Non-parametric modelling of pollution-generating technologies: Theoretical and methodological considerations, with an application to the case of greenhouse gas emissions in suckler breeding systems in French grassland areas

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Thèse Nouveau Régime
Présentée et soutenue publiquement le 15 Juin 2015
Pour l'obtention du titre de Docteur ès Sciences Economiques

Par

K Hervé DAKPO

sous la direction de Laure LATRUFFE et de Philippe JEANNEAUX

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L'Université d'Auvergne n'entend donner aucune approbation ou improbation aux opinions émises dans cette thèse. Ces opinions doivent être considérées comme propres à l'auteur.

Foreword

Almost four years ago when I graduated with my Master in Research in Economics of Development, I did not expect to end up in a PhD degree. This was without accounting for the seven month internship undertaken in the Livestock Farming Economics Laboratory (EGEE-UMRH) within the French National Institute of Agricultural Research (INRA) located in Clermont-Ferrand-Theix. During this internship I learnt how, with complex and sophisticated models, one can derive very practical implications especially in the area of agriculture. Within this environment I rubbed shoulders with different experts who somehow rekindled my flame of research interest. As a consequence I started a PhD position on the 3rd of September 2012. I would like to take advantage of those words to express my deep acknowledgement to all the people and institutions that have accompanied me all along those years, from the beginning of the internship to the completion of the PhD.

First, I am sincerely grateful to my two PhD supervisors Laure Latruffe (INRA, UMR SMART) and Philippe Jeanneaux (Vetagro Sup, UMR Métafort), who are the cement of this work. They spent a lot of time to educate me to research during this PhD. For their presence, their very active involvement, their listening and their understanding, I express my deep gratitude. I would also like to offer my thankfulness to all the members of the committee who followed my PhD research. Each year, through their comments and arguments, they pushed forward the realisation of this three-year work. Hence, I give my thanks to Catherine Araujo-Bonjean, Marc Benoit, Stéphane De Cara, Stéphane Ingrand, Claire Mosnier, and Philippe Polomé. A thank you also goes to all members of the PhD examining committee. I hope you will enjoy the reading of this manuscript.

I would like to give special thanks to all colleagues in the different labs that were involved in this PhD, namely EGEE (UMRH-INRA), Métafort (IRSTEA-VetAgro Sup), SMART (INRA-Agrocampus Ouest), and the Economics Doctoral School of Clermont-Ferrand University (ED245). Their patience, their availabilities when necessary and the numerous discussions that I had with them, largely contributed to forge all the opinions defended in this dissertation. I would like to take the opportunity of this foreword to highlight the hard work of data collection undertaken by the EGEE lab for many years now (the first farm surveys can be dated to 1971). These farm surveys provide a tremendous quantity of information that is useful for the empirical analysis conducted in this PhD, and they constitute an important resource for future collaboration. I am also grateful to all the aforementioned institutions for giving me access to all the bibliographic databases.

It is not an overstatement to say that given all the requirements of a PhD, the realisation of it implies large amounts of money. This PhD was funded by the “Conseil Regional d’Auvergne” (the local government in the French region Auvergne) through a budgetary line called “Projets Structurants en Sciences Humaines et Sociales” (structuring projects in social and human sciences. In its desire to provide sufficient support to research in general, the “Conseil Regional d’Auvergne” has agreed to fund this PhD, and for this financial support that made the opportunity of a PhD concrete, I am truly grateful. I would also like to acknowledge Marc Benoit and Claire Mosnier who have defended the PhD project in front of a funding comity. My thanks also go also to Dominique Vollet, without whom we would have not heard about this funding. I am also grateful to the European project FLINT (“Farm Level Indicators for New Topics in policy evaluation”), in which the French team is managed by Laure Latruffe, for having funded several aspects of my PhD.

In July 2014 I attended a conference in Brisbane, Australia, namely the Asia-Pacific Productivity Conference (APPC), a specialised conference on productivity assessment. There I met Professor Knox Lovell (from School of Economics, University of Queensland, Australia) who gave me the opportunity to work with him for a few days after the conference. His valuable advices have helped to construct what is now Chapter 2 of this PhD dissertation. This encounter gave me confidence to express to other people my idea of this new model, and to go ahead alone with publication of the article. For this, I would like to express my huge gratitude to Professor Knox Lovell and hope that this is just the beginning of further collaboration. By the same occasion I thank Céline Nauges who was at this time in the University of Queensland, for her support when I was there. I would also take the opportunity of this foreword to thank Cyrille Rigolot and Ben Henderson with whom I spent some time at the CSIRO lab in Brisbane. I am also grateful to Amir Arjomandi, whom I met during the APPC, for giving me the opportunity to experience the developments carried out in this PhD with databases applied to other sectors than agriculture. This augurs for future research together.

Apart from travelling abroad to attend conferences, another interesting point while conducting my PhD was my research stay abroad. From September to the beginning of December 2014, I spent three months in Wageningen University in the Netherlands. The work I carried out there was supervised by Alfons Oude Lansink (Business Economics group of Wageningen University) and constitutes Chapter 4 of this PhD dissertation. I would like to give many thanks to Professor Alfons Oude Lansink for all the time he has devoted that was helpful for the accomplishment of this PhD. I have really enjoyed working with him, and this is just the beginning of a long collaboration. I would also like to thank all the colleagues and friends of the

Business Economics Group at Wageningen University. I am also grateful to the SMART (INRA) lab for funding this research stay and many other conferences and trips associated to the PhD.

I also offer great thanks to Professor Timo Sipiläinen (University of Helsinki) for his contribution which was determinant in completing Chapter 2 of the dissertation.

My first steps in Data Envelopment Analysis started from different meetings with David Berre, Jean-Philippe Boussemart and Hervé Leuleu. I would like to thank them for the inspiring discussions.

I would like to seize the opportunity that I have here to give my special thanks to Yann Desjeux (INRA, UMR SMART) for his support in the last days of writing this dissertation and his very useful advices. I am looking forward to collaborating with him on building a new package for R software to account for many of the developments realised during this PhD.

I would also like to underline that this PhD would have not been possible without the technical assistance of various people (administrative staff, IT support and library staff), in particular in EGEE and in SMART; many thanks to them.

The achievement of a PhD does not only require a good working environment, it also needs supportive family and friends. I want to all thank you personally for everything you have done, which gave me a balance in my life, a determining contribution for the completion of this PhD.

I also have a special thought to all farmers present in the databases that I used for the analysis. I hope that these new results can provide them useful information in their search for sustainability.

Finally, I would like to dedicate this PhD to my little brother Ulrich.

Summary

The growing importance of environmental matters in social responsibility of firms has generated many frameworks of analysis in the economic literature. Among those frameworks, performance evaluation and benchmarking using the non-parametric Data Envelopment Analysis (DEA) have increased at a very fast rate. This PhD research focuses on models that include undesirable outputs such as pollution in the overall production system, to appraise eco-efficiency of decision making units (DMUs). Besides, the recent awareness on the large contribution of agriculture and particularly livestock farming to global warming, has highlighted for this sector the challenge of reaching both economic and environmental performances. In this line, the overall objective of this dissertation is to provide a theoretical and empirical background in modelling pollution-generating technologies and to suggest theoretical improvements that are consistent with the particular case of greenhouse gas emissions in extensive livestock systems. Firstly, we showed that all existing approaches that deal with undesirable outputs in the non-parametric analysis (i.e. DEA) have some strong drawbacks. However, the models grounded on the estimation of multiple independent sub-technologies offer interesting opportunities. Secondly, I developed a new framework that extends the by-production approach through the introduction of some explicit dependence constraints that link the sub-technologies in order to build a unified system. Thirdly, an empirical comparison, using a sample of French sheep meat farms, of this by-production modelling extension with the existing approaches, revealed some inconsistencies of these latter. Finally, we expanded this new by-production formulation to account for dynamic aspects related to the presence of adjustment costs. The application to the case of French suckler cow farms underlined the necessity of accounting for dynamic aspects and also showed high heterogeneity in investment strategies of these farmers.

Keywords: eco-efficiency, undesirable output, production technology, Data Envelopment Analysis, by-production, dependence constraints, factor bands, greenhouse gas, livestock farming.

Résumé

La prise en compte des problèmes environnementaux dans la responsabilité sociale des entreprises a généré en économie de nombreuses propositions. Parmi elles, le cadre d'analyse basé sur l'évaluation de la performance en utilisant notamment les techniques d'enveloppement des données (DEA) s'est très vite répandu dans la littérature théorique comme empirique. Ce travail de thèse s'inscrit dans cette logique en mettant l'accent sur la modélisation des technologies polluantes. Par ailleurs, la question des changements climatiques et de la forte contribution de l'agriculture et en particulier de l'élevage dans les émissions de gaz à effet de serre (GES) impose à ce secteur de relever aujourd'hui en plus du défi économique celui de l'amélioration de sa performance environnementale. L'objectif général de cette recherche doctorale est donc de fournir un nouveau cadre d'analyse théorique et empirique dans la modélisation des technologies polluantes afin d'évaluer l'éco-efficience des systèmes productifs, en particulier le cas des émissions de GES en élevage extensif de ruminants. Dans un premier temps, nous montrons les limites théoriques et méthodologiques des modèles existants. Néanmoins, nous insistons sur le fait que les approches basées sur l'estimation de plusieurs sous-technologies indépendantes pour prendre en compte les différents processus présents dans les systèmes productifs sont très prometteuses. Dès lors dans un deuxième temps, nous proposons une nouvelle extension de la méthode « by-production » qui repose sur l'introduction d'interconnections entre les différentes sous-technologies impliquées afin de construire un système plus unifié. Dans un troisième temps, une comparaison empirique utilisant des données d'exploitations de viande ovine de notre extension avec les approches existantes a révélé certaines incohérences de ces dernières. Enfin pour aller plus loin, nous élargissons dans un quatrième temps notre approche afin de prendre en compte les aspects dynamiques et notamment la présence de coûts d'ajustement. Les résultats de l'analyse empirique entreprise avec des données d'exploitations bovines allaitantes (viande) ont révélé la nécessité de prendre en compte ces aspects, mais ont aussi révélé la forte hétérogénéité existante dans les stratégies d'investissements des éleveurs.

Mots-clés: éco-efficience, production indésirable, technologie de production, méthode d'enveloppement des données (DEA), « by-production », contraintes de dépendance, « factor bands », gaz à effet de serre, élevage.

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General Introduction

1. Background: Greenhouse Gas Emissions and livestock farming

1.1. Climate change, agriculture and livestock impacts

Global warming is one the greatest environmental challenges at the beginning of this twenty first century (Böhringer et al., 2002; Philp, 2012; Pittel et al., 2014). Climate change and its global warming effects raise the question of sustainable production behaviour for all sectors of human activity (food, water, health, economy, energy…). The expected consequences (droughts, floods, extreme climatic events…) of temperature increase on a global scale can be devastating in many regions (Stern, 2007; Schellnhuber et al., 2012; Schellnhuber et al., 2013). According to the Intergovernmental Panel on Climate Change (IPCC) "most of the observed increase in globally averaged temperatures since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations. The observed widespread warming of the atmosphere and ocean, together with ice mass loss, support the conclusion that it is very likely that it is not due to known natural causes alone" (Solomon et al., 2007). The recent increase in carbon dioxide (CO_2) concentration in the atmosphere is attributed to anthropogenic activities.[1]

Agriculture is one of those activities. Agriculture-related negative externalities have raised social and political concerns (Guesmi and Serra, 2015). It has even been recommended in the Kyoto protocol the "promotion of sustainable forms of agriculture in light of climate change considerations" (United Nations, 1998). This situation has emphasised the debate around the multifunctionality of agriculture which generates simultaneously side-effects (by-products) along with food furniture (OECD, 2001). Actually, the farming sector, and especially the livestock sector, has been pointed out as one of the biggest contributor to air pollution through greenhouse gas (GHG) emissions (McAlpine et al., 2009; Steinfeld and Gerber, 2010; Herrero et al., 2011). Globally, accounting for direct and indirect impacts, agriculture represents 17% to 32%

[1] It is worth saying that this vision of recent climate change and the contribution from human activities is not shared by all (Capstick and Pidgeon, 2014). Some climate-sceptics question the scientific evidence of global warming, and others cast doubt on the relevance of climate policies to reduce greenhouse gas emissions. As argued in Pottier (2011) and Morel (2012), this climate-scepticism which relies on pseudo-scientific arguments to contest climate change, is rooted mainly on the uncertainties surrounding the expected consequences of climate change. According to these authors (Pottier, 2011; Morel, 2012) the non-believers of climate change actually reject the necessity of political actions to the extent that they finally deny the scientifically evident climate change.

of the total anthropogenic GHG emissions (Bellarby et al., 2008). [2] GHG emissions associated to agricultural activities are expected to increase by half by 2030 in light of the world future challenges (increase in the demand for food products, diet changes…) (Metz et al., 2007; Friel et al., 2009). The Food and Agriculture Organisation of the United Nations (FAO) has stressed that animal breeding is responsible for 13% to 18% of GHG emissions from human source (Steinfeld et al., 2006; Gerber et al., 2013). Red meat production, mainly beef, represents 41% of the GHG emissions associated to this sector (Gerber et al., 2013 pxii). For the United States' Department of Agriculture (USDA), "GHG emissions from livestock are inherently tied to livestock population sizes because the livestock are either directly or indirectly the source for the emissions." (USDA, 2004). This observation is linked to the increasing number of feedlots, which are highly intensive fattening systems, in the United States.[3] The growing number of livestock in intensive production systems has explained the increase in GHG emissions (Paustian et al., 2006). In the same line Vergé et al. (2007) noted that "in recent years, industrial livestock production has grown at twice the rate of more traditional mixed farming systems and at more than six times the rate of production based on grazing". The controversies surrounding livestock breeding and the consumption of red meat have increased recently, and this particularly since the publication of the FAO report "livestock's long shadow" (Steinfeld et al., 2006; Dockès et al., 2012). Medias have relayed these controversies by publishing numerous slogans and headlines. For instance one can read at the head of the *The Guardian* published on July 21, 2014, that "Giving up beef will reduce carbon footprint more than cars, says expert",[4] or the screamer of the Time of December, 16 2013 which reads "The Triple Whopper Environmental Impact of Global Meat Production".[5]

Three main GHGs are at stake namely methane (CH4), arising largely from enteric fermentation (associated to the normal digestive process of animals); nitrous oxide (N2O),

[2] GHG are generated during various stages, from farming to food processing and distribution, and also arise from waste management.

[3] Website: http://www.epa.gov/agriculture/ag101/printbeef.html, consulted on April 21, 2015.

[4] http://www.theguardian.com/environment/2014/jul/21/giving-up-beef-reduce-carbon-footprint-more-than-cars

[5] http://science.time.com/2013/12/16/the-triple-whopper-environmental-impact-of-global-meat-production/. Other headlines can be read for example on http://www.bbc.com/news/science-environment-29007758, http://www.huffingtonpost.com/2014/07/21/beef-environmental-impact_n_5599370.html, http://www.natureworldnews.com/articles/10373/20141115/red-meat-contains-hidden-emissions.htm, http://www.theweek.co.uk/environment/60199/climate-change-why-meat-is-a-bigger-threat-than-cars.

related to nitrogen fertilisers and manure management; and CO2, associated to energy use resources (fossil fuels' consumption, other agricultural inputs' manufacturing, etc.). In Europe ruminant livestock systems account for about 9% of the total GHG emissions and 55% of the GHG associated to agriculture (Freibauer, 2003; Schils et al., 2007; Leip et al., 2010). In France, agriculture accounts for 19% of the national GHG emissions with a share of 53% attributed to animal breeding (Veysset et al., 2011).

It should however be stressed that livestock farming has various positive aspects for human kind. For example, in developing regions of the world, more than 752 million households derive their subsistence from livestock rearing which is an important sector to fight extreme poverty and food insecurity (Otte et al., 2012). In Europe and particularly in France, livestock systems for meat production are predominantly located in grassland disadvantaged areas (Veysset et al., 2013). The farms located in these areas experience the lowest revenue within the French farm population, and this is particularly true for the case of sheep meat producers (Veysset et al., 2014). This situation accentuates the dependency of those farms to European subsidies to live on (Veysset et al., 2005). This low profitability situation, together with the uncertainty around the future of the Common Agricultural Policy (CAP) reforms,[6] and the tension on agricultural prices associated to trade openness with an increase competition, can explain the decrease in the number of meat producers. From another societal point of view, many of these farms located in mountain areas - where there are no other alternative activities than livestock rearing - help maintain the economic vitality of rural areas. In light of all these issues, the livestock sector in general, and specifically in France, faces the double challenge of economic and environmental sustainability.

1.2. Sustainable development and theory of externalities

In 1987 the United Nations World Commission on Environment and Development has stressed in its report titled "Our Common Future" (Brundtland, 1987 p43) that: "Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs. It contains within it two key concepts:

- the concept of 'needs', in particular the essential needs of the world's poor, to which overriding priority should be given; and

[6] One can visit the following website for an overview of the CAP evolution in the last 50 years http://ec.europa.eu/agriculture/50-years-of-cap/index_en.htm

- the idea of limitations imposed by the state of technology and social organization on the environment's ability to meet present and future needs."

Clearly, the concepts of sustainability or sustainable development encompass three interconnected aspects of human life, namely economic and social capital development, and environmental protection.[7] Often the concept is limited to the two pillars related to economics and environment. As such, many studies are grounded on the economics-ecology pair to define sustainability (Engel and Engel, 1990; Klaassen and Opschoor, 1991; Common and Perrings, 1992; Faucheux and O'Connor, 1998).

In the economic literature, environmental concerns are addressed on the basis of the concept of externalities (van den Bergh, 2010; Common, 2011). The origin of this concept can be dated to Alfred Marshall (1842-1924), and it has been fully introduced in the economic analysis by Henry Sidgwick (1838-1900) who first evoked the idea of external costs or benefits, later formalised by Arthur C. Pigou (1877-1959) in the case of market failures. Pigou (1920) initiated the integration of externalities into a partial static analysis framework and supported the idea that public intervention is a factor of efficiency. Welfare economics has thus focused on the processes of internalisation of externalities, which affect resource allocation and generate inefficiencies (Pigou, 1920; Pareto, 1971). More recently, a new formalisation has been proposed by Meade (1952), and the concept has been generalised with the definition of Buchanan and Stubblebine (1962) covering a broad spectrum of market failures from natural monopoly to common goods. According to these authors, the externality incurred by an individual B fundamentally depends on another individual A's activities, that generated the externality and on which B has no control power, and also depends on the social group in which both individuals are operating. Externality then depicts situations where no financial compensation exists, and in general highlights the absence of control of the emitter by the receiver, a necessary condition for distinguishing real externalities (which require public intervention) from false ones (for which the receiver is totally indifferent). Thereafter, this definition has been restrained by Baumol and Oates (1975) who adopted the notion of real (non-monetary) effects. Mishan (1969) and Viner (1931) have proposed the term of technological externality.

The concept of externality can then be used to characterise environmental damages (which thus generate some external social costs) for which markets do not exist.[8] According to

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[7] In some cases a fourth pillar may also be added, known as cultural diversity.

[8] Sankar (2006) made a clear distinction between social costs (due to the presence of externalities) and private costs (depending on a market equilibrium). The author mentioned two reasons for the absence of

Heller and Starrett (1976) "all externality problems can be traced to some more fundamental problem having to do with market failure". At different levels, regulations will play different role aiming at the internalisation of environmental damages. Several possibilities offered to policy-makers have been discussed in the literature (Pigou, 1920; Coase, 1960; Baumol and Oates, 1988). Among these possibilities are taxes or environmental standards, reduction of transactions costs, information on marginal abatement costs, good definition of property rights, etc.[9] Environmental externalities generally meet the non-exclusivity and non-rivalry definitions of public goods.[10] This situation prevents from an adequate definition of property rights. As stressed in Coase (1960), the absence of policy regulation will result in private costs lower than social ones, thereby creating over-use of public goods and loss in social welfare.[11]

At the international scale, the role of policy intervention to integrate environment in decision-making has been clearly stressed at the Earth Summit in Rio in 1992 through three major objectives (United Nations, 1992a):

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markets for externalities: "(a) difficulty in defining, distributing and enforcing property rights and (b) high costs of creation and operation of markets." According to Sankar (2006), "the theory of negative externality is the foundation of environmental economics."

[9] According to Coase (1960), "if transactions costs are zero and property rights are well defined, agents should be able to negotiate their way to an efficient outcome" (Varian, 2000 p292). However this situation, corresponding to the hypothesis of pure and perfect competition, is rare in practice. The point stressed by Coase, who never referred to the term "externality", lays in the existence of transaction costs when confronting (defining) property rights. In terms of regulation, Coase's theorem implies that given the levels of the transaction costs, possible actions are: i-) laissez-faire (let the market self-regulate); ii-) necessity of public intervention; and iii-) give the discretion power to a third party (specialist of law) who will allocate property rights to parties that best use them. Another solution to the problem of an externality is through the definition of a market for this externality (Arrow, 1970). "If a firm produces pollution that harms another firm then a competitive market for the right to pollute may allow for an efficient outcome" (Varian, 2000 p292). In this line Varian (1994) has designed some compensation mechanisms for internalising environmental impacts.

[10] "A good is non-exclusive if it is impossible to exclude individuals from benefitting from the good. A good is non-rival if one person's consumption does not decrease the amount available to others" (Chakravarty, 2002 p678). Some environmental externalities like air or water pollution fit with these two properties. This implies that their monetary and as such are difficult to evaluate using the price system, and often consumers have not any options to not consuming those goods.

[11] Hardin (1968) has referred to this situation in the presence of non-exclusive but rival good as the "tragedy of commons".

- "To incorporate environmental costs in the decisions of producers and consumers, to reverse the tendency to treat the environment as a 'free good' and to pass these costs on to other parts of society, other countries, or to future generations;
- To move more fully towards integration of social and environmental costs into economic activities, so that prices will appropriately reflect the relative scarcity and total value of resources and contribute towards the prevention of environmental degradation;
- To include, wherever appropriate, the use of market principles in the framing of economic instruments and policies to pursue sustainable development."

The United Nations Framework Convention on Climate Change (UNFCCC) has since then been created, through its main organ the "Conference of the parties" (COP), a background for multilateral discussions between countries members, to set up actions against climate change and greenhouse gas emissions (GHG). Within this convention intergovernmental efforts are directed towards the objective of stabilising "greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (article 2) (United Nations, 1992b). As a consequence, countries members have committed to some binding benchmarks.

In summary, the main challenge is the internalisation of negative externalities and the design of policy tools to meet this objective. This challenge nowadays concerns GHG emissions. Solving the climate issue might require relevant actions at the international and local scales, but also at the firms and households' levels. Besides, the global and domestic government interventions must account for the various spheres involved at each stage.

i-) The institutional dimension which delimits the political framework for the climate negotiations. Failure of these negotiations (Maltais, 2014) to adopt common rules in the short, middle and long run exposes the divergence of interest of the different parties (for instance the distribution of the costs and benefits of mitigating GHG), and this despite the warning of the scientific community. A relevant example is the Kyoto protocol signed initially by 38 countries in 1997 including the United States.[12] Four years later, the lack of cooperation of the different parties in the design of the protocol left it non-ratified. More, the levels of GHG emissions of most countries have increased, and the American President Bush, after taking office, has stated

[12] The protocol was about an agreement of the different countries to reduce within the period 2008-2012 their levels of GHG emissions by an average of 5.2% compared to the 1990 emissions levels.

the position of the United States to withdraw from the protocol (Böhringer et al., 2002).[13] For developing countries, ratification of the Kyoto protocol by the United States is a sine qua non condition for the success for international policies for emissions control and adaptation strategies to the ineluctable change. Although the recent agreement between the United States and China (12 November 2014) which sets substantial cuts in their respective emissions, may facilitate future negotiations and overcome the inertia of the institutional system. Because of these institutional brakes,[14] all existing agreements lack of enforcement mechanisms and thereby no one is forced to reduce polluting activities. Still in this institutional sphere, one can also find the direct regulations which define the political and legal considerations that govern for instance the market of innovation (patents), and the implied technical and structural changes, particularly their effect on firms competition.

ii-) The financial dimension, largely absent from the negotiation table. The financial crisis of 2008 has totally eclipsed the environmental negotiations and especially the conference of the parties (COP2009 in Copenhagen). The urgency needs created by this crisis have pushed into the background the environmental problem, as if environment had to wait for economic recovery. The speculative bubbles at the origin of this crisis have revealed the amount of money available on those markets and which could partly be redirected to fund GHG mitigation, e.g. by allocating them towards clean investments. Associating the financial dimension to the issues of global warming can certainly provide more effectiveness to climatic negotiations.

iii-) At the bottom of the institutional and financial dimensions we have in a more restrictive sense the productive sphere. The main actors in pollution generation are decision-making units, which use some resources with the objective to produce economic goods. The internalisation of non-economic goods like pollution by those units requires understanding the possible interactions between these two types of goods, and how the inclusion of the pollution in the units' decisions might affect their overall profitability. The compliance of managers in mitigating their levels of pollution can be influenced by appropriate incentives that conform to the managers' capitalist logic: for example, incentives that provide, when necessary, the right compensation. In other words, the support of the managers highly depends on the cost-

[13] Earlier, on July 25, 1997, the senate of the United States unanimously voted a resolution which explicitly mentions that the United States should not be a signatory to any protocol that did not include binding targets and timetables for developing as well as industrialised nations, or this "would result in serious harm to the economy of the United States" (Cool, 2006).

