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PhD Thesis

Essays on Sustainable Economic growth and Efficiency

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Abstract

The climate emergency and environmental depletion have become important issues for United Nations countries, and Governments are imposing stringent environmental regulation policies to move towards sustainable growth. In this scenario, pursuing green growth requires firms to adopt new strategies in terms of energy saving, the use of renewable power sources, and the adoption of sustainable production processes. These changes have significant economic consequences for firms and industries, as recent and large literature has pointed out. However, few studies have dealt with the role of environmental regulation at the sectoral level. This dissertation contributes to this topic by investigating how environmental regulation affects productivity at the sectoral level in a sample of selected European economies. It studies the effect of these instruments on productivity by measuring the adjusted productivity growth in thirteen Italian manufacturing industries and enlarged the sample by including other four EU countries. Productivity growth is measured using the Malmquist-Luenberger index, which is based on the Directional Distance Function (DDF). The main result of the Italian context investigation is that environmental regulation does not have a negative impact on almost all industries. A bootstrapping approach has been then used to assess the robustness of estimated results. Instead, in the European context, we find environmental regulations have a negative effect on productivity growth in several industries in the manufacturing sector for almost all the countries included in the analysis.

Contents

1. Introduction

Climate change and environmental disasters are a wake-up call that shows that the environment is changing. Human activities, especially the economic one, are the main sources of this phenomena. Overconsumption, overexploitation, pollution, and deforestation are causing destabilization of the ecosystem. As claimed by Georgescu-Roegen (1971), the economic system is an open subset of the ecological system and is therefore subject to the laws of thermodynamics. Economic agents in their production processes use (renewable) energy and (non-renewable) matter given in limited quantities that belong to the ecological system. As a subject to the laws of thermodynamics[1], economic activities have caused significant effects on the environment, which have altered the ecosystem *equilibrium* (Falcitelli and Falocco, 2008).

While the economic system with its faster growth rate has produced many benefits – raising standards of living and improving quality of life across the world – it has also resulted in the depletion of natural resources and the degradation of ecosystems (Everett et al., 2010). Contrary to what transpires from the standard representation of the economic system, anthropogenic activities produce significant effects on the natural capital[2] of the ecosystem. These changes in the state of natural capital, in turn, generate negative feedback on the ecosystem, violating the commonly known hypothesis of "*Gaia*" introduced by Lovelock in (1979)[3]. The activities and the environment built up by humans, which although not part of the "*Gaia*" system, strongly interact with it by modifying the limiting factors such as temperature and chemical compounds (Lovelock, 1990). Global warming, which is the rise of the average temperature of the Earth's climate system, is an evident consequence of the human-drive changes on Earth (Allen, 2018) and a modified "Gaia" system (Lovelock, 1990).

To go through this raising problem, different experts, like environmentalists, policymakers, and economists as well, are moving on to change the humane activities and behavior for a sustainable life and economic growth. By proposing different regulatory instruments, policymakers, and economists, are trying to improve these issues and correct human activities in order to gain green growth. These regulatory instruments are oriented toward limiting the overconsumption of the natural capital from the economic activities, limiting the air emission

[1] According to the first law of thermodynamics, the production process does not create or destroy anything, but is limited to transforming matter and energy into goods and waste which will then be reabsorbed by the biosphere. The second law of thermodynamics also asserts that matter and energy necessary with low entropy, are transformed, as a result of productive manipulation, into goods with high entropy, heat dissipators, and no longer usable (scraps and waste). For a more detailed account, see the volumes by Falcitelli and Falocco (2008) and Tiezzi and Marchettini (1999).

[2] "Natural Capital" is defined as the entire stock of natural goods (living organisms, air, water, soil and geological resources) that contribute to providing goods and services of value, directly and indirectly, to humanity and that are necessary for the survival of the environment from which they are generated. For a more detailed see, Ducoing (2019).

[3] "Gaia" hypothesis argues that; "*the organisms on Earth interact with the local inorganic elements to form a complex synergistic and self-regulating system that affects the maintaining and perpetuate of the conditions for life on the planet*". Among the arguments on which the hypothesis is based there are also those according to which the biosphere and the evolution of organisms influence the stability of global temperature, atmospheric oxygen levels, and other environmental variables that affect the habitability of the Earth (Boston, 2008).

generated by the producer during their production process, and restricting the household's activities that generated waste and damage to the environment. Furthermore, these correction instruments are both, left to the market to autoregulate and protect the ecosystem, i.e., market-oriented regulations, and imposed directly on the economic activities for limiting air pollution and overconsumption of the resources, i.e., command and control regulations[4].

The benefits that the regulatory instruments have provided to the ecosystem and the society were highlighted and reported by a large amount of literature (Cohen, 1998). The first result of improving the air and water quality and consequently the quality of life is archived by the public and non-public authorities in all Europe and world. The European commission registers a reduction in CO_2 of 11.7 percent from the first Kyoto commitment period[5]. These are listed as the progress in moving toward sustainable economic growth and more stringent environmental regulations are further imposed to archive the goal imposed by the United Nations. However, the gains from the regulatory instruments may be discussed due to several negative consequences that they have on the economy and society. The direct consequences to the subject involved in the regulations, such as firms or industries are related to the augmented cost of the production, and reduction of the investments for those firms. This in turn can cause a loss in productivity and competitiveness as well. That being said, the gains from the environmental regulations can be reaped only when preceded by adequate policy reforms aimed at minimizing the risk associated with regulatory instruments.

The trade-off associated with environmental regulations and related concerns has interested an excess of both theoretical and empirical literature during the last decades. However, the mainstream literature is focused on the relationship between environmental regulation and productivity growth at both macro and micro levels and it is difficult to draw a net conclusion on this relationship. In this dissertation, we contribute to the relevant literature with new evidence on environmental regulation and its impact on productivity growth. Specifically, our focus will be on the largest environmental regulation implemented after the Kyoto Protocol in 1997 and the Paris Agreement in 2015 and their role in manufacturing productivity growth, being that they were the starting point.

Our empirical analysis offers new evidence on the role of environmental regulation in manufacturing industries. More particularly, we explore their role in the Italian manufacturing sector and enlarge our samples by introducing other four EU countries. The reason why we concentrated our analysis only on Italian manufacturing analysis is twofold. The first is related to the absence of a study that deals with the sector level in Italy. To the best of our knowledge there is no green policy evaluation at the industry level and providing the first result to the policymakers could help them to improve the design of these policies. The second reason is

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[4] In the literature the environmental regulations are classified into two groups, market-oriented regulation and command and control regulation. The first group enters those regimentations that are left to the market to correct the environmental issues and the second group enters those that are directly controlled and imposed by policymakers (Cole and Grossman, 2003).

[5]Link:https://ec.europa.eu/clima/eu-action/climate-strategies-targets/progress-made-cuttingemissions_en#emissions-monitoring--reporting

related to the fact that the manufacturing sector holds a relevant part of the economic growth in the country and should be evaluated if productivity has archived any changes. To give a statistical interpretation of our result and check the robustness of our analysis we use a Bootstrapping method which concludes that our findings are statistically significant. Using a similar approach, we further extend our evaluation to the other four EU countries. We analyse if productivity growth for manufacturing sectors of these five countries, including Italy, has changed or not by introducing the environmental regulations. The reason why we concentrate only on five countries is related to the data constrain which are available only for a few countries for industries level. Similar to the previous study we are not aware of any studies that deal with the industry level in EU countries and there is no evidence that assesses the consequences of the green policy at the industry level for those five countries. Again, our focus is on the manufacturing sectors with associated industries because even in EU countries it has a large impact on the economic growth and the environment as well.

Results from our empirical analysis show that the productivity growth on average for the Italian manufacturing sector and its associated industries seem not to be affected by the environmental regulation during the period from 1995 to 2017. The results change when we consider other countries in our analysis, and we perform a cross-country industries frontier analysis. The period of study in the second analysis is quite short, from 2008-to 2015, and during this period the productivity growth on average seems to be affected by the environmental regulation for almost all the industries in each country. In both studies, we found that the improvement in productivity growth (ML index greater than one) is caused meanly by the improvement in technical progress (MLTCH). The efficiency changes (catching up of the production frontier) show no changes (MLECH=1) for almost all the industries in our analysis for both studies. For the first study, the results are statistically significant which provides the robustness of our analysis.

Finally, our findings have policy implications and suggest that policies favorable to more incentives for more green investment and product innovation would provide improve industries' productivity and competitiveness. In the EU context, European policymakers should focus their attention on activities that encourage the combination of novel green production technologies with the traditional production processes. As well as the introduction of new reforms oriented toward energy-saving and waste reduction.

The remaining of this dissertation is organized as follows. We report in the second chapter an introduction of the literature on the environmental movement toward a sustainable economy from its early stage. Then we introduce some finding that addresses the trade-off between environmental regulation and productivity growth and we conclude this chapter by introducing the main tools used in productivity analysis. The third chapter presents the general framework for productivity analysis, the direction distance function, and the Malmquist-Luenberger index. The remaining chapter investigates the relationship between environmental policy and productivity growth in the Italian manufacturing sector and the EU manufacturing sector and its associated industries as well. We conclude this dissertation with some final remarks and policy implications.

2. Literature review

In this first part of the thesis we provide a thorough analysis of the relevant literature which we decided to separate on three different fields. The first section focuses on the literature related the environmental movement toward a sustainable economy and the main correction instruments introduced. Next, we introduce the main finding on the consequences of the environmental regulation on productivity growth in both, micro and macro level. Finally, we provide an introduction of the literature on productivity measurement and its application on environmental issues case.

2.1 Environmental movement toward a sustainable economy.

In seriously addressing environmental problems within its disciplinary teachings the economics thought has generally been slow and reluctant. Despite basic concerns relating to human interactions with the environment having been reflected in the classical and neoclassical thought of the 1800s, the doctrine was developed much more later. The first notes about the environmental problem started with Ricardo and Maltuth's concern for the prospect of long-term economic growth due to the environmental limits, namely the limits on the supply of good quality agricultural land and therefore diminishing agriculture retune in agriculture of production (Pearce D, Turner, 1990). In the dominant economic doctrine, the effects of damage to the environment are seen as a negative externality[6] which the market cannot correct (Gallegati, 2018). Those externalities are addressed to the concept of "market failure[7]" and assigning a monetary value has been the main focus of economists and policymakers (Smeets et al., 2021).

In the early study, to alleviate this distortion, economic experts (e.g., Pigou,1920; Coase, 1960; Crocker, 1966; Dales, 1968) have developed different proposals which are the common corrective instruments used by policymakers nowadays. The initial corrective instrument was the carbon tax[8] for CO_2 emission, usually called the "Pigouvian tax". In 1920, the idea of Pigou was to strength the producers to pay a tax equivalent to the external damage generated by their production settlement in order to internalize the externalities. Nowadays literature ti is referred to the so-called pollution charges which, identically to CO_2 emission tax, impose taxes on firms

[6] A negative externality is a cost that is suffered by a third party because of an economic transaction (Endres, 2011). For Pigou (1920), a negative externality arises when the market mechanism doesn't conduct an efficient allocation of the recourses.

[7] The "failure" is related to the lack to achieve an efficient allocation of resources and consequently of maximum collective well-being, to which the neoclassical Environmental Economics responds through a monetary evaluation of the environmental asset considered, or the choice of the best tool that can make the missing compensation (Calafati, 1997).

[8] The carbon tax forces the polluter to defray the cost of each ton of greenhouse gas emissions they emit into the atmosphere. Two types of "carbon tax" are generally found in literature: the first is based on the quantities of emissions generated by an organization produces; the second is the one related to the goods or services that are greenhouse gas-intensive. See the Center for Climate and Energy Solution. Link: https://www.c2es.org/content/carbon-tax-basics/

on their quantity of emissions generated. In addition to the tax on polluting producers, the "right to pollute"[9] is also another corrective instrument to consider. Recognizing the right to pollute as a "property right" that can be freely sold/bought has created the so criticized permit market (PM). The notion of the permit market to regulate emission levels was first developed by Crocker (1966) and Dales (1968). The main idea about the permit market comes out from the Coase theorem[10] which differs from PM from the subjects involved in the negotiation. This second environmental regulation, usually fined in the literature as marketable permits regulation, gives to the producer the possibility to reduce the emission and be compensated at the same time by selling the reduced part. The better-defined property rights which also use the idea of the Coase theorem, are another environmental protection regulation. They are much more oriented toward the direct protection of land and biodiversity.

The above environmental regulations are classified by policymakers and economists as Market-oriented environmental tools which give to the producer the flexibility to reduce the air emission generated by their economic activities (Baldwin et.al. 1988). The other groups of environmental regulations which are considered to be less flexible are Command and control[11] environmental regulation. They are instruments that allow policymakers to explicitly control both the quantity and the process by which a firm should preserve the quality of the environment (Ren et al., 2018). In the literature, those regulations are classified as direct regulation that includes commands and prohibitions for the industries in their resources used in production processes (Iraldo et al., 2011). They are laws that also require that firms invest in anti-pollution equipment. According to economists, the command and control environmental regulations have some weakness which has to be addressed for better implementation and designee of those policies. The first weakness is related to the zero incentive to do better for the polluters. Once the standard set of lows has been satisfied, those laws do not offer any incentives to improve the quality of the environment beyond the standard set (Cole and Grossman, 2003). The second one is related to its inflexibility. Requiring the same standard for all polluters, as well as the same technology for pollution control could reduce the possibility for firms to change their production methods in a way that may decrease pollution even more and at a lower cost.

Therefore, depside the correcting instruments proposed, for the economists it is still an ongoing discussion on how sizable the costs of environmental damages are, and which political

[9] The public agent gives out "pollution rights" in the form of permits to companies that are emitting. The amount of each permit is based on a company's history of pollution. The organization that pollutes handed out this permission from the government without paying. The polluter has the right to sell to the other polluters the proportion that has managed to reduce. See link: https://www.ejnet.org/rachel/rehw442.htm

[10] The Coase theorem claims that: "*in the front onto the market inefficiencies following from externalities, private citizens (or firms) can reach a beneficial agreement and a socially desirable solution as long as there are no costs related to the negotiation process*". An agreement on externalities issues can be reached even without government intervention (Coase, 1960).

[11] Generally, with command-and-control regulation, the government commands the industries to meet certain environmental standards, including directly through legislation or indirectly through delegated authority, and controls their behavior through different sanctions (Sinclair, 1997).

actions are appropriate to encounter it. According to Gallegati (2018), monetizing the environmental damage can be extremely difficult to evaluate, essentially for two reasons. The first reason is related to the difficult to better detect the cause-and-effect relationships. The second reason is associated with the fact that damage often becomes apparent years later or far from the source. Computing the cost of damages is challenging when we have to distinguish between direct and indirect environmental damages (Shechter et al., 1989). Quantifying the cost of indirect damage, such as those caused by climate change, is even more problematic than the quantification of the direct damage done by human during production activities (Gallegati and Danovaro, 2019). Assigning the right social costs of pollution to firms is still an unclear and continuing argument between economists and policymaker.

2.2 Environmental regulation and the productivity growth

Despite the benefits, environmental regulations provide to society in the form of improved environmental conditions and quality of life, concerns remain about how pollution abatement affects the economic viability of firms, industries, and countries. More stringent environmental regulations increase the production costs of firms which, in turn, could cause a loss of productivity and competitiveness. The emphasis on moving toward green growth and sustainable industrial production process has generated debates on how environmental regulation policies can be optimal by comparing the cost and benefit of this regulation. The literature on the productivity effects of environmental regulation is sizable and the subject of several survey articles. Most existing empirical studies are heterogeneous and developed mainly in the context of national and firm-level data. However, the empirical findings of these studies are typically very context-specific and are focused on commonly used indicators of economic performance, such as Multifactor or Total Factor Productivity (TFP).

Among the early studies Meyer (1992) and later on Mayer (1996) discovered a positive, statistically insignificant correlation between stricter environmental policies and State economic growth. Jeon and Sickles (2004) using a sample of 17 OECD countries and 11 Asian countries, apply the Joint Production Model (JPM) to compute the Malmquist-Luenberger productivity index. During their ten-year period of study, 1980-1990, the productivity increase on average by 1.16 percent for the OECD country when the CO_2 is included in the model as a by-production output. Instead, the Asian economies on average show little apparent effect of environmental regulations. Yörük and Zaim (2005) employed both the Malmquist (M) index and Malmquist-Luenberger (ML) index and decomposed sources of productivity change (technical changes and efficiency changes) to analyse productivity growth in OECD countries during 1985–1998. They found that on average the ML index measures an increase in productivity growth of 1.2 percent. Wu and Wang (2008) also employed both M and ML index to compute productivity growth. Using a sample of 17 APEC countries and concentrating their analysis on a period of fifteen years, 1989-2004, the authors conclude the average TFP growth is slightly higher when environmental regulations are taken into consideration compared to the average TFP growth without taking into consideration environmental regulations. Ho (2010) employed the Global Malmquist-Luenberger (GML) index to measure environmentally sensitive productivity growth of 26 OECD countries from 1990 through 2003. The author found the GML index yields a lower productivity growth relative to the standard productivity growth measurement (M index). In a more recent paper, Wang et al., (2019) used panel data of 24 OECD countries and an extended Slack Based Model-Directional Distance Function (SBM-DDF) approach to estimate the ML index. Furthermore, the author using a system Generalized Method of Moments (GMM) method for analyzing the relationship between environmental regulation and green productivity growth (i.e., ML index which include the CO_2 emissions). They conclude that environmental regulation stimulates the green productivity growth in OECD countries.

Berman and Bui (2001) used plant-level data for oil refineries (SIC 2911) in the United States to investigate the productivity effect. To estimate the effects of regulation on productivity, the author coded regulations as a set of binary indicators and ran a regression model. They found that during 1982–1992, productivity for the heavily regulated South Coast (Los Angeles) refineries was 5 percentage points higher than the (declining) national average. Gray and Shadbegian (2003) in their study on plant-level data (i.e., 116 pulp and paper mills) in the United States, used a Generalized Method of Moments (GMM) model to analyse the effect of pollution abatement activity on productivity. The authors discovered the plants with higher pollution abatement activity have significantly lower productivity. Yu et al. (2008) examined the productivity growth of Taiwan's airport sector by studying the operations of four airports during the period from 1995 to 1999. They used a modified Malmquist–Luenberger productivity index to accommodate the presence of aircraft noise caused by the airport's activities. They found the annual productivity growth of Taiwan's airports is 8.0% over this period and ignoring the reduction in undesirable outputs in traditional productivity analysis may seriously bias such upward growth. Lee, Wilson, Pasurka (2015) use the Joint Production Model (JPM) and employed the Malmquist-Luenberger productivity index to examine the consequences of environmental regulation on productivity growth. From their analysis, they found that pollution abatement activities lower productivity growth.

For industries, we find studies that deal with the trade-off between productivity growth and environmental regulations. We focus of these studies is the manufacturing sector. Conrad and Wastl (1995) while investigating 10 manufacturing industries in West Germany from 1975 to 1991, found a decline in total factor productivity due to pollution abatement activities. Similarly, Dufour, Lanoie, and Patry (1998) investigated the consequences of environmental regulation on 19 manufacturing industries in Quebec. Measuring total factor productivity by the Törnqvist index and running a generalized least-square (GLS) procedure based on the cross-sectionally and time-wise autoregressive model, the authors discovered a declining total factor productivity. Domazlicky and Weber (2001) applied a Malmquist-Luenberger (ML) index to a dataset consisting of the manufacturing sectors for 48 states in the USA for a period from 1988 to 1994 and found an increase in state manufacturing productivity of 1.40 percent annual growth rate when toxic releases were accounted for when estimating the production technology. Tsai (2002) examined the period between 1987 and 1997 and computed the total factor productivity for 15 manufacturing industries in Taiwan. Applying a dynamic production model to estimate both total factor productivity and the direct and indirect productivity effects of environmental regulation, the author found the environmental regulation had uneven effect on Taiwan's manufacturing industries. The author found this irregular productivity growth impacting manufacturing industries depends on their market structure, industry characteristics, number, and size structure of plants and factor shares. Aiken et al. (2009) employed the assigned input model to investigate the association between pollution abatement and productivity for eight manufacturing industries in Japan, the Netherlands, Germany, and the United States. The authors found there were negligible effects on the manufacturing sectors in Japan and the Netherlands, while annual productivity growth declined by 0.11 percent in the United States and increased by 0.24 percent in Germany. Chen, Lan, Gao, and Sun (2018) examined 36 industries in China between 2000 and 2014, using the global Malmquist-Luenberger (GML) index. According to their results, using energy consumption and environmental undesirable outputs, the industrial adjusted total factor productivity (TFP) declines by 0.02% per year on average compared to traditional total factor productivity.

