62]Following the seminal paper of Heckman, Ichimura and Todd (1997), many recent papers utilize this method in the literature, such as Gorg et al. (2008); Volpe and Carballo (2008); Girma et al. (2003), and De Loecker (2007).

tions.[63] Y is the outcome variable (for instance TFP). $D_i = 1$ and $D_i = 0$ respectively denote the group of starters and never-exporters. As we mentioned, matching procedure controls for the selection bias arising from observable firm characteristics, while it cannot solve a potential selection issue coming from any unobservable effects. Blundell and Costa Dias (2000) show that PSM-DID estimator performs better than both PSM and DID when they are used alone. Following this approach, we combine PSM with DID. Now, our new estimator considers the outcomes of treatment as differences in outcomes after and before the treatment for the treated and non-treated firms. Thus the estimator can be written as:

$$M_{(ATT_t)}^{DID-PSM}) = \frac{1}{n_i}\sum_{i\in\{D_i^*=1\}}\left[(Y_{i,post} - Y_{i,pre}) - \sum_{j\in\{D_j^*=0\}} w(i,j)(Y_{j,post} - Y_{j,pre})\right] \quad (3.5)$$

where the subscripts, *post* and *pre*, denote the periods after and before entry to export markets. As equation (3.5) shows, the DID model allows us to estimate the difference between differences of outcome for exporters and non-exporters. Let $Y_{i,post}$, and $Y_{j,post}$ stand for post-exporting, and $Y_{i,pre}$, and $Y_{j,pre}$ represent pre-exporting total factor productivities for exporters, and non-exporters, respectively. Basically, this is the mechanism by which the DID estimator removes unobservable firm specific characteristics, such as effects of common shocks. We then compute the PSM-DID estimator for three periods after entry into the export market, with respect to the year prior to entry (t-1).Thus, we obtain ATT effects for entry period, (t-1 to t), and the following three years: t-1 to t+1, t-1 to t+2 and finally t-1 to t+3.

3.4.2.2. Estimation Procedure

We implement the PSM-DID method in three stages; in the first stage, we estimate a propensity score of export entry based upon the variables which could affect the entry decision. There are two important decisions to be made at this stage. The first

[63] Different matching algorithms use different ways to calculate the weight.

one concerns the model specification to be used for the propensity score estimation. Any discrete choice model can be used at this stage. In order to be consistent with Chapter 2, we prefer to use the probit model to estimate propensity scores. The second important decision concerns the variables to be included in the analysis. The variables that we include in our model are selected based on the relevant literature, as well as our findings from Chapter 2.[64] As Caliendo and Kopeinig (2005) highlight only variables that are unaffected by the treatment (exporting) can be included in the model in order to avoid potential endogeneity issues.[65] In order to overcome this issue, we include variables measured before foreign market participation. Namely, we include variables at t-1, since a firm i enters the export market at t. Eventually, we include all relevant variables (lagged one year) which have an effect on outcome. We use the following probit model in order to estimate propensity scores for each firm:

$$Pr(Starter_{it} = 1) = \Phi(TFP_{it-1}, age_{it-1}, Size_{it-1}, Wage_{it-1}, CI_{it-1}, D_{is}, D_{ir})$$

where Φ is a normal cumulative distribution function. $Starter_{it}$ is a dummy variable taking the value 1 for a firm that does not export for at least two years, starts exporting at t, and continues exporting in the following periods. For instance, firms considered as starters in 2005 do not export in 2003 and 2004. They keep exporting in the years following the point at which they are observed. For this reason, as Table 3.3 illustrates, we have starters from years 2005, 2006, 2007, 2008, and 2009.

[64] From the analysis we conduct in Chapter 2, we know that selected variables have an effect on export decision. For further information, please see Bernard et al. (2003), or Bernard et al. (2006).

[65] We address this problem in detail in Chapter 2, where we examine the self-selection effect.

Table 3.3: Export Starters by Year

years	N. of Firms
2005	193
2006	251
2007	304
2008	303
2009	345
Total	1396

TFP stands for the estimated total factor productivity. We use two TFP measures here. The first is TFP_{LevPet} which is the one we obtained in Chapter 2 from a Cobb-Douglas production function, while the second measure, TFP_{SFA}, is estimated from a translog production function. The *age* variable represents the number of years that a firm has been in operation, while $Size$ stands for the number of employees. $Wage$ and CI represent average wage and capital intensity respectively. Finally we include industry, and region dummies. At the second stage, matching is done between export starters (treated) and never-exporters (control) based on the estimated propensity score.[66] De Loecker (2007) shows that sector-level matching may improve the quality of matching. However, when we perform matching for each sector separately the number of starters we obtain is very low for many sectors, due to the low number of observations. Therefore we have decided to use pooled data at this stage, since this gives us opportunity to use the largest possible quantity of data.[67] We employ matching procedure for each year between 2005 and 2009 separately.

[66]We use the Stata routine (psmatch2) provided by Leuven and Sianesi (2003) to perform matching the procedure.

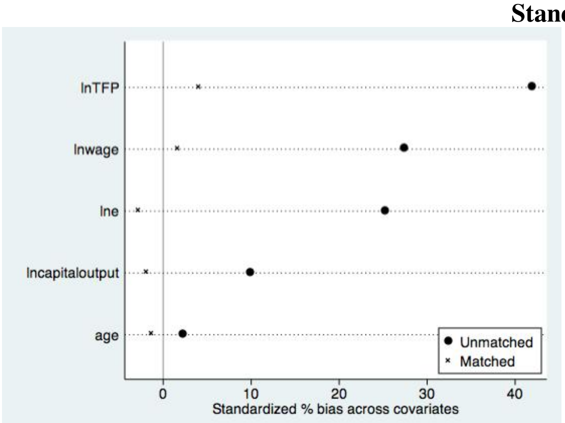
[67]Girma et. al. (2004) and Maggioni (2009) report that they obtain similar results from matching with pooled data, and matching for each sector.

Table 3.4: Assessing the matching quality (Kernel Matching Results)

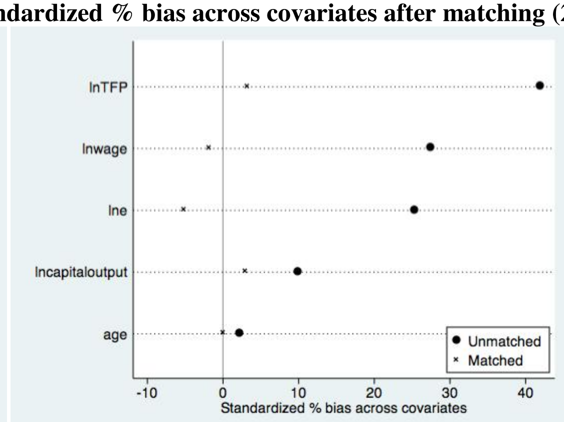
2005	N. of Firms	lnTFP	lnEmp.	age	lnWage	lnCapital Intensity
All treated	193	6.48	4.65	26.85	3.33	2.25
All Controls	2001	5.98	4.23	26.33	3.18	2.12
p-values		0.00	0.00	0.76	0.00	0.19
% bias		42%	25.3%	2.2%	27.5%	9.9%
Treated on Common Support	187	6.46	4.9	26.50	3.32	2.25
Controls	1669	6.41	4.9	26.82	3.32	2.28
p-values		0.69	0.78	0.99	0.84	0.76
% bias		4%	-2.8%	-1.4%	1.6%	-1.9%

Note: P-values refer to t-tests for the significance of the difference of means between the two relevant groups.

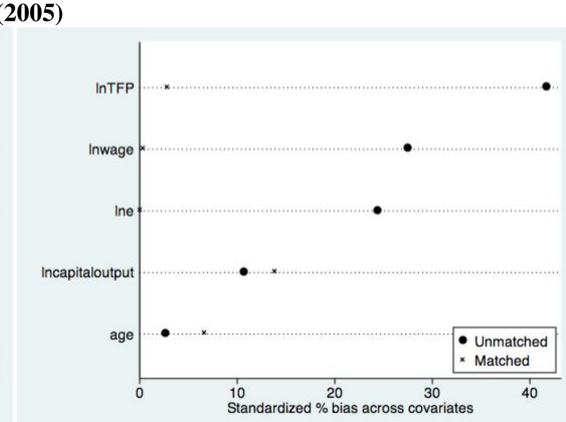
Standardized % bias across covariates after matching (2005)



(Kernel Matching)



(Nearest Neighbour Matching)



(Mahalanobis Matching)

3.4.2.3. Testing the Matching Quality

As we discuss in Appendix 2 Section E, unlike the traditional matching methods which conditions on all covariates, PSM conditions only on the propensity score. For this reason, we need to make sure that the preferred matching algorithm is able to balance the distribution of all variables for export starters and never-exporters. More precisely, a successful matching procedure should provide a matched sample where the covariates are well-balanced. The most commonly used methods to evaluate matching quality in this literature are a standard t-test and the balancing test introduced by Rosenbaum and Rubin (1985).[68] A simple two-sample t-test examines whether the covariates for treated and control groups are significantly different. According to this approach, if these two groups are matched successfully, then there should be no significant difference between them. Another method, the Rosenbaum and Rubin approach, provides detailed information with regard to the success of the matching method in terms of bias reduction. It shows the bias before and after matching, and reports a bias reduction rate, which indicates the high quality of the matching.

Table 3.4 presents our findings from both tests for the matched sample for 2005, and shows that no differences were found in the average level of covariates of export starters and never-exporters. For instance, the average TFP of export starters is 6.48, while it is 5.98 for newer-exporters before matching (with p-value of 0.00). However, after matching, the average level of TFP for export starters becomes 6.46, while the average for never-exporters becomes 6.41. The p-value after matching becomes 0.69, which means we cannot reject the null hypothesis for equality of means of variables after matching. In other words, the Kernel approach successfully matches both groups. Table 3.4 also reports the standard bias for each covariate before and

[68] Please see Appendix 2 Section E for a technical description of the balancing test.

after the matching. For instance, the standardized bias for TFP between both groups is 42% before matching, while it reduces to 4% after matching. We observe that the bias is reduced to below 5% for all variables after matching, which indicates that we have a nicely balanced matched group. The diagrams below Table 3.4 report the performance of other matching methods in terms of matching quality for 2005.[69] The second and third diagrams show standard % bias across covariates after matching from Nearest Neighbour and Mahalanobis methods, respectively. Clearly, the Kernel method provides the best results amongst the three approaches. For this reason, we decide to use Kernel method to examine LBE in the following section.

Besides, Figure 3.1 (below) shows that matching results from the Kernel method also satisfies the common support assumption of PSM.[70] Figure 3.1 illustrates that the Kernel method generates a good common support region where propensity scores of export starters and never-exporters overlap.[71]

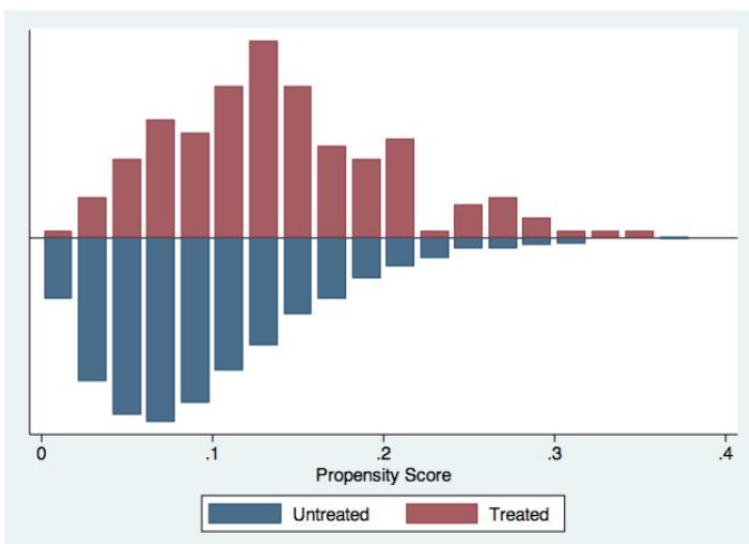


Figure 3.1: Common Support (2005)

[69] Tables A2.2 to A2.5 in Appendix 2 Section A provides matching quality tests results for 2006, 2007, 2008, and 2009.

[70] PSM assumes that a successful matching algorithm creates a common support region where the propensity scores of individuals from both treated and control groups overlap.

[71] Figure 3.2 in Appendix 2 Section A provides common support results for 2006, 2007, 2008, and 2009.

3.5. Results

In the final stage of the matching procedure, Equation (3.5) is estimated to obtain average treatment effect on treated (ATT). In this chapter, ATT refers to the effect of exporting on productivity growth for export starters. More precisely, any positive and significant value of ATT implies a post-exporting productivity improvement which never-exporters do not experience. Thus, a positive and significant value of ATT confirms the learning-by-exporting hypothesis.

There are several available matching methods such as Nearest Neighbour (NN), Mahalanobis, and Kernel.[72] As we discuss in previous section, Kernel matching provides the best results in terms of the matching quality. For this reason, we report our findings from the Kernel estimator, while we also show the findings from the Nearest Neighbour (NN) and Mahalanobis matching methods in Appendix 2 Section A, which will serve as a robustness check with respect to the effect of exporting on productivity.[73]

Table 3.5 reports the effect of exporting on productivity growth (ATT) for 2007, 2008 and 2009.[74] We use three different productivity measures. LP stands for labour productivity, while TFP_{LevPet} represents total factor productivity, which we obtained in Chapter 2 from a Cobb-Douglas production function. As we already mentioned, TFP_{SFA} stands for total factor productivity obtained from a translog production function which allows for VRTS. Additionally, we examine a decomposition of the productivity growth effects of export market entry. TP, SE, and TE represent technical efficiency change, scale efficiency change and efficiency change: these are the components of TFP_{SFA} growth.

We observe some interesting patterns from our results: (i) Any impact of export-

[72] We provide a brief discussion on different matching methods in Appendix 2 Section D.
[73] Please see Appendix 2 Section A, Tables A2.7 to A2.11
[74] Table A2.6, in Appendix 2 Section A, reports our findings for 2005 and 2006.

ing is predominantly attributed to a change in scale efficiency; (ii) Our results from the two different TFP measures (TFP_{LevPet} and TFP_{SFA}) are usually the opposite of one another.

Table 3.5 shows that when we consider TFP_{LevPet} as a measure of productivity, we find that firms which start exporting in 2007 enjoy 8.6% productivity growth from t-1 to t+2 (two years after entry). The rate of productivity growth for export starters from t-1 to t+3 (three years after entry) is around 9.6% higher than that of never-exporters. However, when we consider TFP_{SFA} as a measure of productivity, we only find statistically significant productivity growth three years after entry. In Table 3.5, the final column for 2007 (t+3) reports 11.1% productivity growth which is slightly higher that the finding from TFP_{LevPet} (9.6%). More interestingly, we find that technical and efficiency changes play no role in overall productivity growth, and all the growth is due to scale effects.

For the firms which entered the export market in 2008, we uncover evidence of a negative exporting effect on TFP_{SFA} growth of -6.4%. More importantly, we show that the decline in productivity growth is due to a loss in scale efficiency. Figure 3.3 illustrates that scale inefficiency increases when a firm experiencing DRTS produces more, or when a firm facing IRTS produces less. In the light of this, the negative exporting effect on TFP_{SFA} growth may be due to those firms that entered the export market in 2008 possibly experiencing DRTS. Following their entrance to the export market, they suffer from scale inefficiency as a result of an increase in their output. On the other hand, we do not observe such an effect for the same period when we consider TFP_{LevPet} as a measure of productivity growth. We believe that, since TFP_{LevPet} overlooks the scale effects, it fails to capture the growth effect of exporting, which is detected when we consider TFP_{SFA}. In Appendix 2 Section A we show that the findings from different matching methods also confirm these results.

The results for firms that enter the export market in 2009 are also interesting.

Again, we find a positive treatment effect of exporting on TFP_{LevPet} growth for the entry year, t, as well as the following two years (t+1 and t+2). On the other hand, the effects of export on productivity disappear when we measure productivity growth via TFP_{SFA}. In other words, we cannot confirm any significant effect of exporting on TFP_{SFA} growth for the periods when we find a significant effect on TFP_{LevPet} growth. These results are also robust to applying different matching methods.

