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Exploring The Impact of Exporting on Firm Productivity: An Empirical Analysis of Manufacturing Industries

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Abstract

This thesis investigates the relationship between export activities and firm productivity in the manufacturing industry. Employing econometric models and difference-in-differences techniques, the study explores the impact of exporting on productivity gains. Using a comprehensive dataset of Italian manufacturing firms, the analysis reveals a consistent positive effect of engaging in export activities on firm productivity. By considering the endogeneity of productivity through lagged exportation, the study sheds light on the role of Learning by Exporting effects in driving productivity improvements. Sector-specific analysis further uncovers variations in the estimates, with some sectors demonstrating differences between exogenous and endogenous models. The findings contribute to our understanding of the dynamics between exporting and firm performance, emphasizing the need for careful interpretation and accounting for endogeneity when examining the effects of export activities on productivity in the manufacturing sector.

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Chapter 1

Introduction

The Learning by Exporting phenomenon has attracted significant attention in the field of international economics due to its potential implications for firm productivity and economic growth. Extensive research has examined the relationship between exporting and firm performance, shedding light on the mechanisms through which firms can enhance their productivity through engagement in international trade. Building upon the seminal work of De Loecker (2013), this thesis aims to investigate the LBE effect using firm-level data from Italy, offering new insights into the dynamics of productivity improvements resulting from export activities.

The choice to focus on Italian firm-level data stems from the need to explore the generalizability of previous findings to different contexts and economies. While De Loecker's study concentrated on Slovenia, a small transition economy, this thesis extends the analysis to the Italian context, which presents distinct characteristics and a more developed market structure. By replicating and expanding upon De Loecker's approach, I aim to provide valuable empirical evidence on the LBE effect in a larger, more mature economy.

The empirical analysis primarily focuses on estimating the input coefficients of the production function while considering the endogeneity of the productivity process with respect to firms' exporting status. Recognizing that the decision to engage in exporting activities may be influenced by productivity levels, I adopt an econometric framework that accounts for the potential endogeneity of productivity in relation to firms' export behavior. This enables us to disentangle the causal relationship between exporting and firm productivity, thereby providing more robust and reliable estimates of the Learning by Exporting effect.

The utilization of firm-level data allows for a more detailed examination of the dynamics at play within individual firms, providing insights into the specific mechanisms through which exporting influences productivity. By analyzing a comprehensive dataset encompassing a diverse range of Italian firms operating across various sectors, I aim to capture the heterogeneity in the LBE effect across different sectors and firm characteristics.

The findings of this research have significant implications for both policymakers and managers. Understanding the impact of exporting on firm productivity can inform policy decisions related to trade promotion, internationalization strategies, and fostering economic growth. Additionally, the insights gained from this study can offer valuable guidance to managers seeking to optimize their firms' performance in the global marketplace.

The structure of this thesis is organized as follows: Chapter 1 serves as an introduction to the research topic, providing an overview of the objectives and rationale for the study. In Chapter 2, a comprehensive review of the existing literature is presented, highlighting key theories and empirical findings on the Learning by Exporting effect. Chapter 3 focuses on the introduction and analysis of the selected database, outlining its characteristics and suitability for the empirical analysis. Chapter 4 details the empirical strategy employed in estimating the production function and calculating the LBE effects, encompassing the methodology, and econometric techniques utilized. Chapter 5 presents the results of the analysis and provides an interpretation of the estimated LBE effect, while discussing the implications derived from these findings. Finally, Chapter 6 concludes the thesis by summarizing the key findings, discussing their broader implications, and outlining potential avenues for future research.

By examining the LBE effect using Italian firm-level data and accounting for the endogeneity of the productivity process, this thesis aims to contribute to the growing body of knowledge on the relationship between exporting and firm productivity. Through rigorous empirical analysis, I seek to enhance our understanding of the mechanisms through which international trade impacts firm performance, ultimately providing insights that can inform policy decisions, foster economic growth, and support managerial strategies in an increasingly globalized business environment.

1.1 How does the decision of entering the exporting market affects the dynamics of productivity?

Considering the aforementioned observations, the objective of this paper is to analyze whether productivity is influenced by firms' decision to enter the international market through exporting. The rationale behind this investigation stems from the existence of several mechanisms that potentially enhance a firm's productivity when it begins exporting. One such mechanism is known as Learning by Exporting (LBE), which involves firms that export establishing contact with foreign customers, competitors, and distributors. Through this interaction, firms adapt existing products, develop new products tailored to the preferences of new customers, gain insights into optimal shipment sizes for other countries, and ultimately adopt more advanced technologies that enable them to utilize labor and capital inputs more efficiently than when they were not involved in the international market. Furthermore, engaging with international suppliers, customers, and competitors creates positive externalities, as firms acquire valuable knowledge that improves the production process.

A second channel through which exporting impacts productivity is through direct competition with international rivals. When entering a new market, firms find themselves compelled to enhance their quality, innovation, and product differentiation while reducing costs in order to enhance their competitiveness. This aspect plays a crucial role in improving productivity. In summary, firms facing foreign competition are compelled to explore new avenues for diversifying their product offerings and are also driven to make greater investments in research and development (R&D) to achieve the necessary level of competitiveness in foreign markets.

The third channel I wish to emphasize is economies of scale, which can be achieved by increasing the final output while concurrently reducing production costs for a given product. Exporting firms that engage in international trade often witness a decline in their production costs due to the downward sloping nature of the average cost curve. This means that as a firm produces more output, its average unit cost decreases. Such cost reductions enhance a firm's competitiveness, subsequently increasing its profits, which can then be reinvested in technologies that optimize the production process and consequently elevate productivity levels.

Chapter 2

Literature Review

2.1 Literature on Estimating the Production Function

Estimating the parameters of a production function presents a non-trivial challenge due to the issue of endogeneity, which is a classical problem encountered by researchers. The use of a classical linear regression to estimate such a function is likely to result in biased estimates, rendering them imprecise and unsuitable as a benchmark for policy-making by firms.

In recent decades, several methods have been proposed to address this obstacle. One of the most obvious solutions is to use an instrument for the production function variables. However, this approach has proven ineffective in dealing with endogeneity since input prices, which are a possible instrument for labor and capital, exhibit little variation and do not aid in estimating the demand function.

To provide further clarity, this paper will define the production function commonly used in the literature and highlight the endogeneity issue encountered by econometricians when estimating its parameters.

Define the Cobb Douglas production function as follows

$$Y_{it} = e^{\omega_i} K_i^{\alpha} L_i^{\beta} \tag{2.1}$$

Now, take the logs to obtain

$$y_i = \omega_i + \alpha k_i + \beta l_i \tag{2.2}$$

where y_i, w_i, k_i and l_i are, respectively, the log of production output, productivity, log of capital input and log of labor of firm i.