Among those studies that deal with the industrial sector, we are aware of only four cross-country studies on the productivity effects of environmental regulation. The U.S. Congressional Budget Office (1985) investigated the effect of abatement activities on the manufacturing sectors of Germany, Japan, and the United States and found that the pollution abatement activities reduce the output. Focusing on the manufacturing sectors of Canada, Germany, and the United States, Conrad and Morrison (1989) analyzed the tradeoffs between pollution abatement and productivity. As for Germany and the United States, Valentini (2003) studied the effect of abatement capital expenditures on TFP growth in several manufacturing sectors between 1971 and 1991. Finally, Aiken et al. (2009) investigated the consequences of pollution abatement on productivity in eight manufacturing industries in Japan, the Netherlands, Germany, and the United States using the "assigned input" model.

2.3 The measure of productivity

In its simple definition productivity is defined as the ratio of its output to its input (Fried et al., 2008). The definition becomes more complicated in multiple outputs and inputs cases, where we must assign weights to both, the numerator and denominator in the calculation (Hampf, 2013). As the main source of economic growth and competitiveness, productivity is largely used on evaluating the performance of input used in the production process, such as labor, capital, and multiple inputs performance measurement (OECD, 2011). We focus our analysis in evaluating the Multiple or The Total Factor Productivity (TFP), which is usually interpreted as a measure of technological progress, summarizing how intensively and efficiently inputs are used and organized in the production process.

TFP is an indicator that belongs to the Growth Accounting theory which came to prominence in the 1950s and early 1960s notably through the work of the National Bureau of Economic Research on long-run trends in the American economy (Crafts and Woltjer, 2019). Growth Accounting theory allows for the breakdown of observed growth of GDP into components associated with changes in factor inputs and production technologies (Tzouvelekas et al., 2007). The basic elements that appear in modern theories of Growth Accounting have been provided from the classical economists (e.g., Smith, 1776; Ricardo, 1817; Malthus, 1798; Ramsey, 1928; Young, 1928; Knight, 1944; Schumpeter, 1934) and are largely used nowadays in the economic growth analysis (Barro J. R. et al., 2004). Important economists' studies (e.g., Harrod, 1939; Domar, 1946; Ramsey, 1950; Solow, 1956; Swan, 1956; Denison, 1962; Jorgenson and Griliches, 1967) have extended the classical growth theoretical model for understanding the main factors that drives economic growth. Generally, what emerges from their theoretical model was that the economic growth was resulting from the accumulation of human and physical capital (Lucas, 1988). However, it was empirically observed that positive rates of per capita growth can persist over a century or more (Solow, 1957), and a substantial fraction of this growth rate was not accounted for by the growth rates of measured inputs (conventional labor and capital measures) (Fabricant, 1954; Abramovitz, 1956; Solow, 1957; Kendrick, 1976). Solow (1957) addressed this long-run per capita growth rate not explained by the growth rate of the input to the technological progress (TFP) that was outside their model. After the work of Solow (1957) and Denison (1962, 1967), a substantial role was assigned to technological progress, and it became central to the Growth Accounting approach (Barro J. R. et al., 2004).

The estimation of the correct TFP is a crucial issue in economics and is the fundamental theme of many papers (e.g., Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; Verschelde et al., 2014; Ackerberg, Caves and Frazer, 2015; Silveira et al., 2021). The popular tools for the estimation of the TFP can be divided into three principal groups of similar approaches that include parametric, non-parametric, and semi-parametric techniques.

The parametric models employ predetermine functional forms (mostly translog) of the production/cost/distance function and use the regression models[12] taken from the econometric fundamentals for productivity estimation (Felipe and McCombie 2019). Furthermore, the parametric model can be divided into deterministic and stochastic approaches (Hampf, 2013). The most used deterministic frontier models in productivity and efficiency analysis are the Ordinary Last Squares (OLS), Corrected Ordinary Last Squares (COLS), and Modified Ordinary Last Squares (MOLS) (Bournakis and Mallick, 2018). Those three approaches attributed the distance between an observation and the efficiency frontier to statistical noise or inefficiency, respectively. The main problem with this technique is related to the fact that doesn't account for random errors (Hampf, 2013). Therefore, the stochastic parament method -Stochastic Frontier Analysis (SFA)- which allows for two-part error term estimation, comes

[12] For more details on how to estimate TFP through the regression model see Felipe and McCombie (2019).

about for eliminating the gap of the previously mentioned technique (Pires and Garcia, 2011). SFA measures a noise term that accounts for the deviation from the frontier due to measurement error and an efficiency term that captures deviation due to the inefficiency of the observations (Hampf, 2013). The analysis of the trade-off between environmental regulation and productivity is very limited in the literature on SFA and deterministic frontier analysis due to the specification of the functional form. The literature is limited to considering the environmental aspects as input in the general model.

Instead, regarding the semi-parametric approach, one of the most used is the stochastic non-parametric envelopment of data (StoNED) proposed by Kuosmanen and Kortelainen (2012). StoNED was developed to overcome the limitations of the non-parametric and SFA model by correcting the issues of the right functional form and like SFA by assuming that the residuals are a combination of random error and the inefficiency of the observation (Kuosmanen, 2006). The second block of the semi-parametric approach is that proposed by Olley and Pakes (1996), Levisohn and Petrin (2003), and Ackerberg et al. (2015) which rely upon two-step estimations as well and are designed to address simultaneity bias between unobserved productivity and selection of inputs (Bournakis and Mallick, 2018). A serious disadvantage of the above-mentioned technique is the impossibility to include multiple outputs in the analysis, making those models unfit for environmental analysis which usually employs two or more outputs in the analysis (good and bad outputs).

Differently, the non-parametric approaches do not establish a predetermine function form of the production/cost/distance function. The main deterministic non-parametric approach is the "Data Envelopment Analysis" (DEA) proposed by Charnes et al. (1978). In their paper, the authors solve the problem of productivity measurement by assigning exogenous weight to the amount of output and amount of the input and employ a linear programming problem to estimate productivity. Many authors have used DEA in their work and a large amount of both, empirical applications, and theoretical extensions of DEA, have been published. From a statistical point of view, the most important contribution to the literature was given by Daraio and Simar (2007). Simar and Wilson (1998) developed a bootstrap technique to correct the bias arising from the "curse of dimensionality". Moreover, Wilson (1993, 1995) and Simar (2003) proposed several methods to detect the outliers in the non-parametric technology. Despite, the limitation and the non-statistical interpretation of the results, the DEA remains an important tool for productivity analysis. One of its advantages is that it is suitable for multiple outputs analysis.

Diewert (1981) in his classification of the approaches for productivity measurement also listed the nonparametric indices and the exact index numbers technique. The index numbers[13] have been the most commonly used instruments for the measurement of the growth rate of the

[13] An index number is defined as a real number that measures changes in a set of related variables and they are the most important instruments in measuring changes in levels of various economic variables. In the case of productivity changes measurement, the index numbers are used for computing changes in the level of output produced and the level of input used in the production process across two firms or over two time periods (Coelli et al., 2005).

TFP over time (i.e., measurement of changes in total factor productivity over time and space) (Coelli et al., 2005). The Laspeyres and Paasche index numbers, as well as the Fisher index and Törnqvist index, have the longest and most distinguished history in economics and their contributions date back to the late nineteenth century (Rao, 2004). The computational methods used in deriving an index of TFP (TFP index[14]), either over time or across firms or enterprises are based on the Fisher index and the Törnqvist index. The TFP index may be applied to binary comparisons, where we wish to compare two time periods or two cross-sectional units, or it may be applied to a multilateral situation where the TFP index is computed for several cross-sectional units. In the literature, two types of factor productivity indices are popular and central in several studies, the Hicks-Moorstee TFP index (e.g., O'Donnell, 2008; Briec and Kerstens, 2011; Yang, 2012; Wang and Chen, 2015; Yuan, 2016; Lao and Mo, 2018) and the Malmquist TFP index (e.g., Färe et al., 1994; Ray and Des, 1997; Krüger, 2003; Coelli and Rao, 2005; Kortelainen, 2008; Iliyasu et al., 2014; Nwanosike et al., 2016; Zrelli et al., 2020). The main advantages of this approach are twofold. On one hand, they avoid the usual econometric bias in the estimation of production input parameters, and on the other hand, they have a degree of flexibility in accommodating different underlying production functions (Bournakis and Mallick, 2018).

Furthermore, there is no shortage of studies either that have been introduced in the Growth Accounting (AG) framework the environmental issues. The environment in this theoretical approach has been traded as a factor of production that is not fully compensated and its use in the production process can be captured by introducing it (in many cases is the emission) as an input in the aggregate production function (Becker, 1982; Tahvonen and Kuluvainen, 1993; Bovenberg and Smulders, 1995; Smulders and Gradus, 1996; Mohtadi, 1996; Xepapadeas, 2005; Brock and Taylor, 2005; Tzouvelekas et al., 2007). This way to treat the environment in this approach is related to the fact that the production of goods becomes more costly if environmental issues are introduced (i.e., less pollution is allowed) (Tzouvelekas et al., 2007). However, in the standard growth accounting framework some studies model the environmental issues by using the by-production concept. As, undesirable outputs (bads output) are often produced together with desirable outputs (goods output) different authors (Färe et al., 1994; Chung et al., 1997; Jeon and Sickles, 2004) have tried to model the consequences of environmental factors give rise to a new framework- the Joint Production Model (JPM)- in the standard economic production models.

The most used tools in the estimation of the adjusted total factor productivity growth[15] (ATFP) are, the Data Envelopment Analysis (DEA) framework (e.g., Yörük and Zaim, 2005; Yu et al. 2008; Fleishman et al. 2009; Lee, Wilson and Pasurka 2015; Wang, and Shen 2016; Wu, et al. 2019) and the second one is related to the test of the Porter hypothesis (PH) which use

[14] Generally, the total factor productivity index is the ratio of an Output Index (i.e., the change in production quantities in a given period) and an Input Index (the relative change in inputs utilized to produce them). For more details on the TFP indexes see Coelli et al., (2005).

[15] The adjusted total factor productivity growth refers to the simple modification of the traditional total factor productivity which includes the by-productions of the undesirable output. We calculate it here by the ML index.

regression model as the main tools (e.g., Murty and Kumar, 2003; Rubashkina et al., 2015; Ramanathan et al., 2017; Zefeng et al., 2018; Martínez-Zarzoso, et al. 2019; Wang and Lin, 2022).

3. General concepts

In the following section, we present a short summary of the theoretical foundations and the methodology of the non-parametric productivity and efficiency analysis. First, we describe the traditional and environmental production technologies by introducing the general assumption and the fundamental axiom. Second, we define the directional distance function and explained how it can be computed using the standard linear programming model. Third, we describe how the Malmquist-Luneberger index is constructed and how it can be measured. The general theoretical and empirical concepts are taken from the approach proposed by Färe et al. (1994), Färe and Primont (1995), and Chung et al. (1997).

3.1 The production technology framework

A production technology set T, which contains the inputs, $x \in \mathbb{R}_+^N$, and outputs (goods), $y \in \mathbb{R}_+^M$, can be presented in the following definition

$$T = \{(x, y) \in \mathbb{R}_+^{N+M} : x \; can \; produce \; y\} \tag{2.1}$$

In the general framework, the production set is composed of the set of all feasible input and output vectors combinations $(x\,, y)$. This technology can be equivalently represented by the input correspondence $L = \mathbb{R}_+^M \rightarrow 2^{R_+^N}$ with the following definition

$$L(y) = \{(x) \in \mathbb{R}_+^N : (x, y) \in T\} \tag{2.2}$$

The set $L(y)$ denotes the collection of all input vector $(x) \in \mathbb{R}_+^N$ that yield at last output vector $(y) \in \mathbb{R}_+^M$. The technology can be represented by the output correspondence as well, $P = \mathbb{R}_+^N \rightarrow 2^{R_+^M}$ in the following definition

$$P(x) = \{(y) \in \mathbb{R}_+^M : (x, y) \in T\} \tag{2.3}$$

The set $P(x)$, also called the *Output set,* denotes the collection of all output vectors $(y) \in \mathbb{R}_+^M$ that are obtainable from the input vector $(x) \in \mathbb{R}_+^N$. Even though the input set and the output set model the same production technology, they underline different aspects of the technology. They correspondently, model the input substitution and output substitution. The common feature of the input and output set is that they provide a representation of the technology in terms of input quantities and output quantities.

The technology set must satisfy the following axioms[16] in order to construct the correct representation of the economic behavior of the firm:

1. No free lunch: $(x\,,y) \notin T$ if $x = 0 \wedge y \geq 0$
   According to this axiom specification, a producer cannot produce a positive amount of any output without using positive amounts of at least one input.

2. Strong disposability[17] of inputs: If $(x\,,y) \in T$ and $x' \geqq x$ than $(x', y) \in T$
   The second axiom means that for any given combination of $(x\,,y)$ the same amount of output can be produced by using the more input.

3. Strong disposability of outputs: If $(x\,,y) \in T$ and $y' \leqq y$ than $(x, y') \in T$
   The given axiom means that for any given combination of $(x\,,y)$ it is possible to produce less output by holding the input constant.

4. Convexity: T is a convex set.
   Suppose we have (x^0, y^0) , $(x^1, y^1) \in T$, $(x^0, y^0) \neq (x^1, y^1)$. The convex combinations[18] of the observations are attainable. So, $\alpha(x^1, y^1) + (1-\alpha)\,(x^0, y^0) \in T$, $\forall \alpha \in [0,1]$.

5. Closeness: T is a closed set.
   If we assume that T is a closed set this means that: if $(x^\ell, y^\ell) \rightarrow (x^0, y^0)$ and $(x^\ell, y^\ell) \in T$ for all ℓ, then $(x^0, y^0) \in T$.

Instead, the "upper" boundary of a close technology set is of specific interest for economists when they do productivity and efficiency analysis. The "upper" boundary is also called the production frontier of technology. Herberg (1973) gives a simplified definition of the "upper" boundary of a closed set. The author defines the "upper" boundary Ž of a closed set Z as Ž $= \{\, z : z \in Z$ and $z' > z$ implies $z' \notin Z \,\}$.

The above technology describes a production process that does not account for environmental analysis. When we have to deal with environmental productivity and efficiency analysis, we should specify the presence of the by-production of the undesirable output, e.g., emissions, or add an additional input that is directly related to environmental damage. In our analysis we

[16] See Färe et al. (1994) and Färe and Primont (1995) for a further explanation of the presented axioms.
[17] Disposability generally indicates the ability to stockpile or discard or dispose of unwanted commodities. In the convectional literature, we find types of disposability of interest: the strong disposability which refer to the ability to dispose of an unwanted commodity with no private cost, and the weak disposability which refers to the ability to dispose of an unwanted commodity at a positive private cost (Färe et al., 1994). The differences between strong and weak disposability of the outputs are reported in Appendix A.1.
[18] For a detailed explanation and proof of the convex assumption see Herberg (1973).

follow Färe and Grosskopf (1983) and Färe et al. (1994) approach in presenting the environmental technology set. Based on JPM, firstly proposed by Ayres and Kneese (1969) and Leontief (1970), the authors modeled the environmental technology set to incorporate the undesirable outputs[19] as a by-production with the good outputs. The undesirable output must be introduced in the technology set with the weak disposability assumption of outputs because we cannot consider it as normal conventional output. Assuming strong disposability of the outputs when one of the outputs is "bad" is not logical and realistic because discarding the "bads" is costly for the firms. Strong disposability of the outputs implies that: if $(x, y, b) \in T$ then $(x, y, 0) \in T$, which means that it is possible to break down completely the undesirable outputs without any costs. To overcome this problem new axioms have been introduced which permit the technology set to correctly incorporate the undesirable outputs.
Indeed, the environmental production technology $T^E \subset \mathbb{R}^{N+M+I}$, which accounts for undesirable outputs, $b \in \mathbb{R}_+^I$, production can be defined as follow

$$T^E = \{(x, y, b) \in \mathbb{R}_+^{N+M+I} : x \; can \; produce \; (y, b)\} \tag{2.4}$$

with the input sets

$$L(y)^E = \{(x) \in \mathbb{R}_+^N : (x, y, b) \in T^E\} \tag{2.5}$$

and the output set

$$P(x)^E = \{(y, b) \in \mathbb{R}_+^{M+I} : (x, y, b) \in T^E\} \tag{2.6}$$

The axiom of weak disposability of outputs which was introduced by Shephard (1970), is used by Färe and Grosskopf (2003) to incorporate the bad outputs into the production technology. It assesses that it is only possible to produce less bad outputs if the amount of the good (desirable) outputs is decreased by the same proportional and is presented in the axiom six.

6. If $(x, y, b) \in T^E$ and $\theta b \leqq b$ with $0 \leqq \theta \leqq 1$ then $(x, \theta y, \theta b) \in T^E$

[19] Environmental economists often treat undesirable outputs (e.g., air emissions) as an additional input (see Cropper and Oates, (1992)). As Färe and Grosskopf (2003) underline, this leads to a physically impossible technology. Given a fixed number of conventional inputs and good outputs the assumption of strong disposability of inputs would allow increased emissions without limits. Moreover, as noted by Førsund (2009) the assumption of strong disposability of inputs allows for substitution possibilities between conventional inputs and emissions which are modeled as inputs.

The desirable and undesirable outputs, together with the statement of the weak disposability are supposed to be null-joint:

7. Null-jointness: If $(x, y, b) \in T^E$ and $b = 0$ then $y = 0$

This last axiom simply states that it is impossible to produce positive number of desirable outputs without producing any undesirable outputs.

3.2 Directional Distance function

The single-output production function is the traditional starting point of the economic models of technology. Different parametric functions[20] (e.g., the Cobb-Douglas, the Constant Elasticity of Substitution (CES), and the Translog function) have been widely employed in several empirical works. However, the parametric representations available for single-output production functions are not suitable and convenient when we model multi-output multi-input technology (Färe and Primont, 1995). By using the nonparametric input and output distance functions we can model multi-output multi-input technologies, and, at the same time, represent them with convenient functional forms. The most widely applied distance function, which measures the radial distance from the frontier, is the Shephard distance function (see Shephard (1970) and can be defined as the Shephard outputs distance function

$$D_0(x, y) = inf\{\theta : (x,\ y/\theta) \in T\} \tag{2.7}$$

and Shephard input distance function

$$D_I(x, y) = sup\{\emptyset : (\ x/\emptyset\ , y) \in T\} \tag{2.8}$$

The above functions measure efficiency radially. Specifically, given an input orientated model all inputs can be reduced with the same proportion until the frontier is reached. Identically, in the case of an output-oriented model, all outputs are increased by the same proportion to reach the frontier. An observation in the technology set is defined as input efficient (inefficient) if

[20] Several studies have developed and improved the production functions adapted using different types of variables, such as labor productivity (Sarbu, 2017; Feng et al., 2018), sustainability (Husniah &Supriatna, 2016; Liu et al., 2016; Wei et al., 2020; Zhang et al., 2020), knowledge proxies (Hidalgo and Hausmann 2009; Elmawazini, 2014; Bhattacharya et al., 2021), and energy (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; Ackerberg, Caves and Frazer, 2015; Mirza et al., 2021).