As we mentioned in Chapter 2, labour productivity (LP) is not a preferred measure of productivity. For this reason our main interest is in TFP_{LevPet} and TFP_{SFA}. However, we report the effects of exporting on labour productivity too. This will give us a chance to compare LP results to our findings from TFP measures. We find that exporting has a positive and significant effect on LP only for the firms which start exporting in 2005 and 2007. Table A2.6 reports a positive effect of 5.6% increase in LP in the year of foreign market entry (2005). The first column in Table 3.5 provides our findings for the firms which start exporting in 2007. We observe 7.2% and 8.7% (7.2+1.5) increases in LP, in two and three years after export market entry respectively. Interestingly, we find that the productivity effects of exporting on LP and TFP are not coexisting. In other words, we find no significant effects on TFP for the periods when we observe positive and significant effects on LP. Using different matching methods (Nearest Neighbour, and Mahalanobis), the LP results from Kernel matching are confirmed.

Table 3.5: ATT Effects: PSM-DID estimates from Kernel Method

Entry year (t)		2007				2008				2009		
Periods after entry		t	t+1	t+2	t+3	t	t+1	t+2	t+3	t	t+1	t+2
Labour	ATT	.001	.018	.072	.087	.001	.011	.007	-.034	.014	.031	.010
Prod.	s.e.	(.020)	(.025)	(.032)**	(.035)**	(.019)	(.023)	(.026)	(.044)	(.026)	(.026)	(.039)
TFP	ATT	.021	.007	.086	.096	.020	.030	.061	.018	.085	.145	.088
(Lev-Pet)	s.e.	(.026)	(.037)	(.041)*	(.045)**	(.028)	(.039)	(.037)*	(.063)	(.043)*	(.039)***	(.045)**
N. of	Treated	297	283	269	240	297	284	269	119	334	317	125
Firms	Controls	1956	1799	1651	1451	2047	1850	1640	560	2303	2021	706
TFP	ATT	.057	.004	-.032	.111	-.064	-.020	-.0044	.025	.018	.041	.066
(SFA)	s.e.	(.049)	(.040)	(.049)	(.059)*	(.031)*	(.036)	(.034)	(.050)	(.034)	(.038)	(.051)
TP	ATT	-.0000	-.0001	-.0000	-.0000	-.0000	.0000	.0000	-.0002	-.0000	-.0000	-.0000
(SFA)	s.e.	(.0000)	(.0001)	(.0002)	(.0002)	(.0000)	(.0000)	(.0001)	(.0002)	(.0000)	(.0000)	(.0001)
SE	ATT	-.057	.004	-.032	.111	-.064	-.020	-.0044	.026	.018	.041	.066
(SFA)	s.e.	(.049)	(.040)	(.049)	(.059)*	(.031)*	(.036)	(.034)	(.050)	(.034)	(.038)	(.051)
TE	ATT	-.0000	-.000	.000	-.000	-.0000	-.0000	-.0000	-.0000	-.0000	-.0000	.0000
(SFA)	s.e.	(.0000)	(.000)	(.000)	(.000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)
N. of	Treated	226	211	209	186	251	242	232	102	267	252	101
Firms	Controls	1539	1392	1348	1205	1703	1562	1406	484	1795	1591	550

Standard errors are reported in parenthesis. * indicates statistical significance at the 10% level. ** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

3.6. Conclusion

In this chapter, we aimed to examine the effect of exporting on productivity growth which is, we believe, a highly policy relevant issue. For a policy maker, it is essential to identify which way the causality between productivity and export runs. Assuming that learning by exporting effects exist, several studies in the literature suggest that governments should support firms which aim to export in order to stimulate both firm and industry level productivity improvements. This is a valid policy, as long as firms learn from exporting. However, if exports do not enhance firm productivity, then the policies helping firms which aim to be an exporter will be questionable.[75] For this reason, it is important to examine the links between exports and firm productivity thoroughly, and to understand the mechanisms behind the learning by exporting effects, if there are any.

Initially, we reported that some firms in the UK experience variable returns to scale, which highlights the potential role of scale effects in TFP growth. Based on this finding, first, we aimed to construct a TFP measure which accounts for scale effects, and obtained TFP_{SFA} by employing a translog production function which allows for variable returns to scale. Second, we decomposed TFP_{SFA} growth into its components by utilizing SFA. Finally we showed the effect of exporting on these three components of TFP: technical change, scale change, and efficiency change.

We observed some interesting patterns from our results. First, we found evidence in favour of an LBE effect when we considered the TFP measure which we obtained

[75]On the other hand, industry level productivity increase will automatically arise as a consequence of the self-selection mechanism, even without any government intervention. As Melitz (2003) suggests, more productive firms self-select to enter the export market, while less productive firms only operate in the domestic market, and the least productive firms exit the market: which in turn influences resource allocation within the industry. Since the least productive firms leave the market, resources will be allocated to more productive firms, which in turn raises aggregate productivity in the industry. Thus, in an industry, if self-selection occurs, while LBE effect does not exist, then firm and industry level productivity improvements will be observed even without government intervention.

from a Cobb-Douglas production function (TFP_{LevPet}). However, the evidence of an LBE effect largely disappeared when we considered the TFP measure which accounts for scale effects (TFP_{SFA}). Second, and more importantly, we showed that any productivity growth effects of exporting are predominantly attributable to a change in scale efficiency. In other words, the main source of TFP growth is not technical improvements, but scale efficiency improvements.

In this chapter, we used an unbalanced panel data-set obtained from the FAME database. This data is criticized by Harris and Li (2008) who claim that the dataset is biased towards large enterprises.[76] If this is the case, then this might explain our findings regarding the scale effects to some extent. More precisely, larger firms which start exporting may enjoy greater improvements in terms of scale efficiency, as a result of increasing demand and production. Future work should aim to extend our findings to other datasets.

We believe that our findings regarding the scale effects are very interesting, and they suggest some questions to be addressed in future studies. For instance, given that scale effects play a key role in TFP growth, it would be interesting to investigate what are the available strategies for firms to achieve scale efficiency. Moreover, knowing that scale effects are the dominant component of TFP growth, we will examine the effect of scale efficiency on firms' internationalization decisions, in order to uncover any self-selection effects in terms of scale efficiency.

[76]Although this is not the case for our dataset, their approach is worth considering.

Appendix 2 - Section A:

Tables

Table A2.1: Results for production frontier model

Variable		Coefficient
lnK	β_1	.769
		(.003)***
lnL	β_2	.197
		(.002)***
t	β_3	.011
		(.001)***
$(lnK)^2$	β_4	.001
		(.002)
$(lnL)^2$	β_5	.028
		(.000)***
t^2	β_6	-.005
		(.000)***
$lnK * lnL$	β_7	-.039
		(.002)***
$lnK * t$	β_8	-.003
		(.001)**
$lnL * t$	β_9	-.0004
		(.001)
constant		-.001
		(.048)

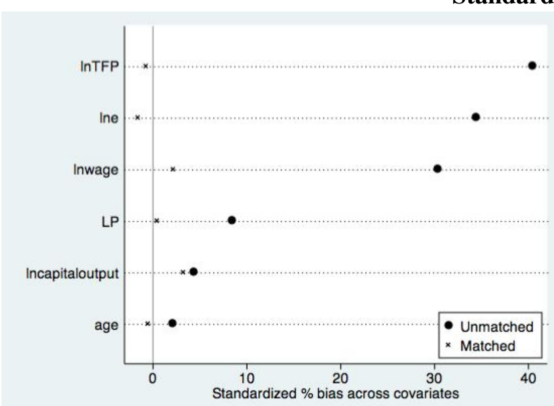
Standard errors are reported in parenthesis.
* indicates statistical significance at 10% .
** indicates statistical significance at 5% .
*** indicates statistical significance at 1%.

Table A2.2: Assessing the matching quality (Kernel Matching Results)

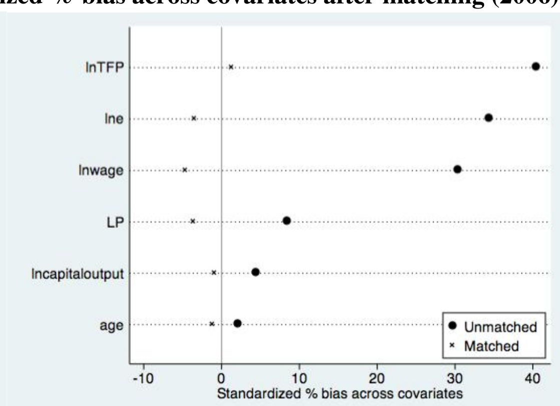
2006	N. of Firms	lnTFP	lnEmp.	age	lnWage	lnCapital Intensity
All treated	251	6.56	4.82	26.50	3.38	2.18
All Controls	2182	6.07	4.26	26.00	3.22	2.12
p-values		0.00	0.00	0.74	0.00	0.51
% bias		40.5%	34.4%	2.1%	30.3%	4.4%
Treated on Common Support	245	6.53	4.79	26.5	3.38	2.20
Controls	1787	6.54	4.81	26.6	3.37	2.16
p-values		0.92	0.85	0.95	0.79	0.87
% bias		-0.7%	-1.5%	-0.5%	2.1%	3.2%

Note: P-values refer to t-tests for the significance of the difference of means between the two relevant groups.

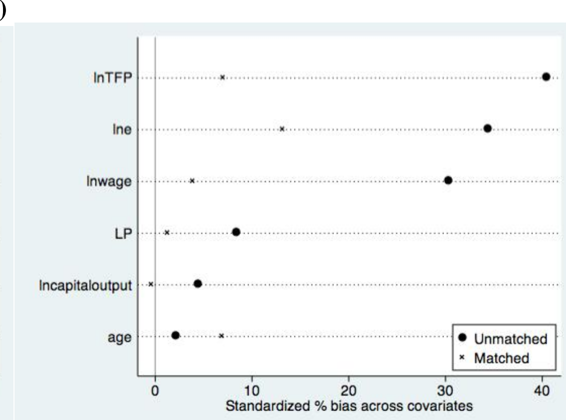
Standardized % bias across covariates after matching (2006)



(Kernel Matching)



(Nearest Neighbour Matching)



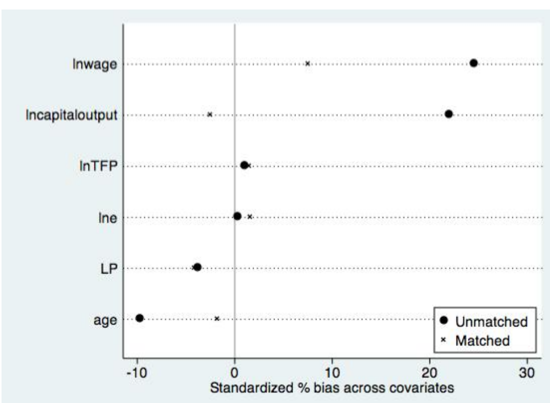
(Mahalanobis Matching)

Table A2.3: Assessing the matching quality (Kernel Matching Results)

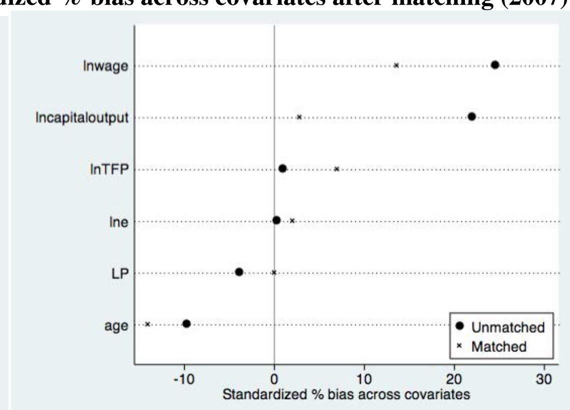
2007	N. of Firms	lnTFP	lnEmp.	age	lnWage	lnCapital Intensity
All treated	304	6.21	4.36	24.25	3.41	2.49
All Controls	2305	6.20	4.35	26.44	3.30	2.19
p-values		0.88	0.96	0.12	0.01	0.01
% bias		1.0%	0.3%	-9.7%	24.6%	22.0%
Treated on Common Support	298	6.21	4.36	24.32	3.41	2.48
Controls	1956	6.20	4.33	24.71	3.38	2.51
p-values		0.38	0.80	0.82	0.31	0.76
% bias		1.5%	1.7%	-1.7%	7.6%	-2.5%

Note: P-values refer to t-tests for the significance of the difference of means between the two relevant groups.

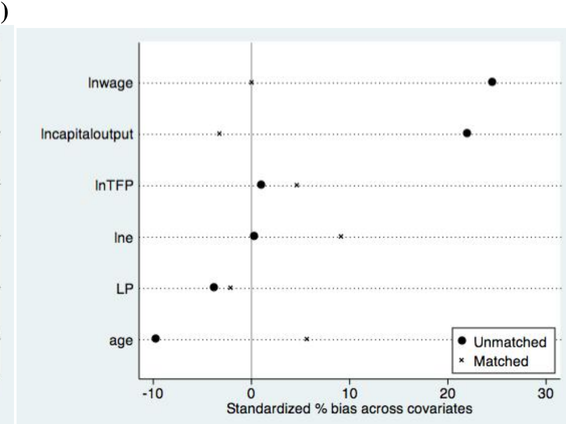
Standardized % bias across covariates after matching (2007)



(Kernel Matching)



(Nearest Neighbour Matching)



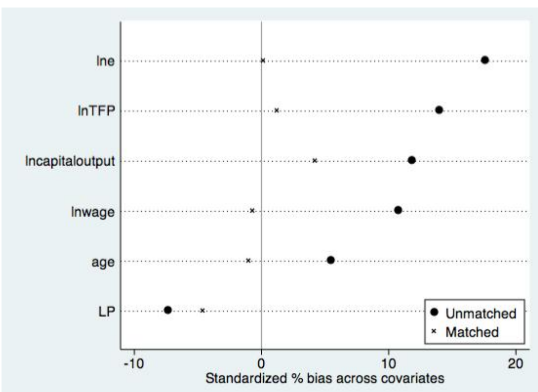
(Mahalanobis Matching)

Table A2.4: Assessing the matching quality (Kernel Matching Results)

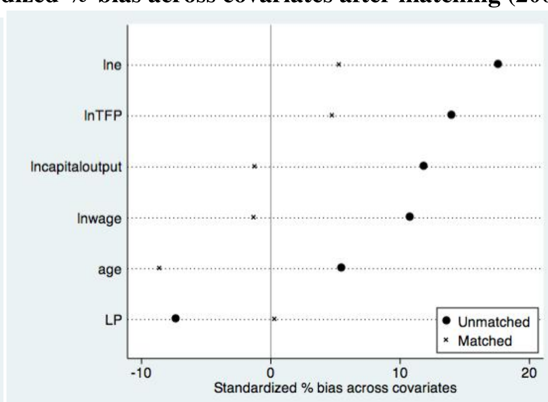
2008	N. of Firms	lnTFP	lnEmp.	age	lnWage	lnCapital Intensity
All treated	303	6.43	4.65	27.97	3.42	2.25
All Controls	2379	6.26	4.39	26.72	3.37	2.10
p-values		0.03	0.00	0.37	0.10	0.06
% bias		14.0%	17.6%	5.5%	10.8%	11.8%
Treated on Common Support	297	6.42	4.63	27.97	3.42	2.25
Controls	2047	6.40	4.63	28.13	3.42	2.20
p-values		0.87	0.98	0.90	0.92	0.60
% bias		1.3%	0.2%	-1.0%	-0.7%	4.2%

Note: P-values refer to t-tests for the significance of the difference of means between the two relevant groups.