[14] One can also refer to the book of Goldstein and Pevehouse (2013 p4-9) where the authors discuss the core principles associated to the collective goods' issue in international relations.

effectiveness of the mitigation actions. This is possible only if at a certain point policy-makers have sufficient information (knowledge), and a large choice of measures (indicators), on which they can ground the design of a targeted policy scheme. This PhD aims at contributing to the knowledge on how negative externalities can be internalised at a firm level, by relying on approaches that include bad outputs in performance assessment.

In the next sub-section we discuss the specific case of livestock systems and how to deal with the problem of GHG emissions in terms of policy and mitigation options.

1.3. GHG mitigation alternatives in livestock farming and policy options

The "Oxford Martin Programme on the Future of Food" has underlined that "the goal of sustainable intensification is to increase food production from existing farmland while minimising pressure on the environment. It is a response to the challenges of increasing demand for food from a growing global population, in a world where land, water, energy and other inputs are in short supply, overexploited and used unsustainably. Any efforts to 'intensify' food production must be matched by a concerted focus on making it 'sustainable.' Failing to do so will undermine our capacity to continue producing food in the future".[15] As defined, the concept of sustainable intensification implies the development of innovative and sustainable agricultural practices through adoption of new technologies or the enhancement of actual agricultural production systems (Ringler et al., 2014). In the same vein, the necessary transformations of agriculture have been summarised by the FAO in the concept of "climate-smart agriculture" (FAO, 2013).[16]

This new concept lays on three objectives: "firstly, increasing agricultural productivity to support increased incomes, food security and development; secondly, increasing adaptive capacity at multiple levels (from farm to nation); and thirdly, decreasing greenhouse gas emissions and increasing carbon sinks" (Campbell et al., 2014). These concepts of sustainable intensification and climate-smart agriculture stress that policies should provide the proper incentives for the adoption of mitigation strategies. In terms of GHG emissions mitigation, agriculture and in particular livestock farming are center sectors. Firstly, agriculture offers the advantage of reducing its own emissions but also the ones generated by other sectors; secondly

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[15] Website: http://www.futureoffood.ox.ac.uk/sustainable-intensification (consulted on 04-13-2015). See also Garnett and Godfray (2012).

[16] As pointed out in this report (FAO, 2013 p27) the concepts of sustainable intensification and climate-smart agriculture are closely related.

agriculture must face the double challenge of mitigation and adaptation, coined "feedback loop"[17] in Raney et al. (2009); and thirdly, according to many experts, the livestock farming sector offers numerous cost effective solutions to the problem of climate change (Intergovernmental Panel on Climate Change - IPCC, 1990; McMichael et al., 2007). Among those solutions one can name sink practices, land management options (relating to grazing and pasture management, tillage reduction…), herd management alternatives, genetic improvement, fertilisers' and other inputs' management options. They have been largely discussed in the literature (Cole et al., 1997; Mosier et al., 1998; Oenema et al., 2001; Janzen et al., 2006; Burney et al., 2010). Further suggestions relate to the promotion of collective actions (OECD, 2013), changes in patterns of consumption (Garnett, 2011), payments for agri-environmental services (Legg, 2009).

Two main types of policy instruments have been proposed to promote environmental-friendly agriculture: market driven mechanisms (such as taxes, tradable permits), and command and control tools (such as pollution standards) (Cole and Grossman, 1999). Within the European Union (EU), a number of measures have been undertaken. For instance, in 1991 the nitrate directive has been introduced to lower nitrogen use in agriculture and prevent water pollution (European Council, 1991). In addition, the EU CAP has introduced with the MacSharry reform in 1992 some financial incentives based on agri-environmental schemes. Agri-environmental schemes, now sitting in the second pillar of the CAP (that is to say within the rural development framework), are tailored for each EU member state in order to reconcile the production of agricultural goods and the respect of the environment, by encouraging the adoption of sound environmental agricultural practices (Lenihan and Brasier, 2009). In addition, the cross compliance of the first CAP pillar links direct payments to some sustainability standards (Latacz - Lohmann and Hodge, 2003). As pointed out in Canton et al. (2009) these policies, designed to compensate farms with incurred costs and forgone revenues, and also to encourage the switching from intensive to extensive systems, are subject to information asymmetry in their implementation. This situation creates distortions and can in turn affect the effectiveness of the policy.

Finally, as a conclusion to this first section, it should be highlighted that the increasing awareness of negative effects of production systems (such as livestock systems) on natural ecosystems, has raised great policy concerns about environmental regulations. Policy regulations in agriculture all target the enhancement of efficiency in farming systems and thereby the

[17] This feedback loop situation correctly represents the complex interaction between agriculture and environment.

lowering of pollution emissions per unit of output. In the presence of such regulations, farmers have to trade-off between the different objectives viz. economic, environment (and social) objectives. What is then at stake is a joint assessment of economic viability and environmental impacts of producing units, to which this PhD contributes.

2. Problem statement, research questions and objective of the PhD

Theoretical and empirical relations between economic returns and environmental impacts have been captured through the concept of eco-efficiency. Eco-efficiency has been defined by the World Business Council for Sustainable Development (WBCSD) in 1992 as "…the delivery of competitively priced goods and services that satisfy human needs and bring quality of life, while progressively reducing ecological impacts and resource intensity throughout the life-cycle to a level at least in line with the Earth's estimated carrying capacity" (UNEP, 2014). Adapted to the present situation, it captures three goals: reduction of resources used, lowering of environmental impacts and increase in the levels of production.

In the scientific community (and mainly among economists), discussions around the concept of eco-efficiency have highlighted two challenges: i-) the measurement of eco-efficiency and, ii-) the nature of the trade-offs between economic (i.e. operational) performance and environmental performance. In the literature many approaches have been developed to assess eco-efficiency and rely on the use of performance benchmarking (Tyteca, 1996). However, many of these approaches are based solely on partial productivity indicators (also named "key performance indicators" (Bogetoft, 2013)) which do not account for all connections between inputs and outputs in a decision making unit (DMU). By contrast, the development of activity analysis with multi-inputs and multi-outputs production frontier estimation - including the main approaches of non-parametric Data Envelopment Analysis (DEA) and parametric Stochastic Frontier Analysis (SFA) grounded on the neoclassical production theory - has offered some interesting possibilities in performance benchmarking. Nevertheless, it is within the DEA framework that the last two decades have seen the greater development of approaches in the treatment of undesirable outputs (pollution being an undesirable output of agricultural production which is a good output). Among those approaches, one can find the model that treats pollution as an additional input or as an additional output under the weak disposability assumption (Haynes et al., 1994; Chung et al., 1997; Kuosmanen and Podinovski, 2009); the models relying on the materials balance principles and the laws of thermodynamics (Coelli et al., 2007; Hampf and Rødseth, 2014); the models based on the estimation of two sub-technologies, one associated to the operational performance and the other related to the environmental efficiency (Sueyoshi and Goto, 2010; Murty et al., 2012).[18]

The various methodologies differ in the way they are implemented but also in their assumptions. The choice of a model in the empirical literature is highly governed by the understanding and the conception a researcher has of a pollution-generating technology. To date there exist no single framework that discusses the theory underlying each of the aforementioned models and their evolution and relevance. This lack in the literature has led to the **first research question** of this PhD.

What are the strengths and weaknesses of the existing approaches aiming at modelling pollution-generating technologies in performance benchmarking within the non-parametric DEA framework?

More precisely, the PhD aims at providing an overview of the current state of the literature on eco-efficiency measurement in the non-parametric framework (i.e. DEA). The first objective is to explain the various approaches developed in the literature, and why they have been developed. The second objective is to discuss the limits and benefits of these approaches, in a view of formulating a more robust approach in modelling pollution-generating technologies. We question whether all existing methods have advantages and drawbacks, and whether some are more promising given their strong theoretical background. This seems to be the case of the models based on the estimation of multiple sub-technologies (one designed to represent good outputs and another one depicting the process of undesirable outputs' generation).

The second research question of the PhD is intrinsically related to the first question as it follows its conclusion.

Which new theoretical model for eco-efficiency evaluation can be formulated in the non-parametric DEA framework, given the pros and cons of the existing approaches?

Here the PhD aims at developing a new approach in eco-efficiency measurement that would overcome some limits inherent to the existing approaches. In this part I argue that the by-

[18] Other models can also be found in the literature like the ones applying a data transformation on the undesirable outputs (Lovell et al., 1995; Seiford and Zhu, 2002), or the ones estimating a frontier eco-efficiency model depicting the relation between good and undesirable outputs ignoring the utilisation of inputs (Kortelainen, 2008; Picazo-Tadeo et al., 2012). Finally, there are also some models that couple Life Cycle Assessment (LCA) and DEA (Lozano et al., 2009; Vázquez-Rowe et al., 2010).

production approach proposed in Murty et al. (2012), which is based on the explicit representation of the processes involved in a production systems (one sub-technology for good outputs and another one for undesirable outputs), has empirical limits despite its theoretical relevance. More precisely, its implementation in the DEA framework fails to unify both sub-technologies since they are treated independently. This part is then be devoted to the development of a new by-production approach, where Murty et al. (2012)'s approach is augmented with dependence constraints, and as such creates a unified technology where both sub-production systems are interconnected. This research question constitutes the heart and the originality of the PhD by proposing a step further in modelling pollution-generating technologies. This originality comes from the fact that we consider a production entity as a set of different individual processes which together contribute to the final objective of the production entity. However, this coordination or interrelation is only possible by building "communication roads" between the different processes, which is the main contribution of this PhD.

After explaining the existing methods in modelling pollution-generating technologies and developed a new approach, all from a theoretical point of view, **the third research question aims at providing an empirical discussion about the convergence or divergence of all these approaches**. As we argue in this part of the dissertation, one lack of the literature in eco-efficiency assessment is the confrontation of existing DEA models to real firms' data. The first objective of this research question is therefore to validate or invalidate the various approaches from an empirical point of view. The second objective is to provide an analysis of the trade-offs between the economic efficiency and the environmental efficiency. Two strands of thought can be found in the economic literature regarding these trade-offs.

Firstly, the common view shared by many economists and managers is that environmental regulations are detrimental to profits of organisations (Palmer et al., 1995). The reason is that environmental policies constrain DMUs in their profit-maximising strategies through the necessary diversion of productive inputs towards the mitigation of environmental impacts. The optimal profits generated under these circumstances are thus lower than in the situation of absence of regulations. This intuitive point of view has governed the construction of the approaches used in DEA performance benchmarking to model pollution-generating technologies. All these models are elaborated to capture the positive correlation between undesirable outputs and good outputs' production, and rely on the idea that environment comes at a cost.

Secondly, in the early nineties a new strand of thought emerged. Some economists introduced the idea of a possible "win-win" situation, in which adequate environmental policies can not only improve firms' environmental performance, but may also increase their economic (i.e. operational) efficiency. This assumption is known as the Porter Hypothesis as it was discussed firstly by Porter (1991) and Porter and van der Linde (1995a, 1995b). Porter (1991) indeed suggested that "strict environmental regulations do not inevitably hinder competitive advantage against rivals; indeed, they often enhance it." Advocates of the Porter Hypothesis believe that the traditional view (where firms lose in a situation of environmental policies) is restricted to a static framework, while in a dynamic world regulations can trigger innovations which can be beneficial both to environmental and economic performances. Among the opponents of the Porter Hypothesis one can mention Portney (1994), who indicated to "disagree fundamentally with the message that we can avoid painful choices when setting environmental goals".[19] Nevertheless, in their statement "the possibility that regulation might act as a spur to innovation arises because the world does not fit the Panglossian belief that firms always make optimal choices", Porter and van der Linde (1995b) clearly pointed out the fact that firms might not make optimal choices due to imperfect information, market and organisational failures (Ambec et al., 2013).[20] In performance benchmarking, the Porter Hypothesis can be related to the fact that adequate environmental regulations may reveal inefficiencies in firms' resource consumption.

Based on all this, **the third research question** is stated as follows:

What lessons from an empirical comparison of pollution-generating technologies within the non-parametric DEA framework, in terms of convergence analysis and trade-offs for French livestock grazing systems?

Recalling that one of the objectives of climate-smart agriculture is to lower agriculture's emissions measured per unit of output, the comparison of the different methodologies undertaken in this part of the PhD dissertation is grounded on the common objective of minimisation of GHG emissions per kilogram of meat production in a sample of French livestock systems located in grasslands areas. Along the same path followed by Hampf and Rødseth (2014), the comparison of eco-efficiency obtained with each model is based on three different assumptions depending on the number of decision variables allowed in the optimisation program. Under the first assumption, technical efficiency with GHG generation is measured given a fixed level of inputs and of the good output. Under the second assumption eco-efficiency

[19] Mohr (2002) is another opponent of the Porter Hypothesis.

[20] More discussion can be found in (Ambec et al., 2013) about recent developments around the Porter Hypothesis.

is evaluated by relaxing the fixity of the good output. Under the third assumption, the most flexible one, eco-efficiency is measured under free choice of input levels and of good and undesirable outputs. In this case the optimisation program evaluates the optimal allocation of inputs that optimises the eco-efficiency level. We define an overall eco-efficiency score based on this third assumption, and as such this score can be decomposed into different sources of efficiency (weak efficiency ratio, allocative efficiency ratio and input efficiency ratio) in light of the work carried out by Hampf and Rødseth (2014). We expect that under the third assumption - where all variables are endogenous in the optimisation - most of the existing pollution-generating technology models (namely the model under the weak disposability assumption (Färe et al., 2005), the model under weak G-disposability, the model relying on the materials balance principles (Hampf and Rødseth, 2014), and the multiple frontier technology based on the unification of natural and managerial disposability concepts (Sueyoshi and Goto, 2012a)) converge to the same results as if pollution is treated as an extra input. We stress that considering pollution as an input is not a correct way of modelling pollution-generating technologies. As for the by-production approach formulated in Murty et al. (2012), it also fails to provide an adequate representation of the technology, and also yields an overestimation of the eco-efficiency score. By contrast, the new approach that I develop within this PhD (by-production model augmented with dependence constraints between sub-technologies) appears to provide sound results in terms of eco-efficiency for the farm systems under analysis. Based on this new approach, we undertake an analysis of trade-offs between operational and environmental performances, and classify the observations into the different categories related to the nature of the trade-offs (the different situations being "win-win", "win-lose" and "lose-win").

As earlier mentioned, the Porter Hypothesis requires assessments on a dynamic basis where investments in new capital (or equipment), that can capture adoption of innovations, are incorporated. However, in a dynamic framework, levels of quasi-fixed inputs (such as capital) cannot be instantaneously adjusted, and therefore investments (as well as disinvestments) in these inputs will incur costs to firms (Caputo, 2005). These costs (internal or external[21])

[21] Internal adjustment costs can be installation and learning costs of new equipment. These internal costs can be qualified as technological costs that occur before any use of investment goods. External adjustment costs are related to the possibility of decreasing returns to scale (DRS) of firms manufacturing investment goods. In the presence of DRS, the marginal costs of producing capital goods increase with the amount of these goods. In this case an infinite demand of investments will implies infinite marginal costs and thereby infinite supply prices. This situation will prevent firms that use investments for production to demand

represent output losses due to adjustment patterns of capital inputs. Adjustment costs can be related to implementation of new equipment (as well as removal of former equipment), learning, restructuring, etc. From this point of view, the fourth research question addressed in this PhD extends the adjustment cost model of the theory of investment, to eco-efficiency measurement. **This fourth question** is formulated as follows:

How do dynamic aspects associated to the nature of investments in quasi-fixed inputs, matter in eco-efficiency appraisal within the non-parametric DEA framework?

This fourth research question contributes to research developments accounting for undesirable outputs in modelling production technologies, with an analysis that makes a clear distinction between static and dynamic measurements of eco-efficiency in light of the adjustment cost theory. We investigate the need to account for this situation in the treatment of undesirable outputs and we empirically test based on the use of a sample of French suckler cows located in grasslands areas. The analysis is undertaken with my new by-production formulation.

All four research questions addressed define **the main objective of this PhD** which is: ***to provide a theoretical and empirical background in modelling pollution-generating technologies and to suggest theoretical improvements that are consistent with the particular case of GHG emissions in extensive livestock systems***.

3. Livestock databases and GHG computations for the empirical applications

The analyses conducted in this work to answer the third and fourth research questions are based on two livestock databases: i-) sheep meat farms and ii-) suckler cow farms, both types being located in the French grassland areas of Massif Central (in Central France) and its northern periphery. The grassland areas include mountain and plain areas and are mainly disadvantaged areas. Both organic and conventional systems are included in the sample. As discussed in Section 1, the major stake of eco-efficiency in red meat production makes particularly relevant these two databases that include farms evolving in a particular farm business activity area in France. The two sample farms (sheep meat and suckler cow) have been

infinite levels of these inputs. In summary, external adjustment costs are monetary costs that firms demanding capital goods pay to firms supplying those goods (Foley and Sidrauski, 1970).

surveyed yearly since long by the livestock farming economic laboratory[22] of the French National Institute of Agricultural Research (INRA) located in Clermont-Ferrand-Theix. The sheep meat database used here covers the period 1987 to 2013 and represents 1,292 farm-year observations and a total of 123 different farms. The suckler cow database used here covers the period 1978 to 2013 and represents 3,142 farm-year observations and 170 different farms. Each sample is unbalanced due to new entries and retirements. The surveys were initially designed to assess structural changes and the evolution of different economic characteristics of the different systems under analysis. For this reason hundreds of variables regarding the production system and various bookkeeping information are available in both databases. The variables relate to the structure of the farms but also some technical and economic results. Such detailed information enables an almost complete representation of the different systems.

Using these data and the strong knowledge[23] of the different farms, an ex-post evaluation of the three main GHGs, namely CO_2, N_2O and CH_4, has been undertaken using the Life Cycle Assessment (LCA) methodology, a necessary step to obtain environmental variables. LCA is a valuable multi-criteria quantitative tool that informs on the environmental considerations that should be integrated within decision-making in view of sustainable development. In ISO 14040 LCA is defined as the "compilation and evaluation of the inputs, outputs and potential environmental impacts of a product system throughout its life cycle" (Guinée et al., 2002). In another words, LCA is a method used to quantify and identify sources of environmental impacts of a product or a system from ‘cradle to grave’ (Ekvall et al., 2007). It means that these impacts are evaluated from the extraction of natural resources up to their elimination or disposal as waste. In the case of agriculture and in particular livestock farming, LCA is widely used and accepted (Gerber et al., 2010). Many application studies have used this method to evaluate the pollution intensities of GHG releases related to breeding systems (Beauchemin et al., 2010; Ripoll-Bosch et al., 2013; Chatterton et al., 2014; Wiedemann et al., 2015).

A particular point of interest in LCA is the definition of the system boundary which delimits the unit process under analysis. For our case, the system boundary covers all activities from the cradle to the farm gate, that is to say it includes all upstream processes in livestock production up to the point where the animals or products leave the farm. This means that we did not take into account the flows associated with the processing of meat products (slaughtering

[22] This lab (EGEE) is one of the several labs involved in this PhD. Affiliation in this lab guarantees the access to the original data sources.

[23] All engineers who conduct the surveys were still present at the time of the PhD.

and transformation) and marketing chains, as it is commonly done. Indeed, in agriculture the majority of LCA studies use the cradle-to-farm gate as the system boundary (Harris and Narayanaswamy, 2009).

LCA is a long and fastidious work that required for our study about two years of work and the adaptation of existing tools that provide the great majority of emission factors required for the estimation of the global warming impact. It should be noted that, since GHG emissions are not observed, they are computed using observed farm data. For instance for one litre of fuel, depending on its quality, we can associate between 2.9 to 3.3 kg of carbon dioxide, and the equivalent CO_2 necessary for the manufacturing of one kilogram of mineral nitrogen is about 5.7 kg. More than 300 variables have been used to compute the LCA results used in this PhD. The use of LCA in agriculture to estimate environmental impacts like GHG emissions is particularly relevant, firstly because the pollution in agricultural systems is non-point source (i.e. it is generated by diffuse different sources), and secondly because it is not an easy task and even financially prohibitive to install some captors in all farms under analysis, and cover the different sources of pollution. One of the implicit concerns of this PhD is also to shed light on how some quantification tools like the LCA can be used to generate the environmental impact variables while maintaining enough heterogeneity in the efficiencies evaluation.[24]

The results of the LCA analysis not only deal with GHG emissions but also with non-renewable energy consumption. Other impacts like eutrophication and nitrification could also be computed. However, the PhD only focuses on GHG emissions, for which the three gases have been aggregated in terms of their Global Warming Potential (GWP)[25] relative to carbon dioxide.

Some descriptive statistics of the two farm samples used in this PhD can be found in **Table 1**. On average suckler cow farms are larger than sheep meat farms in terms of inputs consumption as well as output production (whether good, that is to say meat, or bad, that is to say pollution). However, sheep meat farms are more extensive than suckler cow farms given the

[24] The tools used were GES'TIM (Gac et al., 2011) and Dia' terre® developed by the French environment agency (ADEME – 'Agence De l'Environnement et de la Maîtrise de l'Energie') for the case of French agriculture. Besides, we have developed our own tool using the spreadsheet application Microsoft Excel and VBA programming. A methodological guide which tracks down all the emission factors and our different adaptations is under writing and will be available soon on INRA open archive website (www.prodinra.fr).

[25] The GWP is the warming effect relative to carbon dioxide over a period of 100-year time. It is about 25 for methane and 298 for nitrous oxide.

lower level of the stocking rate of the former.[26] Nevertheless the larger herd size of the suckler cow farms raises the labour productivity of these farms in comparison to the sheep meat systems.[27] A thorough description of these two samples can be found in Veysset et al. (2014).

In terms of income, farm income for suckler cow farms is on average greater than the sheep meat farms by almost 28% over the different years of study. Besides, in 2013 the average farm income per family labour unit was 18,232 Euros in sheep meat farms and 19,660 Euros in suckler cow farms. These values are far below the average revenue value observed in agriculture in general which is 28,900 Euros in France.[28]

[26] The stocking rate is the ratio of the herd size on the farm area. For sheep meat farms it is about 1.03 and for suckler cow farms it is around 1.23.

[27] The labour productivity is computed here as the number of livestock units per unit of labour.

[28] http://www.insee.fr/fr/themes/tableau.asp?reg_id=7&ref_id=agrtc10101, website consulted on April 22, 2015.

Table 1: Descriptive statistics of the French sheep meat farms and suckler cow farms used in this PhD.