$D_0(x, y) = 1\ (< 1)$ and output efficient (inefficient) if $D_I(x, y) = 1\ (< 1)$. These distance functions can be calculated using the DEA model. Therefore, in presence of undesirable output, these models are less suitable because an increase in good output will proportionally increase the undesirable output. Reaching the frontier by increasing the undesirable output is not efficient from an environmental point of view. An appropriate and more flexible approach that allows modeling joint production of good and bads outputs with the environmental efficiency is the directional distance function (DDF). This method has been proposed by Chambers et al. (1996) who based on the work by Luenberger (1992) introduced the input oriented DDF for efficiency measurement. The directional input distance function proposed by the authors can be defined as

$$\vec{D}_I(x, y; g) = sup[\beta \in \mathbb{R}: x - \beta g \in L(y)]$$

$$= sup[\beta \in \mathbb{R}: x \in \beta g + L(y)] \qquad (2.9)$$

where g denotes the direction vector[21], which allows for a maximal translation of $L(y)$ along g that permits keeping x feasible. The directional output distance function is defined as

$$\vec{D}_M(x, y; g) = max\big[\beta: (y + \beta g_y \in P(x)\big] \qquad (2.10)$$

where $g_y \in \mathbb{R}_+^M$, denotes the directional vector that indicates the pathway of output expansion. From this specification we can measures each observation's distance, given the selected direction, to the production frontier. Furthermore, for observations on the frontier, $\vec{D}_M(y, x; g) = 0$ and for any observation below the frontier $\vec{D}_M(y, x; g) > 0$, which denote the inefficiency point. The strength of the directional output distance function is that it accommodates both proportional and non-proportional output expansion, while the Shephard output distance function is restricted to a radial measure of efficiency.

Chung et al. (1997) have extended the Chambers et al. (1996) approach to an output-oriented consideration by incorporating undesirable outputs. In this arrangement the vector of

$$g = \binom{g_y}{g_b} \in \mathbb{R}^{M+I} \qquad (2.11)$$

has been included to define the direction of the efficiency analysis. Introducing the directional vector, the directional distance function (DDF) is definite as

[21] Chambers et al. (1996) describe the notion of a direction as follow: Let x and g be fixed vectors in $\mathbb{R}_n$, then $z = x + \beta g,\ \beta \in \mathbb{R}$, defines a line in the direction of g.

$$\overrightarrow{D_0}(x, y, b: g) = sup\left\{\beta: \left(x, y + \beta_{g_y}, b - \beta_{g_{yb}}\right) \in T\right\} \quad (2.12)$$

where β indicate the efficiency measure asserting how much the desirable outputs can be increased and simultaneously the undesirable outputs can be decreased following the respectively the direction g_y and g_b, holding inputs constant. The DMU that is in the frontier $\overrightarrow{D_0}(x, y, b: g) = 0$ are denoted as efficient DMU and the DMU located fare from the frontier $\overrightarrow{D_0}(x, y, b: g) > 0$ are denoted inefficient DMU. Instead, the output correspondence distance function can be defined as

$$\vec{D}_0\,(x, y, b: g) = sup\{\beta: (y, b) + \beta_g \in P(x)\} \quad (2.13)$$

where the direction vector can be chosen $g = (y, -b)$ in order to increase the good outputs and decries bad outputs proportionally. In the analysis the direction vector g is not predetermined and usually is chosen by the researcher. In the environmental direction distance function, the most used vectors are $g = (y, -b)$ which are given by the amount of observed desirable and undesirable outputs of the given DMU (Hampf, 2013). The measurement of the DDF can be achieved by solving a set of nonparametric linear programming problems. The distance function of observation k' is constructed as:

$$\vec{D}_0\big(\mathrm{x}\,(\mathrm{k}'), \mathrm{y}(\mathrm{k}'), \mathrm{b}(\mathrm{k}'); \mathrm{y}(\mathrm{k}'), -\mathrm{b}(\mathrm{k}')\big) = \mathrm{Max}\ \beta(\mathrm{k}') \quad (2.14)$$

$$\mathrm{s.t}\ \sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z}\,(\mathrm{k})\mathrm{y}_m(\mathrm{k}) \ \geq (1+\beta)\mathrm{y}_m(\mathrm{k}') \qquad \mathrm{m} = 1, \dots, \mathrm{M}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z}\,(\mathrm{k})\mathrm{b}_i(\mathrm{k}) \ = (1-\beta)\mathrm{b}_i(\mathrm{k}') \qquad \mathrm{i} = 1, \dots, \mathrm{I}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z}\,(\mathrm{k})\mathrm{x}_n(\mathrm{k}) \ \leq \mathrm{x}_n(\mathrm{k}') \qquad \mathrm{n} = 1, \dots, \mathrm{N}$$

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{z}\,(\mathrm{k}) \ \geq 0 \qquad \mathrm{k} = 1, \dots, \mathrm{K}$$

The $z(k)$ are the weights assigned to each observation k when constructing a production possibilities frontier. The condition of positivity constraints on the intensity variable, $z(k)$, allows us to construct the model that exhibits constant returns to scale[22]. The inequality constraints on the good outputs, $m = 1,\ldots.,M,$ indicate they are freely disposable. Together with the equality constraints on the bad outputs ($i = 1,\ldots,I$), the bad outputs are not freely disposable.

For illustrating the directional distance function graphically, let consider the following figure, illustrated by Chung et al. (1997), which represent the technology by an output set.

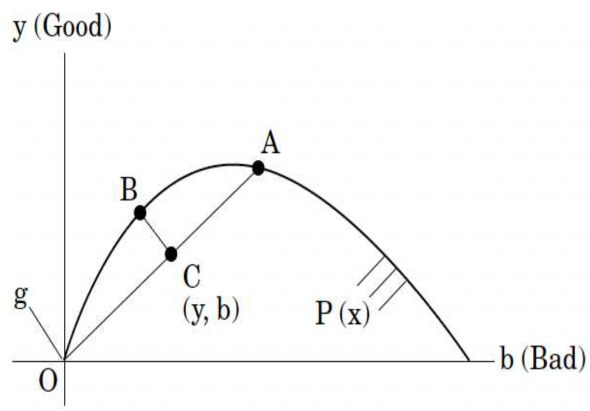

Figure 2.1 Distance functions

Where $P(x)$ denotes the output set, the good output by y and the bad by b. The outputs (y, b) are weakly disposable and y by itself is strongly disposable and they satisfy the above axioms. Using Shephard's distance function, the output vector (y, b) will be placed on the boundary of $P(x)$ at A, and yields a value of OC/OA, i.e., the firm will be efficient if goods and bads were both increased by a factor of OA/OC. Differently, the directional distance function will scale in the direction of increased desirable outputs and decreased undesirable outputs and projects the observation C on the boundary at B. This corresponds to the amount of expansion and contraction equal to the distances (BC/Og).

3.3 The Malmquist-Luenberger productivity index

Malmquist-Luenberger (ML) productivity index is an index that is based on the directional distance function and is a further modification of the Malmquist (M) index. The advantages of ML index over the traditional growth accounting or Törnqvist, Paasche, or Laspeyers index-type productivity measurement consists in the possibility to measure technical inefficiency, it does not presume optimizing behavior, it does not require data on prices, and it allows for multiple outputs without aggregation. It has also computable advantages because it does require strong statistical assumption and it is easy computed by the linear programing model.

[22] Färe and Grosskopf (1996), argue that constant returns to scale is a necessary condition form the resulting productivity indexes to be true total factor productivity index.

The ML, as well as M index, is constructed with the dynamic approach of the direction distance function. With the dynamic approach we refer to introduction of time as another variable of analysis. In the previous section we present a DDF for a sample of n DMUs observed at one point in time. In this section the DDF is constructed with two period, t and $t+1$ and allow for both indices to compute changes in technology set from a period to another.

The first authors that analyses productivity changes using distance function was Caves et al. (1982)[23]. They developed two different version of indexes to analyses the productivity changes and compute the distance of a DMU from the best frontier as a benchmark in t and the best frontier as a benchmark in $t+1$. The first form of the Malmquist index using the technology of the period t as a benchmark is constructed as follow[24]

$$M^t(x_t\,, y_t\,, x_{t+1}, y_{t+1}) = \frac{\vec{D}_0^t(x_{t+1}, y_{t+1})}{\vec{D}_0^t\,(x_t, y_t)} \tag{2.15}$$

and the second form of the Malmquist index which uses the technology of the period $t+1$ as a benchmark is constructed as follow

$$M^{t+1}(x_t\,, y_t\,, x_{t+1}, y_{t+1}) = \frac{\vec{D}_0^{t+1}(x_{t+1}, y_{t+1})}{\vec{D}_0^{t+1}\,(x_t, y_t)} \tag{2.16}$$

Given that those two versions not necessary gives the same results, Färe et al. (1992) suggested the geometric mean of those two indexes for productivity changes analysis. Their composition of M index is defined as

$$M^{t,t+1}(x_t\,, y_t\,, x_{t+1}, y_{t+1}) = \left[\frac{\vec{D}_0^t(x_{t+1}, y_{t+1})}{\vec{D}_0^t\,(x_t, y_t)} * \frac{\vec{D}_0^{t+1}(x_{t+1}, y_{t+1})}{\vec{D}_0^{t+1}\,(x_t, y_t)}\right]^{1/2} \tag{2.17}$$

They further decompose the M index in tow indexes. The technical changes index which is the geometric mean of the shift in the production possibilities frontier is defined as

$$MTCH^{t,t+1} = \left[\frac{\vec{D}_0^t(x_t, y_t)}{\vec{D}_0^{t+1}\,(x_t, y_t)} * \frac{\vec{D}_0^t(x_{t+1}, y_{t+1})}{\vec{D}_0^{t+1}\,(x_{t+1}, y_{t+1})}\right]^{1/2} \tag{2.18}$$

---

[23] The name of this index refers to earlier works on index numbers by Malmquist (1953).

[24] In this notation the superscript for the index and the distance functions refers to the time period of the reference technology while the subscripts for the inputs and outputs refer to the time period of the analyzed input-output combination. Therefore, a mixed-period distance function is, for example, given by $\vec{D}_0^t(x_{t+1}, y_{t+1})$.

and the efficiency changes which measures the ratio of "how close" an observation is to its respective frontiers is defined as

$$MECH^{t,t+1} = \frac{\vec{D}_0^{t+1}(x_{t+1}, y_{t+1})}{\vec{D}_0^{t}\,(x_t, y_t)} \tag{2.19}$$

A graphically interpretation of the indexes is given by the Figure 2.2. Let suppose a production set at time t , S^t , and a production set at time $t+1$, S^{t+1} , and the observation (x^t, y^t) represented by the point F which belongs to S^t, and observation (x^{t+1}, y^{t+1}) represented by the point B which belongs to S^{t+1}. The technical progress is the geometric mean of the shift in the frontier measured at period $t+1$, $\left(\frac{OA}{OD}\right)$, and period t , $\left(\frac{OC}{OE}\right)$ and the changes in efficiency between the two periods is given by the ration among $\left(\frac{OB}{OA}\right)$, and $\left(\frac{OF}{OE}\right)$.

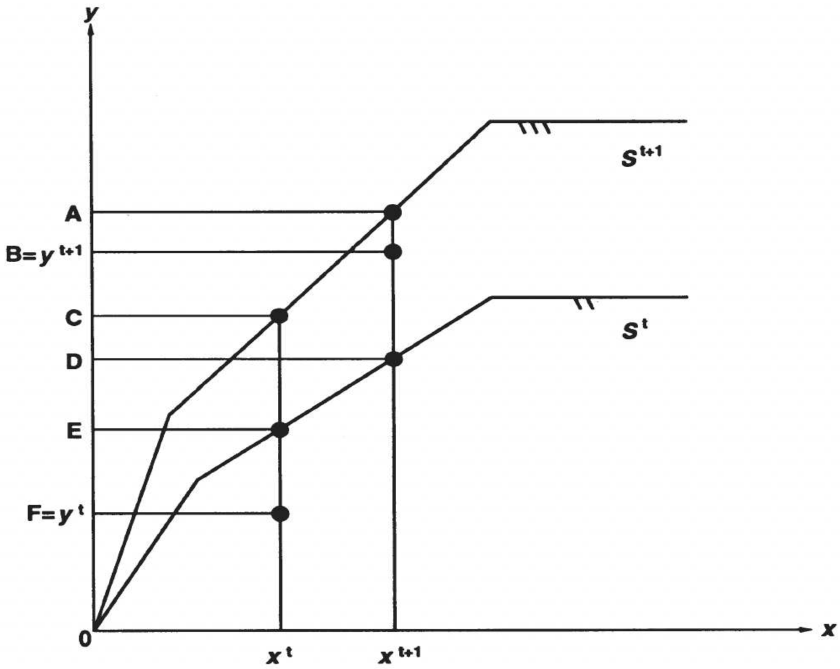

Figure 2.2 Malmquist productivity index

The value of the technical changes and efficiency changes larger than one indicates an improvement of the associated measure and a lower value indicate a decrease in technical changes and efficiency changes.

According to Chung et al. (1997) the Malmquist index could be a good tool on measuring the productivity when of the outputs is considered as undesirable output because it does not require information on prices. One of the strengthens of M index is the distance functions on which it is based on, that could lead in not well-define Malmquist index when we compute the mixt period distance function. Using the distance function does not allow for us for a proportionally decrease the bad and increase the good outputs. Chung et al. (1997) have proposed an extension on the Malmquist index incorporating the direction distance function. The new index, named output-oriented Malmquist-Luenberger index, correct the strengthens of Malmquist index and include the direction vector[25] $g_t = (y_t, -b_t)$. ML is defined as

$$ML_0^{t,t+1} = \left[\frac{\{1 + \vec{D}_0^t(x_t,\ y_t, b_t; g_t)\}}{\{1 + \vec{D}_0^t(x_{t+1,}y_{t+1}, b_{t+1};\ g_{t+1})\}} * \frac{\{1 + \vec{D}_0^{t+1}(x_t,\ y_t, b_t; g_t)\}}{\{1 + \vec{D}_0^{t+1}(x_{t+1,}y_{t+1}, b_{t+1};\ g_{t+1})\}}\right]^{1/2} \quad (2.20)$$

and indicates no change in productivity if it equals unity, $ML_0^{t,t+1} = 1$, an improvement in productivity if it is greater than one, $ML_0^{t,t+1} > 1$ and a decrease in productivity if is less than unity, $ML_0^{t,t+1} < 1$.The Malmquist–Luenberger index can be decomposed as

$$ML_0^{t,t+1} = MLECH_t^{t+1} * MLTCH_t^{t+1} \quad (2.21)$$

where $MLECH_t^{t+1}$ and $MLTCH_t^{t+1}$ denote technological changes and efficiency changes respectively. We can write technical and change efficiency change as

$$MLTCH_0^{t,t+1} = \left[\frac{\{1 + \vec{D}_0^{t+1}(x_t,\ y_t, b_t; g_t)\}}{\{1 + \vec{D}_0^t(x_{t,}y_t, b_t;\ g_t)\}} * \frac{\{1 + \vec{D}_0^{t+1}(x_{t+1},\ y_{t+1}, b_{t+1}; g_{t+1})\}}{\{1 + \vec{D}_0^t(x_{t+1,}y_{t+1}, b_{t+1};\ g_{t+1})\}}\right]^{1/2} \quad (2.22)$$

and

$$MLECH^{t,t+1} = \frac{\{1 + \vec{D}_0^t(x_t,\ y_t, b_t; g_t)\}}{\{1 + D_0^{t+1}(x_{t+1,}y_{t+1}, b_{t+1};\ g_{t+1})\}} \quad (2.23)$$

The technical progress (MLTCH) measures the shifts of the production possibilities frontier in the direction of "more goods and fewer bads", $MLTCH_t^{t+1} > 1$. If the $MLTCH_t^{t+1}$ index equals unity, this indicates there is no shift in the production possibilities frontier. If the $MLTCH_t^{t+1}$ index is less than unity, this indicates an inward shifting of the production frontier in the direction of fewer goods and more bads. Finally, $MLECH_t^{t+1}$ measures the ratio of "how close" an observation is to its respective frontiers. If efficiency changes exceed unity (less than unity), it indicates that the observation is closer (further) to the frontier in period *t+1* than it was in

[25] Briec (1995) specifies a distance function for the growth of the technology like Luenberger's shortage function. See Luenberger (1992a, 1992b, 1994a, 1994b, 1995a, 1995b).

period t. An efficiency index, MLECH, equal to unity indicates that the observation is in the same distance from the production frontier in period $t+1$ as it was in t. The graphical illustration of the output-oriented ML index is reported in appendix A.2.

4. Environmental regulation and green productivity growth: evidence from Italian manufacturing industries

4.1 Introduction

As it is reported in the literature, more stringent environmental regulations increase the production costs of firms which, in turn, could cause a loss of productivity and competitiveness. Imposing, environmental regulation, like market-oriented regulation or command and control regulation, incentives firms to move towards sustainable production by investing in new technologies and using renewable energy. The transaction towards a sustainable production is afforded differently from firms. Investing on green equipment requires extra funds and shifting of the existent recourses on activities that ensure reduction of the pollution and environmental problems. Indeed, this could generate elevated costs resulting in a loss of productivity. These additional costs have adverse consequences and could slow down also the propensity to renew and innovate the firms. Environmental regulation is an important determinant factor for firms' competitiveness, performance, and productivity (Knights et al., 2014; Huiban et al., 2018; Herman and Shenk, 2021), and must be designed properly by policymakers in order to take into account the above issue.

This chapter address this growing international debate on trade-offs between economic growth and environmental protection policies undertaken by governments in the Italian manufacturing industries by using Chung et al. (1997) approach. The Italian government in the context of the Sustainable Economic Development Plan has put emphasis on environmental protection. The Italian economy has made substantial progress in reducing air emissions: according to the ISPRA (Istituto Superiore per la Protezione e la Ricerca Ambientale), the level of CO_2 emissions from the manufacturing and construction sectors decreased up to 44% from 1990 to 2018. Even though the Italian economy has been under environmental regulatory pressure for a long time, only a few studies have addressed the trade-offs between environmental policy and productivity. Among these studies, the vast majority were focused on the national level. We find only two studies that analyze this trade-off in the Italian economy. The first is the work of Beltrán-Esteve, et al. (2019), which investigate 28 EU countries, including Italy. The authors found an improvement in adjusted productivity (modeling good and bad outputs) for Italy from the period 2001-to 2016. The second study is the Jeon and Sickles (2004) investigation where Italy was included as part of their OECD sample. Using the ML productivity index, the authors found an increase in adjusted productivity growth for the Italian economy during the period from 1980 to 1990. To the best of our knowledge, there have not been any studies on the productivity of Italian manufacturing industries that take into consideration environmental issues.

This chapter address this growing international debate on trade-offs between economic growth and environmental protection policies undertaken by governments in the Italian manufacturing industries by using Chung et al. (1997) approach. The reason why we take into consideration only the manufacturing sectors with its thirteen associated industries is twofold. The first reason is that the manufacturing sector produces 29.4 percent of GDP in 2017. Compared to the service it denotes a relevant part of the economic growth in Italy. The second reason is related to the quantity of the emission emitted into the atmosphere. The manufacturing sector and its associated industries generate 33.1[26] percent of the total CO_2 emission emitted in the Italian economy in 2019. It has a significant part in producing emissions compared to the construction and service sectors. We operationalize the model by applying the Malmquist-Luenberger index to a panel dataset of thirteen manufacturing industries in the Italian economy, using a three-output/three-input technology during the period from 1995 to 2017 respectively. For a whole picture of those effects, we measure and also reported the decomposition of the ML index, the technical progress, and efficiency changes.

This study contributes to the literature on the trade-off between environmental regulation and productivity growth in two directions. On the methodological aspects, it contributes by applying a modification of the undesirable outputs constraint for eliminating the infeasible problems. Following Färe et al. (2014) and Färe et al. (2016), we introduce a modified weak disposability assumption that imposes a less than or equal constraint on the undesirable outputs. We calculate the directional distance function by a linear programming model when the undesirable outputs constraint is modified compared to the traditional one proposed by Chung et al. (1997). On the policy implementation aspect, we give the first results on the consequences of the policy applied to the Italian manufacturing industries and we provide as well a deep clarification of which could be the drives of our outcomes.