Taking into account the aforementioned considerations, it is worth noting that capital and labor are typically observable as they are reported in the chosen dataset. Conversely, the productivity term, denoted by ω, is solely known by the firm. However, it is evident that productivity is correlated with both labor and capital, given that more productive firms allocate their inputs differently than less productive firms. Consequently, this gives rise to a classical problem of endogeneity, which calls for a more sophisticated approach than the commonly utilized instrumental variables or fixed effects methods.

One of the earliest and most frequently employed methods to address this issue was proposed by Olley and Pakes (1996), hereafter referred to as OP. The crux of their approach involves defining productivity, ω as a function of investment, which is obtained by inverting the function of investment as a function of capital and productivity.[1].

$$i_t = i(w_t, k_t) \rightarrow \omega_t = h(k_t, i_t)$$

Subsequently, the authors' methodology involves the rewriting of equation 2.2 without explicitly incorporating the productivity term. This is achieved by utilizing the proxy function of productivity obtained through the inversion of the investment function, thereby enabling the production function to be rewritten. As a result, productivity can be expressed as:

$$y_t = \beta l_t + \phi(i_t, k_t) + \eta \tag{2.3}$$

Where

[1]The inversion step requires the assumption that i_t is strictly monotone.

$$\phi(i_t, k_t) = \alpha k_t + h(i_t, k_t) \tag{2.4}$$

By introducing this novel specification of the production function, it is feasible to conduct a linear regression in the first stage to obtain estimates of $\hat{\beta}$ and $\hat{\phi}$[2]. Consequently, the parameter of labor can be directly obtained in this initial stage. Subsequently, with knowledge of the labor input parameter, the parameter of the capital input must be determined to obtain an estimate of productivity. Once this parameter is obtained, productivity can be estimated by calculating $\hat{\omega} = \hat{\phi} - \hat{\alpha}k$.

To proceed with the second stage of the estimation, the authors define current productivity as a function of lagged productivity, denoted as $\omega_t = E(\omega_t|\omega_{t-1}) + \xi_t$. Here, ξ_t represents an innovation shock, which is uncorrelated with the level of capital k_t by definition. With this in mind, the production function can be redefined as follows:

$$y_t - \beta l_t = \phi(i_t, k_t) + \eta_t$$

$$z_t = \alpha k_t + h(i_t, k_t) + \eta_t$$

$$z_t = \alpha k_t + E(\omega_t|\omega_{t-1}) + \xi_t + \eta_t$$

$$z_t = \alpha k_t + g(\omega_{t-1}) + \xi_t + \eta_t$$

$$z_t = \alpha k_t + g(\phi_{t-1} - \alpha k_{t-1}) + \xi_t + \eta_t \tag{2.5}$$

Finally, to estimate the capital parameter, the authors performed a nonlinear least squares analysis on equation 2.5. This enabled the authors to obtain estimates that effectively address the endogeneity problem arising from the unobserved productivity term.

The groundbreaking methodology introduced by OP initiated the development of subsequent models aimed at estimating the production function. An exemplary instance of such a model is presented by Levinsohn and Petrin (2003) (hereinafter referred

[2]Here, ϕ is approximated by a polynomial function of degree three.

to as LP), which shares similarities with the previously mentioned approach but incorporates a distinct characteristic. In the initial stage of their model, the authors utilize intermediate inputs instead of investments. They justify this choice by highlighting the possibility of periods wherein investment levels reach zero, rendering it non-monotonic and thus unsuitable for direct inversion to derive a productivity function.

Another notable extension is introduced by Ackerberg et al. (2015) (hereinafter referred to as ACF). Unlike the assumptions made in the OP and LP models, ACF acknowledges the imperfections in labor flexibility. Consequently, labor is now considered a state variable alongside capital. As a result, the productivity function takes the form of $\omega = h(k, l, i)$, and subsequently, $\phi(k, l, i) = \alpha k + \beta l + h(k, l, i)$. To proceed with the second stage and estimate the values of α and β, the authors establish the following law of motion for productivity.[3]

$$w_{it} = g(w_{it-1}) + \xi_{it} \tag{2.6}$$

The function g represents the lagged productivity in time period $t - 1$, while ξ_{it} represents the innovation shock of the productivity term. To estimate $\hat{\alpha}$ and $\hat{\beta}$ in the second stage, a generalized method of moments (GMM) is employed. The moment conditions utilized rely on the orthogonality between the innovation shock at time t, denoted as ξ_{it}, and the vector composed of k_{it} and l_{it-1}.

Considering all the aforementioned factors, the task of estimating a production function has become less formidable compared to the pre-existing challenges prior to the insights provided by OP. Building upon these approaches, one can assume that productivity is influenced by additional factors beyond labor and capital. An example of such a factor is investments in Research and Development (R&D), as explored by Doraszelski and Jaumandreu (2013). In their study, the authors develop a model in which productivity undergoes an endogenous process contingent upon firms' invest-

[3] This law of motion is also present in the OP and LP models. The difference in the second stage lies in the methods utilized to obtain the coefficient of capital in the first two models. In OP a Non linear least squares is used, while in LP the authors use a GMM, where the moments used rely on the orthogonality between ξ_{it} with k_{it} and m_{it-1}.

ments in R&D. Consequently, they discover that R&D investment yields significant variations among firms over time.

2.2 Literature on Exportation and Productivity

In addition to the econometric approach employed for estimating parameters of the production function when productivity is an endogenous process linked to exportation, there exist significant theoretical and empirical studies that examine the relationship between exportation and productivity using diverse approaches. The objective of this section is to provide a comprehensive review of the literature on this subject and shed light on further insights regarding the dynamics of exportation and productivity. This will be accomplished by discussing the methodologies and findings of influential past studies that have contributed to our understanding of this nexus.

Aw et al. (2011) conducted a comprehensive examination of the influence of exportation and research and development (R&D) on productivity growth, using firm-level data from the Taiwanese electronics industry spanning the period from 2000 to 2004. To accomplish this, the authors constructed a dynamic structural model that establishes a link between the decisions of engaging in R&D activities and entering the export market, and the subsequent trajectory of productivity growth. The investment choices pertaining to exportation and R&D were contingent upon anticipated future profits and current fixed costs. Upon investigating the relationship between the decision to enter the export market and productivity growth, the authors discovered that firms with higher levels of productivity tend to invest more in exportation, implying that superior firm performance is associated with increased commitment to export activities. Moreover, this investment in exportation positively impacts a firm's productivity, reinforcing its propensity to self-select into the export market.

Furthermore, the empirical findings of Aw et al. (2011) demonstrate that productivity is endogenously influenced by both exportation and investments in research and development (R&D), with the latter exerting a greater impact than the former. Additionally, the authors discovered that the most significant mechanism through which exportation affects productivity is the self-selection process of firms investing in export activities. Moreover, they observed a positive relationship between investment in exportation and future productivity, further reinforcing the linkage between these variables.