Farms' type	Sheep meat farms		Suckler cows (beef) farms	
Variables	***Mean***	***Standard deviation***	***Mean***	***Standard deviation***
Utilised Agricultural Area (hectares)	74.4	35.1	104.3	48.5
Labour (full-time equivalents)	1.38	0.48	1.65	0.57
Herd size (livestock units)	76.9	31.5	128.8	64.5
Investments (2005 Euros)	5,740	8,602	16,215	20,680
Intermediate consumption (2005 Euros)	37,098	15,838	50,543	31,556
Average opening capital (2005 Euros)	41,934	24,219	91,836	51,198
Meat (kg of live weight)	20,966	9,961	38,553	22,016
Total GHG emissions (kg CO_2-eq)	340,713	142,515	566,561	309,373
Average animal product per farm (2005 Euros)	67,086	30,318	108,670	52,701
Farm income (before tax) per unit of family labour (2005 Euros)	18,266	11,253	23.293	14,927
CO_2 (kg)	59,427	29,053	81,528	62,910
CH_4 (kg CO_2-eq)	216,838	90,611	374,815	187,640
N_2O(kg CO_2-eq)	64,448	30,714	110,218	67,633
Pollution intensity (kg CO_2-eq/kg meat)	17.5	5.4	15.1	2.3
Number of farm-year observations	1,292		3,142	

Source: the authors

Notes: The production land area is captured here by the fodder area available for meat production. All the areas associated to the production of cereals are not accounted for, since their consumption is evaluated in terms of costs. The livestock unit is a reference unit used for the aggregation of different types of animals on the basis of their nutritional or feed requirement. One livestock unit corresponds to one dairy cow which produces about 3,000 litres of milk per year. CO2-eq means carbon dioxide equivalent. Investments are related to machineries, buildings and land improvements. The intermediate consumption variable represents all the production related costs except depreciation. It is the sum of proportional costs (i.e. all costs related to animal feeding, crop fertilisers, pesticides and all other costs directly associated to the presence of livestock such as veterinary costs, mortality insurance, litter straw costs, and marketing costs) and some structural costs related to mechanisation, buildings, land improvements and also overheads. The average opening capital represents the initial stock of capital for the quasi-fixed inputs which are equipment, buildings and land improvements. The animal products are computed by adding together net sales (i.e. sales minus animal purchases) and the subsidies related to animal breeding. All monetary values are expressed in constant currency (2005 Euros) to allow the aggregation of the data for different periods of time. Generally, in sheep meat systems the meat production is evaluated using kilograms of carcass produced. On the contrary, in beef systems the unit of measurement is the kilogram of live weight. For convenience and comparison purpose, we converted the kilograms of sheep meat carcass in live weight using the ratio of 45%, which sets the yield of meat carcass to 45% of the live weight.

In terms of environment, methane is the biggest contributor of farm total GHG emissions (more than 63% in both production types). It is followed by nitrous oxide - which makes about 19% of the total GHG generation – and carbon dioxide (more than 15%). Enteric fermentation (associated to animal physiology) is the main source of methane emissions. Nitrous oxide is related to nitrogen fertilisers and manure management. As for carbon dioxide, it derives from the manufacturing of farm inputs (feeds, fertilisers) and the use of fossil combustibles. Pollution intensity, which is the quantity of GHG generated per kilogram of live weight, shows that suckler cow farms seem to perform better than sheep meat ones. But this is a gross comparison that does not account for the optimal allocation of the different production inputs.

4. Structure of the dissertation

The PhD dissertation is made of four main chapters (from one to four) completed with a fifth chapter to discuss the results (of the dissertation) in addition, to an introductory part, and a concluding part. The PhD is not a monograph but a compilation of the (four) articles submitted, or to be submitted, for publication to international academic journals.

The four abovementioned research questions are addressed separately in individual chapters. **Chapter 1** (research question 1) provides a critical review of major developments in pollution-generating technology modelling that occurred over the last decades in the non-parametric framework of DEA. **Chapter 2** (research question 2) is related to the formulation of a new approach of modelling pollution-generating technology based on the by-production model as proposed in Murty et al. (2012) but augmented with dependence constraints that link the two sub-technologies. **Chapter 3** (research question 3) is a technical and empirical comparison of the main pollution-generating technology models proposed in the literature as well as the new approach introduced in this dissertation. The application is to the case of sheep meat farms described above. **Chapter 4** (research question 4) is devoted to the incorporation of dynamic aspects in pollution-technology modelling, based on including adjustment costs in the new by-production formulation proposed in this PhD and applied to the case of suckler cow farms described above. The last **Chapter (5)** of the dissertation synthesises and discusses the main results of the PhD. This part highlights some aspects about the different findings, discuss the limitations of the study and suggest future paths of research. The dissertation ends with a short conclusion.

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Chapter 1. Modelling pollution-generating technologies in performance benchmarking: Recent developments, limits and future prospects in the non-parametric framework[1]

[1] This chapter has been written in collaboration with Philippe Jeanneaux (Vetagro Sup, UMR Métafort, Clermont-Ferrand, France) and Laure Latruffe (INRA, UMR SMART, Rennes, France).

1. Introduction

Externalities or spillovers arise in the presence of market failures where some actions of a group of agents generate social costs (or social benefits) that accrue to external parties not involved in the market transaction (McConnell and Brue, 2007). The case of pollution-generating activities is particularly relevant in this context. The question of the internalisation of the social costs arising from pollution has become an important area of interest for economists. In the presence of environmental regulations aimed at the internalisation of pollution costs by firms, some resources within firms might be diverted to mitigate pollution and, hence, best-practice comparisons (i.e. performance benchmarking) that do not account for this would inevitably lead to spurious results (Kopp, 1981). Besides, integrating environmental aspects into productive efficiency can provide policy-makers with helpful information on production systems that can lead to improving the design of new policies. Within this framework, Pittman (1983) used the index number theory of Caves et al. (1982) to develop a new productivity comparison methodology that incorporated undesirable outputs'[2] control behaviour. However, this methodology was based on a translog transformation function which required information on prices for undesirable outputs. Pollution being a non-marketed good, computing Pittman's productivity indices may be challenging. By contrast, the development of activity analysis enables efficiency evaluation based on quantity information only.

Two paradigms have been developed, one involving parametric models (econometric models which require the specification of a functional form) and one using mathematical programming methods (such as Data Envelopment Analysis – DEA). In this chapter we focus on the latter, since such methods offer a large range of possibilities due to their flexibility and the less restrictive assumptions inherent in them. In the literature using such mathematical programming methods, the implicit positive correlation between pollution and desirable outputs has been formalised in different ways.

i-) A first approach treats pollution as a free disposable input (Dyckhoff and Allen, 2001; Hailu and Veeman, 2001b; Yang and Pollitt, 2009).[3] The main argument behind this approach is that emissions of environmentally detrimental products can be viewed as the use of the

[2] Hereafter, the expressions "bad", "undesirable", "detrimental", "incidental", "residual", and "unwanted" goods, as well as "bads", are used to qualify pollution or pollutants. By contrast, "good" outputs are also named "desirable" or "intended" outputs.

[3] The free disposability (strong disposability) of inputs states that if any input is increased (whether proportionally or not), output does not decrease.

environment's capacity that is necessary for their disposal (Paul et al., 2002; Considine and Larson, 2006). Thus, according to the advocates of this approach, considering these emissions as inputs is likely to be a good way of accounting for the consumption of natural resources. Some other scholars (Baumol et al., 1988; Barbera and McConnell, 1990; Cropper and Oates, 1992; Tahvonen and Kuuluvainen, 1993) believe in a positive relationship between good and bad outputs for a reason clearly expressed in Mahlberg and Sahoo (2011) as: "undesirable outputs incur costs for a firm because it requires the diversion of productive inputs from the production of desirable (good) outputs for abatement purposes in compliance with the environmental regulations". However, as argued by Førsund (2009), this idea is more convincing at a macro level where "a single relation with residuals as inputs may be regarded as a reduced form of a larger system". From another perspective, Haynes et al. (1993) stated that undesirable outputs can be viewed as "unavoidable" residuals, which are subsets of pollution-generating inputs, and thus can be treated as inputs. The idea of considering undesirable outputs as additional inputs has, however, been seriously challenged as it deflects from the physical laws (Färe and Grosskopf, 2003) and the materials balance principles (Ayres and Kneese, 1969; Ayres, 1995). Rigorously speaking, undesirable outputs are not inputs, and treating them as additional inputs will not reflect the true production process (Seiford and Zhu, 2002). As summarised by Scheel (2001), when pollution is treated as an input "one abstracts from the underlying input-output structure which is usually defined by the nature of the production process. Instead, the only information needed is whether the data have to be minimized or maximized . . ." Moreover, by assuming free disposability of undesirable outputs, such modelling includes situations where "finite amount of input can produce an infinite amount of bad output, thus violating the law of mass conservation" (Podinovski and Kuosmanen, 2011). Considering bads as inputs is then physically unacceptable because of the violation of the boundedness of output sets. All these criticisms make the model that treats bad outputs as extra inputs unrealistic and thus to be avoided. Based on this situation, we do not discuss this case further in the chapter.

ii-) A second group of approaches extends models such as the frontier eco-efficiency models based on Korhonen and Luptacik (2004) and Lauwers (2009), which construct a production system where only undesirable outputs are used as inputs to produce the good output (Mahlberg et al., 2011). This approach is not discussed here since it is based on an incomplete production process. Another approach known as the LCA+DEA approach associates Life Cycle Assessment (LCA) and DEA (Iribarren et al., 2010).[4] We also ignore this model here because its

[4] 'Environmental LCA is the compilation and evaluation of the material and energy flows as well as the potential environmental impacts of these throughout the life cycle of a product' (Ekvall and Finnveden, 2001).

objective is not the minimisation of undesirable outputs, but rather the potential reduction of these outputs in the case where all production units are technically efficient. The model fails to capture all the input's substitution possibilities that could help optimise the environmental performance. Another range of approaches relies on data transformation so that undesirable outputs can be equivalently treated as good outputs (Lovell et al., 1995; Sahoo et al., 2011). However, Färe and Grosskopf (2004a) showed that the results obtained from such data transformation are inconsistent. This is intuitive since the transformation distorts the real production process. Moreover, the model implies that undesirable outputs can be reduced without any cost, which is not realistic (Du et al., 2014). Hence, we also do not consider this approach in this chapter.

iii-) A third approach considers pollution as outputs by assuming the weak disposability of these bad outputs and the null-jointness of both production types (good outputs and bad outputs) (Färe et al., 1986; Färe and Grosskopf, 2009; Färe et al., 2012). The weak disposability concept describes a situation where outputs are intimately linked and their amounts cannot be changed independently. In the case where bad outputs are present, it implies that reducing the levels of these outputs necessarily requires reducing the quantities of intended outputs in a proportional way. The null-jointness property accounts for situations where if zero levels of good outputs are produced then zero levels of bad outputs are generated. This approach relying on weak disposability and null-jointness is commonly used in the literature. However, as argued by Coelli et al. (2007) and Hoang and Coelli (2011), the weak disposability assumption (WDA) violates the first law of thermodynamics.[5] It can be demonstrated that under certain conditions, such as the presence of end-of-pipe technologies to abate pollution, the WDA and the null-jointness assumption can become compatible with the materials balance principles (Hampf and Rødseth, 2014). Yet, in many situations end-of-pipe equipment is technologically unavailable or economically unaffordable (Rødseth and Romstad, 2013). In addition, making the WDA conform to the materials balance principles, does not mean that the approach is correct. We provide a thorough discussion of the limits of the WDA in the third section.

iv-) With respect to the limits associated with the WDA, an approach based on the materials balance principles was introduced into production theory by Lauwers et al. (1999) and later furthered by Lauwers and Van Huylenbroeck (2003); Coelli et al. (2005). Relying on the mass/energy balance equation – which is simply an accounting identity that links in an

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[5] This law can be related to one of the theses of the Greek philosopher Anaxagore and lately renewed as the famous saying of Antoine Lavoisier "Nothing is lost, nothing is created, everything is transformed".

equivalent way the quantity of materials that goes into a production process to the amount of outputs including residual ones – enables the estimation of an iso-environmental line in the same vein as iso-cost lines. However, as explained by Ebert and Welsch (2007), it essentially focuses on materials inputs and ignores any interaction that might exist between these materials inputs and non-materials ones. The method will thus identify decision making units (DMUs)[6] that use few materials inputs as environmentally efficient, despite their reliance on non-materials inputs. In addition, recently Hoang and Rao (2010) underlined the problem of "the lack of universally accepted weights for various material inputs". Taking the example of eutrophication and gas pollution in agriculture, the authors discussed the difficulties in aggregating these two impacts in the case of the materials balance. They then proposed an extension based on the use of the cumulative exergy[7] balance (see also Hoang and Alauddin (2011)). However, the "premises and conclusions are still being strongly debated" (Dewulf et al., 2008), and the notion of exergy is complicated due to technical and theoretical limitations (Maes and Van Passel, 2014). Along the same lines, Hampf and Rødseth (2014) offered a new approach named the weak G-disposability, which relies on the first two laws of thermodynamics[8] to model a pollution-generating technology without resorting to any transformation of the non-materials inputs. This approach combines the mass/energy identity equation and the G-disposability developed in Chung (1996) around the directional distance function (DDF) (see Färe and Grosskopf (2000) for a discussion of the theory and application of the DDF). We discuss this recent development in this chapter.

v-) Finally, a more recent approach suggests modelling the firm's production technology by using two sub-technologies: one generating the intended outputs and a second generating the unintended outputs (Førsund, 2008; Sueyoshi and Goto, 2010; Sueyoshi et al., 2010; Murty et al., 2012). Operational efficiency and environmental efficiency can then each be evaluated using the specific corresponding sub-frontier. Within this framework, Murty et al. (2012) proposed the by-production model which relies on the cost disposability assumption of the technology with respect to undesirable outputs (for more theory on this, see also Murty (2012)). Based on the

[6] DMUs are production entities which use inputs to produce outputs.

[7] Exergy reflects the maximal usefulness that can be obtained from any type of input. It refers to the maximal mechanical work that can be extracted from a form of energy or, reversely, the mechanical work that is necessary for a system to go back to its equilibrium state (dead state). The exergy can be evaluated as the gross energy value reduced by the losses that occur during the transformation process.

[8] The second law of thermodynamics indicates that residuals are generated with at least some consumption of inputs, and consequently suggests that not all inputs are transformed into good outputs because some residuals are necessarily generated.

idea of the unavoidability of residuals' generation when using materials inputs (that is to say polluting inputs), the approach suggests that for given levels of these inputs there is an associated minimal amount of pollution, and the presence of inefficiency can yield more than this minimal amount. Another recent approach is provided by Sueyoshi and Goto (2012a, 2012b, 2012c) who developed the concepts of natural and managerial disposability to characterise a firm's adaptation potential in the case of pollution mitigation. Natural disposability implies reducing pollution by simply decreasing the levels of (polluting) inputs, thus requiring no managerial effort. By contrast, managerial disposability implies managerial efforts in the form of the adoption of new technologies, such as high quality inputs or other innovative technology, that can mitigate pollution. These two recent and promising approaches are developed in this chapter.

Reviews of works on DEA and environmentally bad outputs can be found in Tyteca (1996), Zhou et al. (2008a), and Manello (2012). This literature focuses mainly on the classical approaches that consider residuals as inputs or as outputs under the WDA, or that use some data transformation functions. this chapter firstly provides an update of the existing reviews by outlining the major recent developments around the inclusion of undesirable outputs in production technology modelling, namely the weak G-disposability assumption, the by-production model and the natural and managerial disposability concepts. Secondly, we discuss the limits inherent in each methodology. In fact, most of the existing literature surveys focus on a simple description of the models without a clear insight into the drawbacks associated with each model. This chapter contributes to filling this gap by synthesising the problems of the commonly-used models and discussing the challenges associated with the recent developments. Thus, the original contribution of this chapter is that we provide in a single place a critical review of all models, not only the ones widely used and already criticised (such as the ones relying on the WDA), but also the recently advanced ones developed to circumvent the shortcomings of previous models, and we show how the different approaches are interrelated.

The remainder of the chapter is organised as follows. The next section explains the methodology followed for our review. The following two sections describe the methods in the order that they appeared in the literature, that is to say methods that were developed to circumvent problems of existing methods. The final section discusses future trends of research and concludes.

2. Methodology for our literature review

The papers used here were identified firstly on the basis of searches on research engines, namely Web of Science (WoS), Scopus, and Google Scholar. Various keywords were used, such as "undesirable output AND data envelopment analysis", "bad output AND data envelopment analysis", "weak disposability", "materials balance AND data envelopment analysis", "joint production AND data envelopment analysis". The WoS gathers a multitude of well-known and quality academic journals. It is an international, multi-editor and multi-disciplinary database that collects a large amount of information in different research areas. This database, hosted by the Web of Knowledge platform of the group ISI Thomson Reuters, gives access to about 10,000 journals. Our request yielded 600 references on the WoS. We did a similar request on the Scopus database, owned by the scientific editor Elsevier as a direct competitor of the WoS and referencing 16,500 journals, and it gave similar results with a total of 509 references. With the WoS and the Scopus databases, we cover scientific production fairly well. In addition, we used the Google Scholar search engine to account for the grey literature and prevent publication bias. Google Scholar yielded more than 4,588 references. Following the discussions in Linder et al. (2015), to increase the precision of the review we conducted a search of some cited references. The references used for this search were identified as the most cited studies identified in Google Scholar. Using a reference management software (Endnote X6), we narrowed the number of studies by removing duplicate references. This operation downsized the number of studies collected to 1,400 references on energy and/or environmental efficiency or eco-efficiency. We then reduced this number further by selecting references on more precise keywords, providing a starting sample of 182 papers. Among these papers we retained mainly the ones that offered some theoretical and methodological improvements.

Secondly, the own references of the papers found through these searches and retained for the analysis have also been used. Most of the papers used here have been published in operational research journals or other high quality scientific journals, or have been cited by such types of publications, which ensures their trustworthiness.

In the next section, we start with the first trend of approaches considered in this chapter, by presenting and discussing the limits inherent in the WDA.

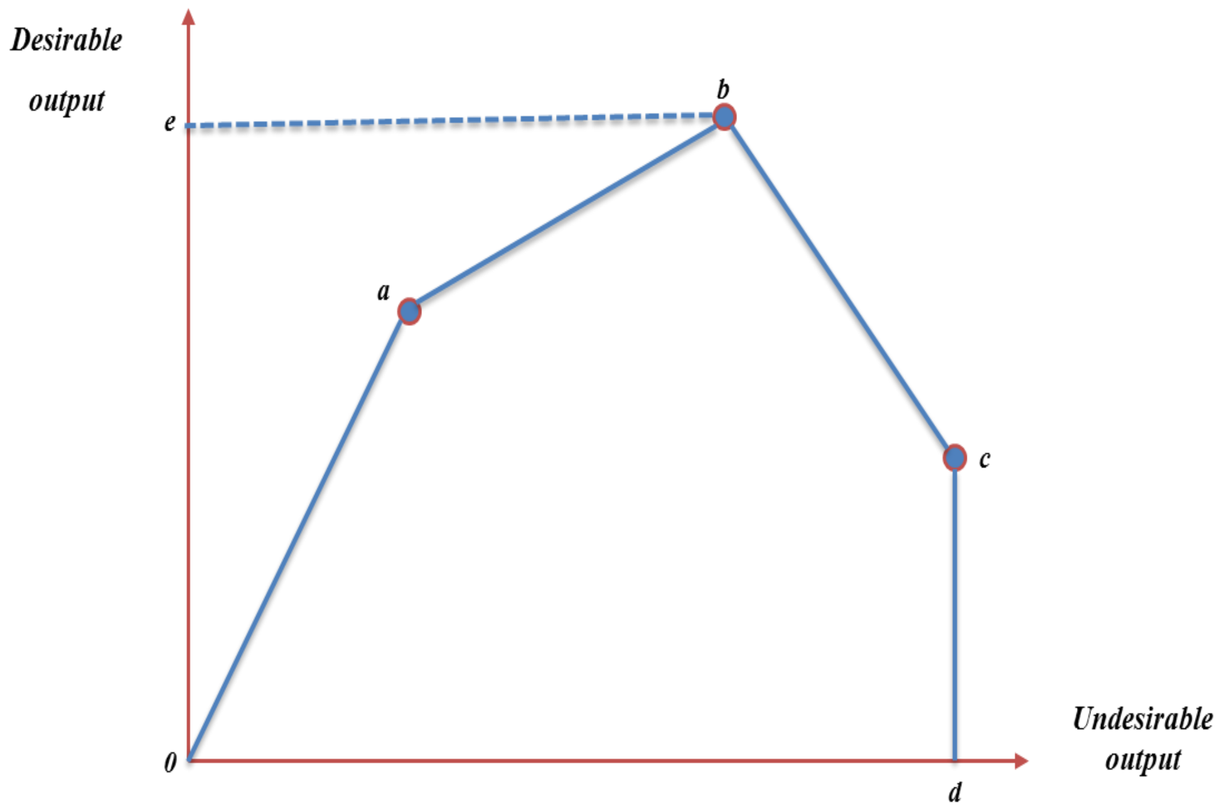
3. The weak disposability assumption (WDA)

3.1. Definition and operationalization

The WDA concept introduced in the neoclassical theory of firm and technology by Shephard (1970, 1974) has been used to characterise input and output variables that cannot be considered as freely disposable. The idea has been used to “model congestion and overutilization of inputs/outputs” (Daraio and Simar, 2007a p22). In an input orientation, it describes a situation where, if all inputs increase proportionally, outputs might decrease (due to occurrence of congestion) and this reflects backward bending of the isoquant (Färe and Svensson, 1980; Färe and Grosskopf, 1983). In efficiency measurement the concept has been extended to characterise technology that includes undesirable outputs (Färe et al., 1986). In this case, the WDA implies that reducing undesirable outputs requires decreasing desirable outputs or increasing inputs by the same factor. More explicitly, the assumption reflects the general thinking that reducing undesirable outputs comes at a cost: good outputs must be simultaneously reduced and thus some revenues are foregone, or capital resources are diverted or reallocated from the production of desirable outputs to the mitigation of undesirable outputs. Thus, any regulation that intends to internalise pollution impacts will inevitably lead to economic losses (Palmer et al., 1995). As summarised by Färe and Grosskopf (2004b p47): “An alternative interpretation is that if we hold inputs constant, then 'cleaning up' undesirable outputs will occur at the margin through reallocation of inputs away from the production of desirable outputs”.

Graphically (**Figure 1**), if undesirable outputs are considered as freely (strongly) disposable (that is to say it is costless to mitigate them), the output set would be represented by $(0ebcd0)$ where the dotted line (eb) specifically materialises this strong disposability by allowing some mix inefficiencies in bad outputs’ generation. Assuming weak disposability of the undesirable outputs restrains the output set to $(0abcd0)$. Note that strong disposability is assumed for the good outputs and is represented by the segment $[cd]$.

Figure 1: Weak disposability of undesirable output.



Source: the authors

Formally, let x represent a vector of inputs ($x \in \mathbb{R}_+^K$), y a vector of good outputs ($y \in \mathbb{R}_+^Q$), b a vector of bad outputs ($b \in \mathbb{R}_+^R$) and N the number of DMUs (identified with subscript i in the following). The production technology including the bad output Ψ_{bad} is then defined by all (x, y, b) such that x can produce y and b. We posit that Ψ_{bad} verifies for the inputs and the good outputs the commonly-assumed axioms in production theory (Shephard, 1953, 1970, 1974; Varian, 1984; Färe et al., 1985; Chambers, 1988; Färe and Primont, 1995) and that the DEA technology is represented under variable returns to scale (VRS), originally known as the BCC model developed in Banker et al. (1984).

Undesirable outputs are said to be weakly disposable if:

$$(x, y, b) \in \Psi_{bad}, 0 \leq \theta \leq 1 \implies (x, \theta y, \theta b) \in \Psi_{bad} \tag{1}$$

This property is also known as the radial disposability property. It should be noted that the WDA is generally accompanied by the null-jointness condition of desirable and undesirable outputs, formalised as:

$$(x, y, b) \in \Psi_{bad} \text{ and } b = 0 \text{ then } y = 0$$
$$\sum_{i=1}^{N} b_i > 0 \,;\, \sum_{r=1}^{R} b_r > 0 \tag{2}$$

where the left inequality indicates that at least one DMU i generates some bad outputs, and the right inequality indicates that at least one bad output r is generated by some DMUs. These two constraints were suggested by Kemeny et al. (1956). This can be related to the idea that there is "no fire without smoke" (Färe et al., 2007; Färe and Grosskopf, 2012), and, consequently, the output set contains the origin.

In this situation the technology Ψ_{bad} explicitly becomes:

$$\Psi_{weak} = \Big[(x, y, b) \in \mathbb{R}_+^{K+Q+R} \Big| y \leq \theta \sum_{i=1}^{N} \gamma_i Y_i \,;\, b = \theta \sum_{i=1}^{N} \gamma_i B_i \,;$$
$$x \geq \sum_{i=1}^{N} \gamma_i X_i \,;\, \sum_{i=1}^{N} \gamma_i = 1; \;\; \gamma_i \geq 0; 0 \leq \theta \leq 1; i = 1, \dots, N\Big] \tag{3}$$

Hereafter, (x, y, b) represents the vector of inputs, good outputs and bad for the DMU under evaluation, and (X, Y, B) represents the vector of inputs, good outputs and bad of the reference set, i.e. all DMUs used to construct the frontier. γ_i is often referred to as the intensity variable and represents the weights associated with all the DMUs that serve as a benchmark (or reference) to the one under evaluation.