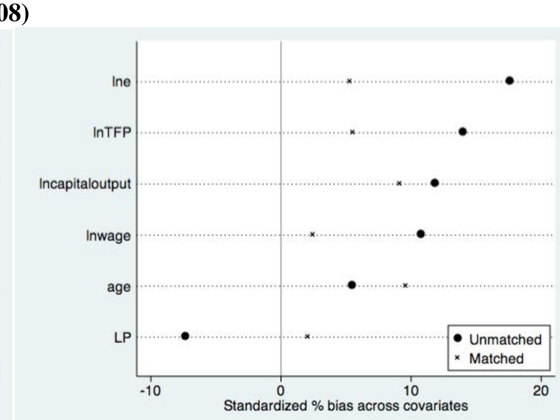
Standardized % bias across covariates after matching (2008)



(Kernel Matching)



(Nearest Neighbour Matching)



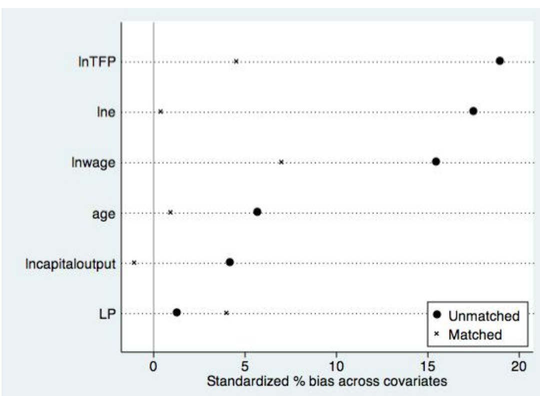
(Mahalanobis Matching)

Table A2.5: Assessing the matching quality (Kernel Matching Results)

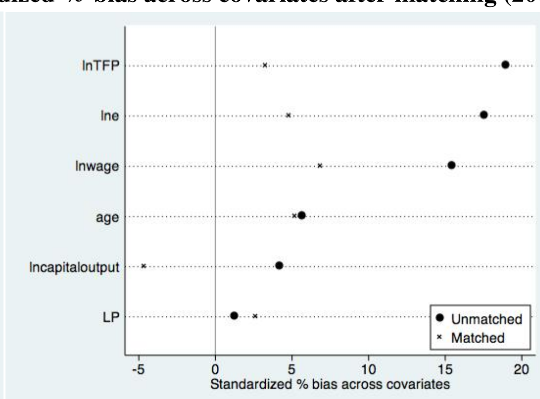
2009	N. of Firms	lnTFP	lnEmp.	age	lnWage	lnCapital Intensity
All treated	345	6.47	4.65	28.35	3.45	2.19
All Controls	3174	6.23	4.38	27.00	3.37	2.13
p-values		0.00	0.00	0.31	0.00	0.48
% bias		19%	17.5%	5.7%	15.5%	4.2%
Treated on Common Support	334	6.44	4.62	28.24	3.45	2.20
Controls	2303	6.39	4.51	28.01	3.41	2.21
p-values		0.54	0.95	0.90	0.34	0.89
% bias		4.5%	0.4%	1.0%	7.0%	-1.0%

Note: P-values refer to t-tests for the significance of the difference of means between the two relevant groups.

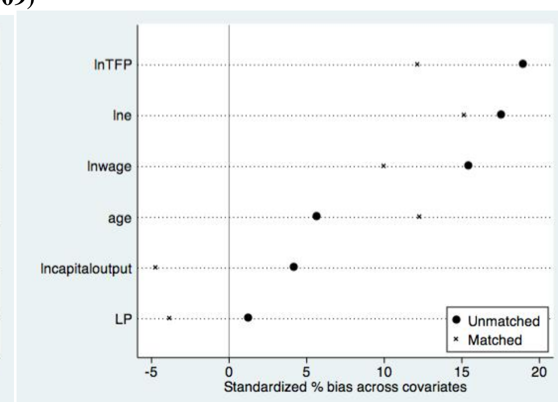
Standardized % bias across covariates after matching (2009)



(Kernel Matching)



(Nearest Neighbour Matching)



(Mahalanobis Matching)

Figure 3.2: Common Support Results from Kernel Matching

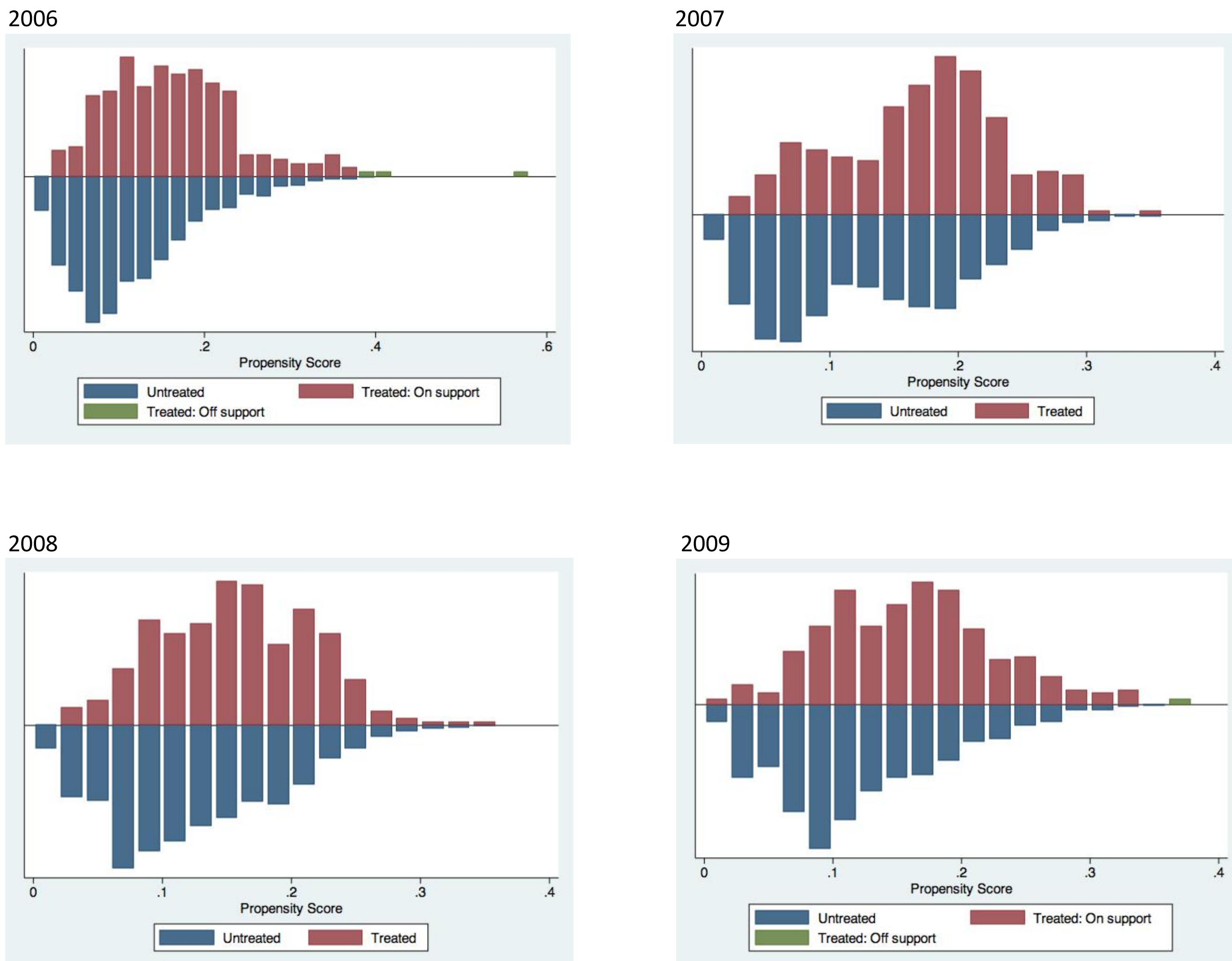


Table A2.6: ATT Effects: PSM-DID estimates from Kernel Method

Entry year (t)		**2005**				**2006**			
Periods After Entry		t	t+1	t+2	t+3	t	t+1	t+2	t+3
Labour	ATT	.056	.024	.010	.030	.006	-.017	-.023	-.027
Prod.	s.e.	(.028)**	(.027)	(.034)	(.043)	(.029)	(.037)	(.040)	(.040)
TFP	ATT	.048	.017	.019	.041	.010	.002	-.042	-.028
(Lev-Pet)	s.e.	(.043)	(.052)	(.056)	(.054)	(.033)	(.045)	(.052)	(.052)
N. of	Treated	187	174	165	157	245	234	227	218
Firms	Controls	1669	1527	1425	1319	1787	1652	1530	1402
TFP	ATT	-.062	.0010	-.031	-.079	-.072	.004	-.008	-.037
(SFA)	s.e.	(.087)	(.060)	(.072)	(.081)	(.059)	(.049)	(.050)	(.055)
TP	ATT	.000	-.0001	-.0004	-.0003	.0000	-.0001	-.0003	.0002
(SFA)	s.e.	(.000)	(.0000)	(.0005)*	(.0004)	(.0000)	(.0001)	(.0002)	(.0002)
SE	ATT	-.062	.0011	.030	-.078	-.072	.004	-.008	-.037
(SFA)	s.e.	(.089)	(.060)	(.072)	(.082)	(.059)	(.049)	(.050)	(.055)
TE	ATT	.000	.000	.000	.000	.0000	-.000	-.000	-.000
(SFA)	s.e.	(.000)	(.000)	(.000)*	(.000)	(.0000)	(.000)	-(.000)	(.000)
N. of	Treated	148	130	121	123	202	191	183	180
Firms	Controls	1402	1260	1185	1104	1424	1289	1207	1162

Standard errors are reported in parenthesis. * indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level. *** indicates statistical significance at the 1% level.

Table A2.7: ATT Effects: PSM-DID estimates from NN and Mahalanobis Methods - 2005

Matching Method		Nearest Neighbour				Mahalanobis			
2005		t	t+1	t+2	t+3	t	t+1	t+2	t+3
Labour	ATT	.062	.051	.079	.079	.046	.010	.017	.019
Prod.	s.e.	(.031)**	(.035)	(.045)*	(.058)	(.029)*	(.033)	(.039)	(.051)
TFP	ATT	.060	.013	.077	.063	.039	.021	.047	.065
(Lev-Pet)	s.e.	(.045)	(.064)	(.074)	(.081)	(.053)	(.066)	(.074)	(.076)
N. of	Treated	188	175	166	158	188	178	169	160
Firms	Controls	1669	1527	1425	1319	1717	1582	1476	1368
TFP	ATT	-.058	-.044	-.064	-.128	-.024	.017	-.001	-.044
(SFA)	s.e.	(.122)	(.092)	(.054)	(.096)	(.100)	(.070)	(.087)	(.096)
TP	ATT	-.001	.0001	.0005	.0001	-.0001	-.0001	-.0002	-.0005
(SFA)	s.e.	(.001)	(.0001)	(.0006)	(.0006)	(.0001)	(.0001)*	(.0006)	(.0004)
SE	ATT	-.058	-.044	-.064	-.127	-.023	.017	-.001	-.043
(SFA)	s.e.	(.000)	(.091)	(.085)*	(.095)	(.100)	(.070)	(.087)	(.094)
TE	ATT	.000	.000	.000	.000	.000	.000	.000	.000
(SFA)	s.e.	(.000)	(.000)	(.000)*	(.000)	(.000)	(.000)	(.000)	(.000)
N. of	Treated	149	131	122	160	154	154	128	129
Firms	Controls	1402	1260	1185	1328	1623	1623	1369	1156

Standard errors are reported in parenthesis. * indicates statistical significance at the 10% level. ** indicates statistical significance at the 5% level. *** indicates statistical significance at the 1% level.

Table A2.8: ATT Effects: PSM-DID estimates from NN and Mahalanobis Methods - 2006

Matching Method		Nearest Neighbour				Mahalanobis			
2006		t	t+1	t+2	t+3	t	t+1	t+2	t+3
Labour	ATT	.039	.004	-.040	.012	.001	-.037	-.038	-.059
Prod.	s.e.	(.035)	(.048)	(.054)	(.071)	(.037)*	(.040)	(.044)	(.045)
TFP	ATT	.024	.048	-.031	-.018	.001	.001	-.059	-.030
(Lev-Pet)	s.e.	(.047)	(.065)	(.064)	(.050)	(.031)	(.051)	(.059)	(.067)
N. of	Treated	247	236	229	220	248	237	230	222
Firms	Controls	1787	1652	1530	1402	1787	1653	1531	1404
TFP	ATT	-.092	.034	-.013	-.021	-.086	.011	-.007	-.051
(SFA)	s.e.	(.073)	(.066)	(.067)	(.073)	(.068)	(.065)	(.061)	(.067)
TP	ATT	.000	.0000	.0001	-.0001	-.0001	-.0002	-.0008	.0009
(SFA)	s.e.	(.001)	(.0001)	(.0003)	(.0003)	(.0001)	(.0001)*	(.0003)*	(.0004)
SE	ATT	-.093	-.034	-.013	-.021	-.086	.011	-.007	-.052
(SFA)	s.e.	(.072)	(.066)	(.067)	(.073)	(.068)	(.065)	(.061)	(.067)
TE	ATT	-.000	.000	.0000	-.000	-.000	-.000	-.000	-.000
(SFA)	s.e.	(.000)	(.000)	(.0000)	(.000)	(.000)	(.000)	(.000)	(.000)
N. of	Treated	202	191	183	180	205	194	186	183
Firms	Controls	1424	1289	1207	1162	1424	1289	1207	1345

Standard errors are reported in parenthesis. * indicates statistical significance at the 10% level. ** indicates statistical significance at the 5% level. *** indicates statistical significance at the 1% level.

Table A2.9: ATT Effects: PSM-DID estimates from NN and Mahalanobis Methods - 2007

Matching Method		Nearest Neighbour				Mahalanobis			
2007		t	t+1	t+2	t+3	T	t+1	t+2	t+3
Labour	ATT	.009	.018	.125	.128	.015	-.037	.064	.081
Prod.	s.e.	(.026)	(.031)	(.042)**	(.045)**	(.023)	(.040)	(.040)*	(.047)*
TFP	ATT	.014	.045	.119	.182	.010	-.0002	.102	.105
(Lev-Pet)	s.e.	(.043)	(.054)	(.065)*	(.072)**	(.037)	(.036)	(.055)*	(.064)*
N. of	Treated	298	284	270	241	298	286	272	243
Firms	Controls	1956	1799	1651	1451	1956	1805	1655	1456
TFP	ATT	.022	-.066	-.008	-.021	.037	-.043	-.032	.095
(SFA)	s.e.	(.064)	(.054)	(.057)	(.073)	(.055)	(.049)	(.048)	(.051)*
TP	ATT	-.0000	-.0000	-.0001	-.0001	-.0001	-.0001	.0000	.0001
(SFA)	s.e.	(.0000)*	(.0001)	(.0002)	(.0003)	(.0001)	(.0001)	(.0002)	(.0002)
SE	ATT	-.022	-.066	-.008	-.021	-.086	-.043	-.032	.095
(SFA)	s.e.	(.064)	(.054)	(.057)	(.073)	(.068)	(.049)	(.049)	(.051)*
TE	ATT	-.0000	-.000	.0000	-.000	-.000	-.000	.000	-.000
(SFA)	s.e.	(.0000)	(.000)*	(.0000)	(.000)	(.000)	(.000)	(.000)	(.000)
N. of	Treated	226	211	207	180	228	213	209	187
Firms	Controls	1539	1392	1335	1162	1555	1405	1348	1216

Standard errors are reported in parenthesis. * indicates statistical significance at the 10% level. ** indicates statistical significance at the 5% level. *** indicates statistical significance at the 1% level.

Table A2.10: ATT Effects: PSM-DID estimates from NN and Mahalanobis Methods - 2008

Matching Method		Nearest Neighbour				Mahalanobis			
2008		t	t+1	t+2	t+3	T	t+1	t+2	t+3
Labour	ATT	.033	.022	.002	-.044	.003	.050	.037	.031
Prod.	s.e.	(.028)	(.029)	(.035)	(.065)	(.023)	(.029)*	(.033)	(.057)
TFP	ATT	.089	.048	.131	.038	.034	.095	.148	.141
(Lev-Pet)	s.e.	(.039)**	(.046)	(.048)**	(.083)	(.034)	(.054)*	(.050)**	(.076)*
N. of	Treated	298	285	270	120	298	285	270	121
Firms	Controls	2047	1850	1640	560	2047	1855	1645	560
TFP	ATT	-.061	-.031	-.0008	.013	-.012	-.024	-.0031	.010
(SFA)	s.e.	(.041)*	(.054)	(.053)	(.066)	(.039)	(.046)	(.045)	(.071)
TP	ATT	-.0000	-.0000	.0001	-.0000	.0000	.0001	.0001	.0003
(SFA)	s.e.	(.0000)	(.0001)	(.0001)	(.0001)	(.0000)	(.0001)*	(.0001)	(.0002)
SE	ATT	-.061	-.031	-.0010	.013	-.012	-.024	-.0031	.010
(SFA)	s.e.	(.041)*	(.054)	(.053)	(.066)	(.039)	(.046)	(.045)	(.071)
TE	ATT	-.0000	-.0000	.0000	-.0000	-.0000	.0000	.0000	-.0000
(SFA)	s.e.	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)
N. of	Treated	252	243	235	102	252	243	235	103
Firms	Controls	1703	1562	1406	484	1703	1562	1406	484

Standard errors are reported in parenthesis. * indicates statistical significance at the 10% level. ** indicates statistical significance at the 5% level. *** indicates statistical significance at the 1% level.