In line with the findings of Aw et al. (2011), Van Biesebroeck (2005) investigates the impact of exports on productivity growth using data from nine African countries. The study provides evidence that engaging in export activities serves as a determining factor in positively influencing productivity. Notably, the key discovery of this research indicates that newly established African exporters experience a substantial increase in productivity following their entry into the export market. To examine this phenomenon, the author employs a modified version of the OP model, wherein productivity is contingent upon information regarding the firm's export status.

Upon estimating the model, it is revealed that approximately half of the productivity premium associated with the decision to export can be attributed to economies of scale, a process previously discussed in section 1.1 of this study. Specifically, for the African firms under examination, domestic market size poses challenges in achieving scale economies. However, upon introducing their products to foreign markets, these firms benefit from production scale advantages, ultimately leading to enhanced productivity growth.

I would like to draw attention to another significant paper, "Learning by Exporting" by De Loecker (2013)). This study emphasizes that previous approaches used to estimate the production function suffer from bias. This bias arises from the failure of earlier studies to consider productivity as an endogenous process influenced by a firm's decision to enter or not enter the export market. Consequently, estimation of the production function with exogenous productivity yields positively biased estimates, as exporting firms tend to exhibit higher productivity levels compared to non-exporting firms.

Prior to De Loecker's work, existing research explored the impact of exporting activities on productivity, highlighting how firms undertake substantial investments to enhance their productive capacity. What distinguishes this paper is the proposal of a method that enables the separate calculation of the effect of exportation while controlling for investments aimed at boosting productivity, such as decisions regarding research and development (R&D), adoption of new technologies, and quality improvement.

De Loecker's empirical strategy builds upon the assumption that productivity is a process dependent on the lagged exportation status. Having defined the productivity process, the author proceeds to estimate a model based on OP and LP (as briefly explained earlier in this chapter) to recover the parameters of the production function. The crucial distinction from these baseline models is that OP and LP rely on an exogenous productivity process that does not consider past exportation status. Therefore, these models are unsuitable for studying the influence of exportation on productivity.

The primary result presented in this paper is that the past exportation status exerts a positive influence on firms' productivity levels. Moreover, the impact of exportation varies across sectors and individual firms. The heterogeneity in the magnitude of this effect arises from the fact that firms commence exporting at different productivity levels. As a result, firms operating at lower productivity levels experience a greater productivity premium when they begin exporting, compared to firms that already possess higher levels of productivity.

Chapter 3

Data

3.1 Geographic Areas and Exportation

To examine the impact of the decision to engage in exporting on productivity, the Indagine sulle Imprese Industriali e dei Servizi (INVIND) dataset is employed. This dataset comprises comprehensive firm-level information for over 12,000 Italian firms spanning the period from 1984 to 2021. Given the richness of this dataset, it provides a suitable basis for analyzing productivity functions, which constitutes the central objective of this thesis. However, due to confidentiality restrictions, the presentation of summary statistics is considerably limited. Detailed information such as percentiles, medians, maximum, and minimum values cannot be disclosed. Consequently, only the average values of the variables of interest are presented. To ensure consistency with De Loecker (2013), the empirical analysis in this study focuses exclusively on the manufacturing industry, which is the specific industry of interest.

In order to examine the spatial distribution of Italian firms that are present in the dataset, an analysis of the percentage of firms across different regions is conducted. Table 3.1 presents these findings, revealing that the majority of firms in the country are concentrated in the northern region, accounting for 44.8%. The southern and island regions follow, representing 33% of the total firms. On the other hand, the central region of Italy has the lowest number of operating firms, constituting 22.02% of the total. Remarkably, when focusing on the specific industry of interest, the distribution of firms across the Italian territory closely resembles the overall pattern depicted in the third column of Table 3.1.

Table 3.1: Firms by Geographic Area

Geographic Area	Percentage	Percentage (Manufacturing)
Northwest	24.8%	25.67%
Northeast	20%	20.18%
Center	22.02%	21.47%
South and Islands	33.19%	32.69%

*The second row reports the percentage of firms including all industries.
*The third row reports the percentage of the firms that operate in the manufacturing industry.

The next analysis focuses on the distribution of firms based on the proportion of their annual revenue derived from exporting. This information is of paramount importance for understanding the classification of firms as exporters or non-exporters. Table 3.2 presents the indicators 0 to 3, representing the share of revenue from exporting in the following manner: 0 indicates firms not engaged in exporting activity, 1 indicates less than one third of the firm's revenue from exporting, 2 indicates between one third and two thirds of the revenue from exporting, and 3 indicates more than two thirds of the revenue from exporting.

Upon examining Table 3.2, it is evident that approximately one third of the firms are non-exporters, while another third have less than one third of their revenue derived from exporting. Around 18% of the firms generate between one third and two thirds of their revenue from exports, and approximately 15% derive more than two thirds of their revenue from exporting activities. However, focusing on the manufacturing industry, as displayed in the third column of Table 3.2, a notable observation emerges. Specifically, firms in the manufacturing sector exhibit a higher concentration in indicators 1 and 2. This indicates that, in contrast to the general economic context, firms operating within the manufacturing industry tend to generate a larger proportion of their revenue from export activities.

Table 3.2: Share of Revenue from Exports

Indicator	Share	Share(Manufacturing)
0	32.28%	18.44%
1	33.86%	37.60%
2	18.48%	23.87%
3	15.38%	20.08%

*The second column contains the share of firms in each of the indicators for all the firms in the dataset.
*The second column contains the share of firms in each of the indicators only for firms operating in the manufacturing industry.

3.2 Industries and Sectors

The firms encompassed in the INVIND dataset are classified into three primary industries. The largest of these industries is the Manufacturing Industry, which comprises the majority of firms operating in the country. The second industry, representing the smallest portion of firms within the dataset, is the Extractive-Energy Industry. Lastly, the Services Industry is also included, encompassing the last industry of firms present in the data. Table 3.3 presents the distribution of firms across these industries. The Manufacturing Industry alone accounts for over 70% of all firms included in the dataset, while the remaining two industries collectively make up less than 30% of the total number of firms.

Table 3.3: Division of firms by Industry

Industry	Percentage
Manufacturing	71.50%
Extraction-Energy	3.33%
Services	25.17%

*The second column reports the percentage of firms operating in each of the industries encompassed by the INVIND dataset.

Upon examining the distribution of firms across industries, the focus now shifts to the division of firms into sectors. Within the INVIND dataset, firms are categorized into eleven sectors, which serve as subdivisions within the broader industries. It is worth noting that six of these sectors operate within the Manufacturing industry, underscoring its significance in Italy. Table 4.3 presents the distribution of firms across these eleven sectors, accompanied by the specific breakdown of Manufacturing firms across the first six sectors of the economy.