Model **(3)** is non-linear. Its linearisation has been proposed by Zhou et al. (2008b) and Sahoo et al. (2011), based on a change of variables $\varphi_i = \theta\gamma_i$. Practically, the WDA has been implemented through two main models: i-) the enhanced hyperbolic efficiency measure (HEM) developed by Färe et al. (1989) which allows for a simultaneous equiproportionate expansion of the good outputs and a contraction of the bad outputs (and inputs) by the same radial factor, and; ii-) the DDF. The latter is the most commonly used for evaluating performance in the presence of unintended outputs.[9] It can be viewed as the generalisation of the Shephard's distance function and, as such, is more flexible and more powerful. The use of the DDF in the case of bad outputs was proposed by Chung et al. (1997). The DDF approach searches for the maximisation of desirable outputs and simultaneously a minimisation of bad outputs, based on a chosen vector of direction $\vec{g}$. It can be specified as:

$$\vec{D}(x, y, b; \vec{g}) = \sup[\phi : (x , y + \phi\vec{g}_y, b - \phi\vec{g}_b) \in \Psi_{weak}] \tag{4}$$

Using **(3)** and **(4)**, the efficiency score over the direction $\vec{g}$ for DMU n is given by:

$$\begin{gathered} DDF(x_n, y_n, b_n) = \max[\phi \mid y + \phi\vec{g}_y \leq \theta \sum_{i=1}^{N} \gamma_i Y_i\,; \\ b - \phi\vec{g}_b = \theta \sum_{i=1}^{N} \gamma_i B_i\,; \\ x \geq \sum_{i=1}^{N} \gamma_i X_i\,; \sum_{i=1}^{N} \gamma_i = 1;\; \gamma_i \geq 0; i = 1, \dots, N; \\ 0 \leq \theta \leq 1\,; (x, y, b) \in \mathbb{R}_+^{P+Q+R}] \end{gathered} \tag{5}$$

Chung et al. (1997) recommended the use of the direction $\vec{g} = (y, -b)$.

The first criticism of the traditional DDF was made by Kuosmanen (2005) and Kuosmanen and Podinovski (2009), who noticed that weak disposability, commonly defined as the proportional reduction of desirable and undesirable outputs, unintentionally assumes that all DMUs share the same uniform abatement effort θ. According to Kuosmanen (2005), "This is at odds with the usual environmental-economics wisdom of focusing abatement efforts in those firms where the abatement costs are lowest". Besides, as pinpointed in Kuosmanen and Podinovski (2009), the technology Ψ_{weak} as defined in **(3)** does not verify the full convexity, which is an important assumption of the Shephard representation. However, the model is still convex on its output sets for any level of inputs (Podinovski and Kuosmanen, 2011). This situation may result in overestimating technical efficiency in **(5)**, since the Kuosmanen

[9] A simple search on Google Scholar (on 31-07-2014) with the key words "directional distance function" and "undesirable outputs" yielded more than 900 papers in 0.04 seconds. Yet, according to Leleu (2013a), many papers have incorrectly modelled the WDA, especially under VRS.

technology is the classic WDA technology (Ψ_{weak}) to which "all missing convex combinations of its activities" are added. Further, this lack of convexity of the global technology may explain the unavailability of a dual interpretation so far (Kuosmanen and Matin, 2011).[10]

The technology set in **(3)** with differing abatement efforts becomes:

$$\Psi_{weak}^{Kuos} = \Big[(x, y, b) \in \mathbb{R}_{+}^{K+Q+R} \Big| y \leq \sum_{i=1}^{N} \theta_i \gamma_i Y_i \,; b = \sum_{i=1}^{N} \theta_i \gamma_i B_i \,; \\ x \geq \sum_{i=1}^{N} \gamma_i X_i \,; \sum_{i=1}^{N} \gamma_i = 1; \ \gamma_i \geq 0; i = 1, \dots, N; \ 0 \leq \theta_i \leq 1\Big] \tag{6}$$

Ψ_{weak}^{Kuos} is non-linear as θ_i is multiplied by γ_i. Kuosmanen (2005) suggested the transformation $\gamma_i = \mu_i + \tau_i$, where $\tau_i = (1 - \theta_i)\, \gamma_i$ is the abated output through scaling down activity. Then $\mu_i = \theta_i \gamma_i$ is the remaining active output, and $\theta_i = \mu_i/(\mu_i + \tau_i)$. The production possibility set can be re-written as:

$$\Psi_{weak}^{Kuos} = \Big[(x, y, b) \in \mathbb{R}_{+}^{K+Q+R} \Big| y \leq \sum_{i=1}^{N} \mu_i Y_i \,; b = \sum_{i=1}^{N} \mu_i B_i \,; \\ x \geq \sum_{i=1}^{N} (\mu_i + \tau_i) X_i \,; \sum_{i=1}^{N} (\mu_i + \tau_i) = 1; \ \mu_i, \tau_i \geq 0; i = 1, \dots, N\Big] \tag{7}$$

Using the selective proportionality approach developed in Podinovski (2004), Kuosmanen and Podinovski (2009) have shown that **(7)** is a full convex technology in contrast to the Shephard weakly disposable technology in **(3)**.

Applications of the Kuosmanen model can be found in Mekaroonreung and Johnson (2009); Berre et al. (2012); D. Berre et al. (2014). Yang and Pollitt (2010) proposed an improvement that is closely related to the nature of undesirable outputs: depending on the "technical features" of the bad outputs, different disposability assumptions should be considered. The authors took the example of a coal fired power plant that generates carbon dioxide (CO_2) and sulfur dioxide (SO_2), and noticed that CO_2 cannot be reduced with the existing

[10] Leleu (2013b) has shown that under some conditions (use of the directional output distance function), one can derive dual formulation of the Shephard weakly disposable technology with interpretations similar to those in Kuosmanen and Matin (2011).

technology. Any effort to abate CO_2 would result in a reduction of the good output, namely electricity generation. This specific gas then perfectly fits the WDA. SO_2 can be reduced through investment in desulphurisation equipment, which can offset more than 90% of this gas. SO_2 then violates the weak disposability property as well as the null-jointness hypothesis. The authors then recommended considering SO_2 as strongly disposable. But this would lead to the case where undesirable outputs are treated like inputs, and as previously argued in the introduction, this approach is not correct.

3.2. Limits of the WDA

Some studies have questioned the relevance of the WDA that is generally imposed when evaluating performance in the presence of detrimental outputs. Hailu and Veeman (2001b) considered that the WDA, represented by the equality constraint in the technology (namely the second constraint in model **(3)**), treated pollutants as neutral rather than as an output or as an input, which is, as stated earlier, not a correct way of modelling pollution-generating technologies. Moreover, according to the authors, this equality allows for negative as well as positive shadow prices for residuals, and implies high efficiency inflation. Färe and Grosskopf (2003) argued that the use of an output-oriented DDF is sufficient to obtain the right sign of bad outputs' shadow prices. Nevertheless Leleu (2013a) showed graphically that, depending on the direction vector, one might still obtain inappropriate signs for shadow prices. The author then developed a new approach that can ensure the right sign for the shadow values of undesirable outputs. However, he underlined that this implies imposing strong disposability for bad outputs as is the case for inputs.

A crucial criticism comes from Murty et al. (2012) who showed that, under the WDA, the HEM and the DDF can produce inconsistent results that do not conform with the materials balance condition which states the inevitability of residuals' generation. The reason is that such results are obtained from a single reduced equation form (that is to say, single side projection) of the production possibility set whereas some alternative projections are possible (Sueyoshi et al., 2010). Murty et al. (2012) stressed that "many commonly used models of pollution-generating technologies, which treat pollution as a freely disposable input or as a weakly disposable and null-joint output, may generate unacceptable implications for the trade-offs among inputs, outputs and pollution". Using the implicit function theorem, the authors estimated the trade-offs between unintended outputs and intended ones on the one hand, and those between unintended outputs and the pollution-generating inputs on the other hand. However, results indicated large possibilities of $(\hat{y}, \hat{b})$ efficient combinations, violating the idea that there is only one minimal amount of undesirable outputs given the levels of inputs: the presence of inefficiencies can generate more than this minimal level. In addition, the negative relationship between pollution-generating inputs and undesirable outputs contradicts the fact that these inputs generate pollution. Moreover, pollution-generating inputs and pollution appear to be substitutes as in the case where undesirable outputs are considered as inputs, which is not realistic. Levkoff (2011) also highlighted that in the case of multiple undesirable outputs, a single representation allows for some trade-offs that are inconsistent with the fact that some specific inputs can only generate a particular undesirable output and not a rich menu of those outputs.

More recently Chen (2014), using an illustrative example, demonstrated three major weaknesses of the WDA in the HEM and DDF efficiency measures. i-) Non-monotonicity in undesirable outputs: a firm's efficiency may increase while polluting more and vice-versa. The backward bending of the production frontier in **Figure 1** through the segment $[bc]$ by imposing the WDA, violates the monotonicity in bad outputs' generation. This has important implications for the efficiency score: an inefficient DMU might improve its efficiency score by increasing the levels of undesirable outputs by directing towards the right part of the frontier,[11] and conversely, might decrease its efficiency score by reducing the levels of undesirable outputs. In addition, non-monotonicity unrealistically gives the possibility of obtaining negative shadow prices for undesirable outputs. Negative shadow prices mean that the production of pollution creates some extra revenue, which contradicts with the widespread view that pollution imposes costs on society. ii-) Misclassification of efficiency status: strongly dominated firms may appear efficient. For example in **Figure 1** the DMU at point c produces lower levels of good output and higher levels of undesirable output than the DMU at point b, yet the DMU at c is deemed efficient because it is located on the boundary of the frontier. iii-) Strongly dominated projection targets: some efficiency scores may be computed with respect to strongly dominated points used as targets. An inefficient DMU located in the interior of the output set represented in **Figure 1** can be projected based on the choice of the directional vector on the dominated segment $[bc]$. This can be associated with situations depicted by Picazo-Tadeo and Prior (2005); Picazo-Tadeo and Prior (2009) as the ones "where the biggest producer is not the greatest polluter". Heavy polluters in these cases can be viewed as outlier DMUs using dirtier production technologies or facing a drop in the production of good outputs in the short run that does not affect the levels of pollution. (Picazo-Tadeo and Prior, 2005; Picazo-Tadeo and Prior, 2009) proposed a

[11] Leleu (2013a) toned down this observation, arguing that the direction vector always seeks for the minimization of the bad outputs and thus all inefficient observations are projected towards the left part of the frontier.

combination of the WDA and the model where pollution is treated as an input, to detect this "complex situation" and discard the negatively-sloped parts of the technology.

Another range of arguments against the WDA relates to the laws of thermodynamics. It has been argued that, despite the above-mentioned criticisms, weak disposability is consistent with the physical laws in the presence of end-of-pipe technologies (Hampf and Rødseth, 2014; Rødseth, 2014).[12] But in many cases the end-of-pipe technology is not commercially available, and in reality there are three ways of meeting environmental regulations: reducing the good output production in the short run; investing in end-of-pipe technology; and investing in new and less polluting technology of the basic production process, usually a longer-term option than end-of-pipe. This implies that performance appraisal in the presence of undesirable outputs should be conducted in a dynamic situation where the different investments are accounted for. Ebert and Welsch (2007) recalled that, according to the second law of thermodynamics which states that pollution-generating inputs cannot be completely transformed into desirable outputs, a non-zero amount of detrimental outputs will be generated from a non-zero amount of pollution-generating inputs. The weak disposability model, assuming null-jointness of good and bad outputs as well as inactivity (where the use of inputs may generate zero pollution), contradicts this second law. Furthermore, the WDA implies a proportional reduction of good and bad outputs given the levels of inputs (including pollution-generating ones), which is inconsistent with the mass/energy conservation condition. From this perspective, Coelli et al. (2007) demonstrated the infeasibility of the solution generated by models under WDA. In addition, Yang et al. (2008) argued that the rare situation where weak disposability can apply is in the presence of "reverse outputs". Reverse outputs or inputs reflect a situation where "higher numerical values represent lower input consumption or lower output production" (Lewis and Sexton, 2004). In the case of reverse outputs, the production of undesirable outputs might not be a joint production of (or accompany) "normal outputs". As early as the end of the 1990s, Førsund (1998) proposed an "intuitive" solution to make a clear distinction between the two mechanisms that generate desirable outputs on the one hand and undesirable outputs on the other.

Finally, Murty et al. (2012) argued that, in the presence of abatement technologies, generating a zero level of bad outputs is possible, thus violating the null-jointness hypothesis

[12] End-of-pipe options refer to the case where "lazy polluters" do not want to implement changes in the production process and prefer to adopt other methods (recycling for instance) to mitigate the produced pollution.

imposed in the WDA approach. Given all these drawbacks associated with the WDA model, new developments have been undertaken in modelling pollution-generating technologies.

4. Recent developments in modelling pollution-generating technologies: materials balance approach and multiple frontier technologies

4.1. The weak-G disposability and the materials balance principles

The materials balance principles (MBP) approach is based on the physical law of mass/energy conservation, namely that all materials' flows used for economic production generate new flows of materials of equal weights. This condition perfectly describes the first law of thermodynamics which states that the amount of materials tied up in the inputs is equal to the amount of the flow of materials embedded in the outputs, plus the residuals (that is to say the bad outputs) (Ayres and Kneese, 1969). This law can be represented by the balance equation as follows:

$$b = W'x - H'y \tag{8}$$

where x and y can be thought of as the vectors of materials inputs and outputs, respectively, and b represents the residual quantity. This equation is linear in inputs and outputs, but one can also formulate a non-linear relationship (Pethig, 2006). W is a $(K \times 1)$ vector (with non-negative scalars) representing the emission factors for the inputs, and H is a $(Q \times 1)$ vector (with non-negative scalars) representing the recuperation factors for the desirable outputs (that is, the ratios specifying the amount of unintended outputs incorporated in the desirable outputs). Due to non-homogeneity in the inputs and outputs and due to the role of some external factors, these two vectors of materials flow coefficients may differ from one DMU to another.

The second law of thermodynamics should also be verified, namely that:

$$\frac{db}{dx} > 0 \tag{9}$$

This second law is probably one of the most difficult concepts in physics (Georgescu-Roegen, 1976 p7). It is related to the notion of entropy which characterises the disorder present in a production system. It has been used in ecological economics to represent the fact that some residuals (with high entropy) are necessarily generated with at least some consumption of inputs, that is to say not all inputs are transformed into good outputs because some residuals b are unavoidably generated (Baumgärtner et al., 2001; Ebert and Welsch, 2007). The law refers to the irreversibility of the production process, in contrast to the first law of energy conservation which does not account for the fact that after a transformation, part of the energy is unavailable. This second law is generally omitted in materials balance studies (Hoang and Rao, 2010). Mainly based on the first law, Coelli et al. (2005, 2007) introduced the MBP in performance evaluation, but ignored non-materials inputs. Another implication of the second law is that, taken together with the mass/energy conservation equation **(8)**, it rules out the WDA which imposes a proportionate decrease in good and bad outputs at any given levels of inputs (Ebert and Welsch, 2007).

A more novel approach in this MBP framework is the extension introduced by Hampf and Rødseth (2014) who proposed a new materials balance technology set Ψ_{MB} based on the usual properties of the production technology and augmented with the following postulates:

MB1 Output essentiality for the unintended outputs: $(x, y, b) \in \Psi_{MB} \wedge b = 0 \Rightarrow x^P = 0$, where x^P represents the vector of pollution-generating inputs.

MB2 Input essentiality for the unintended outputs: $(x, y, b) \in \Psi_{MB} \wedge x^P = 0 \Rightarrow b = 0$. With **MB1**, **MB2** ensures that the second law of thermodynamics is not violated.

MB3 Weak-G disposability of inputs and outputs: $(x, y, b) \in \Psi_{MB} \wedge\ W'g_x + H'g_y - g_b = 0 \Rightarrow (x + g_x, y - g_y, b + g_b)\ \in \Psi_{MB}$ where $g_{(.)}$ are direction vectors which show the direction of the disposability of the inputs and outputs. This postulate implies that "the increases in pollution due to increases in the use of inputs [that is to say $W'g_x$ above] and/or the reduction of good outputs [that is to say $H'g_y$ above] must equal the increases in the bad outputs [that is to say g_b above] when inputs and outputs are disposed" (Hampf and Rødseth, 2014). To better understand this concept let us recall the G-disposability axiom defined in Chung (1996), and assume that DMU_n with coordinates (x, y, b) belongs to the production technology Ψ_{MB}. For any specific direction vector (g_x, g_y, g_b) we can write the following relationship, indicating that with more inputs it is possible to produce less good output and generate more pollution:

$$\text{If } (x, y, b) \in\ \Psi_{MB} \text{ then } (x + g_x, y - g_y, b + g_b)\ \in\ \Psi_{MB} \tag{10}$$

In **(10)**, inputs and outputs are said to be disposable in the G direction. Since the balance condition in **(8)** is still valid, all DMUs satisfying **(10)** must also verify **(8)**. Thus we have:

$$W'(x+g_x) - H'(\,y-g_y) - (b+g_b) = 0 \tag{11}$$

From this, one can easily derive the following condition:

$$W'g_x + H'g_y - g_b = 0 \tag{12}$$

The disposability of the variables as expressed in **(10)** is constrained by equation **(12)**, hence the name weak G-disposability. Hampf and Rødseth (2014) referred to equation **(12)** as the "summing-up" restrictions which impose some constraints on the disposability direction of the different factors and outputs. As opposed to the weak disposability model, inputs are not freely disposable here. Under the WDA, free disposability of inputs implies that, for a given input bundle and a produced output set, it is possible for a higher input bundle to produce the same amount of the output set. But this is technically infeasible under the MBP conditions. The MBP technology set can be defined as follows, where the directions g_x, g_y, g_b are replaced by their empirical counterparts, the slacks (S^x, S^y, S^b):

$$\begin{gathered}
\Psi_{MB} = \Big[(x,y,b) \in \mathbb{R}_+^{K+Q+R} \Big| y + S^y = \sum_{i=1}^{N} \gamma_i Y_i\,; \\
b - S^b = \sum_{i=1}^{N} \gamma_i B_i\,;\; x - S^x = \sum_{i=1}^{N} \gamma_i X_i\,; \\
W'S^x + H'S^y - S^b = 0 \\
\sum_{i=1}^{N} \gamma_i = 1;\;\; \gamma_i \geq 0; i = 1, \dots, N\Big]
\end{gathered} \tag{13}$$

Ebert and Welsch (2007) criticised the MBP framework positively. Using a theoretical representation of the production function, they demonstrated that undesirable outputs "can be treated as a joint output or an input, or can be described by an emission function" and within the MBP framework all these approaches are equivalent. In addition, since the framework, accounting for the presence of non-materials inputs combined with the materials inputs, allows for the possibility of obtaining a higher level of good outputs with the same level of pollution-generating inputs, there is a possibility of substitution between materials and non-materials inputs.

Despite the interesting features of this novel way of dealing with bad outputs, Hampf and Rødseth (2014) showed that under some conditions (constant returns to scale; free choice of good and bad outputs and pollution-generating inputs), the model collapses to the one assuming weak disposability of undesirable outputs. Moreover, the "summing-up" restriction in **(12)** implies that, under fixed levels of inputs, $H'g_y = g_b$; that is to say the materials balance is verified only if the direction vector of bad output (g_b) equals the recuperation associated with the good output direction ($H'g_y$). This suggests very little flexibility for producers in mitigating the generation of bad outputs. Practically, the direction for the reduction of the bad output is highly constrained if one wants to maintain the MBP. Another important practical limit of the MBP framework is the need for knowledge about the emission and recuperation factors (W and H, respectively). Also, in the presence of abatement strategies, the amount of pollution reduction due to abatement investment has to be clearly incorporated in the balance equation. Besides, as explained by Førsund (2009), the materials balance equation in **(8)** does not explicitly specify how the residuals are generated, but simply describes how these residuals are related to the use of materials inputs. In addition, as pointed out by the author, the MBP equation introduces "some limits on derivatives in the system of equations". This may result (when using dual approaches) in, for example, counterintuitive results such as the fact that the use of additional inputs generates extra revenues to the firm, while in reality input consumption incurs costs. Finally, as underlined in Murty et al. (2012 p124), the identity in **(8)** requires all the variables to be measured in a common unit, but "examples exist where it may not be possible to measure intended outputs and material inputs in common mass units and where 'harmless' omissions of some commodities that are not considered relevant by the modeller may result in the violation of the mass-balance condition".[13]

As a conclusion to this section, despite its innovative approach, the weak G-disposability also fails to correctly represent and capture the different trade-offs in a pollution-generating technology. Alternative solutions have been proposed through the estimation of multiple sub-frontiers, discussed in the next sub-section.

4.2. By-production technologies

Although the terms "joint production" and "by-production" are used equivalently to qualify the generation of undesirable outputs in the production process (Färe et al., 2013), Murty and Russell (2002) made a clear distinction between these two expressions. According to these

[13] The "mass-balance condition" is equivalent to the mass/energy conservation equation in **(8)**.

authors, joint production implies the existence of a rich "menu of possible output vector (that is, a production possibility set), possibly including zero amounts of some (all) outputs, given the amounts of the inputs", while by-production accounts for the MBP because it "implies the inevitability of a certain amount of incidental output, given the quantities of certain inputs and/or certain intended outputs (possibly including abatement outputs)".

The by-production approach, introduced in Murty and Russell (2002) and generalised by Murty et al. (2012), appears to be one of the most promising methods in the modelling of pollution-generating technologies. Førsund (2009) indicated that it is a "better approach than operating with output couplings and factor bands"[14] to represent materials balance. The starting point of this approach is that the classical representation of treating bad outputs as inputs, or assuming weak disposability of undesirable outputs and null-jointness, moves away from the five attributes[15] of the technology relative to the by-production of incidental outputs (Murty, 2010a). Following Frisch (1965) and Førsund (1998), trade-offs in by-production technologies cannot be represented by a single implicit production relationship. One should instead consider several relationships to describe a production system. This by-production approach assumes cost disposability of the technology regarding undesirable outputs, pollution-generating inputs, and some intended outputs. Given fixed levels of some inputs and/or some intended outputs, there is a minimal amount of pollution that can be by-produced by the technology. Of course, poor management might create inefficiencies in the production process that could yield more than this minimal level of undesirable outputs.

In the by-production approach two production technology sets are estimated: an intended-production technology and a residual-generation technology. Let us divide the input vector x into two input sub-vectors where x_1 represents the sub-vector of non-pollution-causing

[14] Product couplings refer to the introduction of additional constraints that depict the link between some outputs (here between good outputs and bad outputs), independently of the inputs. Reversely, factor bands refer to the relationship between inputs regardless of the outputs.

[15] These attributes can be summarised as follows. First, using pollution-generating inputs necessarily produces pollution as an incidental output or as a by-product of the good output. Second, non-rivalness or jointness of pollution-generating inputs and their use for the production of one output do not exclude them from the production of the other output. Third, by-product technology does not satisfy the free disposability of bad outputs (the cost disposability is verified). Fourth, correlation between intended outputs and incidental ones is ensured by the previous attributes. Fifth, mitigation opportunities are present: for example, some of a firm's resources may be diverted from the production of good outputs towards cleaning-up activities.

inputs and x_2 the sub-vector of pollution-causing inputs. The general production technology Ψ can be represented by

$$\Psi = \Psi_1 \cap \Psi_2 \tag{14}$$

with

$$\Psi_1 = \left[(x_1, x_2, y, b) \in \mathbb{R}_+^{K_1+K_2+Q+R} \middle| f(x_1, x_2, y) \leq 0\right] \tag{15}$$

$$\Psi_2 = \left[(x_1, x_2, y, b) \in \mathbb{R}_+^{K_1+K_2+Q+R} \middle| b \geq u(x_2)\right] \tag{16}$$

where f and u are both continuously and differentiable functions.

A rigorous modelling of technology Ψ_2 under the materials balance conditions implies equality in the constraint $b = u(x_2)$ meaning that, given the quantity of polluting inputs, the level of undesirable outputs is fixed. The model also implies that there is no recuperation factor, but this possibility can nevertheless be allowed where desirable outputs enter the constraint.

The cost disposability assumption with respect to the unintended outputs can be expressed as follows:

$$(x_1, x_2, y, b) \in \Psi \wedge \bar{b} \geq b \ \wedge \ \bar{x}_2 \leq x_2 \Rightarrow (x_1, \bar{x}_2, y, \bar{b}) \in \Psi \tag{17}$$

This assumption implies that it is possible to pollute more given the levels of x_2; in other words, it means that the set of technology Ψ_2 is bounded below (Murty, 2010b).