Table A2.11: ATT Effects: PSM-DID estimates from NN and Mahalanobis Methods - 2009

Matching Method		Nearest Neighbour			Mahalanobis		
2009		t	t+1	t+2	t	t+1	t+2
Labour	ATT	-.014	.016	-.023	-.012	.030	.002
Prod.	s.e.	(.032)	(.035)	(.055)	(.034)	(.033)	(.059)
TFP	ATT	.079	.178	.116	.071	.146	.133
(Lev-Pet)	s.e.	(.053)	(.047)***	(.067)*	(.057)	(.049)***	(.066)**
N. of	Treated	334	317	126	336	320	129
Firms	Controls	2303	2021	706	2303	2030	711
TFP	ATT	-.008	.035	.038	.013	-.003	-.002
(SFA)	s.e.	(.051)	(.054)	(.083)	(.047)	(.052)	(.084)
TP	ATT	-.0000	-.0000	.0000	-.0000	-.0000	-.0002
(SFA)	s.e.	(.0000)	(.0001)	(.0001)	(.0000)	(.0000)	(.0002)
SE	ATT	-.008	-.035	.038	.013	-.003	-.002
(SFA)	s.e.	(.051)	(.054)	(.083)	(.047)	(.052)	(.084)
TE	ATT	-.0000	.0000	.0000	.0000	-.0000	.0000
(SFA)	s.e.	(.0000)*	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)
N. of	Treated	268	253	102	269	254	104
Firms	Controls	1795	1591	550	1795	1591	550

Standard errors are reported in parenthesis. * indicates statistical significance at the 10% level.
** indicates statistical significance at the 5% level. *** indicates statistical significance at the 1% level.

Appendix 2 - Section B:

The relationship between returns to scale and scale efficiency

A firm producing with constant returns to scale is considered to be scale efficient (Coelli, 2005). According to this approach, firms producing with variable returns to scale (either increasing or decreasing returns) can improve their efficiency by changing their scale of production/operation. This can easily be shown in a one-input, one-output production technology scenario. Suppose there are three firms producing at the points A, B and C respectively. As Coelli (2005) explains, since all these three firms are producing on a production frontier, they are considered to be technically efficient. However, as Figure 3.3 illustrates, these three firms have different levels of productivity, since they are producing on different production frontiers.[77] The firm producing at point A could improve its productivity by increasing the scale of its production (moving towards B), since it is producing within the increasing returns to scale part of the production function. Similarly, as Figure 3.3 shows (below), the firm producing at point C is producing within the decreasing returns to scale part of the production function. Thus, it could enjoy an increase in productivity if it decreases its scale of production (moving towards B). On the other hand, the firm producing at point B cannot improve its productivity by adjusting its scale of production, since it is scale efficient.

[77] Consider that the level of productivity is measured by the ratio of output and input levels (q/x) which is the slope of a frontier. Thus a steeper line is associated with higher productivity.

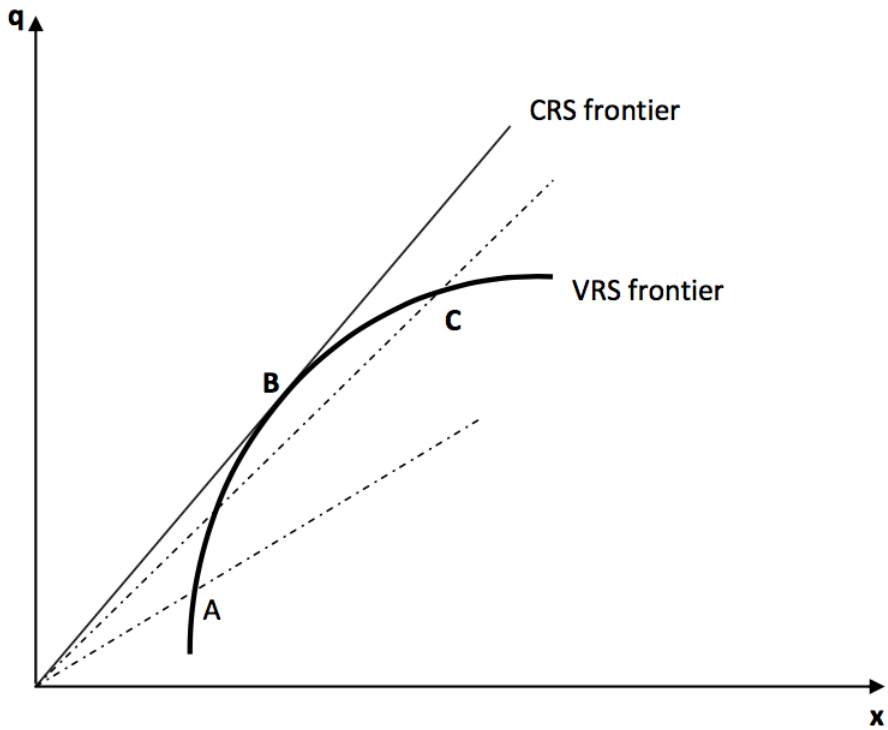


Figure 3.3: Scale Efficiency

Appendix 2 Section C:

Selection Bias and Alternative Solutions

Several methods can be utilized to overcome the selection bias problem. The first one we will review is an instrumental variable (IV) estimation. This method can be used to overcome the problem of the selection biases as long as appropriate instruments for D_i can be found. The method requires instrumental variables that affect participation in the treatment (decision to export) but do not directly affect the outcome (total factor productivity). The main issue with the IV estimation is the limitations on the availability of such instruments (Angrist and Krueger, 2001). Another issue might arise if a treatment affects participants heterogeneously. In addition to this heterogeneity problem, if the treatment effects are correlated with the instruments, then IV estimation will not be able to estimate the average treatment effect (Heckman and Carneiro, 2003). In such a case, the method provides estimations for the local impact of participation on the participants who react to a change in the value of the instrument (Local Average Treatment Effect (LATE)).[78]

The standard Heckman two-stage approach is the second approach that we will review. This method aims to tackle the self-selection issue in two stages. In the first stage, by utilizing a logit or probit estimator, predicted values of the probability are obtained. These values are used to calculate the sample selectivity correction terms which are used at the second stage of the procedure (Heckman, 1979). In this way, the Heckman two-stage approach aims to control for the correlation between participation decision and treatment. However, this approach has been criticized by several researchers, such as Angrist and Krueger (2001) who claim that this procedure produces non-robust results. Puhani (2000), in a survey, specifically highlights a co-

[78]On the other hand, if all firms react to the treatment (export) in same way, the LATE will be equal to the standard IV approach (Heckman and Carneiro, 2003).

linearity issue as a weakness of this approach.

The difference-in-difference (DID) estimator is another method that is used for calculating treatment effect when the information for pre-treatment and post-treatment is available. The impact of treatment can be written as:

$$(E[Y_{it}(1) \mid D_i = 1] - E[Y_{it'}(0) \mid D_i = 1]) - \{E[Y_{it}(0) \mid D_i = 0] - E[Y_{it'}(0) \mid D_i = 0])$$

where pre-treatment and post-treatment are denoted as $t'$and t, respectively.

The first two terms in the above equation show the change in outcomes for participants who received treatment, while the rest represents non-participants' experience between the pre-treatment and post-treatment periods. However, this method imposes a strong assumption that the experience of participant if it never exported is the same with the experience of non-participants.[79] In other words, the assumption suggests that the effect of treatment on the outcome of treated individuals/firms would have been equal to those do not receive the treatment, in the absence of participation. The problem is that this assumption fails if the treated group is a self-selected sub-group that has characteristics that enable them do better (in terms of outcome) if they receive treatment. Thus, this assumption does not exclude the possibility of selection on unobservable characteristics (Hsieh, 2009).

Rubin (1977) proposed a matching method to solve the selection bias problem which arises from the unobservable counterfactual, and this approach has become one of the most popular methods in the "program evaluation" literature. This method evaluates the effect of a treatment (export in our case) by comparing outcomes (total factor productivity) for a treated group (export starters) to those for similar participants in a comparison group (never exporters), controlling for all covariates. The idea is to match each treated individual/firm with a non-treated observation based

[79]This assumption can be shown as: $\{E[Y_{it}(0) \mid D_i = 1] - E[Y_{it'}(0) \mid D_i = 1]\} = \{E[Y_{it}(0) \mid D_i = 0] - E[Y_{it'}(0) \mid D_i = 0]$, thanks to this assumption, the unobserved term can be written as: $E[Y_{it}(0) \mid D_i = 1] = E[Y_{it'}(0) \mid D_i = 1] + \{E[Y_{it}(0) \mid D_i = 0] - E[Y_{it'}(0) \mid D_i = 0]$.

on all observable individual characteristics, and obtain a matched sample where the treated and non-treated groups are the same in all characteristics. This suggests that in the absence of treatment the outcomes will be the same for both groups.[80] As a result, this method provides pairs of control and treated individuals/firms, and solves the unobserved counterfactual problem which we highlight above.

On the other hand, there are a number of issues with the matching procedure worth mentioning. The traditional matching method requires a rich dataset including all variables that have a potential impact on participation in a treatment, in addition to the variables that have an impact on outcomes. This requirement leads to an issue known as the problem of dimensionality, when there are differences in several characteristics of treated and control individuals/firms (Rosenbaum and Rubin, 1983).[81] Because there are several observed covariates in our data that can be used for the matching procedure, such as total factor productivity, age, size, labour productivity, and region, industry or time effects, the traditional matching approach is not appropriate for our study.

An alternative matching method, propensity score matching, is proposed by Rosenbaum and Rubin (1983) in order to tackle the dimensionality problem. They introduce a propensity score, a probability of receiving treatment, given a set of covariates, and show that a matching can be performed based only on this propensity score which can be considered a summary of all observed covariates.[82] They also show that the matching procedure is valid, if the conditional distribution of the covariates, given a function of P(X), is the same for both treated, and control individuals/firms.[83] This can be shown with the following:

$$E[Y_i(1) - Y_i(0)|P(X)] = E[Y_i(1)|D_i = 1, P(X)] - E[Y_i(0)|D_i = 0, P(X)]$$

[80] This implies that $E[Y_i(0) \mid D_i = 1] = E[Y_i(0) \mid D_i = 0]$. Thus matching assumes that $Y_i(1)$ and $Y_i(0)$ are independent of D_i, and eliminates selection bias.

[81] Rosenbaum and Rubin (1983) name this problem as the curse of dimensionality.

[82] Propensity score is usually calculated by utilizing probit or logit regressions.

[83] $Y(0) \perp D \mid X \Longrightarrow Y(0) \perp D \mid P(X)$ where $P(X) = Pr(D = 1 \mid X)$

To sum up, this method enables researchers to tackle the selection bias problem by performing matching based on a single variable, propensity score, instead of all covariates.[84]

Although propensity score matching is currently the preferred methodology in the literature on learning by exporting, some researchers criticize the mechanism behind this method. For instance, Eliasson et al. (2009) suggest that export market participation is a dynamic treatment where some firms decide to enter to the export market earlier than others. Eliasson et al. (2009) also claim that, since the propensity score matching considers export starters as a treated group, while it does consider never-exporters as a control group, it generates an upward bias. Moreover, they suggest that "not-yet" entrants in the export market, rather than never-exporters should be considered as the control group. Additionally, Fernandes and Isgut (2007) also address an upward bias problem with the estimates of propensity score matching. They argue that unobserved productivity shocks might play an important role in firms' decisions to enter the export market, and if this is the case, then the key assumption of the propensity matching method is violated.[85]

[84]This can be shown as: $E[Y_i(1) - Y_i(0) \mid P(X)] = E[Y_i(1) \mid D_i = 1, P(X)] - E[Y_i(0) \mid D_i = 0, P(X)]$

[85]The unconfoundedness assumption suggests that the expected outcomes of treated, and control groups are conditionally independent from the treatment (Heckman and Navarro-Lozano, 2004). Please see footnote 86.

Appendix 2 Section D:

Different Matching Methods

There are several different matching methods available, and it is not an easy task to choose the right one. One would expect to obtain similar results from different methods, since asymptotically all propensity score matching estimators are the same. For small samples, however, the method choice might be important (Heckman, Ichimura and Todd, 1997). In this section, we will review some of the available PSM estimators, and compare and contrast their strengths and weaknesses.[86] Table A2.11 illustrates the bias-variance trade-off for the available PSM estimator. The literature suggests that there is no single best approach which can be used for all studies. Thus, researchers should try several methods to make sure that results provided by different approaches are robust (Bryson, Dorsett, and Purdon, 2002).

Mahalanobis Distance Matching:

This approach is a widely used method of multivariate matching (Rubin, 1980), and it is an alternative to the PSM method. This approach calculates the distance between any two vectors, X_i and X_j, with the Mahalanobis distance function rather than a propensity score:

$$md(X_i - X_j) = \{(X_i - X_j)' S^{-1} (X_i - X_j)\}^{\frac{1}{2}}$$

where S is the sample covariance matrix of X. ATT is estimated by matching each treated individuals with N numbers of closest individuals from control group where the distance between X_i and X_j is measured by $md(.)$ function.

[86] See Smith and Todd (2005) for technical details.

Nearest Neighbour Matching (NN):

This estimator creates a matched pair from treated and control individuals which have the closest propensity score. The method comes with several options, such as matching with replacement and without replacement. If the matching with replacement option is chosen, then observations in the control group can be paired with more than one treated observation. As Table A2.11 shows, this method is useful, since using it increases the matching quality, by reducing variance. On the other hand, if matching without replacement is employed, then bias is reduced, since we can obtain very similar observations. However, it provides less efficient estimates as a result of reduced sample size.

Caliper and Radius Matching:

If the closest neighbour in terms of propensity score is not close enough, NN may produce bad matches. One can overcome this issue by setting a caliper which makes sure that the propensity score differences between treated and control individuals are capped. However, this method may significantly reduce the number of matched pairs which results a variance increase in the estimation results. Another issue is that there are no criteria to assess a correct level for the caliper.

Kernel Matching:

Unlike NN, caliper, and radius matching, this method performs matching based on a weighted average of control group observations. More precisely, a counterfactual outcome for treated individuals is created by using all individuals in the control group.[87] As Table A2.11 reports, the use of this method reduces bias, since more information is used. However, this method is not perfect either. When performing

[87]On the other hand, other methods consider a few observations from the control group as a potential match for a treated individual.

Kernel matching, one has to choose a bandwidth parameter. This causes a problem which is similar to the issue with caliper mentioned above, since it is not easy to choose the correct level of bandwidth parameter.

Table A2.12 Bias-Variance Trade-off

Decision	Bias	Variance
NN matching:		
Multiple neighbours/single neighbour	(+)/(-)	(-)/(+)
with caliper/without caliper	(-)/(+)	(+)/(-)
Use of control individuals		
With replacement/without replacement	(-)/(+)	(+)/(-)
Choosing method:		
NN matching/Radius matching	(-)/(+)	(+)/(-)
Kernel matching/NN matching	(+)/(-)	(-)/(+)
Bandwith choice with Kernel		
Small/large	(-)/(+)	(+)/(-)

Source: Caliendo and Kopeining (2005)

Appendix 2 Section E:

Testing Matching Quality

The basic idea of all approaches is to compare the situation before and after matching and check whether any differences remain after conditioning on the propensity score. If there are differences, matching on the score was not (completely) successful.

Rosenbaum and Rubin (1983) Approach:

According to this approach, a standard bias can be calculated based on a ratio of the difference of sample means, and the square root of the average of sample variances for both control and treated groups. Rosenbaum and Rubin (1983) suggests that the standard bias before matching can be computed by:

$$SB_{before} = 100\frac{(\bar{X_1} - \bar{X_0})}{\sqrt{0.5(\bar{V_1}(X) + \bar{V_0}(X))}}$$

The bias after matching is calculated by:

$$SB_{after} = 100\frac{(\bar{X_{1M}} - \bar{X_{0M}})}{\sqrt{0.5(\bar{V_{1M}}(X) + \bar{V_{0M}}(X))}}$$

For the treatment group, X_1 and V_1 represent the mean and variance before matching, respectively, while X_0 and V_0 are the same values for the control group. For the matched sample, X_{1M} and V_{1M} stand for the mean and variance, while X_{0M} and V_{0M} are the same values for the control group. A matching is considered as successful if it could reduce the bias below 5%, although this not a formally verified rule (Caliendo and Kopeinig, 2005)

T-Test:

A two-sample t-test is another method to examine if there are significant differences between the mean of variables for both groups. According to this approach, differences in both groups, in terms of mean values, are expected before matching, but, a successful match is supposed to eliminate those differences for each variable. The advantage of the t-test is that it shows whether the results are statistically significant.

Chapter 4: Firm Productivity and International Organization of Production of a Firm: Do Motives for Mergers Matter?