The remainder of this chapter is organized as follows. We provide a description of the productivity index in Section 4.2. We present the framework, the DDF, and the further modification made to DDF, without reporting the ML index and its decomposition which has already been discussed in the previous chapter. In Section 4.3 we discuss the data and the results we get from our study. Section 4.4 provides some statistical results from bootstrapping and in Section 4.5 we discuss the conclusions.

[26] Link: https://stats.oecd.org/Index.aspx?DataSetCode=STANi4

4.2 Malmquist-Luenberger productivity index

Malmquist-Luenberger productivity index is an index that is founded on the directional distance function and uses a direction vector that treats the output (or input) asymmetrically. Our model is an output-oriented model, and we choose the direction to be g = (y^t, - b^t), which credits a producer for producing more good outputs and less bad outputs. The choice of this directional is related to the fact that there might be institutional regulations limiting an increase in bad outputs, specifically pollutant emissions. Chung et al. (1997) introduce the ML index arguing that it explicitly credits firms or industries for increasing good outputs and reducing undesirable outputs.

To explain the output-based productivity index, we are reporting the standard framework proposed by Chung et al., (1997). The first assumption is related to the production set. So, the production set P^t for each time period t = 1,…….,T transforms the inputs $x^t \in R^N_+$ into outputs, goods $y^t \in R^M_+$ and bads $b^t \in R^I_+$:

$$P^t(x) = \{(y, b): x \; can \; produce \; (y, b)\}, x \in R^N_+ \tag{4.1}$$

In the general framework, the production set is composed of the set of all feasible input and output vectors. So, for each input vector x^t, the output set P^t is composed of the total amount of good and bad outputs (y^t , b^t) produced by the input vector. To assess the problem related to the fact that the reduction of bad outputs is costly, in the general framework is imposed weak disposability of outputs, i.e.

$$(y^t, b^t) \in P^t(x) \text{ and } 0 \leq \theta \leq 1 \quad \text{imply} \quad (\theta y^t, \theta b^t) \in P^t(x) \tag{4.2}$$

This condition states a reduction of undesirable outputs can be achieved by a simultaneous reduction in the goods, given fixed input levels. So, if x^t can produce output (y^t, b^t), then it is feasible to reduce these outputs proportionally by θ. This axiom can be contrasted with the strong disposability condition:

$$(y^t, b^t) \in P^t(x) \text{ and } (y'^t, b'^t) \leq (y^t, b^t) \text{ imply } \left(y'^t, b'^t \in P^t(x)\right) \tag{4.3}$$

Imposing this condition allows for the non-proportional reduction in both good and undesirable outputs. Generally, we can costlessly dispose of the outputs. While this is acceptable for the good output, it dose not for the undesirable output when there are environmental policies. The assumption that the good outputs are freely disposable is constructed as follow,

$$(y^t, b^t) \in P^t(x) \quad \text{and} \quad y'^t \leq y^t \quad \text{imply} \quad \left(y'^t, b^t \in P^t(x)\right) \tag{4.4}$$

Together, equation (2) and equation (4) model the jointly weakly disposable between the good (freely disposable) and bad (not freely disposable) outputs. The authors also model the property that desirable and undesirable outputs are jointly produced introducing "null-joint." property. In other words, you cannot produce one without the other, i.e.,

$$\text{if} \quad (\theta y^t, \theta b^t) \in P^t(x) \quad \text{and} \quad b^t = 0 \quad \text{then} \quad y^t = 0 \tag{4.5}$$

The calculation of the Malmquist–Luenberger index is achieved by solving a set of nonparametric linear programming problems. The distance function of observation k' at time t is constructed using the time t frontier as:

$$\vec{D}_0^t\left(x^t(k'), y^t(k'), b^t(k'); y^t(k'), -b^t(k')\right) = \text{Max}\ \beta(k') \tag{4.6}$$

$$\text{s.t} \quad \sum_{k=1}^{K} z^t(k) y_m^t(k) \geq (1+\beta) y_m^t(k') \qquad m = 1, \dots, M$$

$$\sum_{k=1}^{K} z^t(k) b_i^t(k) = (1-\beta) b_i^t(k') \qquad i = 1, \dots, I$$

$$\sum_{k=1}^{K} z^t(k) x_n^t(k) \leq x_n^t(k') \qquad n = 1, \dots, N$$

$$\sum_{k=1}^{K} z^t(k) \geq 0 \qquad k = 1, \dots, K$$

The $z^t(k)$ are the weights assigned to each observation k when constructing a production possibilities frontier. The condition of positivity constraints on the intensity variable, $z^t(k)$, allows us to construct the model that exhibits constant returns to scale[27]. The inequality constraints on the good outputs, m = 1,...., M, indicate they are freely disposable. Together with the equality constraints on the bad outputs (i = 1,...,I), the bad outputs are not freely disposable. The calculation of ML productivity index requires solving four distance functions, $\vec{D}_0^{t,t}$, $\vec{D}_0^{t,t+1}$, $\vec{D}_0^{t+1,t}$, $\vec{D}_0^{t+1,t+1}$, which measure distance of an observation to the frontier. The distance functions for the mixed- period LP problems, $\vec{D}_0^{t,t+1}$, $\vec{D}_0^{t+1,t}$, can yield infeasible solutions if the observations are outside the production set (see Appendix B.1). For example, the production possibilities frontier constructed by the observations *t* may not contain

[27] Färe and Grosskopf (1996), argue that constant returns to scale is a necessary condition form the resulting productivity indexes to be true total factor productivity index.

on observation from period *t+1*. This would happen for those observations (country or producer) that are very innovative and their data at time *t+1* are located outside the current (period t) frontier. To avoid infeasible LP problems, we introduce a modification of the standard definition of the bad not being freely disposable, which is modeled in the production function via a strict equality constraint for the undesirable outputs. Following Färe et al. (2014), Färe et al. (2016) and Du et al. (2018), we impose a modified weak disposability assumption, which is modeled by changing the strict equality constraint to a less than or equal constraint on the undesirable outputs. This assumption was firstly introduced by the authors for eliminating the possibility of a downward sloping of the frontier. Modifying the equality to an inequality yields unbounded output sets and treats the undesirable output as not freely disposable. This will not lead to incorrect biases results because weak disposability holds even under strong or free disposability. The assumption has been proved by Färe et al. in their book published in 1994. Also, Cheng (2014) proved that using strong disposability of undesirable outputs will not bias the results and he recommended that strong disposability of bads should be applied when we use direction distance function (DDF) approach. According to Cheng (2014), using the disposability assumption will not lead to infeasible LP and will not bias results because the evaluated DMU will never be projected into the infinitely upward extension of the Production Possibility Set if we treat good and bad outputs asymmetrically (see Appendix B.2). This modified specification assumes that when the good output is optimal, it wouldn't be affected by producing fewer undesirable outputs and could also avoid the slack problem of equality for bad output sets effectively (Du et al., 2019). So, the linear programming model to be solved for observation k' at t will take the form

$$\vec{D}_0^t\left(\mathrm{x}^t(\mathrm{k}'), \mathrm{y}^t(\mathrm{k}'), \mathrm{b}^t(\mathrm{k}'); \mathrm{y}^t(\mathrm{k}'), -\mathrm{b}^t(\mathrm{k}')\right) = \mathrm{Max}\ \beta(\mathrm{k}') \tag{4.7}$$

$$\text{s.t} \quad \sum_{k=1}^{K} z^t(k) y_m^t(k) \geq (1+\beta) y_m^t(k) \qquad m = 1, \dots, M$$

$$\sum_{k=1}^{K} z^t(k) b_i^t(k) \leq (1-\beta) b_i^t(k) \qquad i = 1, \dots, I$$

$$\sum_{k=1}^{K} z^t(k) x_n^t(k) \leq x_n^t(k) \qquad n = 1, \dots, N$$

$$\sum_{k=1}^{K} z^t(k) \geq 0 \qquad k = 1, \dots, K$$

Where the mixed- period LP problem resembles Equation (12) except for the time superscripts on the right-hand side of the constraints that differs from the time superscripts on the left-hand side of the constraints. In other words, for output set from period t and observation from period t+1, the observation under valuation appears on the right-hand side of the constraints and the output set that is determined by all the observations from period t appears on the left-hand side of the constraints.

For comparison purposes, we also calculate the standard Malmquist (M) index, which is the one of the traditional indices we find in the literature for calculating the productivity growth without considering the undesirable output. Its algorithm is being reported in Appendix B.3. We are not reporting the ML index construction in this chapter because it was already introduced in the previous chapter.

4.3 Data and results

Operationalizing the model requires information on input quantities as well as good and bad output quantities. Specifically, we need data on the capital stock, number of employees, intermediate inputs, GDP, and air emissions for Italian manufacturing industries. We obtain the information needed from the OECD website, OECD STructural ANalysis (STAN) Dataset for Industrial Analysis [28]. The technology modeled in this study consists of one good output, Gross output, and two undesirable outputs – carbon dioxide (CO_2) and non-methane volatile organic compounds (NMVOC). We choose these two substances because of their contribution to climate change and health problems for humanity. The inputs consist of total hours worked by all employees for each manufacturing industry, net capital stock, and intermediate inputs. The intermediate inputs include all the inputs (others from capital and labor) that are consumed during the production process. These inputs include energy, materials, and service (including any rentals for machinery and equipment) (OECD, 2001).

Our sample consists of a balanced panel of thirteen manufacturing industries for the period from 1995 to 2017[29]. Table 1 presents summary statistics for our sample, while Appendix B.4 provides information and the trend of the desirable output, undesirable outputs.

Based on the KLEMS standard (capital (K), labor (L), energy (E), materials (M) and service (S) inputs)[30], the technology modeled in this study consists of the following variables:

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[28] Link: https://stats.oecd.org/Index.aspx?DataSetCode=STANi4

[29] We use data downloaded from OECD STAN dataset in January 2020 and September 2020. The current version of STAN is based on the International Standard Industrial Classification of all economic activities, Revision 4 (ISIC Rev. 4). Earlier versions of STAN were based on ISIC Rev. 3 and, prior to 2000, ISIC Rev. 2 (the latter covering the manufacturing sector only).

[30] EU KLEMS is an industry level, growth and productivity research project. Link: https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/eu-klems-capital-labour-energy-materials-and-service_en

(1) Capital input. We use the net capital stock in constant prices (price index 2015) in each industry as a proxy of capital stock. OECD STructural ANalysis (STAN) Dataset for Industrial Analysis, provides data for the net capital stock by industry.
(2) Labor input. The total number of employees is used as a proxy for the labor input. *OECD.stat* dataset provides data for labor input by activity.
(3) Intermediate input. We use the Intermediate input in constant prices (price index 2015) in each industry as a proxy for the Energy, Material, and Service input (including any rentals for machinery and equipment). According to the OECD, intermediate inputs represent the value of inputs into processes of production that are consumed within the accounting period.
(4) Desirable (good) output. We use Gross Domestic Production (GDP) in constant prices (price index 2015) as the proxy. *OECD.stat* is our source for data on GDP.
(5) Undesirable (bad) output. Taking into account data availability, we use the two substances emitted in greater quantities by each industry as the proxy. *OECD.stat* offers data on carbon dioxide (tons of pollution) and non-methane volatile organic compounds (tons of pollution) emissions from industrial processes and product.

Table 1. Descriptive statistic (Millions)

Year	Variable	Units	Mean	Std. Dev.	Minimum	Maximum
1995	Gross output	Euro	65789.15	35528.54	12522.5	119755.4
	Carbon Dioxide (CO_2)	Tonnes	1.39e+07	240008	4.18e+07	1.39e+07
	NMVOC	Tonnes	22392.7	4735	82038	22392.7
	Hours worked-employees	Hours	3.657.413	430.442	1.313.856	3.657.413
	Net Capital Stock	Euro	14268.94	6.613.189	48723.97	14268.94
	Intermediate input	Euro	27161.04	7.565.221	94309.69	27161.04
2017	Gross output	Euro	73595.38	41331.01	21873.77	142963.2
	Carbon Dioxide (CO_2)	Tonnes	6653660	8041646	228084	2.49e+07
	NMVOC	Tonnes	17795	12588.41	1721	43963
	Hours worked-employees	Hours	4.480.506	2.964.953	268.961	9.894.484
	Net Capital Stock	Euro	37370.48	17102.3	16205.69	67613.14
	Intermediate input	Euro	54077.92	31314.34	13848.35	111892.6

Note: Data provided from OECD STAN dataset in January 2020 and September 2020

To model the production technology set we use a contemporaneous frontier. In this setting, the production technology for period t is constructed using observations from period t, while the production technology of period $t+1$ consists of observations from period $t+1$. Assuming the production technology sets are homogeneous across industries, each observation for a given year is compared to a production frontier, which is constructed from a combination of all the industries present in our sample. The model generates results for each two-year pair in our sample. For every 2-year pair, four LP problems are solved for both technologies – one with the regulated undesirable output (ML index) and one without the undesirable output (M index).

Table 2 presents the geometric means of ML and standard M indexes for the period from 1995 to 2017 for the manufacturing sector and its associated industries. Looking at the results for the ML index on an industry-by-industry basis, we observe substantial variation between industries, ranging from a low of 2.42 per cent annual productivity decline for Textiles, Wearing apparel, Leather products industry (C13-C15), to a high of a 1.8 per cent annual growth rate for Transport equipment industry (C29-C30).

Table 2. Decomposition of Average Annual Changes, 1995-2017

		Malmquist-Luenberger			Malmquist		
	ISIC (Rev.4)	ML	MLTCH	MLECH	M	MTCH	MECH
Food products, beverages and tobacco	C10-C12	1.0001	1.0001	1.0000	0.9939	0.9891	1.0049
Textiles, wearing apparel, leather and related products	C13-C15	0.9758	0.9758	1.0000	0.9734	0.9734	1.0000
Wood and paper products; printing and reproduction of recorded media	C16-C18	0.9990	0.9976	1.0014	0.9992	0.9977	1.0015
Coke and refined petroleum products	C19	0.9940	0.9940	1.0000	0.9832	0.9832	1.0000
Chemicals and chemical products,	C20	1.0053	1.0036	1,0017	0.9997	0.9980	1.0017
Basic pharmaceutical products and pharmaceutical preparations	C21	1.0110	1,0110	1.0000	1.0028	1.0028	1.0000
Rubber and plastics products, and other non-metallic mineral products	C22-C23	1,0003	0.9988	1.0015	0.9999	0.9984	1.0015
Basic metals and fabricated metal products, except machinery and equipment	C24-C25	1.0013	0.9997	1.0016	1.0013	0.9997	1.0017
Computer, electronic and optical products,	C26	1.0034	1.0034	1.0000	0.9977	0.9971	1.0006
Electrical equipment,	C27	1.0005	1.0016	0.9990	0.9949	0.9976	0.9974
Machinery and equipment n.e.c.,	C28	1.0029	1.0029	1.0000	0.9994	0.9975	1.0018
Transport equipment	C29-C30	1.0180	1.0180	1.0000	0.9990	1.0015	0.9975
Other manufacturing; repair and installation of machinery and equipment,	C31-C33	0.9968	0.9968	1.0000	0.9964	0.9964	1.0000
Manufacturing	C10-C33	**1.0006**	**1.0003**	**1.0004**	**0.9955**	**0.9948**	**1.0007**

On average, for the ML index, productivity increases by 0.06 percent per year, due mainly from increases in efficiency changes (MLECH), of 0.04 percent per year. The technical changes (MLTCH) shows an improvement of 0.03 percent per year. On the other hand, for the Malmquist index, average productivity declines by 0.45 percent per year, with technical change declining by 0.52 percent per year and the efficiency showing an improvement of 0.07 percent per year for all industries.

If we look at the results for the ML index for those industries with productivity growth, it is evident the growth by technical progress. So, those industries are moving in a direction of higher desirable output and lower undesirable output. The two exceptions are Rubber and plastics products, and other non-metallic mineral products industry (C22-C23) and Basic metals and fabricated metal products except machinery and equipment industry (C24-C25). These industries show increases in productivity thanks to improvements in MLECH, which offsets a declining MLTCH. The industries that show a loss of productivity are also accompanied by a decline in the MLTCH, so when the frontier shifts inward, it moves in the direction of "fewer goods and more bads". Most of these industries show constant MLECH, except the Wood and paper products; printing and reproduction industry (C16-C18) which shows an improvement in MLECH.

The results suggest that for the ML index, most industries are posting higher productivity growth or smaller productivity declines relative to the Malmquist index, except for the Wood and paper products; printing and reproduction industry (C16-C18). The relatively higher productivity growth or smaller productivity decline is attributed to the ML model which incorporates the undesirable output and credits industries for reducing production of the bad output. According to Färe et al. (2001) for a given input vector, if the percent increases in desirable output exceeds (is less than) the absolute value of the percentages decreases in the undesirable output, the growth rate of the traditional productivity (M index) exceeds (is lower than) the growth rate of the adjusted productivity (ML index). Like the M productivity index, MLTCH show a higher productivity growth or smaller productivity decline relative to the Malmquist technical changes (MTCH) index. In contrast, most industries are posting a lower (equal) MLECH index relative to Malmquist efficiency changes (MECH) index, except Electrical equipment industry (C27) and Transport equipment industry (C29-C30). The only industry with virtually the same values for the ML and M indexes, the MLTCH and MTCH indexes and of MLECH and MECH indexes, is "Basic metals and fabricated metal products except machinery and equipment" industry (C24-C25). Both productivity (ML) and its decomposition (MLTCH and MLECH) are not affected by environmental regulations in this industry.

If we look at efficiency changes industry-by-industry, for both ML and M index, we find industries with no efficiency changes (MLECH=1 and MECH=1) and industries with both increasing and decreasing efficiency changes. The only industry that shows a declining MLECH index is the Electrical Equipment industry (C27), with a decline of 0.1 percent per year. For the MECH index, two industries show declining levels of technical efficiency - Electrical Equipment industry (C27) and Transport equipment industry (C29-C30).

We find only four manufacturing industries that exhibit improved efficiency (MLECH >1) for the ML index, which means that those industries are closer to the frontier in period *t+1* than they were in the period *t*. On the other hand, the M index shows a slight improvement of MECH for seven industries. The difference in having more industries with improvements in efficiency changes under the M index relative to the ML index might suggest environmental policies cause the loss of efficiency for those industries with a low MLECH relative to MECH. Food products, beverages, and tobacco industry (C10-C12), under M index shows the highest efficiency changes, 0.5 per cent per year, while for the ML index, Chemicals and chemical products industry (C20) shows the highest MLECH, i.e., 0.17 percent.

In contrast, technical change under ML (MLTCH) shows different trends. If we compare the results industry-by-industry, seven industries exhibit increases in MLTCH, while the other six industries show declining MLTCH. The production possibility frontier of industries with declining MLTCH has shifted inward (i.e., technical regress), in the direction of "fewer goods and more bads", which suggests most of these industries have yet to adopt new technology which increases the desirable output and decreases the undesirable output. Technical changes for the M index (MTCH) shows improvements only for Basic pharmaceutical products and pharmaceutical preparations industry (C21) and Transport equipment industry (C29-C30), respectively 0.28 and 0.15 per cent per year. The other industries, under M index, show a decline in MTCH.

Table 3 presents the geometric mean of productivity change, technical change, and efficiency change for each two-year period analyzed in this investigation.