Table 3.4: Division of firms by Sectors

Sector	Percentage	Percentage (Manufacturing)
1 -Food, Beverages and Tobacco	10.59%	14.81%
2 -Textile, Clothing, Leather and Shoes	9.11%	12.74%
3 -Chemical, Rubber and Plastic	8.53%	11.93%
4 -Non-metallic Minerals	4.90%	6.85%
5 -Metallurgic and Mechanical	29.94%	41.87%
6 -Other Manufacturing Industries	8.44%	11.80%
7 -Other Industries	3.33%	-
8 -Wholesale and Retail	10.86%	-
9 -Hotels and Restaurants	1.92%	-
10 -Transport and Communication	7.17%	-
11 -Real State	5.22%	-

*The second column details the distribution of all firms in the dataset by operating sectors.
*The second column details the distribution of firms operating in the manufacturing industry by sector.
*Note that the manufacturing industries operate only in the first six sectors reported above.

3.3 Size, Revenues and Investments

In order to assess the size and workforce of Italian firms that have answerd the INVIND survey, I introduce firm-level measures of size, revenue, and investments. A notable variable available in the database is the mean number of employees, which provides valuable insights into the scale of firms. Table 3.5 presents the average number of employees for firms within different geographic regions. Additionally, it includes the national average number of employees for reference in its first row.

Upon examining Table 3.5, it is evident that the Northwest region boasts the highest average number of employees, surpassing 550. Following closely is Central Italy, with an average of over 520 employees. Conversely, the South and Islands region has the lowest average number of employees, standing at 122. These findings suggest that larger firms are predominantly concentrated in the Northwest and Central Italy, while smaller firms tend to operate in the South and Islands region.

When considering the Manufacturing Industry, as depicted in the third column of Table 3.5, the order of mean values changes. In this context, the Northeast region emerges as the second-largest contributor to the average number of employees nationwide.

Table 3.5: Average Number of Employees

Region	Average	Average(Manufacturing)
Whole Country	373.52	276.17
Northwest	558.06	515.44
Northeast	392.83	312.33
Center	526.54	217.53
South and Islands	122.47	104.94

*The second column contains the mean value of employees by area including firms operating in all the three Italian industries.
*The third column represents the average number of employees, categorized by geographic area, exclusively for firms operating within the manufacturing industry.

Moving forward, I present the mean values of investments and revenues. To gain a better understanding of the disparities between the Manufacturing Industry and the broader Italian Economy, I provide separate mean values for these variables in the two categories.

Analyzing investments per geographic area, it is evident from Table 3.7 that in the Manufacturing Industry, the mean investment is higher in the Northwest and Northeast regions. Conversely, in the overall Economy, the Northwest and Central Italy exhibit higher mean investment values.

On the other hand, examining mean revenue, as depicted in Table 3.7, both for the entire Economy and the Manufacturing Industry, the Northwest and Central Italy demonstrate greater mean revenue figures.

Table 3.6: Average Investment

Region	Average	Average (Manufacturing)
Whole Country	8,23	4,42
Northwest	11,84	8,98
Northeast	4,75	4,00
Center	17,24	3,84
South and Islands	1,82	1,71

*The second column of the table provides information on average investments divided by geographic area for the broader economy.
*The third column of the table provides information on average investments divided by geographic area for manufacturing industry.
*Values in thousands of Euros

Table 3.7: Average Revenue

Region	Average	Average (Manufacturing)
Whole Country	191	151
Northwest	274	272
Northeast	129	113
Center	362	187
South and Islands	5,2	5,5

*The second column of the table provides information on average revenues divided by geographic area for the broader economy.
*The third column of the table provides information on average revenues divided by geographic area for manufacturing industry.
*Values in thousands of Euros

Chapter 4

Empirical Method

In this chapter, I outline the methods employed to assess the impact of exportation on productivity within the Italian context. It is crucial to note that my methodological choice revolves around examining how the production function behaves when exportation is taken into account as a significant factor. To achieve this, I compare the outcomes of this scenario with the conventional results obtained from models such as OP, ACF, and LP, which do not include the exportation term.

A critical step in the proposed estimation approach is the implementation of the law of motion of productivity as defined in De Loecker (2013). By defining an endogenous productivity process, I aim to demonstrate the divergent results obtained compared to the exogenous productivity process assumed in baseline models. This step is essential to highlight that not accounting for endogenous productivity can introduce bias in estimating the parameters of the production function and ultimately lead to erroneous productivity estimations.

The production function of interest, $y_{it} = \omega_{it} + \beta l_{it} + \alpha k_{it}$, includes the productivity parameter ω, which is known only to the firm itself and remains unobservable to the economist. To overcome this challenge, OP and LP propose using a proxy for the productivity function. Specifically, OP proxies productivity as a function of investment and capital by inverting the investment function, assuming it is strictly monotonic. On the other hand, LP proxies productivity as a function of capital and intermediate inputs.

Building upon the foundations laid by LP and OP, my approach involves studying the production function while considering productivity as an endogenous process dependent on the exportation status. To address the issue arising from unobserved productivity, I construct a proxy function by treating productivity as a function of investments, capital, labor and exportation status. This is achieved by assuming that investments depend on productivity, labor, exportation status, and capital, and then inverting the investment function to obtain the proxy for productivity. Therefore, a crucial assumption in this model is that investment exhibits strict monotonicity; otherwise, the investment function cannot be inverted, and a proxy function for ω cannot be obtained.

After establishing a proxy for productivity, I aggregate the terms of the production function into a new function represented as a third-degree polynomial, following the approach of De Loecker (2013). This polynomial differs from OP and LP as it incorporates not only capital and investment (or intermediate inputs) but also labor and information on exportation, based on the definition of my proxy function and the treatment of labor as a state variable as in ACF. Subsequently, I conduct an OLS regression of output on the polynomial, allowing me to proceed to the second stage where I obtain the production function parameters using a GMM.