Ψ_1 satisfies the standard disposability assumption, as follows:

$$(x_1, x_2, y, b) \in \Psi_1 \ \wedge \ \tilde{x}_1 \geq x_1 \ \wedge \ \tilde{x}_2 \geq x_2 \ \wedge \ \tilde{y} \leq y \ \Rightarrow (\tilde{x}_1, \tilde{x}_2, y, b) \in \ \Psi_1 \tag{18}$$

In the case of activity analysis we have:

$$\Psi_1 = \left[(x_1, x_2, y, b) \in \mathbb{R}_+^{K_1+K_2+Q+R} \middle| y \leq \sum_{i=1}^{N} \nu_i Y_i \ ; \ x_1 \geq \sum_{i=1}^{N} \nu_i X_{i1} \ ; \right. \\ \left. x_2 \geq \sum_{i=1}^{N} \nu_i X_{i2} \ ; \ \sum_{i=1}^{N} \nu_i = 1; \ \ \nu_i \geq 0; i = 1, \dots, N \right] \tag{19}$$

$$\Psi_2 = \left[(x_1, x_2, y, b) \in \mathbb{R}_+^{K_1+K_2+Q+R} \middle| \, x_2 \leq \sum_{i=1}^{N} \xi_i X_{i2} \; ; \right. \tag{20}$$

$$\left. b \geq \sum_{i=1}^{N} \xi_i B_i \; ; \sum_{i=1}^{N} \xi_i = 1; \;\; \xi_i \geq 0; i = 1, \dots, N \right]$$

The first inequality in **(20)** reflects the cost disposability of pollution-causing inputs and the second the cost disposability of residual outputs. The unified technology Ψ is given by **(21)** with two intensity variables ν_i and ξ_i which represent the two different sub-technologies.

$$\Psi = \left[(x_1, x_2, y, b) \in \mathbb{R}_+^{K_1+K_2+Q+R} \middle| \, y \leq \sum_{i=1}^{N} \nu_i Y_i \; ; \;\; x_1 \geq \sum_{i=1}^{N} \nu_i X_{i1} \; ; \right.$$

$$x_2 \geq \sum_{i=1}^{N} \nu_i X_{i2} \; ; \;\; x_2 \leq \sum_{i=1}^{N} \xi_i X_{i2} \; ; \tag{21}$$

$$\left. b \geq \sum_{i=1}^{N} \xi_i B_i \; ; \sum_{i=1}^{N} \nu_i = 1; \;\; \sum_{i=1}^{N} \xi_i = 1; \;\; \nu_i, \xi_i \geq 0; i = 1, \dots, N \right]$$

Murty et al. (2012) suggested that an efficiency score (EFF_{by}) can be derived as an extension of the Russell index proposed byFäre and Lovell (1978):

$$EFF_{by}(x, y, b; \Psi) = \frac{1}{2} \min_{\phi,\omega} [\frac{\sum_q \phi_q}{Q} + \frac{\sum_r \omega_r}{R} \mid (x, y \oslash \phi, \omega \otimes b) \in \Psi] \tag{22}$$

where $1/\phi_q$ represents the potential increase in good output q, and ω_r is the potential decrease in order to reach the minimal level attainable for the undesirable output r; $y \oslash \phi = (y_1/\phi_1, \dots, y_Q/\phi_Q)$; $\gamma \otimes b = (\omega_1 b_1, \dots, \omega_R b_R)$. More simply, $1/\phi_q$ (which is greater than or equal to one) represents the efficiency score of the good output q, while ω_r (which is less than or equal to one) is the efficiency score associated with the bad output r. The efficiency score can be simply rewritten as a sum of two scores:

$$EFF_{by}(x,y,b;\Psi) = \frac{1}{2}\min_{\phi}[\frac{\sum_q \phi_q}{Q} \left| \left(x, \frac{y}{\phi}, b\right) \in \Psi_1 \right] + \frac{1}{2}\min_{\omega}[\frac{\sum_r \omega_r}{R} \mid (x, y, \omega \otimes b) \in \Psi_2] \tag{23}$$

A particularly interesting feature of the by-product technology modelling is that it is very close to the MBP approach explained above, since it obeys the aforementioned laws of thermodynamics. However, as seen in **(8)**, the MBP requires some factors (W' and H') in order to aggregate in a common unit the inputs and the desirable outputs of the model. This can be very challenging since, as previously mentioned, desirable outputs and inputs often cannot be measured in a common unit. By-production modelling can help overcome this situation.

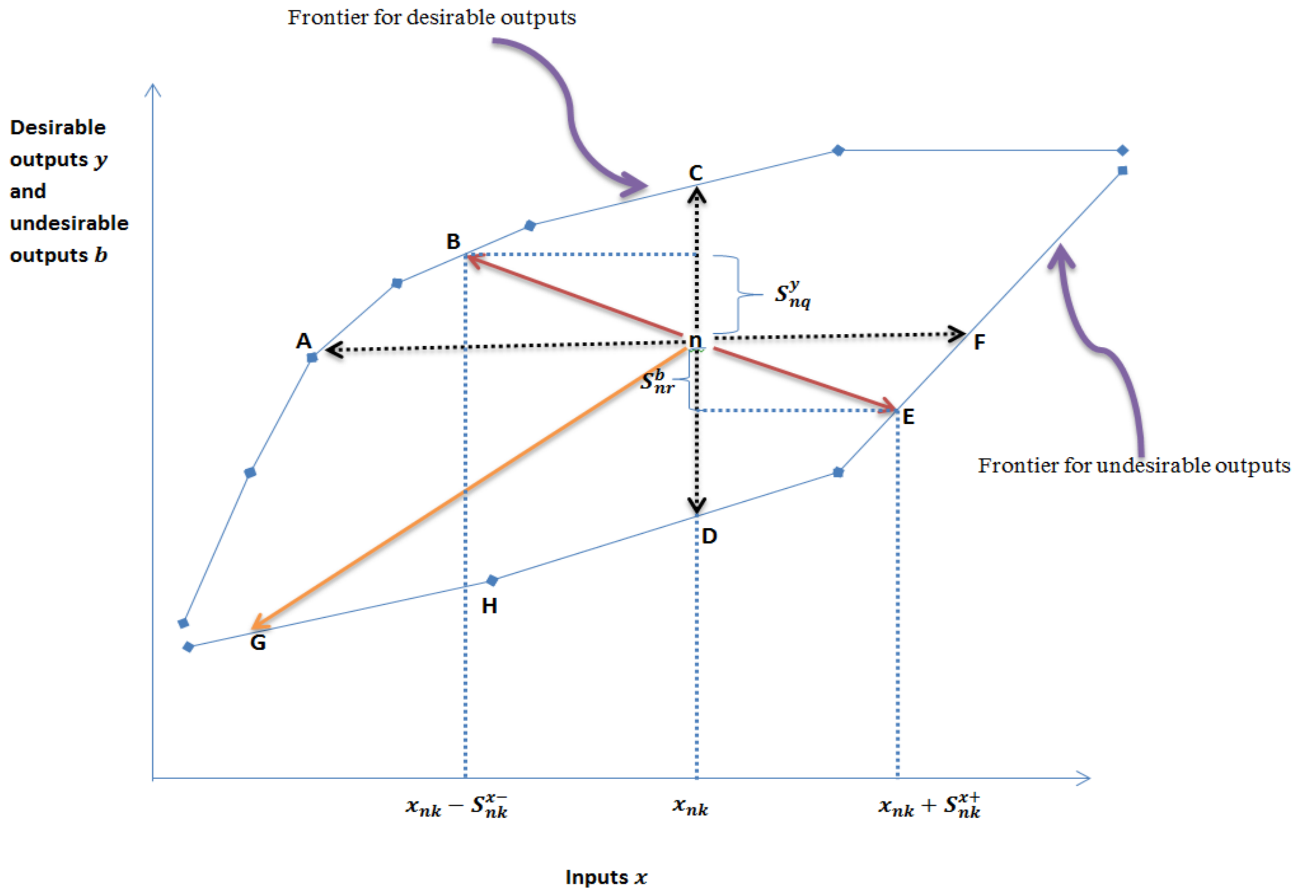
Theoretically, the by-production technology, as the intersection of two sub-technologies (see formula **(14)**), provides a strong background and realism in modelling pollution-generating technology. However, as shown in equations **(21)** to **(23)**, in the practical case of using DEA to estimate the efficiency scores, the model fails to maintain this intersection. Actually, in such non-parametric representation, independence between Ψ_1 and Ψ_2 is assumed. In Murty et al. (2012)'s words, the pollution generating sub-technology Ψ_2 "operates independently of a firm's intended-production technology" represented by Ψ_1. The proposed efficiency score is simply computed as a multiple goal programming with a weight of 50% given to each objective (see equation **(23)**). The direct implication of this set-up in the case of activity analysis is an inconsistency between the optimal levels of inputs under each separate sub-technology. Let us recall that both transformation processes operate in the same entity and not in two distinct ones. Another limit of the by-production model derives from the inputs' separation into polluting and non-polluting ones. Such a separation would need to be made a priori before conducting any efficiency assessment, but it might be hard to decide whether some inputs can be classified into the polluting or non-polluting group. Besides, this categorisation of inputs excludes the possibility that some non-polluting inputs might directly affect the levels of undesirable outputs' generation.

In this multiple frontiers estimation framework, another approach has been developed around new disposability concepts, explained in the next sub-section.

4.3.Non-radial efficiency measure under natural and managerial disposability

Sueyoshi et al. (2010) and Sueyoshi and Goto (2010) proposed two new efficiency models related to the two sub-technologies described above: an operational efficiency model (related to Ψ_1); and an environmental efficiency model (related to Ψ_2). These models use non-radial range-adjusted measures (RAM) (Cooper et al., 1999), and are based on two new disposability concepts aimed at analysing the adaptive behaviours of DMUs to changes in environmental regulations (Sueyoshi and Goto, 2012a, 2012b). i-) The natural disposability concept (or negative adaptation): under this assumption, a decrease in the vector of inputs implies a decrease in the vectors of both desirable outputs and undesirable outputs. This disposability is also termed the "natural reduction" of pollution. The idea is that the aim of a manager is to increase his/her firm's operational efficiency in a way that, given a vector of reduced inputs, the firm increases the desirable outputs as much as possible. No environmental managerial effort needs to be undertaken in order to meet the objective of pollution reduction. ii-) The managerial disposability concept (or positive adaptation): here a firm increases its consumption of inputs in order to increase the volume of desirable outputs and simultaneously decrease the levels of undesirable outputs. This can be achieved through some managerial effort such as the adoption of new technologies that can mitigate pollution. The managerial disposability concept relates to the ideas of scholars such as Porter and van der Linde (1995b) who saw in regulations the opportunity for firms to implement technology innovations which are compatible with both environmental and economic improvements. Graphically, the operational efficiency of DMU n is evaluated using the good outputs' sub-frontier (the upper one in **Figure 2**), and the environmental efficiency is defined with respect to the bad outputs' sub-technology (the lower sub-frontier). Natural disposability is represented by all projections directed towards the southwest part of the figure along the segments defined by points G, H, D. Managerial disposability is defined by the potential increase in input consumption, and thus in **Figure 2** it is represented by all projections to the southeast part, namely points D, E, F. When taken separately, the operational efficiency of DMU n is evaluated using points A, B, C as benchmarks, and the environmental efficiency is evaluated relative to points D, E, F.

Figure 2: Natural and managerial disposability concepts representation.



Source: the authors, adapted from Sueyoshi and Goto (2011a)

Using activity analysis, the two disposability concepts can be estimated by **(24)** and **(25)**:

$$\max \frac{1}{K+Q+R}\left[\sum_{q}\frac{S_{nq}^{y}}{RAN_{q}^{y}}+\sum_{k}\frac{S_{nk}^{x}}{RAN_{k}^{x}}+\sum_{r}\frac{S_{nr}^{b}}{RAN_{r}^{b}}\right]$$

$$subject\ to$$

Natural disposability

$$x_{nk}-S_{nk}^{x}=\sum_{i=1}^{N}\gamma_i X_{ik}\ ,k=1,\dots,K\ ;$$

$$y_{nq}+S_{nq}^{y}=\sum_{i=1}^{N}\gamma_i Y_{iq}\ ,q=1,\dots,Q; \tag{24}$$

$$b_{nr}-S_{nr}^{b}=\sum_{i=1}^{N}\gamma_i B_{ir}\ ,r=1,\dots,R;$$

$$\sum_{i=1}^{N}\gamma_i=1;\ \ \gamma_i,S_{nk}^{x},S_{nq}^{y},S_{nr}^{b},\geq 0 \text{ for all } i,k,q \text{ and } r$$

$$\max \frac{1}{K+Q+R}\left[\sum_{q}\frac{S_{nq}^{y}}{RAN_{q}^{y}}+\sum_{k}\frac{S_{nk}^{x}}{RAN_{k}^{x}}+\sum_{r}\frac{S_{or}^{b}}{RAN_{r}^{b}}\right]$$

$$subject\ to$$

Managerial disposability

$$x_{nk}+S_{nk}^{x}=\sum_{i=1}^{N}\gamma_i X_{ik}\ ,k=1,\dots,K\ ;$$

$$y_{nq}+S_{nq}^{y}=\sum_{i=1}^{N}\gamma_i Y_{iq}\ ,q=1,\dots,Q; \tag{25}$$

$$b_{nr}-S_{nr}^{b}=\sum_{i=1}^{N}\gamma_i B_{ir}\ ,r=1,\dots,R;$$

$$\sum_{i=1}^{N}\gamma_i=1;\ \ \gamma_i,S_{nk}^{x},S_{nq}^{y},S_{nr}^{b},\geq 0 \text{ for all } i,k,q \text{ and } r$$

where:

$$RAN_q^y = \bar{y}_q - \underline{y}_q \ , \bar{y}_q = \max[y_q], \qquad \underline{y}_q = \min[y_q], \qquad q = 1, \dots, Q$$

$$RAN_k^x = \bar{x}_k - \underline{x}_k, \bar{x}_k = \max[x_k], \qquad \underline{x}_k = \min[x_k], \qquad k = 1, \dots, K$$

$$RAN_r^b = \bar{b}_r - \underline{b}_r \ , \bar{b}_r = \max[b_r], \qquad \underline{b}_r = \min[b_r], \qquad r = 1, \dots, R$$

An efficiency score Θ can be obtained as follows:

$$\Theta = 1 - \frac{\left[\sum_q \frac{S_{nq}^y}{RAN_q^y} + \sum_k \frac{S_{nk}^x}{RAN_k^x} + \sum_r \frac{S_{or}^b}{RAN_r^b}\right]}{K + Q + R} \tag{26}$$

However, in the case of the natural disposability assumption, the undesirable outputs are simply treated like any input (same intensity variable γ_i), whereas in the case of the managerial disposability assumption, inputs are modelled as outputs and undesirable outputs are modelled as inputs. Hence, although these two new disposability concepts present some positive aspects, they may suffer from the above-mentioned limits (see previous sections) inherent in the conception of the models. In particular, treating undesirable outputs as inputs results in a wrong specification of the global technology. Besides, considering inputs as good outputs under the managerial disposability is counterintuitive given the fact that the consumption of inputs generates costs to firms.

Sueyoshi et al. (2010) developed a unified framework that, in contrast to Murty et al. (2012), is based on a single intensity variable (although such a framework does not erase the above-mentioned limits). The unification strategy accounts not only for the managerial aspect linked to undesirable outputs, but also for the natural reduction of these outputs. This is possible by splitting the inputs slacks S_{nk}^x into their positive (S_{nk}^{x+}) and negative (S_{nk}^{x-}) parts, as shown in **(27)**. To prevent infeasibilities, the estimation of model **(27)** requires that the two input slacks must be mutually exclusive: $S_{nk}^{x+} \times S_{nk}^{x-} = 0$. This means that the simultaneous occurrence of $S_{nk}^{x+} > 0$ and $S_{nk}^{x-} > 0$ is not possible. Model **(27)** can be estimated in two ways: by adding the constraint $S_{nk}^{x+} \times S_{nk}^{x-} = 0$ and estimating a non-linear mathematical programming; or by transforming the model into a mixed integer linear programming model with the following additional constraints: $S_{nk}^{x+} \leq Lz_{nk}^+$, $S_{nk}^{x-} \leq Lz_{nk}^-$, $z_{nk}^+ + z_{nk}^- \leq 1$, where z_{nk}^+ and z_{nk}^- are binary for each $k = 1, \dots, K$ and L is a very large number that needs to be set.

$$\max \frac{1}{K+Q+R}\left[\sum_{q}\frac{S_{nq}^{y}}{RAN_{q}^{y}}+\sum_{k}\frac{S_{nk}^{x+}+S_{nk}^{x-}}{RAN_{k}^{x}}+\sum_{r}\frac{S_{nr}^{b}}{RAN_{r}^{b}}\right]$$

$$subject\ to$$

Unified efficiency estimation

$$x_{nk}-S_{nk}^{x-}+S_{nk}^{x+}=\sum_{i=1}^{N}\gamma_i X_{ik}\ ,k=1,\dots,K\ ;$$

$$y_{nq}+S_{nq}^{y}=\sum_{i=1}^{N}\gamma_i Y_{iq}\ ,q=1,\dots,Q; \qquad (27)$$

$$b_{nr}-S_{nr}^{b}=\sum_{i=1}^{N}\gamma_i B_{ir}\ ,r=1,\dots,R;$$

$$\sum_{i=1}^{N}\gamma_i=1;\ \ \gamma_i,S_{nk}^{x+},S_{nk}^{x-},S_{nq}^{y},S_{nr}^{b},\geq 0 \text{ for all } i,k,q \text{ and } r$$

As pointed out in Manello (2012 p27), the non-linearity introduced in the unified framework may generate some dominated efficient DMUs. According to the author, there may be identification problems for the efficient DMUs since the two technology sets can generate contradictory results. Another issue is that the dual model of (**27**) is difficult to derive without using Second Order Cone Programming (SOCP) (Sueyoshi and Goto, 2011b). For an inefficient DMU, the solution of the problem in **(27)** may yield inefficiency on the input side. However, given the mutually exclusive characteristics of the input slacks, either S_{nk}^{x-} or S_{nk}^{x+} will arise. Then, the solution to the problem in **(27)** for an inefficient DMU simply results in the linear program **(24)** in the case of S_{nk}^{x-}, or in **(25)** in the case of S_{nk}^{x+}. We mentioned earlier the limits inherent in these models taken separately, which wrongly represent the nature of a pollution-generating technology. Moreover, using a single intensity variable (γ_i) is not an explicit way of representing two distinct sub-technologies.

The idea of considering that a pollution-generating technology is made up of two sub-technologies (one for intended outputs and the other for unintended ones) is basically solid and very convincing regarding the structure of a firm in reality. However, here also the implementation fails to fully capture the theory, proving that there are still challenges left in modelling pollution-generating technologies.

5. Challenges and future trends of research

In this chapter we have extended previous reviews on performance benchmarking in the presence of undesirable outputs to include recent developments and to discuss the limits of each approach. We have discussed the classic WDA, and also the weak-G disposability assumption and the MBP, plus the by-production approach and the approach introducing natural and managerial disposability.

The WDA, although commonly used, is largely questioned with regard to its ability to account for detrimental outputs. Based on the idea that reducing undesirable outputs comes at a cost for the DMUs, the WDA faces the important criticism that it does not comply with the laws of thermodynamics (and the MBP) in the way that there is a minimal amount of residual generation. In addition, negative shadow prices may be obtained, and several problems may appear when estimating efficiency; for example, in relation to strongly dominated firms or targets. However, despite all the drawbacks, this disposability assumption is still extensively used in many environmental performance evaluations. By contrast, methods such as the weak-G disposability are based on the laws of thermodynamics (which govern production processes), tied up in the MBP, and hence present a clear advantage over the WDA models. Discussing the notion of joint production, Baumgärtner et al. (2001) indeed stated that it is “intimately related to the laws of thermodynamics” where each production process is grounded by the transformation of energy and matter. This idea strengthens the MBP which simply states that “what goes in must come out” (Coelli et al., 2005). Yet the famous energy conservation axiom is introduced in the aforementioned model as a simple accounting identity, and therefore does not describe the way undesirable outputs are generated and is limited in the representation of trade-offs in the technology. In addition, from a theoretical point of view, derivatives in the problem may be constrained yielding counterintuitive results, and from a practical point of view the approach requires the measurement of inputs and outputs in common units.

The problem of trade-offs mentioned above is partly circumvented by the by-production modelling. This approach provides a new way of representing pollution-generating technologies, by estimating several frontiers to characterise each process involved in a production system. In the simple case, two sub-technologies are represented: an intended-production technology and a residual-generation technology. Nevertheless, in the operationalisation of this approach in the DEA framework, Murty et al. (2012) assumed independence between the different sub-technologies. Hence, this does not fully capture the trade-offs between operational efficiency and environmental efficiency. In practice this can lead to inconsistent optimal levels of inputs identified under each separate sub-technology. In addition, inputs should be separated a priori into polluting and non-polluting ones, which may not always be possible. Also in a multiple frontier framework, Sueyoshi et al. (2010) developed a unification strategy that relies on two concepts: the natural disposability and the managerial disposability. The former represents the natural reduction of pollution in the production process without additional managerial effort, while the latter requires additional effort such as the adoption of new technologies. However, this unified model also fails to provide a proper representation of pollution-generating technologies, in particular because a single intensity variable is used.

To summarise, the structure of this chapter shows an incremental evolution of the different methods: the WDA is the most used approach, but some authors have cast doubt on its relevance given the violation of the MBP. These authors thus developed an approach grounded in the laws of thermodynamics (which govern production processes) and tied in the MBP. However, the famous mass/energy conservation axiom is introduced as a simple accounting identity and does not describe the way undesirable outputs are generated. From this point, the by-production modelling has emerged, providing a new way of representing pollution-generating technologies, considering one sub-frontier for each process involved in a production system. The approaches using several sub-technologies are the most recently developed in this area of research. In a sense, each method developed has attempted to circumvent problems of previous methods. All the existing models are, however, flawed in the way pollution-generating technologies are implemented in the case of non-parametric production modelling. They all fail to represent the theory. Despite this, the methods based on the estimation of multiple frontier technologies are more promising due to their strong theoretical background (Murty, 2012). For instance, the by-production approach does not theoretically violate the MBP. This approach will probably become the core of future research in eco-efficiency evaluation, and our first suggestion is that more effort should be devoted to addressing the remaining issues for this approach, such as the practical implementation.

However, the fact that models relying on the WDA are still the most widely used despite the strong shortcomings publicly expressed, raises questions. Answers may lie in the complexity of the more advanced models. In this context, a second suggestion for further research is to undertake a data-based comparison of all these approaches to systematically identify convergent and divergent ones. A meta-analysis of existing empirical studies could also be carried out in this context. This data-driven comparison should be associated with expert knowledge on the observations under evaluation to help empirically validate (or invalidate) the different models.

In fact, it may be that different models can yield practically approximately similar results, casting doubt on the necessity of mathematically complex formulations.

A third suggestion is that these approaches should be extended to account for a longer time horizon. A decomposition of productivity indices into various components including eco-efficiency change could provide information on the most important sources of productivity change. This should be useful to policy-makers, since it may help assess the long term effects of environmental regulations. Indeed, the regulations may not be immediately followed by results since, for example, investment in cleaner or mitigating technologies may have delayed effectiveness.

Our fourth suggestion is that future research should also focus on addressing the lack of statistical inference in such approaches, by including noise in the eco-efficiency models along with their robustness to outliers. As noted by Song et al. (2012), these aspects are crucial in decision planning. However, very few attempts have been made in the area of eco-efficiency measurement. In the classical DEA analysis some approaches, such as the bootstrap methodology proposed by Simar and Wilson (1998) and Simar and Wilson (2000), can help derive inference for efficiency scores, as can new developments such as subsampling techniques (Simar and Wilson, 2009; Simar and Wilson, 2011). In addition, Simar and Vanhems (2012) recently widened the statistical analysis to the case of DDF. Alternative models such as the chance constrained and fuzzy DEA (Saati et al., 2011; Momeni and Saen, 2012) and the Stochastic Non-parametric Envelopment of Data (StoNED) (Kuosmanen, 2006; Kuosmanen and Kortelainen, 2007; Andor and Hesse, 2013) also have potential. StoNED is based on the estimation of Convex Non-linear Least Squares (CNLS) and enables some noise to be included in the data under analysis. This approach was applied to the case of undesirable outputs in Mekaroonreung and Johnson (2012), however the approach is grounded on the WDA. As regards robustness, detecting outliers in the case of eco-efficiency measurement can be important as, for instance, the WDA fails partly because of the presence of heavy polluters. Existing approaches in classic DEA studies may be extended in the case of eco-efficiency assessment: Wilson (1993)'s algorithm to detect outliers; Serra et al. (2014)'s approach relying on the super-efficiency model of Banker and Chang (2006) to detect outliers; the order $- m$ frontier by Cazals et al. (2002) and the order $- \alpha$ frontier by Aragon et al. (2005), as well as Simar (2003)'s methodology to detect outliers and extreme observations based on the order $- m$ frontier.