Table 3. Average Annual Changes in each period of the indices

	Malmquist_Luenberger			Malmquist		
	ML	MLTCH	MLECH	M	MTCH	MECH
1995-1996	0.9981	0.9950	1.0034	0.9946	0.9913	1.0033
1996-1997	0.9963	0.9977	0.9985	0.9984	0.9991	0.9993
1997-1998	1.0009	1.0002	1.0007	0.9891	0.9857	1.0035
1998-1999	0.9975	0.9939	1.0040	0.9926	0.9867	1.0060
1999-2000	1.0035	1.0035	0.9999	1.0003	0.9958	1.0045
2000-2001	0.9958	0.9979	0.9977	0.9910	0.9960	0.9950
2001-2002	0.9938	0.9914	1.0027	0.9925	0.9915	1.0011
2002-2003	0.9964	0.9974	0.9989	0.9905	0.9902	1.0003
2003-2004	1.0042	1.0020	1.0023	0.9980	0.9940	1.0041
2004-2005	1.0033	1.0043	0.9989	0.9974	0.9975	1.0000
2005-2006	1.0117	1.0099	1.0019	1.0016	0.9997	1.0018
2006-2007	1.0174	1.0180	0.9993	1.0050	1.0052	0.9998
2007-2008	0.9624	0.9624	1.0000	0.9836	0.9875	0.9961
2008-2009	0.9524	0.9569	0.9948	0.9459	0.9534	0.9921
2009-2010	1.0460	1.0427	1.0034	1.0270	1.0257	1.0013
2010-2011	1.0242	1.0279	0.9961	0.9951	1.0047	0.9904
2011-2012	0.9931	0.9929	1.0002	0.9890	0.9852	1.0038
2012-2013	0.9977	0.9983	0.9994	0.9958	0.9969	0.9988
2013-2014	1.0106	1.0081	1.0028	1.0053	1.0034	1.0018
2014-2015	0.9962	0.9977	0.9984	1.0080	1.0090	0.9991
2015-2016	1.0075	1.0037	1.0040	0.9951	0.9871	1.0081
2016-2017	1.0077	1.0059	1.0019	1.0056	1.0010	1.0045

Both the average ML and M indexes show declining productivity when the world economy was been hit by the global economic crises. For the ML index, the annual changes in productivity growth range from a low of -4.76 per cent in 2008-2009 to a high of 4.60 per cent in 2009-2010. Under Malmquist index, the annual change in productivity growth ranges from an increase of 2.70 per cent in 2009-2010 to a 5.41 per cent decrease in 2008-2009. Given the results for individual industries, it is not surprising that when we compare the average annual changes in each period for the entire manufacturing sector, the ML index shows higher productivity growth or a smaller productivity decline than the M index. Only in 2007-2008 and 2014-2015 we find the reverse, when M index shows a higher productivity increase or a smaller productivity decline. Changes in efficiency for the ML index range from an increase of 0.40 per cent for both 1998-1999 and 2015-2016, to a 0.52 per cent decline for 2008-2009, while technical change ranges from -4.31 in 2008-2009 to 4.27 percent in 2009-2010. The change in efficiency, for the M index, ranges from 0.81 per cent in 2015-2016 to -0.96 per cent for 2010-2011, while technical change posted growth from 2.57 per cent in 2009-2010 to -4.66 per cent in 2008-2009.

Based upon the above results, the conclusions that we can draw are that during the last 23 years, firms in the manufacturing sector made great strides in reducing air emissions. When reducing air emissions, some industries adopted investment in environmental technology strategy (i.e., technical progress), while others adopted best-practise management measures (i.e., improved efficiency). This is evident when we compare MLTCH with MLECH. The proposals to invest in new technology for reducing air emissions seem to put less pressure on Italian manufacturing industries.

4.4 Bootstrapping indices

To provide a statistical interpretation of the results reported in Section 4, we use the bootstrapping approach introduced by Simar and Wilson (1998, 1999, 2000a, b). Simar and Wilson (1999) developed a bootstrap method to estimate the sampling distribution and confidence intervals for the Malmquist index. They introduced a method for correcting the bias of the Malmquist index that accounts for the intertemporal dependencies between the distance functions, thus creating bootstrap samples simultaneously for two periods. Subsequently, the methodology was extended to the analysis of the Malmquist-Luenberger index by Jeon and Sickles (2004). The main problems pointed out in computing the indexes were first, the use of nonparametric programming estimators, which are considered to be deterministic, and second to the measure of the performance based on a true and unobservable production frontier. According to the authors, the estimates of the frontier are based on finite samples, which result in efficiency and productivity measures being subject to the sampling variation of the frontier (Jeon and Sickles, 2004). This methodology was recently used by Lee, et al. (2015) in testing the reliability of the ML index for thirty-five airline companies.

Following Lee, Wilson and Pasurka (2015), we adopt the bootstrapping approach of Hampf (2013), which is reported in Appendix B.5, to test the reliability of our result. To determinate whether changes in productivity growth, efficiency or technical change are statistically significant, we use a 95 per cent confidence interval generated from bootstrapping. We use the original estimators to construct the confidence intervals of the true index. The model replicates the dataset to generate an appropriately large number of pseudo samples (B=2000) and estimates the uncorrected results, the bias-corrected results, and confidence intervals. The indexes are statistically different from unity if the confidence interval does not contain the value of one. The results of bias-corrected estimates for the ML index are presented in Table 4. The results show that there is significant aggregate productivity change for most industries. The confidence intervals derived from the bootstrap show that two industries, i.e., food production, beverage, and tobacco (C10-C12) and textiles, wearing, leather and related production (C13-C15), have significant productivity changes for each two-year pair. Evaluating the disaggregated indexes, MLTCH and MLECH, we cannot conclude if efficiency change or technological change are driving productivity change. For technological change, only food production, beverage, and tobacco (C10-C12) industry does not show significant changes. Instead, the rest of industries show significant changes, mainly for the period of 2006-2011. In addition, for efficiency change, only Chemicals and chemical products shows significative changes during the period of study. The result of bias-corrected MLTCH and MLECH indexes are provided in Appendix B.6 and Appendix B.7.

Table 4. Bias-corrected Estimates of ML index

	Food products, beverages and tobacco,	Textiles, wearing apparel, leather and related products	Wood and paper products; printing	Coke and refined petroleum products	Chemicals and chemical products	Basic pharmaceutical products	Rubber and plastics products, and othe	Basic metals and fabricated metal products	Computer, electronic and optical products	Electrical equipment	Machinery and equipment n.e.c.,	Transport equipment	Other manufacturing; repair and installation of machinery
1995-96	0.9952*	0.9699*	1.0068*	0.9517*	1.0276*	1.0054	1.0019	1.0001	1.0207*	0.9965	1.0086*	0.9987	0.9952
1996-97	1.0124*	0.9918*	0.9925*	1.0226*	1.0003	1.0026	1.0077	0.9983	0.9702*	0.9723*	0.9935	1.0087	0.9805*
1997-98	0.9897*	0.9856*	1.0047	0.9584*	0.9993	0.9985	1.0056	0.9920*	1.0455*	1.0227*	1.0117*	1.0043	0.9896*
1998-99	0.9835*	0.9557*	1.0009	0.9833*	1.0202*	1.0083*	1.0083*	1.0000	0.9983	1.0050	1.0092	1.0063	0.9894*
1999-00	1.0557*	1.0207*	0.9958	0.9674*	0.9862*	1.0056*	1.0073*	1.0014*	0.9794*	0.9798	1.0292*	1.0180*	1.0016
2000-01	0.9788*	0.9831*	1.0082*	0.9675*	0.9902*	1.0022	0.9988	0.9975*	1.0288*	0.9967	1.0088	1.0004	0.9854*
2001-02	0.9890*	0.9484*	0.9926*	0.9767*	1.0203*	1.0005	1.0096*	0.9984	0.9841*	1.0112*	0.9838*	1.0086	0.9979
2002-03	1.0242*	0.9511*	0.9887*	0.9953*	1.0073*	1.0103*	0.9860*	1.0020*	0.9874*	1.0037	1.0203*	0.9908*	0.9838*
2003-04	0.9736*	0.9611*	1.0038*	0.9956*	1.0063*	1.0040	1.0034*	1.0043*	1.0234*	1.0199*	1.0286*	1.0219*	1.0060*
2004-05	1.0267*	0.9672*	0.9935*	1.0110*	0.9965	0.9996	1.0016	1.0161*	1.0142*	1.0012	1.0120*	1.0025	1.0014
2005-06	0.9833*	0.9828*	1.0035*	0.9794*	1.0094*	1.0265*	0.9972	1.0162*	1.0313*	1.0147	1.0337*	1.0660*	1.0075*
2006-07	1.0170*	1.0342*	1.0000	1.0133*	1.0119*	1.0174*	0.9963*	1.0050	1.0221*	1.0147*	1.0329*	1.0548*	1.0025*
2007-08	0.9782*	0.9085*	0.9896*	0.9931*	1.0254*	1.0296*	0.9847*	0.9940	0.8698*	0.8933*	0.8971*	0.9894*	0.9857*
2008-09	0.9823*	0.8994*	0.9836*	0.8987*	0.8940*	0.9812*	0.9721*	0.9470*	1.0398*	0.9893	0.8742*	0.9570*	0.9837*
2009-10	1.0239*	1.0635*	1.0131*	1.0473*	1.0839*	1.0612*	1.0192*	1.0259*	1.0392*	1.0836*	1.0632*	1.0717*	1.0010
2010-11	0.9867*	1.0264*	1.0096*	0.9864*	1.0098*	1.0652*	0.9960*	1.0006	1.0916*	1.0161*	1.0733*	1.0483*	1.0107
2011-12	0.9878*	0.9486*	0.9975*	0.9949*	0.9942*	1.0133*	0.9935	1.0115*	1.0077	0.9735*	1.0184*	0.9863	0.9846*
2012-13	1.0081*	0.9644*	0.9962*	1.0569*	1.0045*	1.0138*	0.9960*	1.0027	0.9451*	1.0014	0.9664*	1.0115*	1.0079*
2013-14	1.0073*	0.9939*	1.0047*	0.9868*	1.0051	0.9866*	1.0063*	1.0132*	1.0226*	1.0183*	1.0349*	1.0541*	1.0048
2014-15	1.0071*	0.9657*	0.9916*	1.0280*	1.0194*	1.0056	0.9976*	0.9998	0.9725*	1.0036	0.9481*	1.0125*	1.0027
2015-16	0.9947*	0.9731*	1.0082*	1.0146*	0.9976	1.0006	1.0062*	1.0114*	0.9968*	1.0155*	1.0072*	1.0572*	1.0152*
2016-17	0.9990	0.9862*	0.9950*	1.0382*	1.0230*	1.0071*	1.0064*	1.0001	1.0008	0.9984	1.0214*	1.0344*	0.9949*

Note: (*) denote significant difference from unit at 0.05

4.5 Conclusions

This study focuses on measuring adjusted productivity growth in Italian manufacturing industries when both desirable and undesirable output are taken into consideration. Using a dataset of thirteen manufacturing industries between 1995 and 2017, a ML productivity index was employed to measure the TFP index and its decomposition indexes (efficiency and technical change index). The average annual increase in ML productivity growth is 0.06 percent per year, which is primarily attributed to efficiency changes. When the undesirable outputs are not included in the production technology, productivity growth (M productivity growth) declines by 0.45 percent per year. An important result stemming from our analysis is that when air emissions are targeted by the Italian government, such policy action lowers adjusted productivity growth for only one industry, i.e., Wood and paper production; printing and reproduction of recorded media (C16-C18), while adjusted productivity is less affected in all other industries.

One important limitation of this study is the small sample size, which is due to data availability. To overcome this problem, we tested the reliability of our results using a bootstrap approach. Moreover, the drawback of using a dataset with a relatively low ratio of observations to constraints is that many observations fall on the production frontier. Hence, these observations are identified as technically efficient. When decomposing changes in productivity into (1) technical change and (2) changes in technical efficiency, we find that changes in productivity are closely linked to technical change. A larger sample size could provide a more accurate picture of productivity growth at industry level. Another limitation of the work is that the model does not explicitly account for productivity differences across industries (i.e., the composition effect), whereas several scholars stress that growth is brought about by changes in sectorial composition (Kuznets, 1971; Rostow, 1971; Chenery and Syrquin, 1975; Baumol et al. 1989). This is another issue that future studies should address in detail.

5. Environmental regulation and green productivity growth: Empirical evidence from EU industrial sectors

5.1 Introduction

Worldwide problems of climate change, energy resources exhaustion, and environmental degradation, are the main focus of each country. Numerous environmental regulation policies, which are directly related to energy consumption and air emission behaviour changes, have been proposed and implemented to prevent this problem. After the Kyoto Protocol was adopted in 1997 and the Paris Agreement was adopted in 2015, the pressure on reducing carbon dioxide emissions and keeping the increases in global average temperature to well below 2 ^{o}C has been increasing. The basic requirement for an industrial green growth includes the control of final energy production and consumption and greenhouse gas emissions generated from industrial activities. Indeed, the industrial production process must move towards activities that ensure energy saving, renewable power sources, and pollution abatement activities for becoming more environmentally sustainable. The emphasis on moving toward green growth and sustainable industrial production process has generated debates on how environmental regulation policies can be optimal by comparing the costs and benefits of regulations. Despite the benefit that it provides to society and future generations in terms of quality of life, environmental regulations can directly affect the economic viability of firms, industries, and nations. Adopting a stringent environmental regulation without receiving any subsidies from the government can lead to increased production costs for firms and a reduction in productivity and competitiveness of those firms. This occurs because rigorous environmental policies necessitate a supplementary charge for firms, also involving the resources used in the traditionally production. If the costs addressed to the pollution abatement activities are relatively higher, the investment in innovation that aims to improve the product quality and production cost will be consequently lower.

To address this issue, we use the total factor productivity (TFP) indicator as a measure of economic performance. In our analysis, we use adjusted total factor productivity which measures the capacity of a nation, an industry, or a firm to produce more good output than it did in the past from a given set of inputs while decreasing the production of the undesirable by-products. The empirical methodology for calculating the adjusted total factor productivity that accounts for the undesirable by-production (air pollution and greenhouse gas emissions) was firstly developed by Pitman (1983) and Färe et al. (1989). In our analysis we follow, Chung et al. (1997) approach. We employ the Malmquist-Luenberger (ML) index to calculate the adjusted total factor productivity which modifies the standard Malmquist index.

In this study, we use panel data from five EU countries manufacturing sectors to examine the effects of environmental regulation on productivity growth. We collect data on seven manufacturing industries during the period of 2008 to 2015 for each country. There are two reasons why we have chosen the manufacturing sector as our research sample. First, the manufacturing sector, and its associated industries of EU countries represent a significant part and play a fundamental role in the economic performance of those countries. Second, the EU countries have implemented several environmental regulation policies for protecting the environment and in the literature, we find few studies that deal with the trade-off between environmental regulation and productivity growth in the manufacturing sector and its associated industries for the EU countries.

The contribution of this study is twofold. First, it provides a picture of how the productivity growth of the manufacturing sector and its associated industries of EU countries, are affected by the environmental regulation policy. Understanding the effect of environmental regulation on productivity growth is essential for the design and choice of environmental regulations promulgated by governments. Second, in the context of methodology, following the idea of Aiken et al., (2009), this study contributes to the literature by proposing a new procedure for constructing the production frontier for the ML index measurement. We apply the meta-production function which was firstly introduced by Hayami (1969) and Hayami and Ruttan (1970,1985) in their study on agriculture sector. The meta-production frontier is constructed as a combination of cross-country industries. Aiken et al., (2009) used the meta-production frontier within the "Input Assigned" model. Differently, we are applying it within the Joint Production Model (JPM). With the cross-country industries combination in the construction of the production frontier problems of heterogeneity come to be eliminated as well as changes in sectoral composition between observations.

The remainder of this study is organised as follows. We begin with the description of the methodology for measuring the productivity growth in section 5.2. The section 5.3 we discuss data collection and the results. Finally, section 5.4 summarizes this study and discusses its policy implementation.

5.2 Malmquist-Luenberger index

We are reporting only the index introduced by Chung et al. (1997) for facility questions and we are not rewrite the output-oriented ML index general farmworker introduced in chapter 4. The authors specify the output-oriented Malmquist–Luenberger productivity index between periods t and $t+1$ as

$$ML_0^{t,t+1} = \left(\frac{\{1+\vec{D}_0^t(x^t,y^t,b^t;y^t,-b^t)\}}{\{1+\vec{D}_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}} * \frac{\{1+\vec{D}_0^{t+1}(x^t,y^t,b^t;y^t,-b^t)\}}{\{1+\vec{D}_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}}\right)^{1/2} \qquad (5.1)$$

which can be decomposed as

$$ML_0^{t,t+1} = MLECH_t^{t+1} * MLTCH_t^{t+1} \qquad (5.2)$$

where $MLECH_t^{t+1}$ and $MLTCH_t^{t+1}$ indicate efficiency changes and technological changes respectively. We can write efficiency changes and technical changes as

$$MLECH_0^{t,t+1} = \frac{\{1+\vec{D}_0^t(x^t,y^t,b^t;y^t,-b^t)\}}{\{1+\vec{D}_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}} \qquad (5.3)$$

$$MLTCH_0^{t,t+1} = \left[\frac{\{1+D_0^{t+1}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}}{\{1+D_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})\}} * \frac{\{1+D_0^{t+1}(x^t,y^t,b^t;y^t,-b^t)\}}{\{1+D_0^t(x^t,y^t,b^t;y^t,-b^t)\}}\right]^{1/2} \qquad (5.4)$$

To avoid infeasible LP problems, as was introduced in the previous chapter, we modified the standard definition of the bad, not being freely disposable and modeled in the production function via a strict equality constraint. Following Färe et al. (2014) and Färe et al. (2016) we introduce a modified weak disposability assumption that imposes a less than or equal constraint on the undesirable outputs. This specification of the undesirable output constraint was introduced in Färe et al. (2014) and in Färe et al. (2016) with the aim to eliminate the possibility of a downward-sloping portion of the frontier.

So, the nonparametric linear programming model to be solved for observation k' at t is the following:

$$\vec{D}_0^t\left(x^t(k'), y^t(k'), b^t(k'); y^t(k'), -b^t(k')\right) = \text{Max}\,\beta(k') \tag{5.5}$$

$$\text{s.t} \quad \sum_{k=1}^{K} z^t(k) y_m^t(k) \geq (1+\beta) y_m^t(k) \qquad m = 1, \dots, M$$

$$\sum_{k=1}^{K} z^t(k) b_i^t(k) \leq (1-\beta) b_i^t(k) \qquad i = 1, \dots, I$$

$$\sum_{k=1}^{K} z^t(k) x_n^t(k) \leq x_n^t(k) \qquad n = 1, \dots, N$$

$$\sum_{k=1}^{K} z^t(k) \geq 0 \qquad k = 1, \dots, K$$

The $z^t(k)$ are the weights assigned to each observation when constructing a production possibilities frontier. The assumption of non-negativity constraints on the intensity variable $z^t(k)$ allows the model to exhibit constant returns to scale[31]. For comparison purposes, we also calculate the standard Malmquist (M) index.

5.3 Data and Results

The model previously discussed requires data on good and bad outputs quantities as well as data on input quantities. The object of our study are the manufacturing industries of the most developed countries in the European Union in terms of GDP[32]. Considering the availability of data, we restrict our study to five European Union countries: Belgium, France, Germany, Italy, and Netherland. The sample considered in this analysis consists of a balanced panel of 7 manufacturing industries for each country. In order to compare industries across countries, we assemble data for the food and tobacco (ISIC 10–12), textiles and leather (ISIC 13–15), wood and paper products (ISIC 16–18), chemical and pharmaceutical products (ISIC 20–21), from basic metals, fabricated metal products to machinery and equipment (ISIC 24–28), transport equipment (ISIC 29-30), other manufacturing (ISCI 31-33) industries[33]. Due to the data limitation on some variables, the other manufacturing industry also includes the industry of

[31] Färe and Grosskopf (1996), argue that constant returns to scale is a necessary condition for the resulting productivity indexes to be true total factor productivity index.