4.1 Estimating the Production Function

First Stage

To begin, define the following investment function:

$$i_{it} = i(k_{it}, l_{it}, \omega_{it}, e_{it}) \tag{4.1}$$

In order to be able to construct a mapping from investments to productivity I rely on the assumption that investments are strictly monotone. By doing so, it is possible to invert the investment function and obtain the proxy for the productivity:[1]

[1]It is crucial to consider that the proxy for the productivity function differs from those employed in OP and LP. Let us assume that l itself is a function of both productivity and capital input, denoted

$$\omega_{it} = h(k_{it}, l_{it}, i_{it}, e_{it}) \tag{4.2}$$

It is important to note that the aforementioned function does not possess a closed form solution. Therefore, I approximate it using a non-linear polynomial of degree three. Subsequently, the production function can be rewritten as follows:

$$y_{it} = \phi_t(k_{it}, l_{it}, i_{it}, e_{it}) + \eta_{it} \tag{4.3}$$

Where η_{it} represents an independent and identically distributed error term, and $\phi_t(k_{it}, l_{it}, i_{it}, e_{it}) = \alpha k_{it} + \beta l_{it} + h(k_{it}, l_{it}, i_{it}, e_{it})$. Subsequently, I perform an ordinary least squares (OLS) regression of y_t on ϕ_t to obtain an estimate for ϕ, denoted as $\hat{\phi}$. The importance of $\hat{\phi}$ lies in the fact that once the parameters of the production function are estimated, it allows for the calculation of an estimation for the value of productivity. Therefore, by utilizing the estimations $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\phi}$, the following equation is employed to estimate ω:

$$\hat{\omega} = \hat{\phi} - \hat{\alpha}k - \hat{\beta}l \tag{4.4}$$

To differentiate from previous studies such as OP, LP, and ACF, this work deviates from the productivity process defined as $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$. It is important to note that utilizing that productivity process neglects the dependence of current productivity on past exportation information. In other words, it fails to capture the correlation between past exportation decisions and current productivity. Hence, in this study, productivity is defined as an endogenous process that depends not only on its own value in the previous time period, denoted as $t-1$, but also on past exporting information:

$$\omega_{it} = g(w_{it-1}, e_{it-1}) + \xi_{it} \tag{4.5}$$

as $l_{it} = l(k_{it}, \omega_{it}) = l(k_{it}, h(k_{it}, i_{it}))$. When estimating the production function, we encounter the equation $y_{it} = \beta l(k_{it}, h(k_{it}, i_{it})) + \phi_t(k_{it}, i_{it}) + \eta_{it}$. Here, labor ($l_{it}$) and the non-parametric function are perfectly collinear, resulting in the inability to estimate β in the initial stage of estimation. As a solution, I define ω according to equation 4.2, where l_{it} is treated as a state variable with an identified parameter in the second stage of estimation.

Following the approach used in De Loecker (2013), this definition of the productivity process allows for the influence of exportation on productivity through the mechanisms discussed in Chapter 1. By adopting this specification of the productivity process, we can now examine how the estimated parameters of the production function differ between the endogenous and exogenous productivity processes. Intuitively, if firms that begin exporting experience productivity growth due to the LBE phenomenon, we would expect the estimator for α to be lower in the endogenous process compared to the exogenous process ($\alpha_{end} < \alpha_{ex}$). This is because more productive firms are able to utilize their inputs more efficiently, leading to higher productivity.

The error term ξ_t in the equation represents the innovation shock in ω_t, and as such, it is defined as being uncorrelated with lagged labor and capital, which were determined in previous time periods. It is important to note that current capital is constructed based on investments made in previous years, which means that it is not correlated with the current innovation shock in ω_t.

With this understanding, we can now define the moment conditions used to identify the parameters of the production function using a GMM estimator. Following the approach outlined by De Loecker (2013), it is worth emphasizing that the production function employed in this study is a sales-generating production function. This implies that firms entering the export market are likely to experience an increase in their revenues (output) through productivity growth resulting from exposure to foreign markets or innovation shocks captured by the term ξ_t.

Based on the preceding discussion, I can now proceed with the estimation step. It is worth noting that, while OP employs a non-linear least squares model, both LP and ACF utilize the generalized method of moments (GMM) to estimate the parameters α and β. In this estimation procedure, since I am estimating labor in the second stage, I adopt the moment conditions proposed by ACF to estimate my model effectively. Specifically, after defining the endogenous productivity process as described in equation 4.5, I employ the moment conditions involving the innovation shock ξ_t in ω_t. Since ξ_t is orthogonal to lagged inputs (and contemporaneous capital), I estimate the following

GMM model:

Second stage

$$E\left\{\xi_{it}(\beta,\alpha)\begin{pmatrix} l_{it-1} \\ \\ k_{it}\end{pmatrix}\right\} = 0 \tag{4.6}$$

To obtain ξ_{it} and construct the moment conditions, I conduct a nonparametric regression of $\omega_{it}(\beta,\alpha) = \hat{\phi}_{it}(k_{it}, l_{it}, i_{it}, e_{it}) - \alpha k_{it} - \beta l_{it}$ on $\omega_{it-1}(\beta,\alpha) = \hat{\phi}_{it-1}(k_{it-1}, l_{it-1}, i_{it-1}, e_{it-1}) - \alpha k_{it-1} - \beta l_{it-1}$. The residual obtained from this nonparametric regression serves as an estimate of the productivity shock ξ_{it}.

4.2 Detecting Learning by Exporting using Difference-in-Differences

The difference-in-differences (DID) method has been commonly employed in the literature to investigate the LBE effects. However, this approach may not be suitable if one erroneously assumes productivity to be an exogenous process. As emphasized in the preceding section, if exportation indeed plays a significant role in productivity growth, inaccurate estimates of the production function may attribute excessive variation in output to fluctuations in capital and labor inputs, while overlooking the influence of the exporting decision. Consequently, this could lead to underestimated measures of the LBE effect when employing the DID approach.

To proceed with the estimation, I adopt a staggered or generalized difference-in-differences framework. This modification is necessary because firms initiate their exporting activities at different points in time, thereby deviating from the typical DID setup with a single time of treatment and distinct treated and control groups. Like any other DID approach, this model relies on crucial assumptions that must hold for unbiased estimates of the LBE effect. The most pivotal assumption is the exogeneity of firms entering the exporting market over time. In other words, the timing of entry should not be correlated with any firm characteristics that may also influence the trend of the outcome variable, which, in this case, is productivity.

Another crucial assumption for correctly identifying the LBE effect is that no other firm policies implemented simultaneously with entering the exporting market affect the productivity trend. Failure to uphold this assumption would introduce confounding factors that jeopardize the identification strategy.

In light of these considerations, I employ a two-way fixed effects model to consistently identify the impact of the LBE effect:

$$\omega_{it} = \nu_i + \gamma_t + \delta Post_{it} + \varepsilon_{it} \tag{4.7}$$

To enhance comprehension of the identification strategy, I consider treatment as the event of entering the exporting market. Consequently, firms that eventually commence exporting are classified as "treated", while non-exporting firms are regarded as "untreated." Moving forward, the variable $Post_{it}$ is a binary indicator that assumes a value of one only during the years in which treated units engage in exporting activities, and zero prior to their decision to export or if the firm never enters the exporting market. In this context, the parameter of primary interest is denoted as δ, as it captures the effect of entering the exporting market on firm productivity, representing the measure of the LBE effect under investigation.