The fifth avenue for future research is that robust models could be extended to the analysis of determinants (such as energy prices, poor economic context and other external factors) explaining eco-efficiency scores. An example of such a model is the conditional robust estimation approach (Bădin and Daraio, 2012; Bădin et al., 2012a, 2012b) which is a one-stage procedure that overcomes the separability condition generally assumed in the two-stage algorithm. Using the WDA, Halkos and Tzeremes (2013a) applied the conditional efficiency estimation in the presence of undesirable outputs. From another perspective, Cordero et al. (2015) applied this conditional approach using a data transformation function for the undesirable outputs. Using the frontier eco-efficiency model, Halkos and Tzeremes (2013b) also applied this conditional measure of eco-efficiency where undesirable outputs are treated as inputs. None of the recent models presented in **Section 4** has so far been extended with this conditional approach.

Sixth, in this chapter we have not discussed in detail the estimation of shadow prices of bad outputs, although from a political perspective these prices can provide interesting information for the design of environmental regulations (e.g. taxes, a market of pollution rights). Attaching a monetary value to environmental outcomes is a current and controversial research topic, and would necessitate further research. As a first step, a review can be found in Zhou et al. (2014).

Finally, the eco-efficiency models may also be an opportunity to test the Porter Hypothesis (Porter and van der Linde, 1995b). According to this hypothesis, more stringent environmental regulations may trigger innovations that can partially or fully offset the costs of complying with them. The idea behind this notion is that regulations can increase productive efficiency, although some authors such as Palmer et al. (1995) expressed their scepticism about this win-win opportunity. The Porter Hypothesis can be related to the natural and the managerial disposability concepts. In fact, the managerial disposability assumption is in line with the Porter Hypothesis, as it implies that firms have the opportunity to increase their good output production levels simultaneously with the reduction of undesirable outputs. Firms would gain with this strategy because the adoption of new technologies may offset the investment costs. Analysing the potential improvements of DMUs in their managerial efficiency can shed light on adequate environmental regulations.

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Chapter 2. On modelling pollution-generating technologies: a new formulation of the by-production approach

1. Introduction

Widespread societal environmental concerns and theory of externalities developments (Mishan, 1971; Cropper and Oates, 1992) have ushered in a new era in production economics with the emergence of multi-type output considerations in methodologies. In addition, the adoption of sustainable production behaviors has become key to many policy recommendations. The performance benchmarking literature (Tyteca, 1996; Allen, 1999; Zhou et al., 2008a; Song et al., 2012) has therefore shown a keen interest in including the generation of undesirable outputs as by-products in production technology modeling.

Following the seminal work produced by Pittman (1983), many non-parametric frontier estimation models have been developed (along the lines of Data Envelopment Analysis (DEA) where all firms are enveloped by a frontier made of the highest performing firms in the sample) to incorporate undesirable outputs into technology modeling. These models are based on the standard transformation function, and rely on specific disposability assumptions used to capture all the production technology's potential trade-offs (substitution between inputs and outputs; marginal productivities).

Most empirical applications treat undesirable outputs as additional inputs (Barbera and McConnell, 1990; Hailu and Veeman, 2000, 2001a; Hailu, 2003; Considine and Larson, 2006) or work them into the technology as outputs, but under the weak disposability assumption (WDA) (Färe et al., 1986; Färe et al., 1989; Coggins and Swinton, 1996; Boyd and McClelland, 1999; Kuosmanen, 2005; Kuosmanen and Podinovski, 2009; Färe et al., 2012). Such assumptions should make for a positive correlation between good and bad outputs. For example under the weak disposability assumption, it is costly for the firm to reduce its undesirable outputs since this implies a proportional reduction in good outputs due to the diversion of resources to the mitigation of undesirable outputs.

The limitations of these models, based as they are on a single functional relationship between inputs and outputs, are now well documented. For instance, Førsund (2009), takes a profit function and a monetized pollutant damage function to show that, under the assumption that bads[1] are outputs (freely disposable), the maximal level of these detrimental outputs is zero. Actually, under this situation where the degree of assortment – defined by Frisch (1965) as the degree of freedom with which inputs can be directed to the production of any of the outputs – is

[1] In this chapter the terms bads, bad outputs, undesirable outputs, unintended outputs, detrimental outputs, pollutants and residuals are used interchangeably.

maximal, all resources can be diverted at no cost to the production of the good outputs and thus generate zero levels of bads. This result appears to be unrealistic in the light of Ayres and Kneese (1969)'s materials balance idea, whereby the generation of pollutants is inevitable because of the use of pollution-generating inputs.

Similarly, considering residuals as inputs is awkward approach. As argued by Førsund (2009), keeping all other inputs constant, an increase in the level of pollution cannot technically explain why a good output increases. Besides, there is no explicit relationship between the common production inputs and the residuals, and only some kind of trade-off between these residuals and good outputs is captured. Moreover, no 'purification possibility' (pollution control) is accounted for. In the same line, Pethig (2003) and Pethig (2006) take the materials balance principles (MBP) to demonstrate that bads cannot be treated as inputs since this is a violation of the first law of thermodynamics relating mass or energy conservation.

In accordance with Frisch (1965), Førsund (2009) recommends using 'product couplings' and 'factor bands' to overcome the above-mentioned drawbacks. Product couplings refer to the introduction of additional constraints that depict the link between some outputs (here between the good output and the bad output) irrespective of the inputs.[2] Factor bands relate to the relationship between inputs regardless of the outputs.[3] With respect to the WDA, although Førsund (2009) specifies the connection with the product couplings idea, the WDA falls down in that some parts of the technology boundary exhibit no opportunity costs in the abatement of unintended outputs. This is a significant limitation since it means that it is not costly to reduce bads (this situation is also investigated by Chen (2014)). Coelli et al. (2007) and Hoang and Coelli (2011) also prove the inconsistency of this assumption with respect to the MBP.

Murty et al. (2012) and Murty and Russell (2002) expand on these criticisms by demonstrating the irregularities that occur when using a single functional relationship to define a pollution-generating technology. It is easy to say that these approaches, based on a single feature of the production technology, work like black boxes in which the 'magic' is misused and hence fails to produce an explicit representation of the production processes involved. Murty et al. (2012) and Murty and Russell (2002) then propose a better alternative, namely the by-

[2] An application of product couplings can be seen in Bokusheva and Kumbhakar (2014) where the authors use a translog hedonic specification to link the good outputs to the bads. In a number of previous studies, Fernández et al. (2002) and Fernández et al. (2005) use an output aggregator function based on the constant elasticity of transformation defined in Powell and Gruen (1968).

[3] This is key to our contribution and will be detailed later in this chapter.

production approach, which is based on a full description of the production processes and has sound theoretical grounds (Murty, 2012). To be more precise, the by-production approach estimates two sub-technologies: one for good outputs and the other for undesirable outputs. Theoretically, the overall technology lies at the intersection of the two sub-technologies. However, practical implementation in the case of the non-parametric DEA analysis proposed by Murty et al. (2012) is based on a modification of the Färe-Grosskopf-Lovell index (Färe et al., 1985) and is simply an estimation of two independent sub-technologies. Under this approach, a firm's efficiency is actually evaluated on the basis of multiple objective programming by assigning a weight of 50% to each objective separately.[4] This comes down to serious drawback with the empirical model proposed by Murty et al. (2012), and it can be argued that these user-defined weights are subjective and are not data-driven in contrast with DEA philosophy. In addition, no condition is introduced to check either the product couplings or the factor band concepts.

In this chapter, we re-examine the by-production approach by introducing an interconnection into the activity analysis model. This connection is set up by means of a number of dependence constraints between the sub-technologies. These constraints, set in keeping with the factor bands principle, mean that the production of residuals can be integrated into the overall technology. When added to the classic Murty et al. (2012) model, the constraints implicitly assume the existence of trade-offs between operational and environmental performances, and link up the two sub-technologies in such a way that the weight assigned to each objective is endogenously determined. We discuss the model under the restrictive assumption of fixed levels of inputs and under the flexible scenario of free choice of input quantities. In addition, we define how overall efficiency can be computed based on our by-production approach with dependence constraints, using non-radial distance function estimation. Once we have described our new model's theoretical foundation, we apply it empirically to a sample of virtual data using the Enhanced Russell-Based Directional Distance Measure (ERBDDM) discussed in Chen et al. (2015). We present the results of the two models applied to this data set: i-) the classic by-production model proposed by Murty et al. (2012), and ii-) our extension introducing dependence constraints enabling trade-offs between operational and environmental performances. For further insight into the economic interpretation of our model, we also discuss the dual of our extended by-production model.

[4] The weights as they are proposed actually give an average value of two independent efficiency scores.

The chapter is organized as follows. **Section 2** reviews the by-production modeling as developed by Murty et al. (2012). **Section 3** presents our new extension of this model, along with the efficiency assessment using the ERBDDM and the associated dual program. **Section 4** compares the two by-production approaches (classic and our extension) using a numerical application based on the generation of virtual decision-making units (DMUs). **Section 5** concludes.

2. The classic by-production modelling

Grounded in ideas put forward by Frisch (1965) and Førsund (1998), the by-production (BP) approach is driven by the view that a production system should be described by several relations (transformation functions), and that this suits bad output-generating technologies particularly well. Frisch (1965) calls this explicit representation of the technology used 'factorially determined multi-output production'. In general, the BP approach posits cost disposability, taken from Murty (2010b), for undesirable outputs, pollution-generating inputs and some good outputs.[5] To be more precise, the approach states that with fixed quantities of some inputs and/or some good outputs, a minimal amount of pollution can be simultaneously generated as a by-product of the technology. In the presence of inefficiencies, a higher level than this minimal level of undesirable outputs may be reached. However, this assumption must coexist with the disposability of the good outputs, which expresses that a set of maximal good output vectors can be produced if levels of inputs are held fixed. The positive monotonicity hypothesis states that an increase in input consumption will not reduce the production of these good outputs, but will inevitably raise the level of minimum attainable bad outputs.

The axiomatization of the by-production approach is discussed in detail in Murty (2012). Two production technology sets are constructed (**Figure 1**): an intended-output production technology, which is a standard neoclassical production function, and a residual-generation technology, which reflects the nature of the polluting emission. The intended-output technology satisfies standard free disposability assumptions and is independent of the level of pollution. Under this sub-technology, a DMU n is dominated by all the observations located in the area delimited by arrows $\overrightarrow{nA}$ and $\overrightarrow{nC}$. The residual-generation technology satisfies, to quote Murty et al. (2012), 'the polar opposite condition', that is to say cost disposability, and is independent of the good output and the non-material inputs (i.e. non-polluting inputs). For this sub-technology,

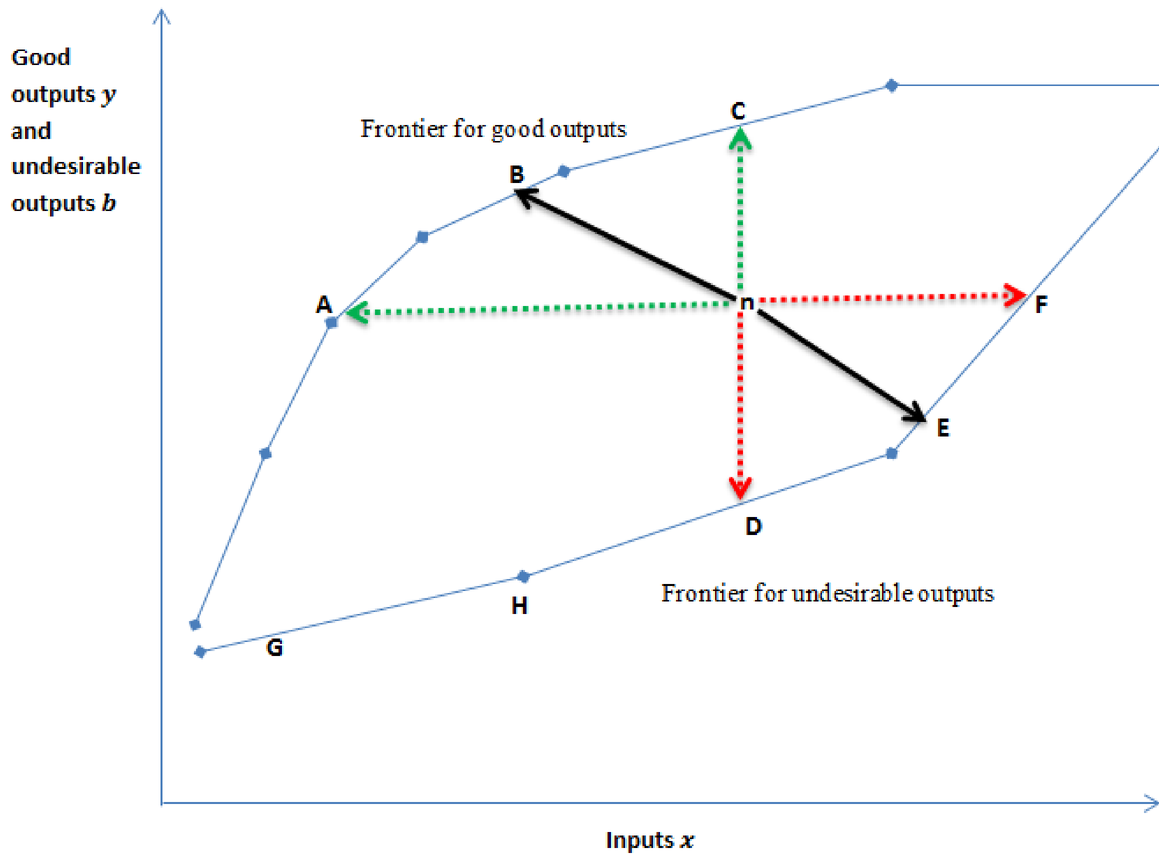
[5] Some good outputs can also generate pollution, but for simplicity we choose here to not consider this situation in the modelling here.

DMU_n is dominated by the points located in the area delineated by arrows $\overrightarrow{nD}$ and $\overrightarrow{nF}$. These dominating observations are characterized by the fact that they use more inputs to produce less undesirable outputs. Thereby, the sub-frontier for any inefficient DMU can be reached by increasing the consumption of inputs and simultaneously decreasing the generation of undesirable outputs. This situation is similar to that described by Sueyoshi and Goto (2010) and Sueyoshi et al. (2010) and later termed as 'managerial disposability' or positive adaptation (Sueyoshi and Goto, 2012a, 2012b, 2012d). The Positive adaptation refers to a situation where input consumption can be increased and pollution reduced by simultaneously raising the production of good outputs. Yet this occurs by means of managerial efforts that lead to structural business transformations and the adoption of new technologies such as high quality inputs and other innovative technologies that can mitigate the levels of pollution. As pointed out by these authors, this concept ties in with the idea developed by Porter and van der Linde (1995b) that regulation might offer innovation opportunities to secure the production of more good outputs and decrease the generation of bad outputs.

In view of the above, the intersection of these two sub-technologies then violates the free disposability assumption for pollution-causing inputs because of their opposite direction with regard to the two sub-technologies.[6] To understand this situation, it is useful to bear in mind that, due to their nature, the levels of good outputs need to be increased while the quantities of undesirable outputs are minimized. To sum up, by-production technology modeling has essentially three options to reduce the levels of detrimental outputs for a fixed technology: firstly, an increase in abatement by means of resource diversion (which is accompanied by a reduction in the production of good outputs); secondly, a reduction in pollution-causing inputs (which decreases the levels of intended outputs except in the case of a substitution with non-polluting inputs to maintain the same amount of good output production); and thirdly, the use of cleaner inputs, i.e. inputs that generate fewer bad outputs and maintain at least the same level of good output production.

[6] However, it supports the free disposability of non-polluting inputs and good outputs, and the cost disposability of undesirable outputs.

Figure 1: Good output and undesirable output sub-technologies representation.



Source: Authors

Formally, Murty et al. (2012) divide the input vector x into two input sub-vectors, where x_1 ($x_1 \in \mathbb{R}_+^{K_1}$) is the sub-vector of non-pollution-causing inputs and x_2 ($x_2 \in \mathbb{R}_+^{K_2}$) is the sub-vector of pollution-causing inputs. Denoting y as a vector of good outputs ($y \in \mathbb{R}_+^{Q}$), b a vector of bad outputs ($b \in \mathbb{R}_+^{R}$) and N the number of DMUs, the general production technology Ψ_{by} can be theoretically represented by

$$\Psi_{by} = \Psi_1 \cap \Psi_2 \tag{1}$$

where

$$\Psi_1 = \left[(x_1, x_2, y, b) \in \mathbb{R}_+^{K_1+K_2+Q+R} \middle| \, f(x_1, x_2, y) \leq 0\right] \tag{2}$$

$$\Psi_2 = \left[(x_1, x_2, y, b) \in \mathbb{R}_+^{K_1+K_2+Q+R} \middle| \, b \geq u(x_2)\right] \tag{3}$$

and f and u are both continuously differentiable functions.[7] The cost disposability assumption with respect to the undesirable outputs can be expressed as follows:

$$(x_1, x_2, y, b) \in \Psi \wedge \bar{b} \geq b \wedge \bar{x}_2 \leq x_2 \Rightarrow (x_1, \bar{x}_2, y, \bar{b}) \in \Psi \tag{4}$$

Cost disposability implies that it is possible to pollute more given the levels of x_2, i.e. that the set of technology Ψ_2 is bounded below (**Figure 1**) (Murty, 2010b). The Ψ_1 technology, however, satisfies the standard disposability assumptions:

$$(x_1, x_2, y, b) \in \Psi \wedge \tilde{x}_1 \geq x_1 \wedge \tilde{x}_2 \geq x_2 \wedge \tilde{y} \leq y \Rightarrow (\tilde{x}_1, \tilde{x}_2, \tilde{y}, b) \in \Psi \tag{5}$$

Empirically, the unified technology under variable returns to scale (VRS) is represented by model **(6)** with two intensity variables ν_i and ξ_i, which represent the two different sub-technologies.

$$\Psi_{by} = \Big[(x_1, x_2, y, b) \in \mathbb{R}_+^{K_1+K_2+Q+R} \Big| \, y \leq \sum_{i=1}^{N} \nu_i Y_i \ ;$$

$$x_1 \geq \sum_{i=1}^{N} \nu_i X_{i1} \ ; \ x_2 \geq \sum_{i=1}^{N} \nu_i X_{i2} \ ; \ x_2 \leq \sum_{i=1}^{N} \xi_i X_{i2} \ ; \tag{6}$$

$$b \geq \sum_{i=1}^{N} \xi_i B_i \ ; \sum_{i=1}^{N} \nu_i = 1; \ \sum_{i=1}^{N} \xi_i = 1; \ \nu_i, \xi_i \geq 0; i = 1, \dots, N\Big]$$

where (X, Y, B) denote the benchmark levels of inputs, good outputs and undesirable outputs, i.e. the reference set.

Interestingly, the technology as presented in model **(6)** does not really represent the overall technology as an intersection of the two sub-technologies.[8] It appears to be a set of all

[7] A rigorous modeling of technology Ψ_2 under the materials balance conditions implies equality in the constraint: $b = g(x_2)$. This means that, given the amount of polluting inputs, the level of undesirable outputs is fixed. The model also implies that there is no recuperation factor, but this can be generalized to allow for possibility where desirable outputs enter in the constraint as abatement output. Moreover, as formulated, the model based on the second technology provides an opportunity to introduce some non-linearity between polluting inputs and residual generation.

[8] In model **(6)**, there is no relationship linking either both types of outputs (product couplings) or inputs (factor bands) under the two separate sub-technologies.

available sub-technologies without explicitly linking one to another ($\Psi_{by} = [\Psi_1 \cup \Psi_2] \neq [\Psi_1 \cap \Psi_2]$). The authors (Murty et al., 2012) actually propose a measure of the efficiency score, which is a slight modification of the output-oriented Färe-Grosskopf-Lovell (FGL) index. The new efficiency score obtained is a weighted addition ($weight = \frac{1}{2}$) of two independent efficiency scores: an operational efficiency score based on Ψ_1 and an environmental efficiency score obtained from Ψ_2. The authors assign equal weights to each objective although the model, as it is formulated, allows for numerous possible combinations of weights. The weights can be adapted to the users' objective (or the manager, policy-maker or researcher). Actually, the easiest way to solve a multi-objective problem is the weighted sum, which calls for some specific user weights. This flexibility in the choice of weights places a significant limitation on the BP approach. It could even prevent a weight-free[9] comparison of different DMUs. Besides, the logic behind DEA is that all comparisons are based on a direct flexible data-driven approach, that is to say there is no a priori specification of weights (weights are chosen for the best possible efficiency and to reflect the sample's characteristics).

In this chapter, we then propose an improvement on model **(6)** to overcome this drawback with the BP as implemented by Murty et al. (2012). Taking the ERBDDM, an overall efficiency score under the classic by-production can be derived using:

$$
\begin{aligned}
\vec{D}(x, y, b; \vec{g}_y, \vec{g}_b) = \mathrm{Max}\,\theta^n &= \frac{1}{2}\left[\frac{1}{Q}\sum_{q=1}^{Q}\theta_q^n + \frac{1}{R}\sum_{q=1}^{R}\theta_r^n\right] \\
s.t.\quad \sum_{i=1}^{N}\nu_i Y_{qi} &\geq \theta_q^n \vec{g}_y^{\,q} + y_{qn} \quad q = 1, \dots, Q \\
\sum_{i=1}^{N}\nu_i X_{ki} &\leq x_{kn} \quad k = 1, \dots, K \\
\sum_{i=1}^{N}\xi_i B_{ri} &\leq b_{rn} - \theta_r^n \vec{g}_b^{\,r} \quad r = 1, \dots, R \\
\sum_{i=1}^{N}\xi_i X_{ki2} &\geq x_{kn2} \quad k_2 = 1, \dots, K_2 \\
\sum_{i=1}^{N}\nu_i = 1 \;;\; \sum_{i=1}^{N}\xi_i = 1 \;;\; &\nu_i, \xi_i \geq 0; i = 1, \dots, N \;;\; \theta \geq 0
\end{aligned}
\tag{7}
$$

[9] i.e. independent of the choice of the users.

In **(7)**, $\vec{g}_y, \vec{g}_b$ represents the directional vectors of good outputs and undesirable outputs respectively, and θ_q^n, θ_r^n the inefficiency scores associated with good output q and undesirable output r.

In keeping with the recommendation by Chung et al. (1997) for directional vector $\vec{g}_y, \vec{g}_b$, we use the observed vectors for the different outputs: $\vec{g}_y = \vec{y}$ and $\vec{g}_b = \vec{b}$. The ERBDDM in model **(7)** is somewhat similar to the FGL index applied by Murty et al. (2012), except that the results here are expressed in terms of inefficiency. Using the range adjusted measure (RAM – see Cooper et al. (1999)), Sueyoshi and Goto (2011b) introduce inputs into the objective function by the means of two groups of input slacks (namely input surpluses and input shortfalls), which respectively capture the opposite direction in terms of disposability. An adaptation of the RAM approach to the ERBDDM is provided in model **(8)**:

$$\vec{D}(x, y, b; \vec{g}_x, \vec{g}_y, \vec{g}_b) = \text{Max}\, \theta^n = \frac{1}{4}\left[\frac{1}{Q}\sum_{q=1}^{Q} \theta_q^n + \frac{1}{R}\sum_{q=1}^{R} \theta_r^n + \frac{1}{K}\sum_{k=1}^{K} \theta_k^{n-} + \frac{1}{K_2}\sum_{k2=1}^{K_2} \theta_{k2}^{n+}\right]$$

$$\begin{aligned} s.t. \quad & \sum_{i=1}^{N} v_i Y_{qi} \geq \theta_q^n \vec{g}_y^q + y_{qn} \quad q = 1, \dots., Q \\ & \sum_{i=1}^{N} v_i X_{ki} \leq x_{kn} - \theta_k^{n-} \vec{g}_x^k \quad k = 1, \dots, K \\ & \sum_{i=1}^{N} \xi_i B_{ri} \leq b_{rn} - \theta_r^n \vec{g}_b^r \quad r = 1, \dots, R \\ & \sum_{i=1}^{N} \xi_i X_{k_2 i} \geq x_{k_2 n} + \theta_{k_2}^{n+} \vec{g}_x^{k_2} \quad k_2 = 1, \dots, K_2 \\ & \sum_{i=1}^{N} v_i = 1 \;;\; \sum_{i=1}^{N} \xi_i = 1 \;;\; v_i, \xi_i \geq 0; i = 1, \dots, N \;;\; \theta \geq 0 \end{aligned} \tag{8}$$

where $\vec{g}_x^k$ represents the directional vector of all the inputs under the good outputs sub-technology while $\vec{g}_x^{k_2}$ is the vector of materials inputs under the bad outputs sub-technology representation; and $\theta_k^{n-}, \theta_{k_2}^{n+}$ are the associated inefficiency scores.