[32] The classification of the top 10 most developed EU countries in terms of GDP has been extracted from World Bank national accounts data, and OECD National Accounts data files (2020). Link: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=EU&most_recent_value_desc=true

[33] We use data downloaded from OECD STAN dataset in August 2021 and September 2021. The current version of STAN is based on the International Standard Industrial Classification of all economic activities, Revision 4 (ISIC Rev. 4). Earlier versions of STAN were based on ISIC Rev. 3 and, prior to 2000, ISIC Rev. 2 (the latter covering the manufacturing sector only).

rubber and plastics (ISIC 22-23). We collected the data needed over the period 2008-2015 from the *OECD.stat*[34] and *Eurostat*[35]. Based on KLEMS standard (capital (K), labor (L), energy (E), materials (M) and service (S) inputs)[36], the technology modeled in this study consists of the following variables:

(6) Capital input. We use the net capital stock at constant prices (price index 2015) in each country as a proxy of capital stock. OECD STructural ANalysis (STAN) Dataset for Industrial Analysis offers the data for the net capital stock by activity.
(7) Labor input. The hours of worked-employees are used as a proxy of labor input. *OECD.stat* dataset offers data for labor input by activity.
(8) Energy input. The final energy consumption by activity is used as a proxy of the energy input in our study. The data are collected from the *Eurostat* dataset and the unit of measurement is in thousand tons of oil equivalent. Final energy consumption is based on Standard international energy product classification (SIEC) and it includes all fuel and energy delivered to users for both their energy and non-energy uses, and which do not involve a transformation process[37].
(9) Material and Service input. We use the Input-Output Tables (IOTs) from the *OECD.stat* dataset, that describe the relationships between producers and consumers in terms of sale and purchase in the economy. We use the total flows derived from all the industries, excluding the flows coming from Coke and refined petroleum products (ISIC 19) and Electricity, gas, water supply (ISIC 35-39) industries. These industries are excluded because they are classified as energy inputs. Since the unit of measurement is in US Dollar (Millions) we convert it into Euro using a single Purchasing power parities (PPPs) for each country each year. The data for the PPPs rate is derived from OECD data[38].
(10) Desirable (good) output. We use the Gross Domestic Production (GDP) in constant prices (price index 2015) as the proxy. OECD.stat is our source for the data on GDP.
(11) Undesirable (bad) output. We use the principal sources of the greenhouse gas (GHG) as proxy. *OECD.stat* offers data on Carbon dioxide (tons of pollution) generated from the industrial processes. The descriptive statistics for all the key variables used are provided in Table 1.

To construct the production frontier, we follow O'Donnell et al. (2008) and Akien et. al (2009) and use a meta-production frontier to estimate the production frontier for each manufacturing

[34] Link: https://stats.oecd.org/Index.aspx?DataSetCode=STANi4
[35] Link: https://ec.europa.eu/eurostat/data/database
[36]EU KLEMS is an industry level growth and productivity research project. Link: https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/eu-klems-capital-labour-energy-materials-and-service_en
[37]Link: https://www.irena.org/-/media/Images/IRENA/Agency/Data-Statistics/Caribbean-Renewable-Energy-Statistics-Training/Presentations/3-Introduction-to-Energy%20Statistics.pdf?la=en&hash=30693AD7B3A904DDFF4235DEAA1C041F9A4ABA7C
[38]Link: https://data.oecd.org/conversion/purchasing-power-parities-ppp.htm

industry. Each observation for a given year and a given country is examined compared to a production frontier which is constructed as a combination of cross-country industries, i.e., if we want to analyze food and tobacco (ISIC 10–12) industries, for a given year and a given country, the reference production frontier will be constructed from the food and tobacco industry (ISIC 10-12) of Belgium, France, Germany, Italy, and the Netherlands. By virtue of such a design, the production frontier will eliminate the common problem of composition effect between industries.We calculate our meta-production frontiers using a contemporaneous technology. For example, the production technology for period *t* is constructed using observation from period *t*, while the production technology of period *t+1* consists of observations from period *t+1*. Table 2 presents the geometric means of ML and standard M indexes for the two-year pairs from 2008 to 2015 for the manufacturing sector and its related industries for each country.

Table 1. Summary statistic of the variables.

	Units	Mean	Std. dev.	Minimum	Maximum
Belgium					
Gross output	Euro, Millions	26529.9	15727.41	5040.8	56455.9
Carbon Dioxide	Tonnes	4052772	3942198	101144	1.38e+07
Hours worked-employees	Hours, Millions	110.8929	62.81547	30.7	286.7
Net Capital Stock	Euro, Millions	16287.84	10120.09	2791.3	36770.9
Final Energy Consumption	Thousand tonnes of oil equivalent	1462.72	1235.246	126.821	4297.263
Material and Service	Euro, Millions	18545.58	11402.48	3042.952	44943.47
France					
Gross output	Euro, Millions	100113.1	52687.64	15983	181437
Carbon Dioxide	Tonnes	1.14e+07	9727104	567970	2.81e+07
Hours worked-employees	Hours, Millions	565.9733	382.898	133.294	1322.486
Net Capital Stock	Euro, Millions	46312.79	28576.72	4725	102309
Final Energy Consumption	Thousand tonnes of oil equivalent	3871.059	2434.061	296.084	10412.26
Material and Service	Euro, Millions	67265.46	38857.1	8070.928	144903.9
Germany					
Gross output	Euro, Millions	237811.6	191795.6	21694	672638
Carbon Dioxide	Tonnes	2.10e+07	1.87e+07	859461	5.72e+07
Hours worked-employees	Hours, Millions	1451.375	1273.51	193	4471
Net Capital Stock	Euro, Millions	109837	86176.61	8547	275168
Final Energy Consumption	Thousand tonnes of oil equivalent	7822.969	5196.89	471.035	16798.33
Material and Service	Euro, Millions	147263.3	117877.4	11560.87	462910.3
Italy					
Gross output	Euro, Millions	124780.8	84080.76	47128.75	364447.6
Carbon Dioxide	Tonnes	1.22e+07	1.19e+07	304831	4.82e+07
Hours worked-employees	Hours, Millions	848.8697	638.2541	292.7553	2564.086
Net Capital Stock	Euro, Millions	60450.96	39718.85	22513.35	150854.1
Final Energy Consumption	Thousand tonnes of oil equivalent	3895.282	2883.82	364.861	10756.92
Material and Service	Euro, Millions	81116.39	57365.51	23891.51	279978.8
Netherland					
Gross output	Euro, Millions	37144.66	28743.2	3308	98409
Carbon Dioxide	Tonnes	4750127	5834753	154804	1.82e+07
Hours worked-employees	Hours, Millions	168.875	134.2803	20	413
Net Capital Stock	Euro, Millions	22044.25	15156.18	2000	46116
Final Energy Consumption	Thousand tonnes of oil equivalent	1856.937	2301.796	87.484	7452.727
Material and Service	Euro, Millions	26779.57	21676.33	1868.7	73217.77

Note: Data provided from *OECD.stat* and *Eurostat* dataset in August-September 2021

Table 2. Decomposition of Average Annual Changes, 2008-2015

	ISIC (Rev.4)	Malmquist-Luenberger			Malmquist		
		ML	MLTCH	MLECH	M	MTCH	MECH
Belgium							
Manufacturing	10-33	1.0231	1.0221	1.0010	1.0262	1.0238	1.0023
Food products, beverages and tobacco	10-12	1.0168	1.0173	0.9995	1.0203	1.0207	0.9995
Textiles, wearing apparel, leather	13-15	1.0135	1.0135	1.0000	1.0167	1.0167	1.0000
Wood and paper products; printing and reproduction of recorded media	16-18	1.0027	1.0027	1.0000	1.0152	1.0152	1.0000
Chemicals and chemical products, and basic pharmaceutical products	20-21	1.0184	1.0184	1.0000	1.0196	1.0196	1.0000
From basic metals and fabricated metals products to machinery and equipment n.e.c.	24-28	1.0406	1.0328	1.0076	1.0406	1.0328	1.0076
Transport equipment	29-30	1.0413	1.0413	1.0000	1.0400	1.0307	1.0090
Other manufacturing; repair and installation of machinery and equipment	31-33	1.0291	1.0291	1.0000	1.0313	1.0313	1.0000
France							
Manufacturing	10-33	1.0259	1.0233	1.0026	1.0283	1.0261	1.0022
Food products, beverages and tobacco	10-12	1.0223	1.0223	1.0000	1.0227	1.0227	1.0000
Textiles, wearing apparel, leather	13-15	1.0121	1.0121	1.0000	1.0147	1.0147	1.0000
Wood and paper products; printing and reproduction of recorded media	16-18	1.0138	1.0138	1.0000	1.0214	1.0238	0.9977
Chemicals and chemical products Basic pharmaceutical products	20-21	1.0212	1.0212	1.0000	1.0216	1.0216	1.0000
From basic metals and fabricated metal products to machinery and equipment n.e.c.	24-28	1.0558	1.0372	1.0177	1.0554	1.0368	1.0180
Transport equipment	29-30	1.0364	1.0364	1.0000	1.0427	1.0427	1.0000
Other manufacturing; repair and installation of machinery and equipment	31-33	1.0202	1.0202	1.0000	1.0203	1.0203	1.0000
Germany							
Manufacturing	10-33	1.0273	1.0285	0.9988	1.0305	1.0318	0.9988
Food products, beverages and tobacco	10-12	1.0267	1.0267	1.0000	1.0266	1.0266	1.0000
Textiles, wearing apparel, leather	13-15	1.0182	1.0265	0.9918	1.0202	1.0286	0.9918
Wood and paper products; printing and reproduction of recorded media	16-18	1.0332	1.0332	1.0000	1.0342	1.0342	1.0000
Chemicals and chemical products Basic pharmaceutical products	20-21	1.0244	1.0244	1.0000	1.0427	1.0427	1.0000
From basic metals and fabricated metal products to machinery and equipment n.e.c.	24-28	1.0217	1.0217	1.0000	1.0226	1.0226	1.0000
Transport equipment	29-30	1.0412	1.0400	1.0012	1.0416	1.0403	1.0012
Other manufacturing; repair and installation of machinery and equipment	31-33	1.0259	1.0273	0.9986	1.0261	1.0275	0.9986
Italy							
Manufacturing	10-33	1.0238	1.0238	1.0000	1.0249	1.0245	1.0004
Food products, beverages and tobacco	10-12	1.0291	1.0291	1.0000	1.0256	1.0256	1.0000
Textiles, wearing apparel, leather	13-15	1.0231	1.0231	1.0000	1.0259	1.0259	1.0000
Wood and paper products; printing and reproduction of recorded media	16-18	1.0148	1.0148	1.0000	1.0148	1.0148	1.0000
Chemicals and chemical products Basic pharmaceutical products	20-21	1.0158	1.0158	1.0000	1.0195	1.0195	1.0000
From basic metals and fabricated metal products to machinery and equipment n.e.c.	24-28	1.0177	1.0177	1.0000	1.0271	1.0332	0.9941
Transport equipment	29-30	1.0295	1.0295	1.0000	1.0226	1.0139	1.0086
Other manufacturing; repair and installation of machinery and equipment	31-33	1.0369	1.0366	1.0002	1.0389	1.0386	1.0003
Netherlands							
Manufacturing	10-33	1.0247	1.0247	1.0000	1.0286	1.0236	1.0049
Food products, beverages and tobacco	10-12	1.0208	1.0208	1.0000	1.0225	1.0225	1.0000
Textiles, wearing apparel, leather	13-15	1.0201	1.0201	1.0000	1.0243	1.0155	1.0086
Wood and paper products; printing and reproduction of recorded media	16-18	1.0228	1.0228	1.0000	1.0296	1.0208	1.0086
Chemicals and chemical products Basic pharmaceutical products	20-21	1.0270	1.0270	1.0000	1.0275	1.0275	1.0000
From basic metals and fabricated metal products to machinery and equipment n.e.c.	24-28	1.0296	1.0296	1.0000	1.0346	1.0257	1.0086
Transport equipment	29-30	1.0340	1.0340	1.0000	1.0382	1.0382	1.0000
Other manufacturing; repair and installation of machinery and equipment	31-33	1.0184	1.0184	1.0000	1.0238	1.0151	1.0086

Looking at the results we can notice that in general, the ML index shows lower productivity growth compared to the standard Malmquist index for almost all industries in each country. In contrast, the transport equipment (ISIC 29-30) industry for Belgium, the basic metals and fabricated metal products to machinery and equipment n.e.c. (ISIC 24-28) industry for France and food products, beverages and tobacco (ISIC 10-12) industry for Germany post higher productivity growth under ML index than the M index. Also, food products, beverages and tobacco (ISIC 10-12) and transport equipment (ISIC 29-30) industries for Italy post higher productivity growth under the ML index than the M index. Regarding the manufacturing sector (ISIC 10-33) for each country, we notice the Malmquist-Luenberger index, which is measured as the average of the ML indexes of industries in their respective countries, shows a lower productivity growth compared to the Malmquist index for all countries. If we compare technical change under ML (MLTCH) with technical change for the Malmquist (MTCH) index for the industries in each country, we observe the same behavior as the ML index, so the MLTCH index is lower than the MTCH index for almost all industries. Like the ML index, the MLTCH index is higher than the MTCH index for the industries previously mentioned and for the two more industries in Netherland, exactly, for the basic metals and fabricated metal products to machinery and equipment n.e.c. (ISIC 24-28) and the other manufacturing; repair and installation (ISIC 31-33) industries. If we considering only the aggregate manufacturing sector (ISIC 10-33) for each country, we notice the same situation as the ML index, so the aggregate manufacturing sector (ISIC 10-33) has a lower technical change under the ML index compared to the M index, except for the Dutch manufacturing sector that shows a slightly higher MLTCH index (2.47 percent per year) than MTCH index (2.36 percent per year). Observing the efficiency changes for both indexes it seems we do not have changes (MLECH=1 and MECH=1) for most industries. For those industries that show improvement in changes in efficiency (MLECH>1 and MECH>1) we fund that the improvement of MLECH is lower than the improvement of the MECH index, except the basic metals and fabricated metal products, machinery and equipment n.e.c. (ISIC 24-28) industry for Belgium and transport equipment (ISCI 29-30) industry for Germany where the MLECH equals MECH. For the manufacturing sector (ISIC 10-33) in each country we find all cases, higher/lower or equal MLECH index

Focusing our attention on the country level results, we can confirm that for Germany and Netherland all the manufacturing industries are affected by the environmental regulations. They all lose productivity due to the restrictions on pollution. In contrast, for Belgium only transport equipment (ISIC 29-30) industry appear to be not affected by environmental regulations. For the French and Italian manufacturing industries, environmental regulations do not affect more than two industries. Also, the manufacturing sector (ISIC 10-33) for each country appears to be adversely affected by the environmental regulations.

In order to examine variation in annual changes that are obscured by the averages reported in Table 2, we plot the ML and M indexes for the manufacturing sectors for each country in Fig. 1.

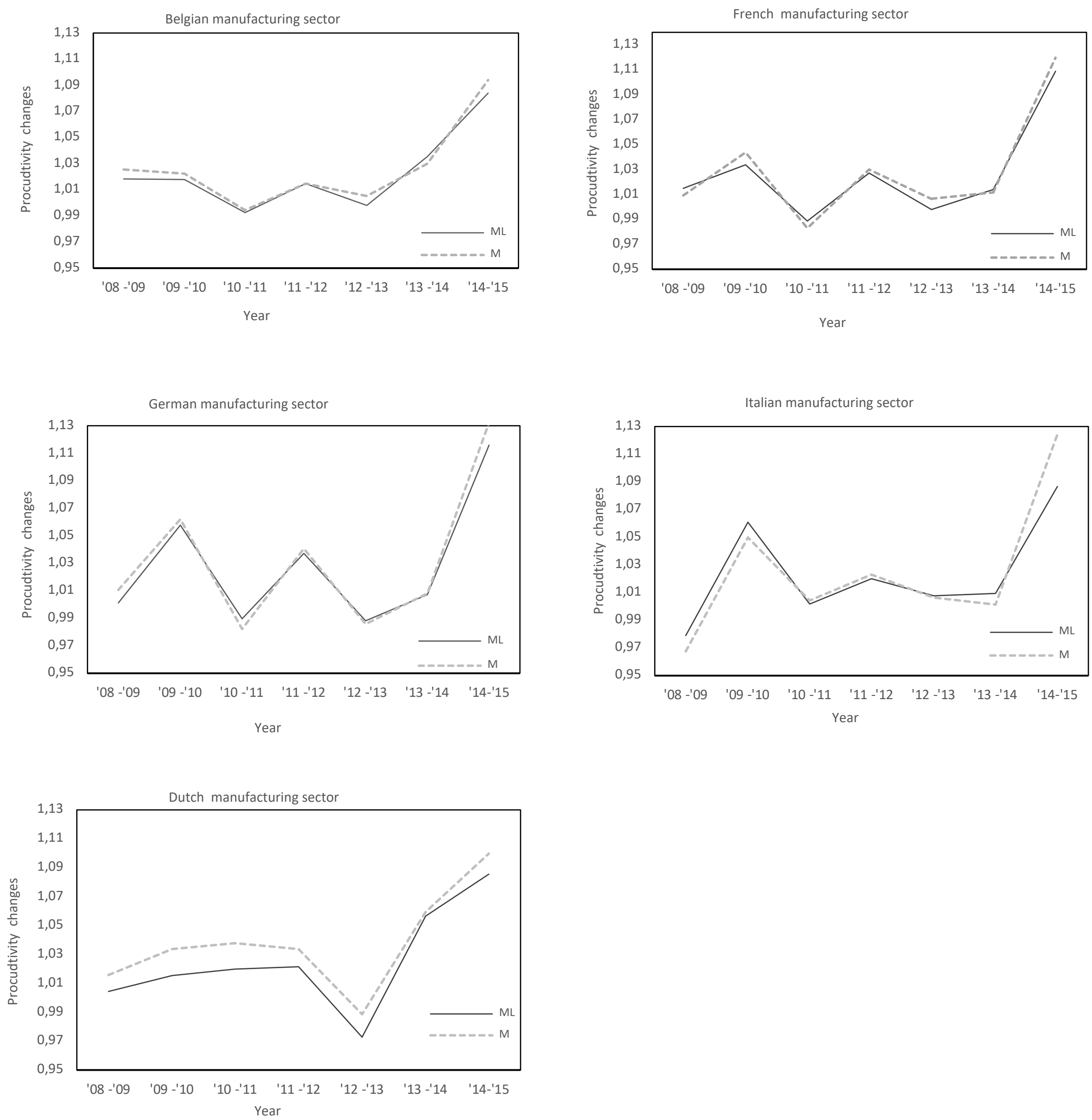

Figure 1. Trends in ML and M index for manufacturing sector in the five EU counties (2008-2015), (ISIC (10-33).

Viewing these figures allows us to make the following observation. For the manufacturing sector of Belgium and the Germany the two indexes, ML index and M index, show the same path and the differences between the two indexes are very small for all years. Even if they show the same path, productivity growth using the ML index continues to be lower than productivity growth using the M index for Belgium and for Germany the indexes appear to have alternated trend. For the Netherlands manufacturing sector, the indexes have the same path but the differences between ML index and M index are more evident than the previously mentioned countries. For the two remaining countries, France and Italy, the indexes appear to have alternative trends, especially the Italian manufacturing sector when the differences among ML and M indexes are much larger. For the Italian manufacturing sector, during the period of 2013-2014 the indexes show an opposite sign for the productivity change, the ML index shows an increase in productivity of 0.19 percent, while the M index shows a decrease of -0.5 percent. Furthermore, the manufacturing sector for all countries under both indexes show the highest productivity-increases from 2014-2015. In contrast, the lowest productivity decline for Belgium, France and Italy is during 2010-2011 and for Germany and Netherland is during 2012-2013. When we compare the average annual changes in each 2-year pair, for most the ML index shows lower productivity growth than the M index. The cases when productivity growth is higher for the ML index than the M index, are 2013-2014 for Italy, and from 2010-2011 for France, and Germany.