Furthermore, the term ν_i in the equation represents a firm fixed effect, encompassing firm-specific characteristics that remain constant over time. Similarly, γ_t denotes a year fixed effect, capturing common shocks experienced by all firms in the sample during a given year. Lastly, the error term ε_{it} is assumed to be independently and identically distributed (i.i.d).

4.2.1 Controlling for lagged variables

One potential limitation of the approach outlined thus far is that the timing of entering the exporting market may not be exogenous. As highlighted in various previous studies, such as Aw et al. (2011), Van Biesebroeck (2004), and De Loecker (2013), firms tend to self-select into the exporting market, whereby more productive firms are more likely to engage in exporting compared to less productive firms. Consequently, it is reasonable to argue that the exogenous timing assumption required to identify the causal effect of interest may be overly stringent. To address this potential issue, I propose the following specification, which represents a modified version of the equation presented in Equation 4.7:

$$\omega_{it} = \theta\omega_{it-1} + \gamma_t + \delta Post_{it} + \varepsilon_{it} \tag{4.8}$$

In contrast to the initial approach presented in Equation 4.7, which relied on invariant firm-specific unobservables ν_i to identify the causal effect δ, the revised specification introduces lagged variables to ascertain whether a firm enters the exporting market or not. Building upon insights from prior literature, it can be argued that the crucial omitted variables in this analysis are not static but rather dynamic in nature. Thus, considering the well-supported argument that more productive firms tend to self-select into the exporting market, it becomes necessary to adopt an identification strategy that incorporates lagged productivity variables.

When estimating the model presented in Equation 4.8, an additional argument can be made concerning the influence of time-invariant unobserved variables on the firm's decision to enter the export market. It is worth noting that certain factors, such as the level of managerial motivation and talent, can contribute to higher productivity levels and consequently influence the self-selection of firms into exporting activities. Therefore, it is essential to include the term ν_i in Model 4.8 to account for these constant unobservables that impact the timing of entry into the export market.

However, it is important to acknowledge that when both individual fixed effects and lagged variables are included in the model, a perfect estimation of both parameters is not feasible due to an inherent identification problem. The differentiation process necessary to estimate the fixed effects model generates differenced variables that are correlated with the error term, rendering the estimation of consistent parameters unattainable. Therefore, simultaneous estimation of individual fixed effects and lagged variables is not feasible due to the inherent correlation between the differenced variables and the error term.

4.3 Estimating LBE Effects Nonparametrically

In contrast to previous studies, De Loecker (2013) introduced a significant innovation by allowing for the direct of nonparametric estimation of LBE alongside the estimation of the production function. In earlier research, scholars often relied on a misspecified productivity process that treated productivity as exogenous, only examining the impact of exportation on productivity in a separate analysis. To provide a clearer understanding, let me revisit the correctly specified productivity process, as it will be instrumental in explaining De Loecker's method.

$$\omega_{it} = g(\omega_{it-1}, e_{it-1}) + \xi_{it} \tag{4.9}$$

To commence, it is important to note that in this method, the timing of the arrival of the productivity shock ξ_{it} enables the identification of the LBE effect. When firms enter the export market, they encounter significant costs associated with this transition. As a result, the substantial sunk costs they face prevent firms from instantaneously adjusting their export status in response to productivity shocks, i.e., $E(e_{t-1}\xi_{it}) = 0$. Expected levels of productivity based on a company's previous export activities are, then, determined by comparing the current productivity of firms that exported and those that did not export during a specific period, while keeping their input usage consistent. Moreover, controlling for productivity levels at a previous time period helps to account for any unobservable differences that may vary over time among firms.

An important concern in examining the LBE phenomenon is the potential bias introduced by the self-selection of more productive firms into the export market. This issue can lead to imprecise estimation of the effect of LBE. When comparing an exporter to a non-exporter, the higher productivity observed in the exporter may not solely be attributed to its engagement in exporting activities, but rather to the fact that it already possessed higher productivity prior to entering the export market. However, by including the term ω_{it-1}, I am already controlling for the potential impact of past productivity on current productivity. To see why this is the case, rewrite the productivity process in equation 4.9:

$$\omega_t = g(g(\omega_{it-2}, e_{it-2}) + \xi_{it-1}, e_{it-1}) + \xi_{it} \tag{4.10}$$

It is noteworthy that by expressing past productivity ω_{it-1} as a function of ω_{it-2} and e_{it-2}, it becomes evident that in the process of identifying the LBE effect at period t, I am examining the changes in output at time period t, while holding the input level constant at time t, and simultaneously accounting for potential productivity disparities between time periods $t-1$ and $t-2$. Consequently, the process of self-selection into engaging in international trade through exporting is being appropriately taken into consideration.

Therefore, in order to nonparametrically estimate the LBE effect, I employ De Loecker's (2013) precise specification, which primarily relies on $\frac{\partial g}{\partial e_{t-1}}$. Initially, following the estimation of the coefficients of the production function as outlined in section 4.1, an estimate of productivity can be obtained, denoted as $\omega_{it} = \hat{\phi} - \hat{\alpha} k_{it} - \hat{\beta} l_{it}$. Subsequently, the productivity process described in equation 4.9 can be defined in the following manner:

$$\begin{aligned} \omega_{it} = {} & \theta_1 \omega_{it-1} + \theta_2 \omega_{it-1}^2 + \theta_3 \omega_{it-1}^3 + \theta_4 e_{t-1} + \theta_5 \omega_{t-1} e_{t-1} + \theta_6 \omega_{t-1}^2 e_{t-1} \\ & + \theta_7 \omega_{t-1}^3 e_{t-1} + \xi_{it} \end{aligned} \tag{4.11}$$

Following the specification of the aforementioned productivity process, an ordinary least squares (OLS) regression is performed to estimate the parameters of the equation. Subsequently, upon obtaining estimates for the values of the parameters θ, it becomes feasible to derive the nonparametric estimates of the LBE effect, as defined below:

$$LBE = \theta_4 + \theta_5 \omega_{t-1} + \theta_6 \omega_{t-1}^2 + \theta_7 \omega_{t-1}^3 \tag{4.12}$$

Chapter 5

Results

This chapter presents the findings from the models discussed in Chapter 4. To facilitate clarity and organization, the chapter is divided into sections corresponding to the previously presented models. Firstly, the results of estimating the production function parameters while accounting for the endogeneity of productivity based on past productivity information are reported. Secondly, the measures of Learning by Exporting obtained through the differences-in-differences models are presented, along with the nonparametric measures of LBE.

5.1 The Production coefficients

To begin, I estimated the production function parameters using the model presented in the first section of the previous chapter. To facilitate comparisons, I first estimated a model without an endogenous process of productivity using the ACF method, which is commonly used for estimating the production function. Subsequently, I estimated the production function considering the endogenous process of productivity, which is dependent on lagged exportation as specified in equation 4.5.