4.1. Introduction

Following the trade liberalization wave in the world economy, the number of firms involved in international trade activities has dramatically increased. Cross-border mergers and greenfield FDI have become the main strategies through which these firms internationalize their production process. Additionally, over the last two decades cross-border mergers, have become more popular compared to greenfield FDI. The share of cross-border mergers in total foreign direct investment (FDI) flows has increased and almost caught up with the share of greenfield FDIs (UNCTAD 2008).[88] Following the recent trend in the international trade literature, the literature on trade and investment has started to uncover the effects of firm-productivity on cross-border mergers.[89]

In a recent paper, Nocke and Yeaple (2007: here-after NY) examines the relationship between firm efficiency and foreign market entry decisions in a heterogeneous firm framework. In their paper, NY consider that the efficiency motive is the main driver of merger activities, and show that the most productive firms engage in cross-border mergers, while relatively less efficient firms choose greenfield FDI, and the least efficient firms export or only serve the domestic market.[90]

[88]As a result of the global economic crisis of 2008-09, both total FDI flow, and the level of cross-border mergers decreased dramatically, but, recently they have tended to recover from the crisis episodes (UNCTAD 2013).

[89]The heterogeneous nature of FDI has been largely neglected by the international trade literature. However, some recent studies that we survey in the following section address this issue.

[90]This result is valid for Sector M in NY, which is the main interest of this paper.

The present chapter contributes to the literature by extending NY's approach to include the industry concentration effect of cross-border mergers. Focusing on a monopolistically competitive environment, NY ignore any strategic motives for a merger. In this chapter, we introduce the market-concentration effect of cross-border mergers by developing a two-country oligopoly model of product differentiation, where firms are heterogeneous in terms of their productivity.

The main finding of this chapter is that, in the presence of a higher market-concentration under merger, a relatively low productive firm may prefer cross-border merger while a relatively high productive firm may prefer either greenfield FDI or export. Our results are more likely to hold if the product differentiation is low, so that the associated competition effect is large.

In contrast to Helpman et al. (2004), and NY, our findings suggest that a strict productivity ranking in terms of the choice of foreign market entry mode may not occur.[91] Empirical evidence on this issue is very limited. Some recent empirical studies provide mixed results regarding the relationship between entry mode decision and firm productivity, which is consistent with our predictions. Trax (2011), for instance, finds that the most efficient UK firms choose cross-border merger over greenfield FDI in high intangibles industries, while she cannot find such evidence in the low intangibles sector. On the contrary, Raff et al. (2012) show that the most productive Japanese firms prefer greenfield investment over cross-border merger.[92] We believe that the findings from our model, which shows that the relationship between productivity and merger/greenfield FDI decisions is non-monotonic, can offer an explanation for the mixed results from empirical studies in the literature.

[91] According to Helpman et al. (2004) the most productive firms undertake FDI, while less productive firms export. Nocke and Yeaple (2007) extend this analysis by considering the heterogeneous nature of FDI.

[92] Nocke and Yeaple (2008) also find that more productive firms choose greenfield FDI, while less efficients firms prefer cross-border merger, if there are factor price differences between countries in terms of wages. They also show that greenfield FDI is not a preferred strategy for neither type of firm, when the factor price differences vanish.

The paper proceeds as follows. In section 4.2, we provide a review of recent theoretical and empirical literature, then we describe the model and discuss the results in sections 4.3 and 4.4. Finally, in section 4.6 we offer some concluding remarks and a future research agenda.

4.2. Related Literature

Two recent developments in the literature on FDI are worth mentioning.[93] Until recently, the literature has focused on the determinants of an internationalization decision of a firm by treating firms within an industry as homogeneous. However, the emerging empirical literature shows that firms selling abroad are rare among all producers in both developing and developed countries, and their decisions to participate in international markets are not random (Bernard and Jensen, 1999). Furthermore, Bernard and Jensen (1999) show that firms engaging in international trade are different in terms of their size, productivity and capital intensity than those who operate domestically only.

Following these new findings, the seminal work of Melitz (2003) and Bernard, Eaton, Jensen and Kortum (2003) provided theoretical proof for the link between firm-level productivity and the export decisions of firms. Melitz (2003) introduced firm-level productivity heterogeneity by adapting Hopenhayn's (1992) model to a dynamic model of a monopolistic competitive industry. The main finding of Melitz (2003) is that the productivity of a firm determines its decision to enter the international market. More precisely, more productive firms enter foreign markets, since only they can overcome sunk entry costs, while less productive firms operate only domestically. Finally, the least productive firms stop producing, and exit the market.

Helpman, Melitz, and Yeaple (2004) contribute to this branch of FDI literature

[93]See Antràs and Yeaple (2014) or Markusen (2002) for a survey.

by explicitly considering two ways to serve the foreign market -export and FDI- and they show that only the most productive firms within an industry engage in FDI, while the less efficient firms serve foreign markets via export.[94]

The second important development in the FDI literature concerns the composition of FDI. Until recently, researchers such as Helpman et al. (2004), and Head and Riese (2003), have mainly focused on two alternative ways of accessing foreign markets, exports and FDI. In spite of the fact that cross-border merger is considered to be an important type of FDI, the relevant literature did not pay much attention to this aspect.[95] Some recent papers, on the other hand, such as Ferrett (2005), Bjorvatn (2004), and Neary (2009), explicitly model the two different components of FDI to examine the internationalization decisions of firms.

Ferrett (2005), for instance, examines firms' choice between greenfield investment and acquisition-FDI in a model where the decision of a firm between the two is endogenous. He shows that acquisitions may dominate greenfield investment by considering the role of endogenous R&D investment. This finding highlights the importance of taking both components of FDI in to account in a single framework. Bjorvatn (2004) also examines firms' choice between greenfield investment and cross-border merger, and shows a positive relationship between economic integration and incentive for cross-border mergers.[96] Although Ferrett (2005), Bjorvatn (2004), and Neary (2009) highlight the importance of modeling greenfield investment and cross-border merger simultaneously, unlike our study, they ignore the productivity differences amongst firms.

[94]Mrázová and Neary (2013) confirms the findings of Helpman et al. (2004) only if a firm's variable costs of production and the transportation costs it faces are complementary. Moreover, they show that it may not be the case when they consider different preference structures, where firms cannot be sorted on the basis of their productivity in a way that Helpman et al. (2004) proposed.

[95](UNCTAD 2008).

[96]Similarly, they report a positive relationship between lower level of trade cost and incentive for cross-border mergers.

A recent paper by NY combines the recent developments in the literature on FDI. In their model, they consider firm heterogeneity along with the heterogeneous nature of FDI, where firms which want to sell abroad have the following options: export, greenfield FDI, and cross-border merger. In their paper, firm heterogeneity arises from the fact that firms have different types of capability. NY consider two sectors: sectors M and N. Firms are heterogeneous in terms of their internationally mobile capabilities in sector M, while in sector N, the source of heterogeneity is the immobile capabilities that firms own.[97] NY suggest that the motivation of a firm engaging in a cross-border merger is closely linked to a firm's heterogeneous capabilities. So, a target or an acquiring firm's main motivation for undertaking cross-border merger is to exploit complementarities when combining the firm-specific capabilities.[98] Considering different possibilities regarding the nature of acquirers' firm-specific assets and targets' assets: NY confirm the standard findings of the literature on FDI, suggesting that firms engaging in greenfield investment are more efficient than exporters. Moreover, when they consider the sector where firms differ in terms of their internationally mobile capabilities only (sector M), they show that the more productive firms prefer cross-border merger over greenfield FDI.[99]

NY claim that their findings are in connection with "superstar" phenomenon proposed by Rosen (1981). More precisely, NY suggest that the best mobile capabilities, i.e. the most advanced technology, are allocated to cross-border merger, since those capabilities are the superstars in an industry. For this reason, NY conclude that foreign firms with the best technology prefer to combine their assets via cross-border merger with a home target firm which has knowledge of local market conditions.

[97] While the production technology of a firm is considered as an example of mobile capabilities, local marketing experience or supply networks are associated with immobile capabilities.

[98] Greenfield investment, on the other hand, can be considered as a more direct way for a firm to utilize its own firm-specific assets.

[99] However, they find that firms that engage in cross-border merger are the least efficient in industry N where firms differ in terms of internationally non-mobile capabilities.

As we described in the paragraph above, unlike our paper, NY consider that the efficiency motive is the only motive for a merger, since they consider monopolistic competition. In this chapter, we introduce the competition reducing effect of merger by considering a duopolistic competition framework.[100] Unlike NY, we show that a decrease in productivity may increase incentives for cross-border merger, while an increase in productivity may increase incentives for greenfield FDI. These results might be interpereted as follows: In our framework, more productive firm may prefer greenfiled FDI in order to access home country market, since it might eleminate less productive firms in home market and obtain monopoly power. On the other hand, a relatively less productive firm may prefer cross-border merger to greenfield FDI in order to enjoy market concantration effect of merger. In such case, merged entity will adopt the technology of the more productive firm and produce with better technology. By doing this, it aims to behave as a monopolist in the market.[101]

In the following section, we describe our model where we consider both strategic and efficiency motives for cross-border merger; and we show that the predictions of NY do not necessarily hold when the competition-reducing effect of merger is considered.

4.3. The Model

Consider an economy with two countries: home (H) and foreign (F), and two rival firms, each already settled in one of these countries. Assume that Firm F is located in the foreign country, while Firm H is located in the home country.[102] We assume

[100]We also consider a case where there are N firms in the home country ($N > 2$). So, in addition to strategic motive, we also consider the efficiency motive of merger arising from technology transfer when firms merge.

[101]In such case, cross-border merger might create a similar effect in terms of cost advantage as if the merged firm had undertaken a drastic innovation.

[102]We show in Section 4.5 that our qualitative results also hold when we consider that there are N number of firms located in the home country, where $N > 2$.

that these firms produce differentiated products and compete in the home-country market:

Export (X): Firm F serves the H market through export by incurring a positive per-unit transportation cost t.

Greenfield FDI (G) : Firm F undertakes greenfield FDI by incurring a setup cost, G.

Cross-border Mergers (M): Firm F and firm H merge and the merger activity involves a fixed cost of K.

Although Firm F has another option, i.e. not serving the home-country market, we will assume the parameters values in a way so that this option will not occur in equilibrium. We will do this because considering the option of not serving the home-country by Firm F will not add much new insights to our analysis.

We consider that labour is the only factor of production (as in NY), and the wage rates in both countries are the same and equal to w. Firms differ in terms of their labour productivities, and the technology of Firms F and H are $q_F = L_F/\lambda$, and $q_H = L_H$, respectively, where λ is the inverse of labour productivity. Lower λ implies higher labour productivity in this context, and this implies that Firm F is more productive than Firm H.[103] We finally assume that Firm F can transfer its technological advantage to the merged entity so that it can produce at the same marginal cost it faces in its home country. This assumption makes our results comparable to findings provided by NY for Sector M in their paper, where firms are heterogeneous in terms of their internationally mobile capabilities.

Following Bowley (1924), we assume that the representative consumer in country H has the following utility function:[104]

[103] Hence we obtain labour demand for Firm F and H: $L_F = \lambda q_F$ and $L_H = q_H$

[104] The Bowley type of market demand function is commonly used in the industrial organization literature.

$$U_H = (q_F + q_H) - \left(\frac{q_F^2}{2} + \frac{q_H^2}{2}\right) - \gamma q_F q_H + m$$

where m stands for the numeraire commodity, and the parameter $\gamma \in (0, 1)$ is the degree of product differentiation. The resulting inverse demand function for goods q_F and q_H are:

$$p_H = 1 - q_H - \gamma q_F$$

where p_H is price, q_F, q_H are outputs. The products are perfect substitutes if $\gamma = 1$, while the goods are isolated for $\gamma = 0$. We avoid these two extreme cases in our analysis, and assume that $\gamma \in (0, 1)$.

We consider the following two-stage game. At stage 1, Firm F determines whether to export or to undertake greenfield FDI or to merge with Firm H. At stage 2, firms compete in the home market if Firm F either exports or undertakes greenfield FDI. There is no competition if Firms F and H merge. We will consider Cournot competiton in the next section and will consider Bertrand competition in Section 4.5.1. It may worth mentioning that if Firms F and H merge, the merged firm becomes a monopolist with two differentiated products. The profits are realized according to Firm F's production decision. We solve the game through backward induction.

4.4. Equilibrium Analysis

4.4.1. Export vs. Greenfield FDI

Firstly, we consider that the foreign firm chooses between export and greenfield investment in order to access the host country's market.

If Firm F chooses to export, it determines output by maximizing the following expression:

$$\underset{q_F}{Max}(1 - q_F - \gamma q_H - \lambda w - t)q_F \tag{4.1}$$

Expression (4.1) shows that Firm F can sell q_F units of product with a transportation cost of tq_F, while the production cost is equal to $\lambda w q_F$. Firm H determines its output to maximize the following expression:

$$\underset{q_H}{Max}(1 - q_H - \gamma q_F - w)q_H \tag{4.2}$$

Maximizing (4.1) and (4.2) provides us with the equilibrium outputs of Firms F and H. Let q_F^X and q_H^X are equilibrium outputs:

$q_F^X = \frac{(2-\gamma-w(2\lambda-\gamma)-2t)}{(4-\gamma^2)}$, and $q_H^X = \frac{(2-\gamma-w(2-\lambda\gamma)+\gamma t)}{(4-\gamma^2)}$

Let π_F^X (π_H^X) represent Firm F's (Firm H's) operating profit if Firm F chooses to export. Then the profits of Firms F and H are:

$$\pi_F^X = \frac{(2-\gamma-w(2\lambda-\gamma)-2t)^2}{(4-\gamma^2)^2} \tag{4.3}$$

$$\pi_H^X = \frac{(2-\gamma-w(2-\lambda\gamma)+\gamma t)^2}{(4-\gamma^2)^2} \tag{4.4}$$

We assume that q_F^X and q_H^X are positive, i.e. $t < \frac{(2-2\lambda w-\gamma+w\gamma)}{2} \equiv \bar{t}$

In contrast, if Firm F undertakes greenfield investment, it maximizes the following profit function:

$$\underset{q_F}{Max}(1 - q_F - \gamma q_H - \lambda w)q_F - G \tag{4.5}$$

while the profit function for Firm H is:

$$\underset{q_H}{Max}(1 - q_H - \gamma q_F - w)q_H \tag{4.6}$$

Maximizing (4.5) and (4.6), we obtain the equilibrium outputs of Firms F and H under greenfield investment are (q_F^G and q_H^G):

$q_F^G = \frac{(2-\gamma-w(2\lambda-\gamma))}{(4-\gamma^2)}$; and $q_H^G = \frac{(2-\gamma-w(2-\lambda\gamma))}{(4-\gamma^2)}$

Let π_F^G (π_H^G) represent Firm F's (Firm H's) profit if Firm F chooses to undertake greenfield FDI. Then the profits of Firms F and H are:

$$\pi_F^G = \frac{(2-\gamma-w(2\lambda-\gamma))^2}{(4-\gamma^2)^2} - G \tag{4.7}$$

$$\pi_H^G = \frac{(2-\gamma-w(2-\lambda\gamma))^2}{(4-\gamma^2)^2} \tag{4.8}$$

We assume that q_F^G, q_H^G are positive, i.e. $w < \frac{(2-\gamma)}{2-\lambda\gamma} \equiv \overline{w}$.

Firm F prefers greenfield FDI compared to export if and only if $\pi_F^G > \pi_F^X$ or:

$$G < \left(-\frac{4t(-2+t+2\lambda w+\gamma-w\gamma)}{(-4+\gamma^2)^2}\right) \equiv G_1 \tag{4.9}$$

where $G_1 > 0$. Firm F prefers export over greenfield FDI if and only if $G > G_1$. Differentiating G_1 with respect to λ we find that $\frac{\partial G_1}{\partial \lambda} = -\frac{8tw}{(-4+\gamma^2)^2} < 0$. The following result summarizes the above discussion.

Proposition 1: *If greenfield FDI is available as an alternative to exporting, i.e. $G < G_1$, Firm F's incentive to pursue greenfield investment increases in its productivity.*

The above finding indicates that if Firm F becomes more productive, i.e. lower λ, its incentive to pursue greenfield investment increases, i.e. G_1 increases. The reason behind this is the fact that when the productivity of Firm F increases, it produces more, and faces a higher trade cost in total. Since this cost can be avoided by greenfield FDI, Firm F's incentive to pursue greenfield FDI increases. This result is in line with findings of the recent literature on FDI that we mentioned in the previous section (for instance Helpman, Melitz and Yeaple (2004)).