5.3.1 Cross-country industries productivity growth (ML index) comparison

The reason why we are focusing our analysis on a cross-country comparison of industries instead of industry-by-industry within a single country is related to the DEA approach. In our analysis, we construct production frontiers for cross-country industries. Therefore, all the other industries in their respective countries post an increase in productivity under the ML index which is ranges from a low value of 1.00 up to 4.13 percent annual increases.

Starting from the first industry of the ISIC classification, the food products, beverages and tobacco (ISIC 10-12) industry, the highest annual productivity growth rate is posted from the Italian food products, beverages and tobacco (ISIC 10-12) industry and the lowest annual productivity growth is posted from Belgian food products, beverages and tobacco (ISIC 10-12) industry, respectively 2.91 and 1.68 percent per year. For the textiles, wearing apparel, leather (ISIC 13-15) industry, all countries are showing an increase in productivity between 1.21 and 2.31 percent per year. Italian textiles, wearing apparel, leather (ISIC 13-15) industry is showing the highest annual productivity growth rate, 2.31 percent per year, and the lowest annual productivity growth rate is shown from French textiles, wearing apparel, leather (ISIC 13-15) industry. Identically, the wood and paper products; printing and reproduction of recorded media (ISIC 16-18) industry seem to have an increase in productivity in all countries. This increase in productivity ranges from a low of 0.27 percent for Belgian to a high of 3.32 percent per year for German wood and paper products; printing and reproduction of recorded media (ISIC 16-18) industry. Furthermore, the chemical and chemical production/basic pharmaceutical production (ISIC 20-21) industry for each country show an increase in productivity. The increase in productivity ranges from a low of 1.58 percent per year for Italian to a high of 2.70 percent per year for Dutch (ISIC 20-21) industry. For the basic metals and fabricated metal products to machinery and equipment n.e.c. (ISIC 24-28) industry, the productivity seems to have an increase in all the countries. The highest productivity growth for this industry is shown by the French (ISIC 24-28) industry, 5.58 percent per year. Instead, the lowest productivity growth is from the Italian basic metals and fabricated metal products to machinery and equipment n.e.c. (ISIC 24-28) industry, 1.77 percent per year. Moreover, the transport equipment (ISIC 29-30) industry, shows an increase in productivity for all the countries. The Belgian transport equipment (ISIC 29-30) industry shows the highest productivity growth, while the Italian transport equipment (ISIC 29-30) industry shows the lowest productivity growth, respectively 4.13 percent per year and 2.95 percent per year. Finally, other manufacturing (ISIC 31-33) industries, are showing an increase in productivity for the period of 2008-2015. As was previously mentioned, the highest productivity growth is shown by the Italian other manufacturing (ISIC 31-33) industries, 3.69 percent per year, while the lowest productivity growth is shown by the Dutch other manufacturing (ISIC 31-33) industries, 1.84 percent per year.

From the decomposition of the Malmquist–Luenberger index we can confirm the productivity growth for each industry in each country is triggered mainly from technical progress. If we observe the technical changes (MLTCH) index, we note the trend is the same as the ML index. Therefore, productivity improvement is caused by an improvement in technology. Regarding the efficiency changes (MLECH) almost all industries for each country show no changes in efficiency (MLECH=1). The exceptions that show an improvement in MLECH are the basic metals and fabricated metal products to machinery and equipment n.e.c. (ISIC 24-28) industry for Belgium (0.76 percent) and France (1.77), the other manufacturing (ISIC 31-33) industry for Germany (0.12 percent), and transport and equipment Italian industry (0.02 percent). Even though those sectors show an improvement in MLECH, the productivity growth is still driven by technical progress. The sectors that have lose efficiency in our analysis are the food products, beverages and tobacco (ISIC 10-12) Belgian industry, -0.05 percent per year, and the textiles, wearing apparel, leather (ISIC 13-15) and other manufacturing (ISIC 31-33) for German industries, -0.82 and -0.14 percent per year.

Considering the aggregate manufacturing sector for each country (ISIC 10-33) all are posted increases in productivity with the ML index. The highest productivity growth is posted by the German manufacturing sector (ISIC 10-33) and the lowest is posted by the Belgian manufacturing sector (ISIC 10-33), respectively, 2.73 percent per year and 2.31 percent per year. The manufacturing sector (ISIC 10-33) for the remaining countries shows an increase in productivity that ranges from 2.38 percent per year to 2.59 percent per year. Regarding the decomposition of the ML index, identically we conclude the productivity growth for each Manufacturing sector (ISIC 10-33) is mostly due to technical progress. The MLTCH index reports the same values as the ML index only for Italian and Dutch manufacturing sector (ISIC 10-33). The Belgian and French manufacturing sector (ISIC 10-33) are posting improvement in both indexes, the MLTCH and the MLECH. We can confirm that those two countries are doing well in both prospective, technical and efficiency changes. The only manufacturing sector (ISIC 10-33) that has register a higher improvement in technical changes and is losing efficiency changes is the German manufacturing sector (ISIC 10-33). So, the German frontier of the manufacturing sector (ISIC 10-33) has shifted in time upward but has failed in catching the frontier every year.

5.4 Conclusions

In presence of worldwide concerns about the environmental issues and the growing debate over the trade-off between environmental regulation and productivity growth, this chapter assesses changes in productivity growth in five European Union countries between 2008 and 2015. Therefore, we contribute to the Malmquist-Luenberger meta-production frontier framework, which, in addition to GDP and labor and capital inputs, accounts for environmental effects through the greenhouse gas pollutants. It includes the final energy consummation as well from each sector as additional input. Moreover, our analysis accounts for heterogeneity problems and changes in sectorial composition through the construction of a production frontier with industries belonging to the same ISIC classification between countries.

According to our results, the productivity growth of the manufacturing sector for almost all countries seems to be affected by environmental regulation. They appear to lose productivity due to pollution regulations. Focusing our attention on industry-by-industry we can confirm that, for all manufacturing industries in Netherland the productivity growth appears to be affected by the environmental regulation. Instead, for the remaining countries, we can find at least one industry that is not affected by environmental regulation. For our period of study (2008-2015) we found that the improvement in productivity growth (ML index greater than one) is caused meanly by the improvement in technical progress (MLTCH > 1). Regarding the efficiency changes, we can notice that the efficiency changes show no changes (MLECH equal to one) for all the Dutch industries. The rest of the countries we can find industries that shows improvement on efficiency changes as well as losing efficiency (MLECH). According to our result the German manufacturing sector is losing efficiency (MLECH = -0.12 percent per year), indicating a worrying failure to catch up of the production frontier. This loss is compensated by an improvement in technical efficiency (MLTCH = 2.85 percent per year), i.e., indicating that the production frontier is shifting upward each year.

Conclusively, we should acknowledge some of the limitations of our research and make several suggestions for future research. One concern with the methodology is the small sample size. Constructing the best production frontier with a relatively small number of Decision Making Unit (DMU) the DEA approach could overestimate the efficient DMUs. Furthermore, the characteristics of the technology (production possibility set) are limited on including only the bad outputs related to the air emission substances. It is possible to extend our investigation by including supplementary environmental pressures, e.g., soil and water contaminants or the use of natural resources.

6. Final remarks and policy implication

The benefits of environmental regulation are sizable and were discussed by a large amount of literature to date. These instruments help on improving the quality of the environment and the quality of life as well. Moreover, imposing environmental regulations, like market-oriented regulation and command and control regulation helps reduce pollution, resource overconsumption, and natural capital degradation. The implementation and benefits provide by environmental regulation are subject to a large discussion and criticism in the nowadays literature. Concerns remain about the costs that those instruments cause to the economic system by the loss of productivity and competitiveness, and to the society by raising the cost of living too. Therefore, it is also difficult to conclude the effect of these instruments because the findings to date are very heterogeneous and even the applied methods, which are often novel, and the analyzed dataset are very dissimilar. Our work in this dissertation contributes to the relevant literature with new evidence on environmental regulations and their potential impact on development and growth. We have focused our analysis on the role that these instruments have on the manufacturing industries' productivity growth. To the best of our knowledge, the existing literature has not examined the role of environmental regulations on productivity at the industry level for the EU countries. Focusing our analysis on Italian manufacturing sectors and enlarging the sample with other four more EU countries, we provide the first evidence on productivity growth at the industry level.

In chapter four of this dissertation, we address this trad-off on Italian manufacturing sector and its associated industries. The productivity growth has been measured using the Malmquist-Luenberger index which is based on the directional distance function. The directional distance functions have been measured by the data envelopment analysis approach and are not reported in this dissertation. We operationalize the model by using a panel data set of thirteen manufacturing industries in the Italian economy and constructed our technology set by using a three-output/three-input technology during the period from 1995 to 2017 respectively. We use a contemporaneous frontier which is contracted using all thirteen industries. What emerges from our research is that when air emissions are targeted by the Italian government, such policy action lowers adjusted productivity growth for only one industry, i.e., Wood and paper production; printing, and reproduction of recorded media (C16-C18), while adjusted productivity is less affected in all the other industries. Another important result stemming from our analysis is that the productivity growth for about fifty percent of the industries is largely towed by technical progress (i.e., shifting upwards of the frontier). The productivity growth is drawn from efficiency changes (i.e., caching up the frontier) only in three industries. By Bootstrapping the ML index, we provide the robustness of our analysis. The Bootstrapping results show that our resalt are statistically significant, but we cannot conclude if technical progress or efficiency changes have towed the growth or decreases of productivity.

In chapter fifth, we extend our analysis by including in our dataset the information on the manufacturing sector and its associated industries of the other four EU counties (i.e., Belgium, France, Germany, the Netherland, and Italy as well). The second study differs from the first in the technology set construction, period of study, and the construction of the production frontier. The technology set which uses a two output/four input technology, is constructed by separating the intermediate input (i.e., in final energy consummation, and material and service) and by introducing only the CO_2 as an undesirable output. The period of the study refers to the period from 2008 to 2015 and the production frontier is constructed using cross counties industries. Identically to the previous study, we use the contemporaneous frontier analysis and the same approach, as well as the same index to calculate productivity growth. The outcome of our results suggests that the environmental regulations proposed by the EU countries taken in the analysis have adversely affected the productivity growth of the manufacturing sectors. Almost all the industries in each country seem to lose productivity due to pollution regulations. Like the previous study, productivity growth has been drawn from technical progress. Regarding the efficiency changes, we have an alternated situation where some industries have improved their efficiency while others have not. We draw also interesting results on productivity growth when we compare the cross-country industries, but we cannot conclude which country has the best situation in industries productivity growth compared to the others.

We expect these results can provide Industrial policymakers valuable information and help them design better environmental policies. On one side, additional policy intervention is needed, aimed at encouraging investments in green technologies capable of shifting the production technology (i.e., production frontier) in the direction of fewer undesirable outputs and more good output. Promoting green investment involves reinforcing some current EU environmental policies and proposing new environmental policies which consider the performance loss from those regulations. The focus of the policymakers should be on increasing and reforming public innovation budgets in green technologies and promoting international agreements regarding investment in green technologies that aim to save energy and reduce pollution. On the other hand, European policymakers should concentrate their attention on activities that encourage the combination of novel green production technologies with the traditional production processes. For the purpose of catching-up with the best-available production technology (i.e., production frontier) various measures are necessary, such as expanding the markets for products and services that contribute to a greener economy and establishing fiscal measures that penalize the polluter and subsidies the use of green practices.

Moreover, it is important to stress some future work that can be done by the upcoming researcher. For a more in-depth underspending of the productivity growth trend, we should consider in our analysis the determinants of the adjusted productivity growth. Enlarging the sample size by involving other countries in our analysis could enrich our results and using a system General method of moment (GMM) technique for exploring the determinants, represents an interesting avenue for further analysis in this expanding field of research. Furthermore, by specifying which policy we are referring to, i.e., market-oriented or command and control regulation, we can provide more detailed results which can help the policymaker to better design the further policy. We hope that the public government and the research centers will provide information about this policy two policies in the future, in order to carry out a most detailed analysis in the next forthcoming work.

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Appendix

A. Appendix to chapter III

A.1 Weak and strong disposability of outputs in graphic illustration

In the figure 1 we reported two production possibility frontiers, Isoq[39] $P(x)$ and Isoq $P(\lambda\, x), \lambda > 1$, which describe the combination of the outputs u_1 and u_2 that can be archived given the quantities of inputs. Starting at point b, the reduction of the u_1 requires a reduction of the u_2 when the inputs is assumed unchanging $(b \rightarrow d)$ or requires an increase in inputs to maintain the same outputs of u_2 $(b \rightarrow c)$. Consequently, outputs u_1 is weakly disposable; to dispose of it from b is costly, either in terms of scarifying the u_2 or in terms of increase the inputs requirements. Starting at point a, though, a decrease in u_2 can be archived at no cost to the producer, either in terms of scarifying u_1 or in terms of increase inputs requisite, and so output u_2 is strong disposable.

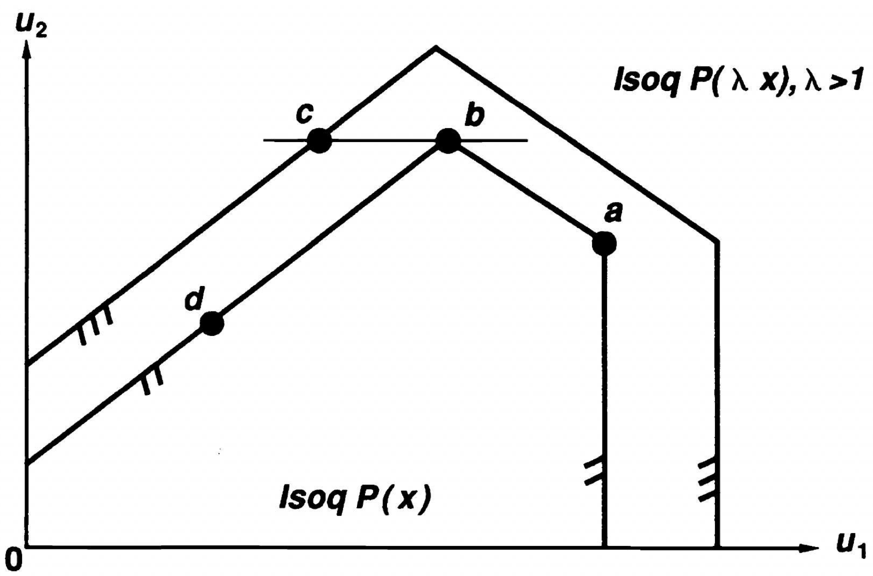

Figure 1. Färe et al. (1994) Weak and Strong Disposability of Outputs

[39] The notions are taken from Färe et al., (1994) where the Isoq $P(x)$ it refers to the isoquant $P(x)$ and the Isoq $P(\lambda\, x), \lambda > 1$ to a second isoquant which can be archived by augmenting the production of goods by λ holding the strong disposability of inputs.

A.2 Malmquist-Luenberger index a graphical illustration

If we suppose a production set at time t, $P^t(x^t)$, bounded by $0ACDE$ and production set at time $t+1$, $P^{t+1}(x^{t+1})$ bounded by $0FGHJ$ and the observation $(y^{t,k},\ b^{t,k})$, which is represented by point *K*, and belongs to , $P^t(x^t)$, and $(y^{t+1,k},\ b^{t+1,k})$,, which is represented by point L and belongs to $P^{t+1}(x^{t+1})$ but not to $P^t(x^t)$, the ML index is measurement as follow

$$ML^{t,t+1} = \left(\frac{oc}{od} * \frac{ob}{oa}\right)\left[\frac{^{oc}/_{of}}{^{oc}/_{od}} * \frac{^{oa}/_{ob}}{^{oa}/_{oe}}\right]^{1/2} = \left(\frac{oc}{od} * \frac{ob}{oa}\right)\left[\frac{od}{of} * \frac{oe}{ob}\right]^{1/2} \qquad (1)$$

and the four-distance function to be solved are the following:

- $\vec{D}_0^t\,(x^t, y^t, b^t; y, -b) \rightarrow$ distance of K from 0ACDE
- $\vec{D}_0^t(x^{t+1}, y^{t+1}, b^{t+1}; y, -b) \rightarrow$ distance of L from 0ACDE
- $\vec{D}_0^{t+1}\,(x^t, y^t, b^t; y, -b) \rightarrow$ distance of K from 0FGHJ
- $\vec{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y, -b) \rightarrow$ distance of L from 0FGHJ

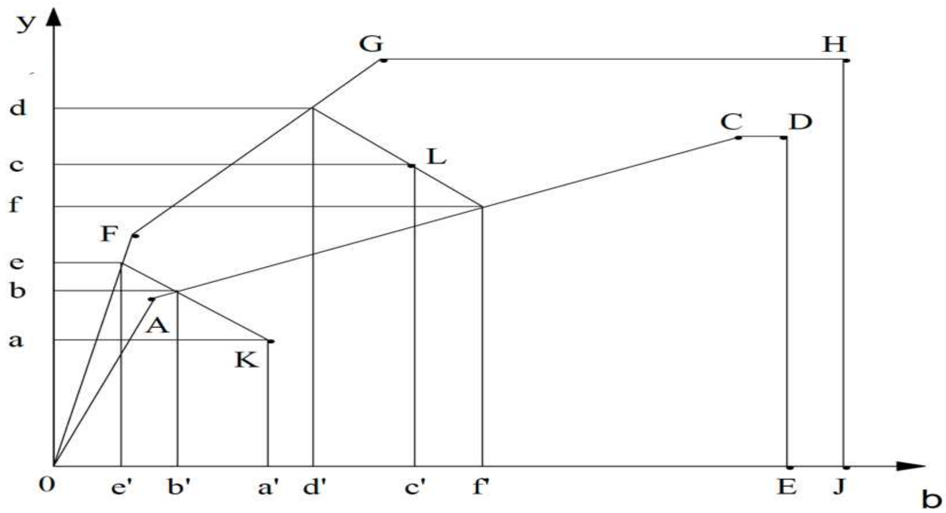

Figure 2. Färe et al. (2001) Malmquist-Luenberger productivity index

B. Appendix to chapter IV

B.1 Graphical illustration of the Infeasible solution

Figure 2 illustrates the potential problem of infeasible solution, when no simultaneous proportional expansion of the desirable output and contraction of the undesirable output on production set 0ABCDE is possible.

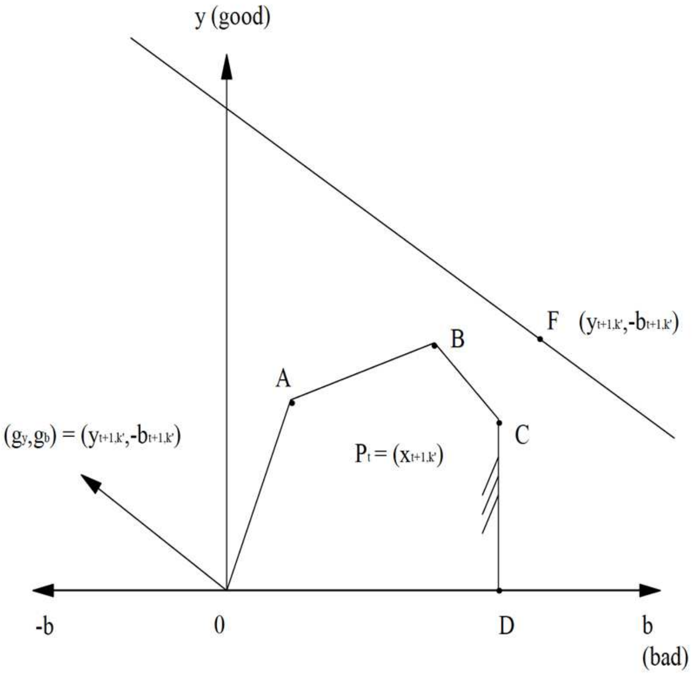

Figure 3. The Directional distance function

B.2 The modified weak disposability assumption

Projection into Production Possibility Set under the modified weak disposability assumption.