As mentioned earlier, the key distinction between these two models lies in the assumption that, in the exogenous specification, a significant portion of the variation in the final output is attributed to variations in capital. However, it is important to recognize that some of the observed output variation actually stems from productivity gains resulting from the decision to engage in exporting.

Upon analyzing the results, I found that the point estimates of the capital coefficient (α_{end}) are lower than those of the exogenous specification (α_{ex}). However, when considering the 95% confidence intervals of the parameters, it becomes evident that the estimates of the capital coefficients in the endogenous model predominantly fall within the interval of the estimates in the exogenous specification model. Similarly, the coefficients of the exogenous model largely fall within the confidence interval of the endogenous model's coefficients. These findings are further illustrated in Tables 5.1 and 5.2, which present the point estimates, standard errors, and confidence intervals of the exogenous and endogenous models, respectively. Table 5.1 corresponds to the exogenous model, while Table 5.2 pertains to the endogenous model discussed in the first section of Chapter 4.

Table 5.1: Production Function Coefficients Exogenous Model

Sector	β_{ex}	α_{ex}	95% Conf. Interval
Manufacturing Industry	0.881***	0.185***	(0.858 - 0.902);(0.176 - 0.193)
	(0.011)	(0.004)	
Food, Beverages and Tobacco	0.866***	0.207***	(0.829 - 0.904);(0.192 - 0.221)
	(0.019)	(0.007)	
Textile, Clothing, Leather and Shoes	0.898***	0.168***	(0.834 - 0.963); (0.146 - 0.190)
	(0.039)	(0.011)	
Chemical, Rubber and Plastic	0.872***	0.187***	(0.815 - 0.929);(0.165 - 0.209)
	(0.029)	(0.011)	
Non-metallic Minerals	0.852***	0.211***	(0.766 - 0.938);(0.183 - 0.240)
	(0.044)	(0.014)	
Metallurgic and Mechanical	0.872***	0.186***	(0.840 - 0.904);(0.173-0.198)
	(0.016)	(0.006)	
Other Manufacturing Industries	0.860***	0.187***	(0.795 - 0.925);(0.156-0.218)
	(0.033)	(0.016)	

Standard errors reported in parentheses.
*,** and *** represent significance at the 90%, 95% and 99% levels, respectively.

In Tables 5.1 and 5.2, it is evident that, similar to De Loecker (2013), the estimation of the capital input parameters is smaller in the endogenous model, which accounts for the impact of exportation on productivity, compared to the plain exogenous model. This finding aligns with the theoretical explanation that variation in output is influenced by productivity gains resulting from Learning by Exporting (LBE) effects. However, unlike De Loecker, who presents only the point estimates of the production function models, I incorporate measures of dispersion and confidence. By including these measures, particularly the 95% confidence interval, I can argue that there is insufficient statistical evidence to differentiate between the parameters of each model.

To provide a clearer explanation, let us consider the case of the α coefficients for the entire Manufacturing Industry without dividing the analysis into different sectors. Referring to the first row of Tables 5.1 and 5.2, we observe that the estimated capital parameters are 0.185 and 0.182 in the exogenous and endogenous models, respectively. Despite the difference in their numerical values, it is noteworthy that their confidence intervals are identical, ranging from a minimum of 0.176 to a maximum of 0.193. Consequently, if we acknowledge that both estimates can plausibly fall within this interval, it becomes evident that we cannot ascertain with certainty whether they are truly different from each other.

However, it is important to note that when I conduct a sector-specific analysis within the manufacturing industry, the distinction between the α_{end} and α_{ex} estimates becomes more pronounced, as depicted in Tables 5.1 and 5.2. Notably, some sectors, such as Textile, Clothing, and Leather Shoes, as well as Other Manufacturing Industries, exhibit the exact same estimates for both the exogenous and endogenous models. On the other hand, the Chemical, Rubber, and Plastic sector demonstrates the greatest disparity, with α_{ex} equal to 0.187 and α_{end} equal to 0.182.

Moreover, most of the point estimates obtained from the endogenous model tend to be smaller. However, it is important to exercise caution in interpreting the significance of these differences. While the results align with the general direction indicated by De Loecker's findings, it is crucial to consider the estimation of confidence intervals.

Claiming that the discrepancy between the exogenous and endogenous estimates is statistically significant may be an overly strong assertion.

Table 5.2: Production Function Coefficients Endogenous Model

Sector	β_{end}	α_{end}	95% Conf. Interval
Manufacturing Industry	0.864***	0.182***	(0.858 - 0.870);(0.176 - 0.193)
	(0.007)	(0.003)	
Food, Beverages and Tobacco	0.861***	0.204***	(0.826 - 0.902);(0.190 - 0.219)
	(0.021)	(0.031)	
Textile, Clothing, Leather and Shoes	0.894***	0.168***	(0.828 - 0.960); (0.146 - 0.190)
	(0.009)	(0.024)	
Chemical, Rubber and Plastic	0.888***	0.182***	(0.830 - 0.946);(0.159 - 0.205)
	(0.011)	(0.030)	
Non-metallic Minerals	0.846***	0.212***	(0.764 - 0.929);(0.184 - 0.241)
	(0.042)	(0.0146)	
Metallurgic and Mechanical	0.883***	0.183***	(0.850 - 0.916);(0.170-0.196)
	(0.006)	(0.016)	
Other Manufacturing Industries	0.853***	0.187***	(0.798 - 0.917);(0.157-0.219)
	(0.032)	(0.016)	

Standard errors reported in parentheses.
*,** and *** represent significance at the 90%, 95% and 99% levels, respectively.

5.2 The Estimations of Learning by Exporting

5.2.1 The Differece-in-Differences Models

In this section, I present the results of the LBE effects using a difference-in-differences approach, similar to De Loecker (2013). However, my model differs from De Loecker's in that it employs a staggered treatment design. The rationale behind this choice is that firms begin exporting at different points in time, resulting in staggered treatment. This approach contrasts with a conventional setup where treatment occurs at a single point in time for a specific group, thereby defining clear treatment and control groups.

In my model, some units are treated earlier, some later, and some never experience treatment.

Given that I allow for the potential impact of exportation on future productivity, it is crucial to ensure consistency in estimating the LBE effects. Specifically, it is important to correctly specify the endogenous relationship between productivity and past exporting experience, as outlined in the first section of the Empirical Strategy Chapter. The rationale for incorporating exportation as a determinant of productivity lies in the fact that attributing output variations solely to increases in capital stock would lead to downward bias in the estimated LBE effects. By accounting for the productivity gains facilitated by exporting experience, a more accurate assessment of the LBE effects can be obtained.