4.4.2. Export vs. Cross-Border Merger

From equation (4.9) we know that Firm F prefers greenfield investment if and only if $G < G_1$, otherwise it prefers to export. In this sub-section, we assume that $G > G_1$, in other words, Firm F prefers export compared to greenfield FDI. Now, we will see Firm F's preference for cross-border merger with Firm H compared to export when $G > G_1$.

We know from (4.3) and (4.4) that if Firm F chooses to export, the profits of Firms F and H are:

$\pi_F^X = \frac{(2-\gamma-w(2\lambda-\gamma)-2t)^2}{(4-\gamma^2)^2}$, and $\pi_H^X = \frac{((2-\gamma-w(2-\lambda\gamma)+t\gamma)^2}{(4-\gamma^2)^2}$

On the other hand, if Firms F and H merge, the merged entity maximizes the following profit function:

$$\underset{q_F,q_H}{Max}(1 - q_F - \gamma q_H - \lambda w)q_F + (1 - q_H - \gamma q_F - \lambda w)q_H - K \qquad (4.10)$$

The merged firm produces differentiated products in the home country. Firm F avoids the trade cost via cross-border merger, there is a cost of merger, K. In equation (4.10) λ stands for the productivity of the merged firm. Since we assume that Firm F is more efficient than Firm H, the merged firm uses the technology of Firm F after the merger.

If Firms F and H merge, the equilibrium output and the profit of merged firm are:

$q_F^M = q_H^M = \frac{(1-\lambda w)}{2(1+\gamma)}$, and

$$\pi_{F+H}^M = \frac{(1-\lambda w)^2}{2(1+\gamma)} - K \qquad (4.11)$$

The merger between firms F and H occurs if the profit of merged entity π_{F+H}^M, exceeds the total profits of Firms F and H under export by Firm F, i.e. if:

$\pi_{F+H}^M > \pi_F^X + \pi_H^X$

while π_F^X and π_H^X denote the profits of Firms F and H under export by Firm F. It follows from (4.3), (4.4) and (4.11), that Firm F prefers cross-border merger compared to export if and only if:

$$K < \frac{(1-\lambda w)^2}{2(1+\gamma)} - \left(\frac{(2-\gamma-w(2\lambda-\gamma)-2t)^2}{(4-\gamma^2)^2} + \frac{(2-\gamma-w(2-\lambda\gamma)+t\gamma)^2}{(4-\gamma^2)^2}\right) \equiv K_1 \qquad (4.12)$$

Condition (4.12) tells us that Firm F prefers a cross-border merger over export if the cost of merger, K, is less than K_1. This shows the maximum gain of Firm F from merger compared to export, thus a higher value of K_1 suggests that the Firm F has a higher incentive to pursue a cross-border merger.

Now we show how the incentive for merger changes with respect to productivity. In order to examine this we rearrange the derivative of K_1 with respect to λ. Equation (4.12) shows that K_1 consists of the profit of the merged entity, and the profits of Firm F and H when Firm F chooses to export. All these profits in equation (4.12) depend on productivity term λ. Therefore, the relationship between K_1 and λ depends on how these three profit terms react to a productivity change. If the difference between the profit of the merged firm and the combined profit of Firms F and H under export by Firm F increases (decreases) in λ, we can conclude that a lower productivity increases (decreases) Firm F's merger incentive. Before examining this, we define:

$$t^* = \frac{8w\gamma(1+\gamma)-(-2+\gamma)^2(2+\gamma(\gamma+2))+\lambda w(8+\gamma(-8+\gamma(-10+\gamma(-2+\gamma)))}{2(1+\gamma)(4+\gamma^2)}$$

where $t^* > 0$ if $w > \frac{(\gamma-2)^2(2+\gamma(\gamma+2))}{8\gamma(1+\gamma)+\lambda(8+\gamma(-8+\gamma(-10+\gamma(-2+\gamma)))} \equiv w^*$, and $w^* > 0$.

Proposition 2: *If export is Firm F's preferred choice as an alternative to merger, ($G > G_1$), a higher productivity of Firm F increases (reduces) the incentive for cross-border merger if $t \in (t^*, \bar{t})$ or if ($t \in (0, t^*)$).*

Proof: *By using condition (4.12) we can show that* $\frac{\partial K_1}{\partial \lambda} < (>)\ 0$ *for* $t > (<)\ t^*$*, where* $t^* < \bar{t}$*.* ∎

The above result is in contrast to Nocke and Yeaple (2007) for $t < t^*$ who shows that the most efficient firm chooses cross-border merger. The intuition behind this finding is that a decrease in the productivity of Firm F causes an increase in Firm H's profit, while the profit of Firm F decreases. If the trade cost is below a certain threshold ($t < t^*$), thus creating a higher competition in the home-country market, the decrease in profit of Firm F outweighs the increase in profit of Firm H, and the total profit of these two firms, given by the total value inside parenthesis in equation (4.12), decreases. This leads to an increase in K_1.

The proposition above shows that the per-unit trade cost, t, plays a crucial role in obtaining this result. The level of trade cost is important, because it determines the intensity of competition between the firms, which affects the outputs and the profits of the firms under export by Firm F.

Another driving force of the level of competition in our model is the level of product differentiation, γ. In order to see the effect of the level of product differentiation on our findings, we consider how the value of t^* changes with respect to the level of γ.

Proposition 3: *A lower level of product differentiation, i.e. higher* γ*, increase the range for* t*, which ensures that Proposition 2 holds true where* $t < t^*$*.*

Proof: *Differentiating* t^* *with respect to* γ*, we find that:*

$$\frac{\partial t^*}{\partial \boldsymbol{\gamma}} = \frac{(-4+\boldsymbol{\gamma}^2)(-8-\boldsymbol{\gamma}(8+\boldsymbol{\gamma}(16+\boldsymbol{\gamma}(2+\boldsymbol{\gamma})))+w(-8(1+\boldsymbol{\gamma})^2+\lambda(16+\boldsymbol{\gamma}(24+\boldsymbol{\gamma}(24+\boldsymbol{\gamma}(\mathbf{2}+\boldsymbol{\gamma})))))}{2(1+\gamma)^2(4+\gamma^2)^2} > 0 \ \blacksquare$$

The above result implies that as product differentiation reduces, the finding proposed in Proposition 2 for $t < t^*$ is more likely to hold true. The reason behind this is because competition effect increases, as product differentiation reduces. Thus the condition of $t < t^*$ can be satisfied for a higher t.

4.4.3. Greenfield FDI vs Cross-Border Merger

In this sub-section, we consider that $G < G_1$, i.e. Firm F prefers greenfield FDI compared to export.

We know from equations (4.7), and (4.8) that if Firm F undertakes greenfield FDI, the profits of firms Firms F and H are:

$\pi_F^G = \frac{(2-\gamma-w(2\lambda-\gamma))^2}{(4-\gamma^2)^2} - G$, and $\pi_H^G = \frac{((2-\gamma-w(2-\lambda\gamma))^2}{(4-\gamma^2)^2}$

If Firms F and H merge, we know from (4.11) that the profit of the merged entity is:

$\pi_{F+H}^M = \frac{(1-\lambda w)^2}{2(1+\gamma)} - K$

If greenfield FDI is the alternative to merger, a merger between firms F and H is profitable if:

$\pi_{F+H}^M > \pi_F^G + \pi_H^G$

where π_{F+H}^M denotes the post-merger profit of the merged entity, while π_F^G and π_H^G denote the profit of Firms F and H under greenfield FDI by Firm F. Hence, the cross-border merger occurs if and only if:

$$K < \frac{(1-\lambda w)^2}{2(1+\gamma)} - \left(\frac{(2-\gamma-w(2\lambda-\gamma))^2}{(4-\gamma^2)^2} + \frac{((2-\gamma-w(2-\lambda\gamma))^2}{(4-\gamma^2)^2} - G\right) \equiv K_2 \tag{4.13}$$

Condition (4.13) tells us that Firm F prefers to do cross-border merger over greenfield FDI if the cost of merger, K, is less than K_2, which shows the maximum gain of Firm F from merger compared to greenfield FDI. A higher value for K_2 suggests that Firm F has a higher incentive for cross-border merger.

Before further analysis we define:

$$w^{'} = \frac{(\gamma-2)^2(2+\gamma(2+\gamma))}{8\gamma(1+\gamma)+\lambda(8+\gamma(-8+\gamma(-10+\gamma(-2+\gamma))}>0.$$

Proposition 4: *If greenfield FDI is Firm F's preferred choice as an alternative to merger, i.e.* $G < G_1$*, Firm F's incentive for undertaking cross-border merger increases (reduces) with lower* λ*, i.e higher productivity, if* $w \in (0, w^{'})$ *or if* $(w \in (w^{'}, \overline{w}))$*.*

Proof: *The proof follows from rearranging the derivative of* K_2 *with respect to* λ*. Straightforward calculation shows that* $\frac{\partial K_2}{\partial \lambda} < (>)\ 0$ *for* $w < (>)\ w^{'}$*. The rest of the proof follows immediately.*[105] ■

Again, this result is in contrast to Nocke and Yeaple (2007) for $w > w^{'}$. The proposition above suggests that when wages are below a certain threshold, the foreign firm's incentive to undertake cross-border merger increases with higher productivity. On the other hand, if wages are sufficiently high, (bigger than $w^{'}$), higher productivity reduces the foreign firm's incentive to undertake cross-border merger. This can be explained as follows. It is a straightforward result of equation (4.13) that an increase in the productivity of the foreign firm causes a decrease in the domestic firm's profit, while the profit of foreign firm increases. Similarly, in the case of merger, higher productivity results in a higher profit. When wages are high (above $w^{'}$), the cost advantage of the foreign firm over the home country firm is relatively higher than it is when wages are low (below $w^{'}$). For this reason, when wages are high, a productivity increase causes a more dramatic profit increase for the foreign firm than it would when wages are low. This increase is higher than the increase in the profit of the merged firm when wages are high. This explains why cross-border merger becomes less attractive as the productivity of the foreign firm increases when wages are high.

[105] *Please see Appendix 3 Section C.1 for the proof of* $\overline{w} > w^{'}$

Now we show how the range of w over which a higher productivity reduces the incentive for a cross-border merger varies with product differentiation.

Proposition 5: *A lower level of product differentiation, i.e. higher γ, increases w', i.e. increases the range of w over which a higher productivity reduces the incentive for a cross-border merger.*

Proof: *The proof is documented in Appendix 3 Section C.2*

The proposition above suggests that lower level of product differentiation (higher γ) increase the range of w suggesting that lower productivity is associated with higher incentive for cross-border merger. The intuition is similar to that of Proposition 3.

4.5. Robustness and Extentions

4.5.1. Bertrand Competition

As Salant et al. (1983), and Deneckere and Davidson (1995) show, Bertrand and Cournot models sometimes provide different findings when it comes to merger analysis.[106] Thus, in this section we will consider Bertrand competition by assuming that firms compete by setting prices rather than quantities. In order to solve the Bertrand game, first we obtain the direct demand functions by utilizing the inverse demand functions. They take the following form:

$q_F = \frac{(1-\gamma)-P_F+\gamma P_H}{1-\gamma^2}$, and $q_H = \frac{(1-\gamma)-P_H+\gamma P_F}{1-\gamma^2}$

For our analysis under Bertrand competition, we illustrate the calculations for equilibrium outputs and profits in Appendix 3 Section A.

[106] Salant et.al (1983) show the merger paradox under Cournot competition, unless all firms that merge create a monopoly. On the other hand, Deneckere and Davidson (1985) show that mergers can be profitable for both insiders and outsiders in a model of Bertrand competition with differentiated products, i.e. the merger paradox does not hold.

4.5.1.1. Equilibrium Analysis

Export vs Greenfield FDI

Consider that the foreign firm chooses between export and greenfield investment in order to access the home country's market. If Firm F chooses to export, q_F^X and q_H^X are equilibrium outputs, and positive if $t < 1 - \lambda w - \frac{(w-1)\gamma}{\gamma^2-2} \equiv \bar{t}$. However, if Firm F undertaked greenfield FDI, q_F^G and q_H^G are equilibrium outputs, and they are positive if $w < \frac{(\gamma-1)(2+\gamma)}{\gamma+\lambda(-2+\gamma^2)} \equiv \overline{w}$. We assume that these conditions hold.

Firm F chooses to undertake greenfield FDI if and only if $\pi_F^G > \pi_F^X$ or:

$$G' < \left(\frac{t(-2+\gamma^2)(-2(-2+t+2\lambda w)+2(-1+w)\gamma+\gamma^2(-2+t+2\lambda w))}{(-4+\gamma^2)^2(-1+\gamma^2)}\right) \equiv G_2 \tag{4.14}$$

Export vs. Cross-Border Merger

From equation (4.14) we know that Firm F prefers greenfield FDI compared to export if and only if $G' < G_2$; otherwise it prefers to export over greenfield FDI. If $G' > G_2$, i.e. export is Firm F's available strategy as an alternative to merger, we find that cross-border merger is profitable compared to export if and only if:

$$\begin{aligned} K' < \; & \frac{(-1+\lambda w)^2}{2(1+\gamma)} - [(-\frac{(2(-1+t+\lambda w)+\gamma-w\gamma-(-1+t+\lambda w)\gamma^2)^2}{(-4+\gamma^2)^2(-1+\gamma^2)}) \\ & +(-\frac{(2+\gamma(-1+t-\gamma)+w(-2+\gamma(\lambda+\gamma)))^2}{(-4+\gamma^2)^2(-1+\gamma^2)})] \equiv K_3 \end{aligned} \tag{4.15}$$

Let's define:

$$t^{**} = \frac{-8+8(1+w)\gamma+2\gamma^2-4(1+w)\gamma^3+\gamma^4+\gamma^5-\lambda w(-8+\gamma(16+\gamma(2+\gamma(-8+\gamma+\gamma^2)}{2(4-3\gamma^2+\gamma^4)}.$$

where, $t^{**} > 0$ if $w > \frac{(\gamma-1)(\gamma+2)^2(2+(-2+\gamma)\gamma)}{4\gamma(-2+\gamma^2)+\lambda(-8+\gamma(16+\gamma(2+\gamma(-8+\gamma+\gamma^2))))} \equiv w^{**} > 0$

Proposition 6: *If export is Firm F's preferred choice as an alternative to merger, ($G' > G_2$), a higher productivity of Firm F increases (reduces) the incentive for cross-border merger, if $t \in (t^{**}, \bar{t})$ or if ($t \in (0, t^{**})$.*

Proof: *By using condition (4.15) we can show that* $\frac{\partial K_3}{\partial \lambda} < (>)\ 0$ *for* $t > (<)\ t^{**}$, *where* $t^{**} < \bar{t}$. ■

Like the case under Cournot competition, this result is in contrast to NY for $t < t^{**}$. The intuition is similar to that of Proposition 2.

Greenfield FDI vs Cross-Border Merger

Consider in this sub-section that $G^{'} < G_2$, i.e. greenfield FDI is preferable in the absence of merger. We find that cross-border merger is profitable compared to greenfield FDI by Firm F if and only if:

$$\begin{aligned} K^{''} < \; & \frac{(-1+\lambda w)^2}{2(1+\gamma)} - \left(-\frac{(2+\gamma(-1+w-\gamma)+\lambda\gamma(-2+\gamma^2))^2}{(-4+\gamma^2)^2(-1+\gamma^2)} - G' + \right. \\ & \left. \left(-\frac{(-2+\gamma+\gamma^2-w(-2+\gamma(\lambda+\gamma)))^2}{(-4+\gamma^2)^2(-1+\gamma^2)}\right)\right) \equiv K_4 \end{aligned} \tag{4.16}$$

Condition (4.16) tells us that Firm F prefers to do cross-border merger over greenfield FDI if and only if $K^{''} < K_4$.

Let's define:

$$w^{''} = \frac{-8+8\gamma+2\gamma^2-4\gamma^3+\gamma^4+\gamma^5}{-8\lambda-8\gamma+16\lambda\gamma+2\lambda\gamma^2+4\gamma^3-8\lambda\gamma^3+\lambda\gamma^4+\lambda\gamma^5} > 0.$$

Proposition 7: *If greenfield FDI is Firm F's preferred choice as an alternative to merger,* $(G^{'} < G_2)$, *Firm F's incentive for undertaking cross-border merger increases (reduces) with higher productivity, if* $w \in (0, w^{''})$ *or if* $(w \in (w^{''}, \overline{w}))$.

Proof: *By using condition (4.16) we can show that* $\frac{\partial K_4}{\partial \lambda} < (>) 0$ *for* $w < (>) w^{''}$. The intuition is similar to that of for Proposition 4.