The independence assumed in the Murty et al. (2012) BP model allows for the counterintuitive possibility of measuring input inefficiency in the opposite direction depending on the associated sub-technology.

3. A new model: extension of the by-production approach

3.1. Definition of the extension

In the Murty et al. (2012) BP model, inputs need to be divided into two groups based on whether or not they generate pollution. This input breakdown makes sense in theory, but is not always possible in practice. We cannot say with certainty that the inputs classified as non-pollution-generating inputs do not directly interact with the pollution-generating sub-technology. We then recommend estimating a full dimension by-production model where all the inputs are treated as pollution generators.

The BP approach described theoretically by Murty et al. (2012) offers the advantage of separating operational from environmental performances. However, as argued above, it assumes independence between the two sub-frontiers and thus the autonomy of the two performance measures. To overcome this issue we propose to adding some additional constraints with respect to the optimal levels of input consumption (factor bands), as follows:

$$\sum_{i=1}^{N} \nu_i X_{ik} = \sum_{i=1}^{N} \xi_i X_{ik} \qquad k = 1, \dots, K \tag{9}$$

These dependence constraints state that the efficient combination level of the inputs should be equal in both sub-technologies. They can be viewed as the integration of residual production into the overall technology, implying that it is not just the production of good outputs that matters, but also the generation of detrimental outputs. By adding constraints **(9)** to model **(6)** we link up the two sub-technologies in such a way that the weight assigned to each objective is endogenously determined. These constraints implicitly account for the trade-offs between operational and environmental performances. The equality in **(9)** simply transcribes the idea stated by Førsund (2009) as follows: 'obviously the direction of a coupling . . . is unrestricted in sign, as well as the corresponding direction within a factor band'.

In terms of dominance, as earlier pointed out, under Ψ_1, a DMU n is dominated by those DMUs that use fewer inputs to produce more good outputs $[X \leq x_n \,\&\, Y \geq y_n]$. Under the second sub-technology Ψ_2, DMU_n is dominated by the set of observations that pollute less by using more inputs $[X \geq x_n \;\&\; B \leq b_n]$. In the BP model proposed by Murty et al. (2012) and reported in model **(6),** these two dominating sets of DMU_n are treated separately to build an overall efficiency score and, therefore, the interaction between the two objectives is ignored. At optimality, the model proposed by Murty et al. (2012) will result in unexpected different levels of inputs between the two sub-technologies. This can be explained by the fact that the model relies on two independent benchmarks. In **Figure 1**, this independence can result, in the case of sub-technology Ψ_1, in a projection of DMU_n onto the upper sub-frontier in B corresponding to an input level x_B. In the case of sub-technology Ψ_2, however, DMU_n is projected towards the lower sub-frontier in point E associated with input quantities x_E. It is obvious that the two optimal levels of inputs are not equivalent ($x_B \neq x_E$). By contrast, the introduction of constraints **(9)** can create a unique benchmark (a convex combination of different DMUs) and the trade-off between the two objectives of operational and environmental performance improvements can be accounted for. These constraints completely reshape the overall technology and allow for several possibilities, as follows.

- **Fixed levels of inputs**

Under the assumption of fixed levels of inputs, inputs are not directly considered in the dominance analysis, and, therefore new dominating DMUs are identified. For given levels of inputs x_n (associated with the DMU_n under evaluation), the dominating set of observations is made up of DMUs producing more good outputs under Ψ_1 and polluting less under Ψ_2. This set can be constructed using:

$$D_n = \left[(x, y, b) \in \mathbb{R}_+^{K+Q+R} \mid Y \geq y_n \;\&\; B \leq b_n \text{ given } X = x_n \right] \tag{10}$$

The equality condition on inputs in **(10)** might be seen as too restrictive.[10] To relax this restriction, one can build the dominance set with DMUs in the neighborhood of x_n. In cases where inputs are continuous variables, we recommend to basing the neighborhood determination on smoothing technique and optimal kernel density bandwidth estimation (Silverman, 1986; Scott, 2009). Following some discussion of efficiency measurement in the literature (Bădin and Daraio, 2012), the bandwidth selection is based on the least squares cross-validation method (Hall et al., 2004). Instead of estimating one bandwidth for the overall

[10] Indeed, in practice, under the dominance analysis scheme, the set of observations in **(10)** can only include one observation in the shape of the DMU under evaluation, and this DMU will therefore be deemed efficient.

technology, we can estimate two different bandwidths with respect to each sub-frontier. For greater accuracy Bădin et al. (2010) suggest that these bandwidths can be computed using dominating observations. For instance, under Ψ_1, the bandwidths can be based on observations that produce more good outputs than the DMU under evaluation. Similarly, under Ψ_2, the bandwidths are determined by the observations that generate less pollution than DMU_n. According to this procedure, there will be as many bandwidths (for each sub-technology) as observations in the sample. However, Simar, Vanhems, et al. (2013) recently argue that this procedure is 'numerically very demanding' for large sample size. In addition, the monotonicity properties of the efficiency score are not always guaranteed. Simar, Vanhems, et al. (2013) therefore recommend estimating one bandwidth (here, one for each sub-technology and the whole sample) independently of y (in the case of the good output sub-technology) and b (for the bad output sub-technology). The cross-validation method explained by Li and Racine (2008) can be used by applying kernel conditional density bandwidth selection. For the good output sub-technology, a bandwidth $\tilde{h}_1$ can be computed using conditional density function $\mathrm{F}^1(y|x)$. Similarly, for the bad output sub-technology, bandwidth $\tilde{h}_2$ is obtained using $\mathrm{F}^2(b|x)$. Since we are interested in the probability density function instead of the conditional distribution, $\tilde{h}_1$ and $\tilde{h}_2$ have to be corrected by a proper rescaling factor: $h_1 = \tilde{h}_1 \times N^{-\frac{Q}{(K+4)(K+Q+4)}}$ and $h_2 = \tilde{h}_2 \times N^{-\frac{R}{(K+4)(K+R+4)}}$. The dominance set constructed in **(10)** can be reviewed using:

$$D_n^{h_1 h_2} = \left[(x,y,b) \in \mathbb{R}_+^{K+Q+R} \,\middle|\, Y \geq y_n \ \ (\text{for } |X - x_n| \leq h_1) \ \ \& \right. \\ \left. B \leq b_n \ \ (\text{for } |X - x_n| \leq h_2)\right] \tag{11}$$

where h_1 and h_2 are the bandwidths[11] associated respectively with Ψ_1 and Ψ_2. Let's define the smallest bandwidth:

$$h = \min\ (h_1, h_2) \tag{12}$$

The dominance set can be further revised as follows:

$$D_n^h = \left[(x,y,b) \in R_+^{K+Q+R} \,\middle|\, Y \geq y_n \,\&\, B \leq b_n \ \text{ given} \right. \\ \left. |X - x_n| \leq h\right] \tag{13}$$

[11] These bandwidths can be computed using R software and the 'np' package (Hayfield and Racine, 2008).

In **(13)** the use of h provides a more general benchmark, because the observations delimited by the smallest bandwidth are embedded in those associated with the largest bandwidth and the intersection condition is verified.

- **Free choice of inputs**

To better capture the trade-offs between operational and environmental performances, inputs can be endogenously determined under the most flexible assumption of free choice of input quantities. The production technology can be defined as in **(14)**. Given this flexibility, the model evaluates the optimal allocation of inputs that will guarantee the highest operational and environmental performances.

The endogenous levels of the inputs create different situations in comparison to the case where input levels are imposed as fixed:

- Win (operationally) – win (environmentally): in this situation, a DMU improves both performances when the inputs are freely allocated.
- Win – lose: operational efficiency increases while environmental performance decreases.
- Lose – win: contrary to the previous case, the associated DMUs decrease in operational performance while environmental efficiency increases.
- Lose – lose: this situation is probably the most expected due to the fact that the introduction of flexibility into the choice of input levels might reveal more deficiencies in the production systems.

The categorization of DMUs into these four outcome groups can help identify the DMU characteristics able to perform with respect to both aspects (operational and environmental) or just one aspect. From here, it can help suggest policy recommendations. Finally, it should be stressed that the by-production model with dependence constraints is particularly well suited to model production systems where the amounts of a specific input to produce good outputs or generate bad outputs cannot be identified.

$$\begin{gathered}\Psi_{by}^{free} = \left[(x,y,b) \in \mathbb{R}_{+}^{K+Q+R} \middle| \; y \leq \sum_{i=1}^{N} \nu_i Y_i \; ; \; b \geq \sum_{i=1}^{N} \xi_i B_i \; ; \right. \\ \left. \sum_{i=1}^{N} \nu_i X_i = \sum_{i=1}^{N} \xi_i X_i \; ; \; \sum_{i=1}^{N} \nu_i = 1; \; \sum_{i=1}^{N} \xi_i = 1; \; \nu_i, \xi_i \geq 0; i = 1, \ldots, N \right]\end{gathered} \tag{14}$$

3.2. Efficiency assessment under the new extended BP approach

In this section we define how overall efficiency can be computed based on our approach, the by-production approach with some dependence constraints, using non-radial distance function estimation (under DEA). Performance is appraised using the ERBDDM (Chen et al., 2015). In the case of the most restrictive model with fixed levels of inputs, the model can be written as:

$$\vec{D}(x, y, b; \vec{g}_y, \vec{g}_b) = \text{Max}\,\theta^n = \frac{1}{2}\left[\frac{1}{Q}\sum_{q=1}^{Q}\theta_q^n + \frac{1}{R}\sum_{q=1}^{R}\theta_r^n\right]$$

$$\begin{aligned}
s.t.\ &\sum_{i=1}^{N} v_i Y_{qi} \geq y_{qn}(1 + \theta_q^n) \quad q = 1, \ldots, Q \\
&\sum_{i=1}^{N} v_i X_{ki} = x_{kn} \quad k = 1, \ldots, K \\
&\sum_{i=1}^{N} \xi_i B_{ri} \leq (1 - \theta_r^n) b_{rn} \quad r = 1, \ldots, R \\
&\sum_{i=1}^{N} \xi_i X_{ki} = x_{kn} \quad k = 1, \ldots, K \\
&\sum_{i=1}^{N} v_i = 1\ ;\ \sum_{i=1}^{N} \xi_i = 1 \\
&v_i, \xi_i \geq 0; i = 1, \ldots, N\ ;\ \theta \geq 0
\end{aligned} \tag{15}$$

Under the assumption of fixed levels of inputs for both sub-technologies, the model in **(15)** appraises technical inefficiency in output production. In the case of bad outputs, as previously explained, only a minimal quantity of undesirable output can be produced when inputs levels are held fixed. However, poor management may lead a firm to produce more than this minimal level. This model can then be used to evaluate the managerial capacity of a firm to by-produce detrimental outputs without departing from the materials balance conditions.

The dual[12] of the model in **(15)** can be written as:

$$\vec{D}(x, y, b; \vec{g}_y, \vec{g}_b) = -\max \sum_{q=1}^{Q} W_q y_{qn} - \sum_{k=1}^{K} (W_k + U_k) x_{kn} - \sum_{r=1}^{R} U_r b_{rn} - W_c - U_c$$

$$\begin{aligned} s.t. \quad & \sum_{q=1}^{Q} W_q Y_{qi} - \sum_{k=1}^{K} W_k X_{ki} - W_c \leq 0 \quad i = 1, \dots, N \\ & \sum_{r=1}^{R} U_r B_{ri} + \sum_{k=1}^{K} U_k X_{ki} + U_c \geq 0 \quad i = 1, \dots, N \\ & W_q y_{qn} \geq \frac{1}{2Q} \quad q = 1, \dots, Q \\ & U_r b_{rn} \geq \frac{1}{2R} \quad r = 1, \dots, R \\ & W_q, U_r \geq 0 \\ & W_k, U_k, W_c, U_c \quad \text{unrestricted} \end{aligned} \tag{16}$$

W_c and U_c are the dual variables associated with the convexity constraints that ensure variable returns to scale. They appear in the objective function as intercepts of the hyperplanes associated with each sub-technology. The nature and magnitude of returns to scale can be derived from their position (sign). W_k represents the shadow price relating to the k-th input in the good output production sub-technology, and U_k represents the equivalent shadow price of this input under the bad output generation sub-technology. $W_q y_{qn}$ is equivalent to the shadow revenue of producing good output q by means of DMU_n, and $U_r b_{rn}$ is the shadow cost associated with the by-production of bad output r by means of DMU_n. The model's non-radial nature guarantees the positivity of the shadow revenue and shadow cost associated with each type of output (with the constraints $W_q y_{qn} \geq \frac{1}{2Q}$ and $U_r b_{rn} \geq \frac{1}{2R}$).

The objective function in **(16)** can then be interpreted as profit maximization. The impact of the dependence constraints is captured by the unrestricting sign of the input prices under both sub-technologies. The global impact of the inputs is measured by the sum of the two shadow values $[(W_k + U_k) x_{kn}]$. This lack of restriction can have significant policy implications. In a

[12] In the literature analysts often refer to the dual model as the multiplier model where the different weights are known as multiplier variables.

situation where there is no regulation of the polluting emissions, sub-technology Ψ_2 does not influence the producer's decision, and the overall technology is simply equivalent to the good output technology. In the case where regulations exist to internalize the production of detrimental outputs, the overall technology becomes that reported in **(6)** augmented by the dependence constraint in **(9)**. This constraint can be associated with the presence of regulations. In the case where input value balance $\sum_{k=1}^{K}(W_k + U_k)x_{kn}$ has a negative sign, the regulation is beneficial to the firm since it helps generate higher revenues. This observation is known as the Porter hypothesis (Porter and van der Linde, 1995b). Conversely, if this input value balance is positive, the environmental regulation comes at a cost for the firm; a common view shared by many economists (Palmer et al., 1995) and supported by a number of empirical assessments (Brännlund et al., 2009). In **(16)**, the first group of constraints indicates that the maximal profit generated using the shadow variables obtained with the good output sub-technology and associated with DMU_n cannot exceed zero for any of the DMUs defining the data set. This is similar to the idea expressed in the multiplier version of the DEA developed by Charnes et al. (1978) and Banker et al. (1984). The second group of constraints relating to the bad output sub-technology shows that the cost associated with pollutant generation plus the value (positive or negative) of an efficient use of the inputs should not be less than zero. With respect to the non-restriction of input shadow prices U_k, it is possible to obtain zero values for some DMUs. Where this is the case, it shows that these DMU inputs with zero shadow prices are not really pollution generators. However, this is endogenously obtained (through the model) rather than specified exogenously as in the classic BP approach taken by Murty et al. (2012).

In terms of trade-offs, the marginal rates between good outputs and bad outputs can be obtained using partial derivatives:

$$\frac{dy_q}{db_r} = \frac{U_r^*}{W_q^*} \qquad q = 1, \ldots, Q\ ; r = 1, \ldots, R \tag{17}$$

where U_r^*, W_q^* are the optimal shadow prices for the both good output q and undesirable output r obtained from solving the model in **(16)**. Given the number of good and bad outputs, $Q \times R$ different combinations are possible. The ratio in **(17)** evaluates the changes in good output q (dy_q) when bad output r is altered by db_r. The ratio in **(17)** is expected to be greater than zero to ensure a positive correlation between good and bad outputs. This implies that good and bad outputs are complements instead of substitutes.

We use the directional derivatives approach discussed by Rosen et al. (1998). The advantage of this approach is to provide upper and lower bounds for the trade-offs by estimating the derivatives respectively to the 'right' and to the 'left'. Prior and Surroca (2006) apply this approach to the banking system in Spain and show how marginal rates can be computed for inefficient DMUs using both primal and dual approaches. Other examples can be found in Chambers and Färe (2008) and Chambers et al. (2014). Based on this literature, we propose estimating the maximum and minimum of the trade-off between a good output and a bad output using the formulation in **(18)**. In **(18)**, $\vec{D}^*(x, y, b; \vec{g}_y, \vec{g}_b)$ represents the inefficiency score computed in **(15)** and it appears in the first constraint imposing the computation of trade-offs for points lying on the frontier. The condition for the value associated with the good and bad outputs of the DMU under evaluation prevents the left derivative (TR^-) from equaling zero. However, an infinite value can be obtained for the right derivative (TR^+). In this situation, we recommend using the same result as for the left derivative. When using proper transformations (Charnes and Cooper, 1962), **(18)** can be solved as a common LP model.

$$
\begin{aligned}
&[\max TR^+, \min TR^-] = \left[\max \frac{U_r}{W_q}, \min \frac{U_r}{W_q}\right] \\
&s.t. \sum_{q=1}^{Q} W_q y_{qn} - \sum_{k=1}^{K} (W_k + U_k) x_{kn} - \sum_{r=1}^{R} U_r b_{rn} - W_c - U_c = -\vec{D}^*(x, y, b; \vec{g}_y, \vec{g}_b) \\
&\sum_{q=1}^{Q} W_q Y_{qi} - \sum_{k=1}^{K} W_k X_{ki} - W_c \leq 0 \quad i = 1, \dots, N \\
&\sum_{r=1}^{R} U_r B_{ri} + \sum_{k=1}^{K} U_k X_{ki} + U_c \geq 0 \quad i = 1, \dots, N \\
&W_q y_{qn} \geq \frac{1}{2Q} \quad q = 1, \dots, Q \\
&U_r b_{rn} \geq \frac{1}{2R} \quad r = 1, \dots, R \\
&W_q, U_r \geq 0 \\
&W_k, U_k, W_c, U_c \quad \text{unrestricted}
\end{aligned}
\tag{18}
$$

Under the most flexible assumption of free choice of all the inputs, **(15)** can be transformed into:

$$\vec{D}(x, y, b; \vec{g}_y, \vec{g}_b) = \text{Max}\,\theta^n = \frac{1}{2}\left[\frac{1}{Q}\sum_{q=1}^{Q}\theta_q^n + \frac{1}{R}\sum_{q=1}^{R}\theta_r^n\right]$$

$$s.t.\ \sum_{i=1}^{N} \nu_i Y_{qi} \geq y_{qn}(1 + \theta_q^n) \quad q = 1, \ldots., Q$$

$$\sum_{i=1}^{N} \xi_i B_{ri} \leq (1 - \theta_r^n) b_{rn} \quad r = 1, \ldots, R \tag{19}$$

$$\sum_{i=1}^{N} \nu_i = 1 \ ; \ \sum_{i=1}^{N} \xi_i = 1$$

$$\sum_{i=1}^{N} \nu_i X_{ik} = \sum_{i=1}^{N} \xi_i X_{ik} \qquad k = 1, \ldots, K$$

$$\nu_i, \xi_i \geq 0; i = 1, \ldots, N\ ;\ \theta \geq 0$$

The main difference with **(15)** is the deletion of the constraints relative to the consumption of inputs x_n by DMU_n ($\sum_{i=1}^{N} \nu_i X_{ki} \leq x_{kn}$ & $\sum_{i=1}^{N} \xi_i X_{ki} \geq x_{kn}$). As explained earlier, since the observed input levels of the DMU under evaluation do not influence the attainable level of the objective function, some constraints can be removed. However, the dependence constraints relative to the optimal levels of input consumption explicitly appear in the model. At optimality, the adequate quantities of inputs can be lower or higher than the observed levels actually used by the DMUs.

The dual version of the model in **(19)** can be expressed as in **(20)**. Since there is freedom of choice of inputs , their relative costs (or values) do not appear in the objective, which in this case is simply a profit function based on the revenue of good output production and the costs associated with bad output generation. D_k is the shadow price associated with the respective dependence constraint. It plays a crucial role in delineating the possible sets of solutions for the linear program (through the constraints).

$$\vec{D}(x,y,b;\vec{g}_y,\vec{g}_b) = -\max \sum_{q=1}^{Q} W_q y_{qn} - \sum_{r=1}^{R} U_r b_{rn} - W_c - U_c$$

$$s.t. \sum_{q=1}^{Q} W_q Y_{qi} - \sum_{k=1}^{K} D_k X_{ki} - W_c \leq 0 \quad i = 1, \dots, N$$

$$\sum_{r=1}^{R} U_r B_{ri} - \sum_{k=1}^{K} D_k X_{ki} + U_c \geq 0 \quad i = 1, \dots, N \qquad (20)$$

$$W_q y_{qn} \geq \frac{1}{2Q} \quad q = 1, \dots, Q$$

$$U_r b_{rn} \geq \frac{1}{2R} \quad r = 1, \dots, R$$

$$W_q, U_r \geq 0$$

$$D_k, W_c, U_c \quad \text{unrestricted}$$

4. A numerical application

We run the ERBDDM models on a sample of virtual DMUs to illustrate the differences between the two sets of models previously discussed (by-production with and without dependence constraints). For this application, we generate a thousand artificial DMUs that use three inputs (x_1 , x_2 , x_3) to produce one good output (y_1) and two bad outputs (b_1 , b_2). The high number of DMUs generated prevents dimensionality issues associated with non-parametric estimations and is based on convergence rates of DEA models (see Daraio and Simar (2007a) for further discussion on this topic). The main results are summarized in **Table 1**. For simplicity, we run the models under convexity and variable returns-to-scale assumptions. We do not present the results based on the bandwidth parameters given the fact that this is useful mainly for deriving efficiency from a dominance analysis (Free Disposal Hull - (Deprins et al., 1984)) in the situation where inputs are fixed.

The first difference between the two BP approaches - the classic approach by Murty et al. (2012) based on independent sub-technologies and ours with dependence constraints - is the overestimation of inefficiency scores by the Murty et al. (2012) model. However, in the case of our available data, the differences are quite small when inputs are assumed to be fixed: for instance, on average, the overall inefficiency score with independent sub-frontiers is 0.571, while it is 0.517 when dependence constraints are introduced. This small difference is fairly understandable given the low flexibility present in this situation of fixed levels of inputs. Nevertheless, the difference can be accentuated in the presence of high inefficiency observations in terms of input usage.

Table 1: Descriptive statistics for ERBDDM inefficiency scores under several models.