With this in mind, the estimation of the difference-in-differences model is guided by equations 4.7 and 4.8. In both specifications, the coefficient of interest is denoted by δ, representing the causal effect captured by the variable $Post_{it}$. In the context of my analysis, δ represents the average productivity gain associated with entering the exporting market, thereby capturing the causal effect of export initiation on firm productivity. It is important to note that since I do not utilize multiple post-treatment periods, δ reflects the average effect over the years following treatment.

In the second section of Chapter 4, I introduce two models to be estimated using the staggered difference-in-difference approach. The first model is a two-way fixed effect model, where I include both a firm fixed effect and a year fixed effect. These fixed effects help control for firm-specific constant heterogeneity and common shocks affecting all firms, respectively. On the other hand, in the second model outlined in equation 4.8, I incorporate the vector of lagged productivity for each firm i. However, the inclusion of lagged variables raises potential issues if I also want to control for firm unobservables, as it may introduce endogeneity problems. Consequently, I no longer employ the firm fixed effect in this latter specification.

Next, in Table 5.3, I provide a detailed breakdown of the causal effects (δ), categorizing them by industry and model. The second column of the table presents the effects of exportation on productivity for the first specification referred to as "Fixed Effect," corresponding to Model 4.7. Similarly, in the third column, I present the results obtained for the "Lagged Variable" model specified in equation 4.8.

Table 5.3: Difference-in-Difference Estimates of LBE

Sector	Fixed Effect	Lagged variable
Manufacturing Industry	0.281***	0.271***
	(0.019)	(0.016)
Food, Beverages and Tobacco	0.210***	0.290***
	(0.038)	(0.036)
Textile, Clothing, Leather and Shoes	0.232***	0.427***
	(0.103)	(0.114)
Chemical, Rubber and Plastic	0.342***	0.218***
	(0.065)	(0.049)
Non-metallic Minerals	0.396***	0.191***
	(0.052)	(0.052)
Metallurgic and Mechanical	0.216***	0.254***
	(0.035)	(0.031)
Other Manufacturing Industries	0.328***	0.308***
	(0.044)	(0.031)

Standard errors reported in parentheses.
*,** and *** represent significance at the 90%, 95% and 99% levels, respectively.

In the case of the overall Manufacturing Industry, the Fixed Effect model indicates that commencing export activities has a positive effect on productivity, with an estimated value of 0.281. This implies that firms that enter the export market experience, on average, a productivity increase of 0.281 compared to firms that do not engage in exporting. Similarly, when employing the lagged variable specification, I find a slightly lower estimate of 0.271, which is still in close proximity to the result obtained from the first model.

Furthermore, when examining the industry breakdown, I consistently observe a positive impact of exporting on productivity across sectors. Notably, the Textile and

Clothing sector demonstrates the largest estimate, with a value of 0.427 in the lagged variable model. This finding suggests that firms operating in this sector experience an average productivity gain of 0.427 when they initiate export activities.

5.2.2 The Nonparametric Estimates of LBE

As delineated in the previous chapter's exposition of the nonparametric model, the assessment of the LBE effect is intertwined with the estimation of the production function parameters. The identification of the LBE effect entails scrutinizing the alteration in output ascribed to the choice of entering the export market, while holding the inputs constant and accounting for prior heterogeneity in productivity, which influences the decision to engage in exporting. Consequently, when comparing firms that participated in exporting with those that did not, the potential erroneous attribution of output variation to past high productivity is effectively mitigated.

Given the aforementioned considerations, the outcomes of the LBE effect calculations are presented in Table 5.4. The analysis reveals a significant positive influence of exporting, with a notable impact of 10.22% for the manufacturing industry as a whole. This finding substantiates our initial hypothesis that entering the export market has the potential to significantly enhance a firm's productivity. Specifically, keeping inputs constant and accounting for past productivity disparities, firms that initiate exporting activities during time period t experience an approximate 10% increase in productivity compared to firms that do not engage in such activities during the same time period.

Moreover, an important observation emerges: all sectors within the manufacturing industry exhibit a positive impact of entering the export market on productivity. This finding aligns with the outcomes obtained from the estimation of the differences-in-differences model, thereby corroborating the consistency of the results across different analytical approaches.

Table 5.4: Nonparametric Estimates of LBE

Sector	Average LBE effects
Manufacturing Industry	10.22%
Food, Beverages and Tobacco	11.79%
Textile, Clothing, Leather and Shoes	10.25%
Chemical, Rubber and Plastic	5.91%
Non-metallic Minerals	12.13%
Metallurgic and Mechanical	11.09%
Other Manufacturing Industries	9.56%

Chapter 6

Conclusion

In conclusion, this thesis has provided a comprehensive analysis of the LBE effect using firm-level data from the Italian context. By replicating and expanding upon previous research, I have contributed to the understanding of how engaging in export activities influences firm productivity.

Through my empirical analysis, I have uncovered several key findings. First, I have confirmed the existence of a positive relationship between exporting and firm productivity in the Italian manufacturing sector. My results demonstrate that firms that engage in exporting experience significant productivity gains compared to their non-exporting counterparts. This finding aligns with previous research and supports the notion that international trade can serve as a catalyst for productivity improvements.

Furthermore, I have demonstrated the heterogeneity of the LBE effect across different industries and firm characteristics. While all sectors within the manufacturing industry exhibit a positive impact of exporting on productivity, the magnitude of this effect varies. This highlights the importance of considering sector-specific factors and firm-level characteristics when examining the relationship between exporting and productivity.

My analysis has also accounted for the endogeneity of the productivity process in relation to firms' export behavior. By employing an econometric framework that addresses potential biases and endogeneity concerns, I have strengthened the reliability and robustness of my findings. This has allowed me to obtain more accurate estimates of the LBE effect and better understand the causal relationship between exporting and firm productivity.

The implications of this research extend beyond academic contributions. Policymakers can draw upon my findings to design targeted policies and strategies aimed at promoting export activities and fostering productivity growth in the manufacturing sector. Moreover, managers can benefit from the insights gained from this study by understanding the potential benefits and challenges associated with entering foreign markets through exporting.

It is important to acknowledge the limitations of my study. While I have utilized a comprehensive dataset and employed rigorous econometric techniques, there may still be unobserved factors and omitted variable biases that could influence the estimated LBE effect. Future research could explore these limitations further and delve into the mechanisms underlying the LBE effect, such as the role of learning, technology transfer, and network effects.

To sum up, this thesis contributes to the existing body of knowledge on the relationship between exporting and firm productivity. By examining the LBE effect in the Italian context, we have provided valuable insights that can inform policymakers, assist managers in decision-making, and contribute to the broader understanding of the dynamics of international trade and its impact on firm performance. Continued research in this field will further advance our understanding and enable the formulation of effective strategies to enhance productivity and foster economic growth in an increasingly interconnected global marketplace.

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