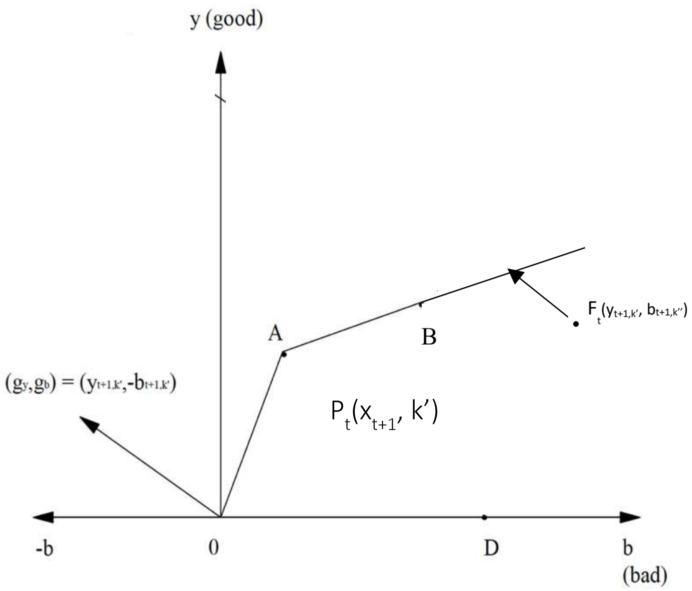

Figure 4. The Directional distance function

B.3 The linear programming of Malmquist index

The distance function of observation k' at t for Malmquist productivity index is constructed by the linear program:

$$\left(D_0^t\left(x^t(k'), y^t(k'), b^t(k')\right)\right)^{-1} = \text{Max } \beta(k') \tag{2}$$

$$\text{s.t} \quad \sum_{k=1}^{K} z^t(k) y_m^t(k) \geq \beta\, y_m^t(k) \qquad m = 1, \ldots, M$$

$$\sum_{k=1}^{K} z^t(k) x_n^t(k) \leq x_n^t(k) \qquad n = 1, \ldots, N$$

$$\sum_{k=1}^{K} z^t(k) \geq 0 \qquad k = 1, \ldots, K$$

B.4 Graphs trend of the outputs

The graphs below present the trend of the total manufacturing undesirable outputs (CO2 and MNVOC) and desirable output (GDP) for the period of 1995-2017.

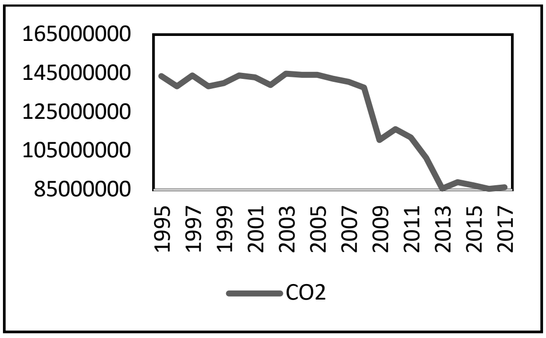

Figure 4. Total CO_2 trend

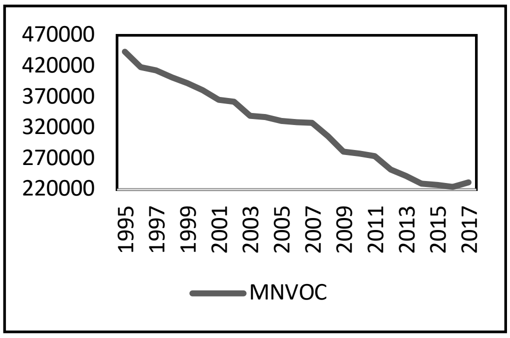

Figure 5. Total MNVOC trend

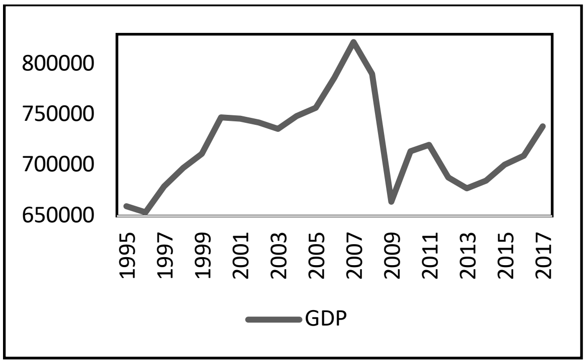

Figure 6. Total GDP trend

B.5 Bootstrapping the ML index

The algorithm used to get bootstrap samples to correct the bias of the indices is being recapitulated by the following stages[40]

1. The algorithm is firstly gone thought the estimations of the directional distance functions $\hat{\beta}^t(x_{t,i}, y_{t,i}, u_{t,i}; g_t) = \hat{\beta}_i^t(t)$ and $\hat{\beta}^{t+1}(x_{t+1,i}, y_{t+1,i}, u_{t+1,i}; g_{t+1}) = \hat{\beta}_i^{t+1}(t+1)$ for $i = 1, \ldots\ldots, n$. Denote

$$\boldsymbol{A} = \left[1 + \hat{\beta}_1^t(t), \ldots\ldots, 1 + \hat{\beta}_n^t(t)\right]^T \qquad (3)$$

and

$$\boldsymbol{B} = \left[1 + \hat{\beta}_1^{t+1}(t+1), \ldots\ldots, 1 + \hat{\beta}_n^{t+1}(t+1)\right]^T \qquad (4)$$

where the elements of elements of the matrix $\boldsymbol{A}$ and $\boldsymbol{B}$ are bounded from below at unity.

2. Then compute the matrix of reflected values as

$$\Delta = \begin{bmatrix} A & B \\ 2-A & B \\ 2-A & 2-B \\ A & 2-B \end{bmatrix} \qquad (5)$$

where 2 denotes a n x 1 vector of twos.

3. It estimates the covariance matrix $\hat{V}$ of the columns of $[A \quad B]$ and the covariance matrix $\hat{V}_R$ of the columns of $[2-A \quad B]$.

4. It draws with replacement n rows from Δ and the results are denoted by Δ^* matrix which is an 2 x n dimension. Furthermore, the elements of the Δ^* matrix are denoted by δ_{ij} with $i = 1, \ldots\ldots, n$ and $j = 1, 2$. The mean values of the columns of the Δ^* matrix, are given by $\delta_{ij} = \frac{1}{n}\sum_{1=1}^{n} \delta_{ij}$.

[40] In this presentation we follow the specification and the adoption of the algorithm to the Malmquist -Luenberger index, given by Hampf (2013, pp.91-93). The notion used are those presented by Hampf (2018). u_t denotes the undesirable outputs and g_t the direction vector.

5. Additionally, it computes the lower triangular matrix of a Cholesky decomposition of the covariance matrix $\hat{V}$ and indicate the results

$$L = \begin{bmatrix} l_1 & 0 \\ l_2 & l_3 \end{bmatrix} \tag{6}$$

6. It draws $2n$ times from a standard normal distribution and from n pairs (z_1, z_2).

7. It constructed a $\boldsymbol{E}$ matrix with n x 2 dimension where the ith row consist of $\left(l_{1\,z_1}, l_{2z_2} + \ l_{3z_2}\right)$ if the corresponding row of the Δ^* matrix was drawing from $[A \quad B]$ or $[2 - A \quad 2 - B]$ and of $\left(l_{1\,z_1}, -l_{2z_2} + \ l_{3z_2}\right)$ if the corresponding row of Δ^* matrix was drawn from $[2 - A \quad B]$ or $[A \quad 2 - B]$. The rows of $\boldsymbol{E}$ simulate draws from bivariate normal distribution $N\left(0, \hat{V}\right)$ and $N\left(0, \hat{V}_R\right)$.

8. It calculated the n x 2 matrix $\boldsymbol{\Gamma}$ as follow

$$\boldsymbol{\Gamma} = \ (1 + \ h^2)^{-1/2}\left(\Delta^* + h\boldsymbol{E} - \boldsymbol{C}\begin{bmatrix} \bar{\delta}_1 & 0 \\ 0 & \bar{\delta}_2 \end{bmatrix}\right) + \boldsymbol{C}\begin{bmatrix} \bar{\delta}_1 & 0 \\ 0 & \bar{\delta}_2 \end{bmatrix} \tag{7}$$

   where $\boldsymbol{C}$ denote a n x 2 matrix of ones and the bandwidth h is equal to $\left(\frac{4}{5n}\right)^{1/6}$. This bandwidth is chosen by Simar and Wilson (1999) following suggestion by Silverman (1986).

9. To remove the reflection around unity Hampf (2013), denote the elements of $\boldsymbol{\Gamma}$ as γ_{ij} and set $\gamma^*{}_{ij} = \gamma_{ij}$ if $\gamma_{ij} \geqq 1$ and $\gamma^*{}_{ij} = 2 - \gamma_{ij}$ otherwise. The simulated derivations from the frontier are denoted as $\beta^*{}_i^t(t) = \gamma^*{}_{i1} - \ 1$ and $\beta^*{}_i^{t+1}(t+1) = \gamma^*{}_{i2} - \ 1$.

10. For constructing a bootstrap sample $\left(x_{t,i}^*, y_{t,i}^*, u_{t,i}^*\right)$ with $i = 1, \ldots., n$ the simulated distance functions are used and

$$x_{t,i}^* = \ x_{t,i} \tag{8}$$

$$y_{t,i}^* = \ \left(1 + \hat{\beta}_i^t(t)\ \right) / \left(1 + \beta^*{}_i^t(t)\right) \ * \ y_{t,i} \tag{9}$$

$$u^{*}_{t,i} = \left(1 - \hat{\beta}^{t}_{i}(t)\right) / \left(1 - \beta^{*t}_{i}(t)\right) * u_{t,i} \tag{10}$$

and for period $t + 1$

$$x^{*}_{t+1,i} = x_{t+1,i} \tag{11}$$

$$y^{*}_{t+1,i} = \left(1 + \hat{\beta}^{t+1}_{i}(t+1)\right) / \left(1 + \beta^{*t+1}_{i}(t+1)\right) * y_{t+1,i} \tag{12}$$

$$u^{*}_{t+1,i} = \left(1 - \hat{\beta}^{t+1}_{i}(t+1)\right) / \left(1 - \beta^{*t+1}_{i}(t+1)\right) * u_{t+1,i} \tag{13}$$

11. To generate a B bootstrap sample we repeat the step 4 and 10 B times, and we use it to estimate the bootstrap Malmquist-Luenberger index $\widehat{ML}^{t,t+1}_{bi}$ and their components $\widehat{MLTCH}^{t,t+1}_{bi}$ and $\widehat{MLECH}^{t,t+1}_{bi}$.

The obtained values can be used to estimate the bias of the ML index as

$$\widehat{Bias}_{B}\left(\widehat{ML}^{t,t+1}_{i}\right) = \frac{1}{B}\sum_{b=1}^{B}\left[\widehat{ML}^{t,t+1}_{bi} - \widehat{ML}^{t,t+1}_{i}\right] \tag{14}$$

The index is corrected for the bias as

$$\widehat{ML}^{t,t+1,BC}_{i} = \widehat{ML}^{t,t+1}_{i} - \widehat{Bias}_{B}\left(\widehat{ML}^{t,t+1}_{i}\right) \tag{15}$$

if

$$\frac{\widehat{Bias}_{B}\left(\widehat{ML}^{t,t+1}_{i}\right)}{\sigma_{\widehat{ML}^{t,t+1}_{bi}}} \geq \frac{1}{\sqrt{3}} \tag{16}$$

where $\sigma_{\widehat{ML}^{t,t+1}_{bi}}$ denotes the standard deviation of the bootstrapped values of the index.

B.6 . Bias-corrected Estimates of MLTCH index

	Food products, beverages and tobacco,	Textiles, wearing apparel, leather and related products,	Wood and paper products; printing	Coke and refined petroleum products	Chemicals and chemical products	Basic pharmaceutical products	Rubber and plastics products, and othe	Basic metals and fabricated metal products	Computer, electronic and optical products	Electrical equipment	Machinery and equipment n.e.c.,	Transport equipment	Other manufacturing; repair and installation of machinery
1995-96	0.9952	0.9699	1.0050	0.9517	0.9831	1.0054	1.0085	0.9983	1.0207	0.9965	1.0086	0.9986	0.9952
1996-97	1.0123	0.9915	1.0020	1.0226	1.0016	1.0026	1.0118	1.0014	0.9702	0.9723	0.9935	1.0087	0.9805
1997-98	0.9897	0.9868	0.9881	0.9600	1.0079	0.9985	1.0019	0.9923	1.0497	1.0227	1.0144	1.0043	0.9896
1998-99	0.9835	0.9564	0.9949	0.9850	0.9849	1.0083	1.0056	0.9956	0.9983	1.0050	1.0092	1.0063	0.9894
1999-00	1.0557	1.0211	0.9999	0.9685	0.9865	1.0056	1.0028	1.0010	0.9794	0.9798	1.0292	1.0180	1.0016
2000-01	0.9788	0.9831	0.9973	0.9675	1.0194*	1.0022	0.9987	1.0026	1.0309	0.9967	1.0088	1.0004	0.9881
2001-02	0.9890	0.9484	0.9902	0.9744	1.0041	1.0005	0.9959	1.0056	0.9841	1.0112	0.9838	1.0086	0.9931
2002-03	1.0253	0.9511	0.9909	0.9966	1.0032	1.0103	0.9953	0.9977	0.9874	1.0037	1.0221	0.9977	0.9816*
2003-04	0.9736	0.9611	1.0020	0.9969	0.9929	1.0040	1.0013	1.0057	1.0234	1.0199	1.0305	1.0128	1.0047
2004-05	1.0267	0.9672	0.9988	1.0123	1.0024	0.9996	0.9991	1.0021	1.0142	1.0012	1.0128	1.0203	1.0001
2005-06	0.9833	0.9828	1.0023	0.9803	1.0181	1.0265*	1.0010	1.0021	1.0313	1.0147	1.0362	1.0539*	1.0075
2006-07	1.0170	1.0342*	0.9997	1.0133	1.0121	1.0174	0.9983	1.0141	1.0221	1.0085	1.0355	1.0548*	1.0025
2007-08	0.9782	0.9063*	0.9899*	0.9945	1.0136	1.0296*	0.9903	1.0003	0.8664*	0.8933*	0.8971*	0.9894	0.9857*
2008-09	0.9823	0.8994*	0.9682*	0.8987*	0.9708*	0.9812	0.9626*	0.9454*	1.0398	0.9893	0.8742*	0.9570*	0.9837
2009-10	1.0239	1.0654	1.0186*	1.0473	1.0410*	1.0612*	1.0168	1.0258*	1.0392	1.0836*	1.0632	1.0717*	1.0010
2010-11	0,9867	1.0275	1.0095	0.9874	1.0298*	1.0652*	1.0032	1.0163*	1.0949*	1.0161	1.0733*	1.0483*	1.0107
2011-12	0.9878	0.9486	0.9849*	0.9972	1.0090	1.0133	0.9875	0.9883	1.0077	0.9969	1.0184	0.9863	0.9846
2012-13	1.0081	0.9644	1.0060	1.0606	1.0114	1.0138	0.9988	1.0030	0.9429	0.9854	0.9651	1.0158	1.0079
2013-14	1.0073	0.9939	1.0020	0.9841	0.9895	0.9866	1.0039	1.0011	1.0241	1.0193	1.0362	1.0541*	1.0048
2014-15	1.0071	0.9657	1.0104	1.0288	1.0180	1.0056	1.0118	1.0011	0.9705	0.9999	0.9481	1.0125	1.0027
2015-16	0.9947	0.9731	0.9982	1.0164	0.9778*	1.0006	1.0003	0.9965	0.9983	1.0155	1.0072	1.0572	1.0152
2016-17	0.9990	0.9862	0.9896	1.0382	1.0104	1.0071	0.9797*	0.9995	1.0008	1.0176	1.0214	1.0344	0.9949

Note: (*) denote significant difference from unit at 0.0

B.7 . Bias-corrected Estimates of MLECH index

	Food products, beverages and tobacco,.	Textiles, wearing apparel, leather and related products,	Wood and paper products; printing	Coke and refined petroleum products	Chemicals and chemical products	Basic pharmaceutical products	Rubber and plastics products, and othe	Basic metals and fabricated metal products	Computer, electronic and optical products	Electrical equipment	Machinery and equipment n.e.c.,	Transport equipment	Other manufacturing; repair and installation of machinery
1995-96	1.0000	1.0000	1.0018	1.0000	1.0452*	1.0000	0.9935	1.0018	1.0000	1.0000	1.0000	1.0000	1.0000
1996-97	1.0000	1.0000	0.9905	1.0000	1.0004	1.0000	0.9927	0.9981	1.0000	1.0000	1.0000	1.0000	1.0000
1997-98	1.0000	1.0000	1.0150	1.0000	0.9915	1.0000	1.0016	1.0010	1.0000	1.0000	1.0000	1.0000	1.0000
1998-99	1.0000	1.0000	1.0060	1.0000	1.0359*	1.0000	1.0027	1.0044	1.0000	1.0000	1.0000	1.0000	1.0000
1999-00	1.0000	1.0000	0.9959	1.0000	0.9997	1.0000	1.0032	1.0004	1.0000	1.0000	1.0000	1.0000	1.0000
2000-01	1.0000	1.0000	1.0109	1.0000	0.9690*	1.0000	1.0024	0.9954	1.0000	1.0000	1.0000	1.0000	0.9952
2001-02	1.0000	1.0000	1.0024	1.0000	1.0161	1.0000	1.0167	0.9928	1.0000	1.0000	1.0000	1.0000	1.0048
2002-03	1.0000	1.0000	0.9977	1.0000	1.0020	1.0000	0.9927	1.0043	1.0000	1.0000	1.0000	0.9931	1.0022
2003-04	1.0000	1.0000	1.0028	1.0000	1.0135	1.0000	1.0041	0.9985	1.0000	1.0000	1.0000	1.0069	1.0016
2004-05	1.0000	1.0000	0.9948	1.0000	0.9941	1.0000	1.0025	1.0140	1.0000	1.0000	1.0000	0.9809*	1.0012
2005-06	1.0000	1.0000	1.0012	1.0000	0.9915	1.0000	0.9976	1.0140	1.0000	1.0000	1.0000	1.0077	1.0000
2006-07	1.0000	1.0000	1.0003	1.0000	0.9998	1.0000	0.9980	0.9932	1.0000	1.0000	1.0000	1.0000	1.0000
2007-08	1.0000	1.0000	0.9997	1.0000	1.0177	1.0000	0.9943	0.9889	1.0000	1.0000	1.0000	1.0000	1.0000
2008-09	1.0000	1.0000	1.0159	1.0000	0.9209*	1.0000	1.0098	0.9950	1.0000	1.0000	1.0000	1.0000	0.9902
2009-10	1.0000	1.0000	0.9946	1.0000	1.0412*	1.0000	1.0023	1.0039	1.0000	1.0000	1.0000	1.0000	1.0000
2010-11	1.0000	1.0000	1.0001	1.0000	0.9764*	1.0000	0.9928	0.9845*	1.0000	1.0000	1.0000	1.0000	1.0000
2011-12	1.0000	1.0000	1.0129	1.0000	0.9854	1.0000	1.0083	1.0201*	1.0000	0.9765	1.0000	1.0000	1.0000
2012-13	1.0000	1.0000	0.9902	1.0000	0.9932	1.0000	0.9972	0.9996	1.0000	1.0124	1.0000	1.0000	1.0000
2013-14	1.0000	1.0000	1.0027	1.0000	1.0179	1.0000	1.0024	1.0112	1.0000	0.9990	1.0000	1.0000	1.0000
2014-15	1.0000	1.0000	0.9799*	1.0000	1.0033	1.0000	0.9859	0.9994	1.0000	1.0016	1.0000	1.0000	1.0000
2015-16	1.0000	1.0000	1.0112	1.0000	1.0172	1.0000	1.0054	1.0150	1.0000	1.0000	1.0000	1.0000	1.0000
2016-17	1.0000	1.0000	1.0055	1.0000	1.0125	1.0000	1.0279	1.0005	1.0000	0.9859	1.0000	1.0000	1.0000

Note: (*) denote significant difference from unit at 0.05