4.5.2. N Firms in the Home Country

To convey our point in the simplest way, we assumed in section 2 that there is only one firm in the home country. We show in this section that our findings of section

2 hold true when there are n symmetric firms in the home-country, where $n > 2$. When we rearrange the inverse demand functions for the case of N firms, the resulting inverse demand function for Firm F and for the ith home-firm are respectively:

$$p_F = 1 - q_F - \sum_{i=1}^{n} q_i$$

$$p_i = 1 - \sum_{i=1}^{n} q_i - q_F$$

where $p_F,\ and\ p_i$ are prices, q_F, q_i are outputs.

We assume in this section that the firms compete like Cournot oligopolists. We illustrate the calculations for equilibrium outputs and profits in Appendix 3 Section B.

Equilibrium Analysis

Export vs Greenfield FDI

First, consider Firm F's choice between export and greenfield FDI.

If Firm F chooses to export, q_F^X and q_H^X are equilibrium outputs, and positive if $t < \frac{1-\lambda w+nw-\lambda nw}{(1+n)} \equiv \bar{t}$. On the other hand, if Firm F chooses to undertake greenfield FDI, q_F^G and q_H^G are equilibrium outputs, positive if $w < \frac{1}{(2+\lambda)} \equiv \overline{w}$. We assume that these conditions hold.

Firm F prefers greenfield FDI over export if and only if:

$$G'' < \left(-\frac{(1+n)t(-2+t+nt+2(\lambda+(-1+\lambda)n)w)}{(n+2)^2}\right) \equiv G_3 \qquad (4.17)$$

If condition (4.17) is not satisfied, Firm F prefers export to greenfield FDI.

Export vs. Cross-Border Merger

On the other hand, we find that cross-border merger is profitable compared to export by Firm F if and only if:

$$K'' < \frac{(1-\lambda nw+w(n-1))^2}{(n+1)^2} - \left(\frac{(1-\lambda w(n+1)-\mathrm{t}(n+1)+wn)^2}{(n+2)^2} + \frac{(1-2w+\lambda w+t)^2}{(2+n)^2}\right) \equiv K_5 \quad (4.18)$$

A cross-border merger between Firm F and the ith firm in the home country is not preferable over export if the cost of merger, K'', is greater than K_5, showing the maximum gain from merger compared to export.

Let's define:

$$t^{***} = \frac{-n(3+2n)+(2+n(9+5n)-\lambda(2+3n(2+n)))w}{(1+n)^2(2+n(2+n))}$$

Moreover, $t^{***} > 0$ if $w > \frac{n(3+2n)}{-2+2\lambda-9n+6\lambda n-5n^2+3\lambda n^2} \equiv w^{***}$, where $w^{***} > 0$

Proposition 8: *If export is Firm F's preferred choice as an alternative to merger,* $(G'' > G_3)$*, Firm F's higher productivity increases (reduces) the incentive for cross-border merger, if* $t \in (t^{***}, \bar{t})$ *or if* $(t \in (0, t^{***})$*.*

Proof: *By using condition (4.18) we can show that* $\frac{\partial K_5}{\partial \lambda} < (>)\ 0$ *for* $t > (<)\ t^{***}$*, where* $t^{***} < \bar{t}$*.* ■

This result is in contrast to Nocke and Yeaple (2007) for $t < t^{***}$.

Greenfield FDI vs Cross-Border Merger

We consider in this subsection that $G'' < G_3$, i.e. greenfield FDI is Firm F's preferred choice as an alternative to merger. Firm F undertakes cross-border merger compared to greenfield FDI if and only if:

$$K'' < \frac{(1-\lambda nw+w(n-1)^2}{(n+1)^2} - \left(\frac{(1-\lambda w(n+1)+wn)^2}{(n+2)^2} + \frac{(1-2w+\lambda \mathrm{w})^2}{(n+2)^2} - G''\right) \equiv K_6 \quad (4.19)$$

Condition (4.19) tells us that Firm F prefers cross-border merger over greenfield investment if the cost of merger, $K^{''}$, is less than K_6. This shows the maximum gain of Firm F from merger compared to greenfield investment. A higher value for K_6 suggests that Firm F has a higher incentive for cross-border merger.

Let's define:

$$w^{'''} = \frac{-3n-2n^2}{-2+2\lambda-9n+6\lambda n-5n^2+3\lambda n^2}.$$

Proposition 9: *If greenfield FDI is Firm F's preferred choice as an alternative to merger,* $(G^{''} < G_3)$*, Firm F's incentive for undertaking cross-border merger increases (reduces) with its higher productivity if* $w \in (0, w^{'''})$ *or if* $(w \in (w^{'''}, \overline{w}))$*.*

Proof: *The proof follows from rearranging the derivative of* K_6 *with respect to* λ*. A straightforward calculation shows that* $\frac{\partial K_6}{\partial \lambda} < (>)\ 0$ *for* $w < (>)\ w^{'''}$*. The rest of the proof follows immediately.* ■

Again, this result is in contrast to Nocke and Yeaple (2007) for $w > w^{'''}$.

4.6. Conclusion and Future Research Agenda

In this chapter, we showed how the productivity of a foreign firm affects the incentive for a cross-border merger. In a two-country oligopolistic model with differentiated goods, we showed that the predictions of Nocke and Yeaple (2007), suggesting that the most productive firms prefer cross-border merger, may not hold true if the competition reducing effect of a merger is considered. We observed a non-monotonic relationship between productivity and a cross-border merger, and showed that our results hold under both Cournot and Bertrand competition.

Interesting results in terms of welfare implications can be obtained from our framework. We showed in Appendix 3 Section D that if a less productive foreign firm chooses between export and cross-border merger, then the home country government may allow for merger. Although cross-border merger creates market-concentration effects, which have a negative effect on consumer surplus, the home country government may allow merger since the foreign firm avoids the trade cost (t) via merger, which has a positive effect on consumer surplus. We found that, for a given w, γ and λ, the home country welfare gain is higher under cross-border merger than under exporting by the foreign firm. On the other hand, we considered another scenario where the foreign firm experiences a productivity improvement, and chooses between greenfield FDI and cross-border mergers. Clearly, in such a case, the home country's government does not allow the merger, since it does not create any welfare benefit, and it causes market concentration.

In order to focus on the strategic motive for merger, we kept our model simple by assuming that there is only one foreign firm. However, it would be interesting to investigate a model where there are two or more asymmetric (in terms of productivity) foreign firms, to examine the strategy of different foreign firms, where competition among the foreign firms for greenfield FDI and cross-border merger creates further strategic effects. We leave this issue for future research.

Appendix 3 Section A:

Bertrand Competition and The International Organization of Production

Equilibrium Analysis

Export vs Greenfield FDI

First, consider firm F's choice between export and greenfield FDI. If Firm F chooses to export, the objective functions for Firms F and H are $\pi_F^X = (P_F - \lambda w - t)q_F$ and $\pi_H^X = (P_H - w)q_H$ respectively. The resulting equilibrium prices, and profits are:

$$P_F^X = -\frac{2-\gamma+2\lambda w+\gamma w+2t-\gamma^2}{-4+\gamma^2}, \text{ and}$$

$$\pi_F^X = -\frac{(2(-1+t+\lambda w)+\gamma-w\gamma-(-1+t+\lambda w)\gamma^2)^2}{(-4+\gamma^2)^2(-1+\gamma^2)} \tag{A3.1}$$

$$P_H^X = -\frac{2-\gamma+2w+\lambda\gamma w+t\gamma-\gamma^2}{-4+\gamma^2}, \text{ and}$$

$$\pi_H^X = -\frac{(2+\gamma(-1+t-\gamma)+w(-2+\gamma(\lambda+\gamma)))^2}{(-4+\gamma^2)^2(-1+\gamma^2)} \tag{A3.2}$$

If Firm F undertakes greenfield FDI, the objective functions for firms F and H are $\pi_F^G = (P_F - \lambda w)q_F - G'$ and $\pi_H^X = (P_H - w)q_H$ respectively. The resulting equilibrium prices, and profits are:

$$P_F^G = -\frac{2-\gamma+2\lambda w+\gamma w-\gamma^2}{-4+\gamma^2}, \text{ and}$$

$$\pi_F^G = -\frac{(2+(-1+w-\gamma)\gamma+\lambda\gamma(-2+\gamma^2))^2}{(-4+\gamma^2)^2(-1+\gamma^2)} - G' \tag{A3.3}$$

$$P_H^G = -\frac{2-\gamma+2w+\lambda\gamma w-\gamma^2}{-4+\gamma^2}, \text{ and}$$

$$\pi_H^G = -\frac{(-2+\gamma+\gamma^2-w(-2+\gamma(\lambda+\gamma)))^2}{(-4+\gamma^2)^2(-1+\gamma^2)} \tag{A3.4}$$

Firm F undertakes greenfield FDI if and only if $\pi_F^G > \pi_F^X$ or:

$$-\frac{(2+(-1+w-\gamma)\gamma+\lambda\gamma(-2+\gamma^2))^2}{(-4+\gamma^2)^2(-1+\gamma^2)} - G' > -\frac{(2(-1+t+\lambda w)+\gamma-w\gamma-(-1+t+\lambda w)\gamma^2)^2}{(-4+\gamma^2)^2(-1+\gamma^2)}$$

which can be shown as follows:

$$G' < \left(\frac{t(-2+\gamma^2)(-2(-2+t+2\lambda w)+2(-1+w)\gamma+\gamma^2(-2+t+2\lambda w))}{(-4+\gamma^2)^2(-1+\gamma^2)}\right) \equiv G_2 \tag{A3.5}$$

Export vs. Cross-Border Merger

From equation (A3.5) we know that Firm F prefers greenfield FDI if and only if $G' < G_2$, otherwise it prefers to export.

Let's assume that $G' > G_2$, in other words, export is Firm F's preferred choice as an alternative to merger. We know from (A3.1) and (A3.2) that if Firm F exports, the equilibrium profits of Firms F and H are:

$$\pi_F^X = -\frac{(2(-1+t+\lambda w)+\gamma-w\gamma-(-1+t+\lambda w)\gamma^2)^2}{(-4+\gamma^2)^2(-1+\gamma^2)}, \text{ and } \pi_H^X = -\frac{(2+\gamma(-1+t-\gamma)+w(-2+\gamma(\lambda+\gamma)))^2}{(-4+\gamma^2)^2(-1+\gamma^2)}$$

On the other hand, if Firms F and H merge, the merged firm maximize the following expression:

$$\pi_{F+H}^M = (P_F - \lambda w)q_F + (P_H - \lambda w)q_H - K'$$

The merged firm produces both the products, and the equilibrium prices and the profit of merged firm are:

$$P_F^M = P_H^M = \frac{(1+\lambda w)}{2},$$

$$\text{and } \pi_{F+H}^M = \frac{(-1+\lambda w)^2}{2(1+\gamma)} - K' \tag{A3.6}$$

Cross-border merger is profitable compared to export by Firm F if:

$$\pi_{F+H}^M > \pi_F^X + \pi_H^X$$

where π_{F+G}^M denotes the profit of the merged firm, while π_F^X and π_H^X denote the profit of Firms F and H under export by Firm F.

Following (A3.1), (A3.2) and (A3.6), we get that cross-border merger if preferable to export by Firm F if and only if:

$$\frac{(-1+\lambda w)^2}{2(1+\gamma)} - K' > \left(-\frac{(2(-1+t+\lambda w)+\gamma-w\gamma-(-1+t+\lambda w)\gamma^2)^2}{(-4+\gamma^2)^2(-1+\gamma^2)} + \left(-\frac{(2+(-1+t-\gamma)\gamma+w(-2+\gamma(\lambda+\gamma)))^2}{(-4+\gamma^2)^2(-1+\gamma^2)}\right)\right)$$

or

$$K' < \frac{(-1+\lambda w)^2}{2(1+\gamma)} - \left(-\frac{(2(-1+t+\lambda w)+\gamma-w\gamma-(-1+t+\lambda w)\gamma^2)^2}{(-4+\gamma^2)^2(-1+\gamma^2)} - \frac{(2+(-1+t-\gamma)\gamma+w(-2+\gamma(\lambda+\gamma)))^2}{(-4+\gamma^2)^2(-1+\gamma^2)}\right) \equiv K_3$$

Greenfield FDI vs. Cross-Border Merger

Now consider the case of $G' < G_2$, i.e. greenfield FDI is Firm F's preferred choice as an alternative to merger. We know from (A3.3) and (A3.4) that when Firm F undertakes greenfield FDI, the profits of firm F and H are:

$$\pi_F^G = -\frac{(2+\gamma(-1+w-\gamma)+\lambda\gamma(-2+\gamma^2))^2}{(-4+\gamma^2)^2(-1+\gamma^2)} - G', \text{ and } \pi_H^G = -\frac{(-2+\gamma+\gamma^2-w(-2+\gamma(\lambda+\gamma)))^2}{(-4+\gamma^2)^2(-1+\gamma^2)}$$

However, if Firms F and H merge, we know from (A6) that:

$$\pi_{F+H}^M = \frac{(-1+\lambda w)^2}{2(1+\gamma)} - K''$$

A cross-border merger between Firms F and H is profitable compared to greenfield FDI by Firm F if:

$$\pi_{F+H}^M > \pi_F^G + \pi_H^G$$

where π_{F+G}^M denotes the profit of the merged firm, while π_F^G and π_H^G denote the profits of Firms F and H under greenfield FDI by Firm F. Following (A3.3), (A3.4) and (A3.6), we get that cross-border merger is profitable than greenfield FDI by Firm F if and only if:

$$\frac{(-1+\lambda w)^2}{2(1+\gamma)} - M'' > \left(-\frac{(2+(-1+w-\gamma)\gamma+\lambda\gamma(-2+\gamma^2))^2}{(-4+\gamma^2)^2(-1+\gamma^2)} - G' + \left(-\frac{(-2+\gamma+\gamma^2-w(-2+\gamma(\lambda+\gamma)))^2}{(-4+\gamma^2)^2(-1+\gamma^2)}\right)\right)$$

or

$$K'' < \frac{(-1+\lambda w)^2}{2(1+\Upsilon)} - (-\frac{(2+(-1+w-\Upsilon)\Upsilon+\lambda\Upsilon(-2+\Upsilon^2))^2}{(-4+\Upsilon^2)^2(-1+\Upsilon^2)} - G' + (-\frac{(-2+\Upsilon+\Upsilon^2-w(-2+\Upsilon(\lambda+\Upsilon)))^2}{(-4+\Upsilon^2)^2(-1+\Upsilon^2)})) \equiv K_4$$

Appendix 3 Section B:

N Firms in the Home Country

To show our results in the simplest way, we assumed in section 2 that there is only one firm in the home country. We show in this section that our results in section 2 hold true even if there are n symmetric firms in the home country, where $n > 2$. If there are n home-country firms, the resulting inverse demand functions are:

$$p_F = 1 - q_F - \sum_{i=1}^{n} q_i$$

$$p_i = 1 - \sum_{i=1}^{n} q_i - q_F$$

where $p_F,\ and\ p_i$ are prices, q_F, q_i are outputs.

Equilibrium Analysis

Export vs Greenfield FDI

First, consider the foreign firm's choice between export and greenfield FDI. If Firm F exports, it determines output by maximizing the following expression:

$$\underset{q_F}{Max}(1 - q_F - \sum_{i=1}^{n} q_i - \lambda w - t)q_F$$

while profit maximization problem of ith firm in home country is:

$$\underset{q_i}{Max}(1 - \sum_{i=1}^{n} q_i - q_F - w)q_i$$

The resulting equilibrium outputs and profits are:

$q_F^X = \frac{(1-\lambda w(n+1)-\mathrm{t}(n+1))+wn)}{(n+2)}$, and

$\pi_F^X = \frac{(1-\lambda w(n+1)-\mathrm{t}(n+1))+wn)^2}{(n+2)^2}$ (A3.7)

and output and profit of the *ith* home-country firm are:

$q_i^X = \frac{(1-2w+\lambda w+t)}{(2+n)}$, and

$\pi_i^X = \frac{(1-2w+\lambda \mathrm{w}+t)^2}{(2+n)^2}$ (A3.8)

If firm F undertakes greenfield FDI, it maximizes the following profit function

$\underset{q_F}{Max}(1 - q_F - \sum_{i=1}^{n} q_i - \lambda w)q_F - G$

while the profit maximization problem of the ith home-country firm is:

$\underset{q_i}{Max}(1 - \sum_{i=1}^{n} q_i - q_F - w)q_i$

The resulting equilibrium outputs and profits are:

$q_F^G = \frac{(1-\lambda w(n+1)+wn)}{(n+2)}$ and

$\pi_F^G = \frac{(1-\lambda w(n+1)+wn)^2}{(n+2)^2} - G$ (A3.9)

and output and profit of the *ith* home-country firm are

$q_i^G = \frac{(1-2w+\lambda \mathrm{w})}{(n+2)}$ and

$\pi_i^G = \frac{(1-2w+\lambda \mathrm{w})^2}{(n+2)^2}$ (A3.10)

So, Firm F prefers greenfield FDI compared to export if $\pi_F^G > \pi_F^E$ or:

$$\frac{(1-\lambda w(n+1)+wn)^2}{(n+2)^2} - G'' > \frac{(1-\lambda w(n+1)-\mathrm{t}(n+1))+wn)^2}{(n+2)^2}$$

which can be shown as follows:

$$G'' < \left(-\frac{(1+n)t(-2+t+nt+2(\lambda+(-1+\lambda)n)w)}{(n+2)^2}\right) \equiv G_3 \qquad \text{(A3.11)}$$

Export vs. Cross-Border Merger

From (A3.11) we know that Firm F prefers greenfield FDI if and only if $G'' < G_3$, otherwise it prefers to export.

Let's assume that $G'' > G_3$, i.e. export is Firm F's available strategy as an alternative to merger.

We know from (A3.7) and (A3.8) that when Firm F chooses to export, the profits of Firm F and the *ith* home-country firm are:

$\pi_F^X = \frac{(1-\lambda w(n+1)-t(n+1))+wn)^2}{(n+2)^2}$, and $\pi_i^X = \frac{(1-2w+\lambda w+t)^2}{(2+n)^2}$

However, if Firm F and the *ith* home-country firm merge, the merged firm determines output to maximize the following profit function:

$$\underset{q_M}{Max}(1 - q_M - \sum_{j=1}^{n-1} q_j - \lambda w)q_M - K''$$

and each of the remaining home-country firm, say, firm j, determines output to maximize the following expression:

$$\underset{q_i}{Max}(1 - \sum_{j=1}^{n-1} q_j - q_M - w)q_i$$

If Firms F and the *ith* home-country firm merge, the equilibrium output and the profit of merged firm are:

$q_M^M = \frac{(1-\lambda nw+w(n-1)}{(n+1)}$, and

$$\pi_M^M = \frac{(1-\lambda nw+w(n-1)^2}{(n+1)^2} - K'' \qquad \text{(A3.12)}$$

A merger between Firms F and the *ith* home-country firm is preferable compared to export by Firm F if

$\pi_M^M > \pi_F^X + \pi_i^X$

Following (A3.7), (A3.8) and (A3.12), we get that merger occurs if and only if:

$$\frac{(1-\lambda nw+w(n-1))^2}{(n+1)^2} - M'' > \frac{(1-\lambda w(n+1)-\mathrm{t}(n+1))+wn)^2}{(n+2)^2} + \frac{(1-2w+\lambda w+t)^2}{(2+n)^2}$$

which can be shown as follows:

$$K'' < \frac{(1-\lambda nw+w(n-1)^2}{(n+1)^2} - \left(\frac{(1-\lambda w(n+1)-\mathrm{t}(n+1))+wn)^2}{(n+2)^2} + \frac{(1-2w+\lambda w+t)^2}{(2+n)^2}\right) \equiv K_5 \quad \text{(A3.13)}$$

Greenfield FDI vs Cross-Border Merger

In this sub-section, we consider that $G'' < G_3$, i.e. greenfield FDI is Firm F's available strategy as an alternative to merger.

We know from equations (A3.9) and (A3.10) that if Firm F undertakes greenfield FDI, the profits of firms Firm F and the *ith* home-country firm are:

$\pi_F^G = \frac{(1-\lambda w(n+1)+wn)^2}{(n+2)^2} - G$ and $\pi_i^G = \frac{(1-2w+\lambda \mathrm{w})^2}{(n+2)^2}$

If Firm F and the *ith* firm merge, we know from (A3.12) that the profit of the merged firm is:

$\pi_M^M = \frac{(1-\lambda nw+w(n-1)^2}{(n+1)^2} - K''$

A merger between Firm F and the *ith* home-country firm is profitable compared to greenfield FDI by Firm F if:

$\pi_M^M > \pi_F^G + \pi_i^G$ or

$$K'' < \frac{(1-\lambda nw+w(n-1))^2}{(n+1)^2} - \left(\frac{(1-\lambda w(n+1)+wn)^2}{(n+2)^2} + \frac{(1-2w+\lambda \mathrm{w})^2}{(n+2)^2} - G'''\right) \equiv K_6 \quad \text{(A3.14)}$$

Appendix 3 Section C:

Section C.1: Proof of $\overline{w} - w^{'} > 0$

$$\overline{w} - w^{'} = \left((\gamma - 2)\left(\frac{1}{\lambda\gamma-2} + \frac{4+2\gamma-\gamma^3}{8\gamma(1+\gamma)+\lambda(8+\gamma(-8+\gamma(-10+(\gamma-2)\gamma)))}\right)\right)$$

$\overline{w} - w^{'} > 0$ if $\lambda\epsilon[0,1]$ and $\gamma\epsilon(.732, 1]$ (see Figure 4.1 below)

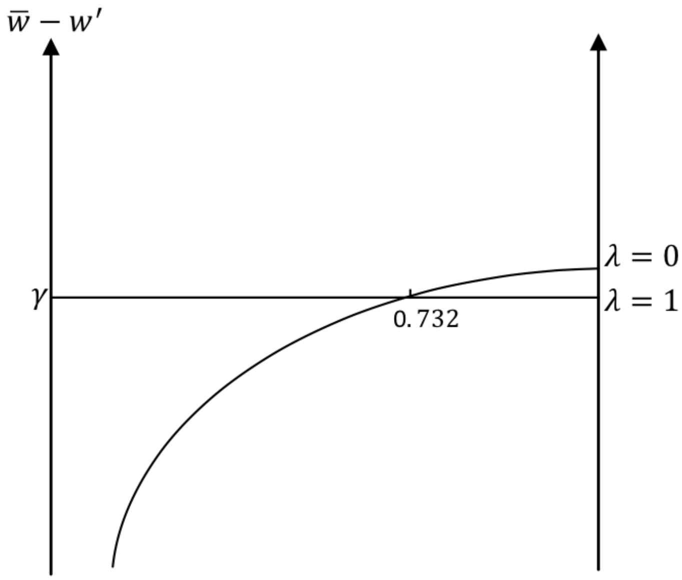


Figure 4.1: $(\bar{w} - w^{'}) > 0$

Section C.2: Proof of Proposition 5

$$\frac{\partial(\overline{w} - w^{'})}{\partial\gamma} = \left[\begin{array}{c} \frac{1}{\lambda\gamma-2} + \frac{4+2\gamma-\gamma^3}{8\gamma(1+\gamma)+\lambda(8+\gamma(-8+\gamma(-10+(\gamma-2)\gamma)))} + \\ (\gamma-2)\left(\frac{-\lambda}{(\lambda\gamma-2)^2} + \frac{2(1+2\gamma)(-4-2\gamma+\gamma^3)(4+\lambda(-4-2\gamma+\gamma^2))}{(8\gamma(1+\gamma)+\lambda(8-8\gamma-10\gamma^2-2\gamma^3+\gamma^4))^2}\right) \\ +(\gamma-2)(\frac{2-3\gamma^2}{8\gamma(1+\gamma)+\lambda(8+\gamma(-8+\gamma(-10+(\gamma-2)\gamma)))}) \end{array}\right]$$

Plotting the above expression for $\lambda\epsilon(0,1)$ and $\gamma\epsilon(0,1)$ completes the proof:

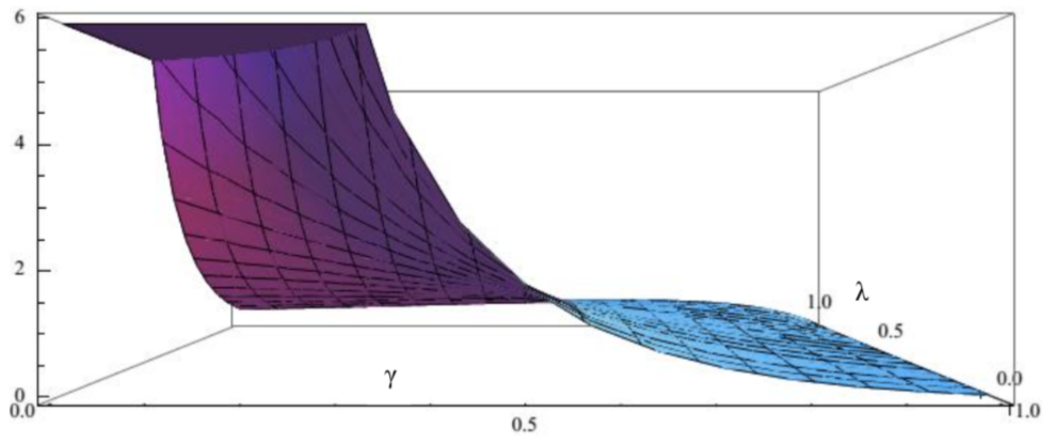


Figure 4.2: $\frac{d(\bar{w}-w')}{d\gamma} > 0$ for $\lambda \in (0,1)$ and $\gamma \in (0,1)$

Appendix 3 Section D:

If the foreign firm, Firm F, chooses between export and cross-border merger:

$$maxW^M = \pi^M_{F+H} - \pi^X_F + \tfrac{1}{2}\left((q^M_{F+H})^2 + (q^M_{F+H})^2 + 2\gamma(q^M_{F+H} + q^M_{F+H})\right) \text{ and}$$

$$W^X = \pi^X_H + \tfrac{1}{2}\left((q^X_H)^2 + (q^X_F)^2 + 2\gamma(q^X_H + q^X_F)\right)$$

where $maxW^M$ stands for the maximum possible home country welfare, which can be obtained when Firms F and H merges, while W^X represents the home country welfare under Firm F exporting.

Home country's welfare gain (ΔW) if it allows merger can be calculated as:

$$\Delta W^X = maxW^M - W^X$$

$$\Delta W^X = \frac{1}{4}\left(\begin{array}{c} -4K + \frac{(-1+\lambda w)^2+(-1+\lambda w)^2\gamma}{(1+\gamma)^2} + \frac{2(-1+\lambda w)^2}{(1+\gamma)} - \frac{4(-2+2t+2\lambda w+\gamma-\gamma w)^2}{(-4+\gamma^2)^2} \\ +\frac{2(4-2t+t^2-6w-2\lambda w+2\lambda wt+3w^2+L^2w^2-2(-1+w)(-1+t+Lw)\gamma)}{(-4+\gamma^2)^2} \end{array}\right)$$

We cannot obtain the sign of the above expression. Hence, we will use a numerical example to show that home country government may allow merger since it provides higher welfare compared to welfare under foreign firm exporting, i.e. $\Delta W^X > 0$.

Figure 4.3 illustrates ΔW^X for $K = 0.05 = 0.5$, $w = 0.5$, $\lambda = 0.8$, $\gamma = 0.5$ and $t \in (0, 0.5)$.

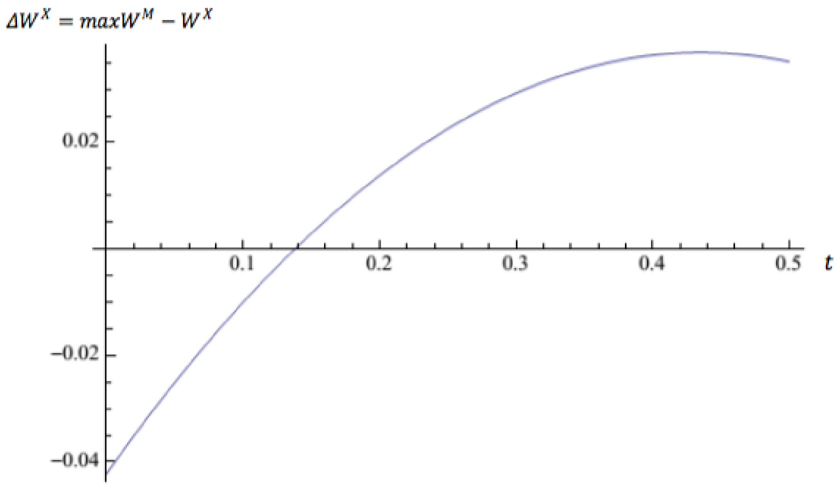


Figure 4.3: $\Delta W^X > 0$ for higher t.

Chapter 5: Conclusions

This thesis consists of three papers examining different aspects of some recent debates around the productivity-internationalization nexus, where each chapter focuses on a specific research question. For this reason, we will provide individual summaries of each chapter.

In Chapter 2, first, we examined the main finding of Melitz (2003) regarding the relationship between firm level productivity and the firm's internationalization decision, where we focused on UK firms for the period between 2003 and 2011. Namely we tested the self-selection hypothesis. Initially, we used a dataset where firms from all industries pooled together. We confirmed Melitz's result when we did not consider the sunk cost effect (as many empirical studies did in the literature). However, according to Melitz (2003), the most productive firms self-select themselves to enter the export market, since only such firms can overcome the sunk cost of exporting activity. In other words, the sunk cost is expected to have an effect on a firm's internationalization decision. Following this, we explicitly controlled for the sunk cost effect, and showed that the evidence for self-selection vanished. Moreover, we found that the coefficient of the previous year's export status (which represents the sunk cost effect) is positive and significant, which clearly showed that the sunk should be included in our analysis. As we have already highlighted, the above results were obtained from a pooled panel dataset. However, Nocke and Yeaple (2007) criticize this approach, since it avoids all differences between industries. For this reason, we repeated the analysis above for each industry separately. Eventually, we reported some findings that are the opposite of those proposed by the self-selection hypothesis. We showed that in some industries in the UK, such as Non-metal Minerals and Motor Vehicles/Parts, less productive firms are more likely to export.

Second, we tested one of the key assumptions of Melitz (2003), the constant marginal costs assumption. Showing that the average rates of sales growth in domestic and foreign markets are negatively correlated in many industries, such as Paper/Printing, Coke/Chemicals, and Basic/Fabricated Metals, we concluded that the constant marginal costs assumption of Melitz (2003) is not valid for these UK industries. Moreover, we observed that in those industries where firms produce at increasing marginal cost, the self-selection hypothesis cannot be confirmed.

As we have explained in the introductory chapter, two hypotheses aim to explain why exporting firms are more productive than non-exporters in the literature on heterogeneous firms: the self-selection and learning-by exporting hypotheses. We focused on the self-selection hypothesis in Chapter 2. In Chapter 3, we tested the learning-by-exporting hypothesis for UK firms by using the same dataset that we used in Chapter 2. We started our analysis by showing that some of the UK firms experience variable returns to scale. Based on this finding, which contradicts any assumption of CRTS, we computed firm-level TFP by controlling for VRTS. By using this TFP measure, we estimated the effect of exporting on productivity growth. Moreover, in order to examine the different channels through which exporting influences TFP growth, we decomposed TFP growth into its components: technical change, scale change, and technological progress (efficiency) change. We showed that the assumption of returns to scale matters when it comes to TFP computation. More precisely, we provided evidence for an LBE effect when we consider the TFP measure, which we obtained from a Cobb-Douglas production function. However, the evidence of LBE vanishes when we considered the TFP measure, which considers variable returns to scale. We also found that the main source of TFP growth changes is attributable to a change in scale efficiency. In other words, unlike several other studies in the literature, we observed that technical improvements -arising from exporting- do not play any role in productivity growth effects of exporting.

In Chapters 2 and 3, we considered export as the only way to access foreign markets, in order to be consistent with Melitz (2003). In Chapter 4, we followed some recent developments in the literature on trade, and examined the productivity-internationalization nexus by considering three different options: export, greenfield FDI, and cross-border merger. We revisited Nocke and Yeaple's (2007) findings, which show that the most productive firms engage in cross-border mergers, while relatively less efficient firms choose greenfield FDI, and the least efficient firms export or only serve the domestic market. Nocke and Yeaple (2007), in their model, consider that the efficiency motive is the only motive for a merger, and ignore any strategic motives. In Chapter 4, we introduced the market-concentration effect of cross-border mergers by developing a two-country oligopoly model of product differentiation, where firms are heterogeneous in terms of their productivity. Eventually, we showed that in the presence of a higher market-concentration under merger, a relatively less productive firm may prefer cross-border merger while a relatively more productive firm may prefer either greenfield FDI or export, which contradicts the findings of Nocke and Yeaple (2007).

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