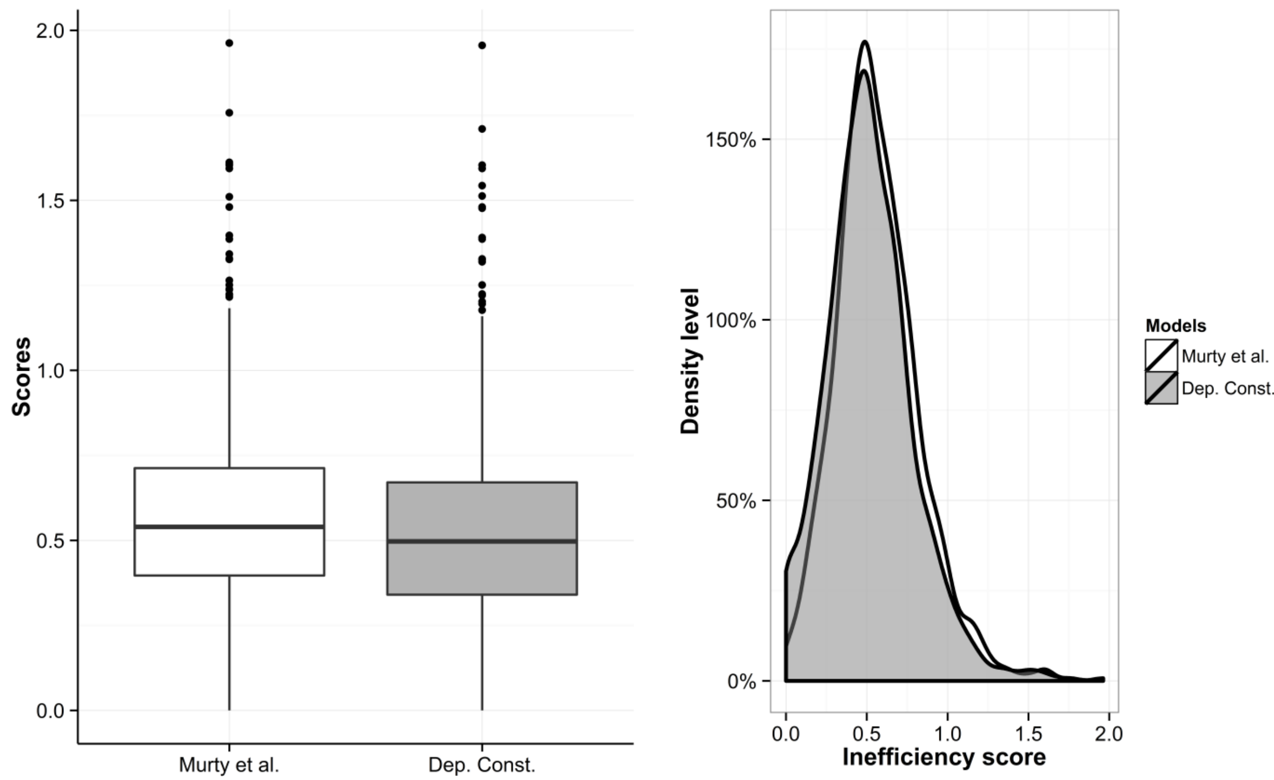
Variables	Type of inefficiency	Minimum	Median	Mean	Standard deviation	Maximum
Classic Murty et al. (2012) BP model with fixed levels of inputs	**Overall**	**0**	**0.540**	**0.571**	**0.262**	**1.963**
	Operational	0	0.648	0.737	0.498	3.395
	Environmental	0	0.437	0.404	0.171	0.778
Classic Murty et al. (2012) BP model with free levels of inputs	**Overall**	**0.492**	**1.667**	**1.971**	**1.473**	**26.344**
	Operational	0	2.403	3.025	3.000	52.640
	Environmental	0	0.930	0.917	0.064	0.984
Our BP model with dependence constraints and fixed levels of inputs	**Overall**	**0**	**0.497**	**0.518**	**0.272**	**1.955**
	Operational	0	0.589	0.673	0.491	3.395
	Environmental	0	0.388	0.362	0.182	0.778
Our BP model with dependence constraints and free levels of inputs	**Overall**	**0**	**0.770**	**0.842**	**0.426**	**3.341**
	Operational	0	1.420	1.533	0.938	6.533
	Environmental	0	0.115	0.151	0.141	0.604
Number of observations	1,000					

Source: Author

Note: The ERBDDM is based on the directional distance function approach. Thereby all scores in **Table 1** should be interpreted as inefficiency levels

The small differences between the models when inputs are fixed can also be seen from **Figure 2** where the boxplots and density plots seem to overlap.

Figure 2: Inefficiency distribution comparison between two BP approaches when inputs are fixed.

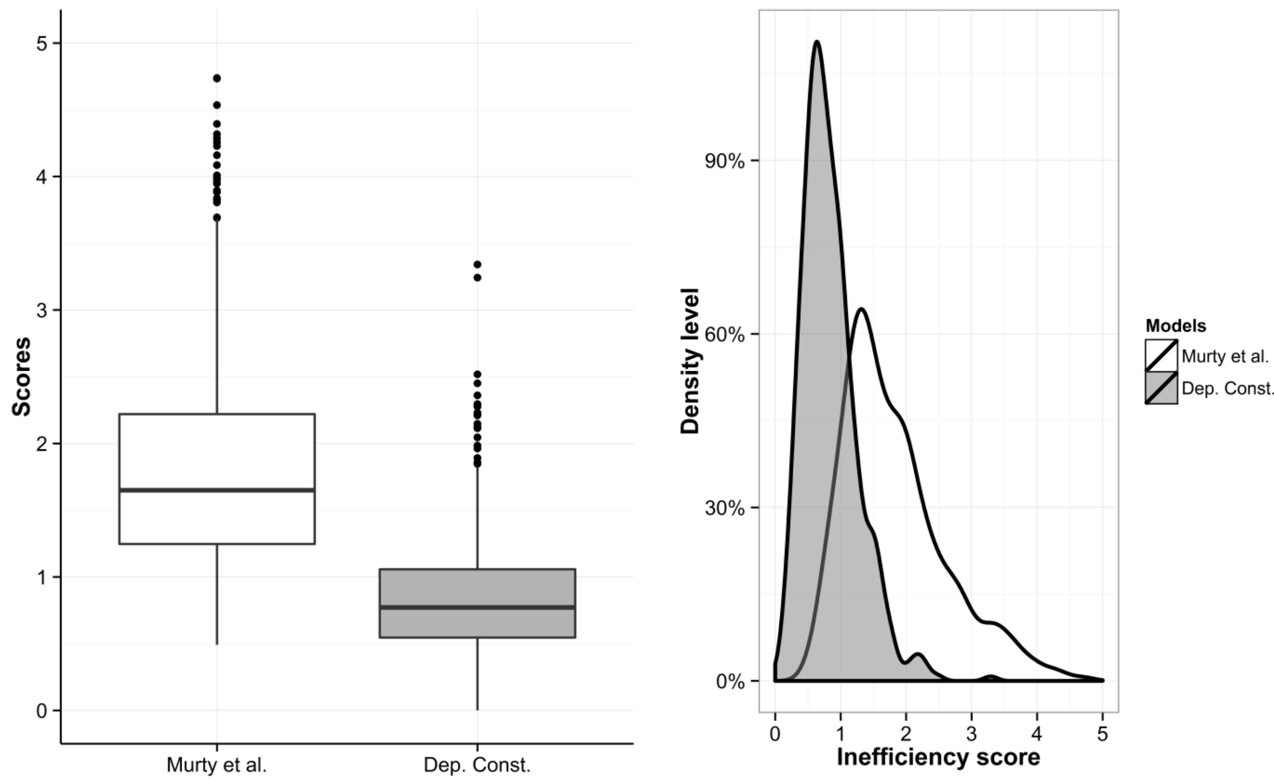


Source: Author

Note: 'Murty et al.' indicates the classic BP model of Murty et al. (2012), while 'Dep. Const.' indicates our BP model with dependence constraints.

When the constraints on inputs are relaxed so that they can be freely chosen, the difference between the two models is clearly accentuated (**Figure 3**). The model of Murty et al. (2012) greatly overestimates inefficiency compared to our extension. This situation can be explained by the poor treatment of inputs under this approach. A common feature of all these models is that they all point up the same main source of inefficiency (operational performance). But this can simply be attributed to the data under analysis.

Figure 3: Inefficiency distribution comparison between two BP approaches when inputs are freely chosen.



Source: Author

Note: 'Murty et al.' indicates the classic Murty et al. (2012) BP model, while 'Dep. Const.' indicates our BP model with dependence constraints.

5. Conclusion

This chapter proposes a practical extension of the by-production modeling formulated by Murty et al. (2012). The Murty et al. (2012) approach, based on the estimation of a number of sub-technologies to characterize an overall pollution-generating technology, is one of the most promising models for capturing the production of undesirable outputs. The main advantage of this approach is that it is based on a full description of production processes. The theoretical aspects of such an approach are now clearly defined (Murty, 2012).

However, we argue in this chapter that the use of DEA proposed by Murty et al. (2012) fails to unify the two sub-technologies as developed in the theory. We have thus developed an extension of the Murty et al. (2012) BP approach by including some dependence constraints. These additional constraints offer some interesting opportunities to theoretically and empirically discuss the nature of regulations designed to integrate detrimental output generation into managers' strategic decisions. In fact, the dual of the models presented in this chapter helps evaluate the cost or gain related to this integration, allowing for an assessment of how an environmental regulation might affect productivity in a beneficial or detrimental way. Another interesting feature of the by-production approach is the possibility of explicitly incorporating abatement outputs in the production processes.

Given the sensitivity of non-parametric approaches to outliers, an extension to the estimation of robust versions will be necessary (Cazals et al., 2002; Aragon et al., 2005; Daouia and Gijbels, 2011). It will also be important to develop algorithms for the estimation of conditional inefficiency scores along with the derivation of statistical inference in light of the discussions by Simar and Wilson (2013) and Simar, Wilson, et al. (2013).

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Chapter 3. Greenhouse gas emissions and efficiency in French sheep meat farming: a comparison of pollution-generating technologies in non-parametric modelling[1]

[1] This chapter has been written in collaboration with Philippe Jeanneaux (Vetagro Sup, UMR Métafort, Clermont-Ferrand, France) and Laure Latruffe (INRA, UMR SMART, Rennes, France).

1. Introduction

As underlined by the Intergovernmental Panel on Climate Change (IPCC) in its five assessment reports, scientific evidence points to the key role played by anthropogenic activities in greenhouse gas (GHG) emissions (Solomon et al., 2007). Among these activities, livestock farming has received particular attention over the last decade, since more than 13% of the total GHG emissions are attributed to this sector (Steinfeld et al., 2006; Gerber et al., 2014). Several studies concluded that livestock breeding is responsible for the emissions of three main GHGs: methane (CH_4), which is mainly generated by enteric fermentation and manure management; carbon dioxide (CO_2), which stems from the consumption of non-renewable energy; and nitrous oxide (N_2O), arising from the use of nitrogen fertilisers and from manure management (Casey and Holden, 2006; Lovett et al., 2006; Garnett, 2009; De Vries and De Boer, 2010; Dalgaard et al., 2014). The livestock sector is facing future global challenges, such as an increase in the demand for animal products, together with increased concerns regarding the scarcity of natural resources and climate change. In this context, in 2010 the Food and Agriculture Organisation of the United Nations (FAO) proposed a 'global agenda for sustainable livestock' with a threefold strategy: i-) improving the efficiency of natural resource use; ii-) encouraging actions for environmental (ecosystem) services such as carbon sequestration; and iii-) reducing emission and pollution intensity (FAO, 2010).

Some mitigation options have since been proposed in the literature relating to the enhancement of feed and energy efficiency, changes in fertiliser and pasture management, adoption of farm practices aimed at increasing carbon sequestration in soils, and specific policy and institutional reforms (Chatterjee, 2011; Obiora and Madukwe, 2011; Bellarby et al., 2013). There is, however, no clear evidence on the economic consequences of such greening actions (Ambec et al., 2013). It is generally agreed that a reduction in environmentally-detrimental outputs would come at a cost (Kopp, 1981; Kopp et al., 1982; Palmer et al., 1995). For example, studies relying on various modelling strategies (partial or general equilibrium models, bio-economic models, production frontier technology approaches, etc.) have estimated the marginal abatement costs of pollution-cleaner actions (Gollop and Swinand, 1998; Vermont and De Cara, 2010; Lengers and Britz, 2012). The concept of eco-efficiency can also shed light on the links between the economic and environmental aspects of production. This concept describes a situation where a decision making unit (DMU) (i.e. a farm or a firm) produces more value with lower environmental impact (Couder and Verbruggen, 2005 p317; Huppes and Ishikawa, 2005).

The eco-efficiency computation in non-parametric frontier modelling aims to find the maximal attainable ratio of a good output (the agricultural production) to a bad output (the environmental negative externality considered, such as GHG emissions). Since the pioneering work of Pittman (1983) to account for bad outputs (also termed undesirable outputs, unwanted outputs, detrimental outputs, pollutants, bads or residuals) in production technology modelling, many models have been developed for the case of non-parametric analysis. In general, pollutants are treated either as an extra input that is added to the technology (Hailu and Veeman, 2001b; Hailu, 2003; Mahlberg et al., 2011) or included as an output under the weak disposability and the null-jointness assumptions (see definitions later) (Färe et al., 1989; Chung et al., 1997; Färe et al., 2005). However, these two approaches have been criticised for their inadequacy in properly modelling pollution-generating technologies (Coelli et al., 2007; Podinovski and Kuosmanen, 2011; Murty et al., 2012; Chen, 2014). In this debate, two recent developments have emerged: firstly, models linked to the materials balance principles that rely on the laws of thermodynamics and assume the inevitability of residuals generation (Hampf and Rødseth, 2014); and secondly, models relying on the estimation of separate sub-technologies, one for the good outputs and one for the bad outputs (Førsund, 2009; Murty et al., 2012; Sueyoshi and Goto, 2012a; Dakpo, 2014).

The objective of this chapter is to compute the eco-efficiency of sheep meat breeding farms located in French grassland areas, covering a long period of observation from 1987 to 2013. The good output is the volume of meat produced on each farm, while the bad output is the aggregation of the three aforementioned GHGs (namely, CH_4, CO_2 and N_2O). Focusing on the non-parametric approach Data Envelopment Analysis (DEA) for which the majority of models have been proposed,[2] we compare the results obtained from major existing non-parametric models in the literature (including the latest innovative ones) and discuss their suitability for application to real data in livestock farming. In addition, following Hampf and Rødseth (2014) we propose a decomposition of eco-efficiency into different potential sources of improvement, depending on the assumptions regarding the flexibility available to producers in their decision-making. We also estimate shadow price values for the good and bad outputs.

This chapter thus provides an empirical contribution to the literature investigating the options available to farms to account for environmental concerns in their decision-making process while maintaining their competitiveness. This chapter is one of the rare micro-economic

[2] DEA uses mathematical programming methods to construct the efficient frontier, and therefore does not require the specification of a functional form, in contrast to parametric models.

studies in agriculture focusing on GHG emissions, since most of the empirical studies have focused on nitrogen pollution.[3] This chapter also contributes to the literature from a methodological point of view, by comparing the existing non-parametric models available for computing eco-efficiency. While the comparison of models has previously been undertaken from a theoretical point of view (see, for example, Tyteca (1996); Zhou et al. (2008a)), empirical applications of several models on the same data have not been carried out so far, whether in agriculture or any other field of research.

The chapter is organised as follows. The background **Section 2** explains the significant features of each model and reviews applications in agriculture. **Section 3** describes the data and methodology used. **Section 4** presents the empirical results. **Section 5** concludes.

2. The modelling of pollution-generating technologies in the literature

The technology, denoted Ψ_{bad}, is represented by the set of Q good and R bad outputs (y, b) that can be produced by K inputs (x) (**1**):

$$\Psi_{bad} = [(x, y, b)|\ x\ \in \mathbb{R}_{+}^{K}, x \geq 0, \text{can produce } y\ \in \mathbb{R}_{+}^{Q}, y \geq 0 \text{ and } b \in \mathbb{R}_{+}^{R}, b \geq 0] \tag{1}$$

We assume classical postulates: no free lunch; non-emptiness, closeness, boundness, and convexity of the production possibility set; free (strong) disposability of inputs and good outputs; and variable returns to scale (VRS). For simplicity we consider one single good output and one single bad output, similarly to the empirical application in our case study, although all models presented here can be extended to multiple good and bad outputs.

2.1. Different models available that include bad outputs in the production technology

Bad outputs as inputs

Considering that pollution generates social costs, some authors recommend introducing bad outputs as extra inputs, and assume their free disposability since this accounts for the consumption of natural resources that is necessary for their disposal (e.g. Dyckhoff and Allen, 2001; Prior, 2006). The technology can be represented as **(2)**:

[3] See Annex.

$$\Psi_{bad}^{inputs} = [(x, y, b) \in \mathbb{R}_{+}^{K+1+1} \,|\, y \leq \sum_{i=1}^{N} \lambda_i Y_i \,;\; b \geq \sum_{i=1}^{N} \lambda_i B_i \,;$$

$$x \geq \sum_{i=1}^{N} \lambda_i X_i \,;\; \sum_{i=1}^{N} \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \dots, N] \tag{2}$$

where subscript $i = 1, \dots, N$ represents the i-th DMU, (X, Y, B) are the levels of inputs, good output and bad output, respectively, of the DMUs that constitute the reference set against which an evaluated DMU is compared.

However, this approach has been criticised in the literature because it violates the physical laws of thermodynamics and, in particular, it contradicts the idea of the inevitability of residuals generation (Färe and Grosskopf, 2003).

Bad outputs as outputs

Another modelling strategy considers bad outputs as extra outputs, but imposes weak disposability and null-jointness of both types of output (good and undesirable) (Färe et al., 1989; Chung et al., 1997; Färe et al., 2007). These assumptions can be represented by equations **(3)** and **(4)**, respectively:

$$(y, b) \in \Psi_{bad}\,, 0 \leq \theta \leq 1 \implies (\theta y, \theta b) \in \Psi_{bad} \tag{3}$$

$$(y, b) \in \Psi \text{ and } b = 0 \text{ then } y = 0 \tag{4}$$

The null-jointness assumption (equation **(4)**) implies that no bad outputs are produced in the case of zero production of good output. The weak disposability assumption (WDA) (equation **(3)**) implies that reducing bad outputs is not without cost; good outputs also need to be reduced for a given level of inputs since resources must be diverted to abatement activities in order to mitigate the pollution level. Under this assumption the production technology is defined by equation **(5)**:

$$\Psi_{bad}^{weak} = [(x, y, b) \in \mathbb{R}_+^{K+1+1} \big| \; y \leq \theta \sum_{i=1}^{N} \lambda_i Y_i \; ; \; b = \theta \sum_{i=1}^{N} \lambda_i B_i \; ;$$

$$x \geq \sum_{i=1}^{N} \lambda_i X_i \; ; \; \sum_{i=1}^{N} \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \dots, N \; ; 0 \leq \theta \leq 1] \tag{5}$$

As formulated in model **(5)** the WDA implies a common proportional reduction of desirable and undesirable outputs, and hence considers that all DMUs have the same uniform abatement effort θ. In order to account for the fact that abatement costs may differ across DMUs, Kuosmanen (2005) and Kuosmanen and Podinovski (2009) assumed a firm-specific abatement factor and replaced θ by θ_i in technology **(5)**. Despite this, some recent studies have cast doubt on the relevance of the WDA, and in particular the inconsistencies linked to this assumption (e.g. Murty et al. (2012), Chen (2014)). For example, the negative relationship between the pollution (i.e. the bad output) and the inputs that generate it contradicts the fact that these inputs are polluting. Besides, the equality constraint related to the bad output ($b = \theta \sum_{i=1}^{N} \lambda_i B_i$) allows for the possibility of negative shadow prices for the bad output, which is in opposition to the fact that undesirable outputs generate social costs.

The materials balance principles

Instead of the WDA, Hampf and Rødseth (2014) suggested using the weak G-disposability assumption, which is based on the materials balance approach related to the first two laws of thermodynamics.[4] Let the input set be divided into two different sub-sets: the sub-set of material inputs x^M, that is to say inputs which generate pollution; and the sub-set of non-material inputs x^{NM} which are non-polluting. The technology set under the weak G-disposability assumption can be defined by equation **(6)**:

[4] The first law of thermodynamics gives the principle of mass/energy conservation, that is to say 'what goes in, comes out'. The second law, also known as the law of entropy, means that using polluting inputs will inevitably result in pollution generation.

$$\Psi_{bad}^{weak\,G} = [(x, y, b) \in \mathbb{R}_+^{K+1+1} \big| \; y + s_y = \sum_{i=1}^{N} \lambda_i Y_i \;\; ; \; b - s_b = \sum_{i=1}^{N} \lambda_i B_i \;\; ;$$

$$x^M - s_{x^M} = \sum_{i=1}^{N} \lambda_i X_i^M \;\; ; \;\; x^{NM} - s_{x^{NM}} = \sum_{i=1}^{N} \lambda_i X_i^{NM} \;\; ; \qquad (6)$$

$$W' s_{x^M} + H s_y - s_b = 0 \; ; \sum_{i=1}^{N} \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \dots, N \,]$$

where $X^M$and X^{NM} represent, respectively, the material and non-material inputs' consumption of the DMUs that make the benchmark; s_x, s_y and s_b are, respectively, input excess (also named input slack), good output shortfall and bad output excess, that are present in the technology due to inefficiency; W is the vector of input pollution factors and H represents the recuperation factor associated with the good output; the equation relating W and H is called the mass/energy conservation equation.

However, Førsund (2009) pointed out that this mass conservation equation does not explicitly show how residuals are generated and introduces 'some limits on derivatives in the system of equations'. Furthermore, Hampf and Rødseth (2014) demonstrated that, under some assumptions, the weak G-disposability assumption is equivalent to the WDA, which is a questionable assumption as explained above.

The by-production technology

In order to keep the relevance of the materials balance principles but without the drawbacks of the weak G-disposability assumption, Førsund (2009) recommended the use of the by-production methodology proposed by Murty and Russell (2002) and generalised by Murty et al. (2012). This approach, which relies on the estimation of two separate technology sub-frontiers whose intersection corresponds to the global technology, assumes the cost disposability of bad outputs, that is to say that a minimal level of pollution is generated by the technology. Murty et al. (2012) defined this global technology by equation **(7)**:

$$\Psi_{bad}^{by} = (x^M, x^{NM}, y, b) \in \mathbb{R}_+^{K^M+K^{NM}+1+1} | \; y \leq \sum_{i=1}^{N} \nu_i Y_i \; ;$$

$$x^M \geq \sum_{i=1}^{N} \nu_i X_i^M \; ; \; x^{NM} \geq \sum_{i=1}^{N} \nu_i X_i^{NM} \; ; x^M \leq \sum_{i=1}^{N} \xi_i X_i^M \; ; \tag{7}$$

$$b \geq \sum_{i=1}^{N} \xi_i B_i \; ; \; \sum_{i=1}^{N} \nu_i = 1; \; \sum_{i=1}^{N} \xi_i = 1; \; \nu_i, \xi_i \geq 0; i = 1, \ldots, N]$$

The by-production approach presents the advantage of separating the (classic) operational performance (i.e. relating to the good outputs) and the environmental performance (i.e. relating to the bad outputs). A drawback of this approach is that it empirically assumes independence between the two sub-technologies which is not realistic. To interconnect both sub-technologies, Dakpo (2014) developed an extension by augmenting model **(7)** with dependence constraints relative to the pollution-generating inputs, expressed in equation **(8)**:

$$\sum_{i=1}^{N} \nu_i X_i^M = \sum_{i=1}^{N} \xi_i X_i^M \tag{8}$$

Sueyoshi et al. (2010) and Sueyoshi and Goto (2010) proposed a unification strategy showing the two different adaptation strategies that can be followed by the DMU's manager: natural disposability, where the manager chooses to reduce the consumption of inputs as the strategy for decreasing pollution; managerial disposability, where managerial efforts (such as the adoption of cleaner technologies or the substitution of clean inputs for polluting ones) enable an increase in the consumption of inputs and simultaneously a reduction in the pollution generated. However as discussed in Manello (2012 p27), the non-linearity condition for inputs may generate some identification problems where some dominated DMUs are deemed efficient.

In conclusion, most of the approaches presented above have shortcomings, although it seems that the most recent models proposed in the literature (such as the by-production modelling and the natural/managerial disposability concepts) are more grounded in the theory and more intuitive.

2.2. Eco-efficiency assessment and decomposition, and shadow price computation

Eco-efficiency assessment and decomposition

As explained above, eco-efficiency is related to the ratio of desirable output to undesirable output. The eco-efficiency score of a DMU is computed by comparing the attainable optimal ratio, resulting in the following:

$$\mathrm{Eco_{eff}} = \frac{\mathrm{b^{optimal}}}{\mathrm{b^{observed}}} \Big/ \frac{\mathrm{y^{optimal}}}{\mathrm{y^{observed}}} = \frac{\alpha}{\phi} \qquad (9)$$

where $\alpha = \frac{\mathrm{b^{optimal}}}{\mathrm{b^{observed}}}$ is the environmental efficiency score and $\frac{1}{\phi} = \frac{1}{\frac{\mathrm{y^{optimal}}}{\mathrm{y^{observed}}}}$ is the operational efficiency score.

Based on the work of Hampf and Rødseth (2014), the eco-efficiency score can also be decomposed into several ratios that reflect the assumptions relative to the possible choices available to the producers. These choices are represented by the number of decision variables (endogenous) in the model.

- **Assumption 1** - The most restrictive assumption specifies that the producer cannot freely choose either the inputs or the good output. Both inputs (x) and good output (y) are given to the producer, who can only freely choose the level of bad output. This assumption enables the technical inefficiency arising from pollution generation to be assessed. Let's denote by $\mathrm{r^*_{x,y/f}}$ the optimal ratio obtained under this assumption.
- **Assumption 2** - In a second case, a less restrictive assumption specifies that both good and bad outputs are free of choice and, hence, are endogenous in the optimisation program. By contrast, the inputs (x) are given to the producer who cannot choose their amount freely. This ratio can help evaluate the existence of allocative inefficiency arising in the production of good and bad outputs. Let's denote by $\mathrm{r^*_{x/f}}$ the optimal ratio obtained in this case.
- **Assumption 3** - A third, more flexible, possibility is to allow the producer free choice of the amount of all variables: inputs, good output and bad output. This implies that all these variables are endogenously determined in the optimisation program. Let's denote by $\mathrm{r^*_{./f}}$ the optimal ratio.

The following further decomposition of the eco-efficiency score can be made:

$$\mathrm{Eco_{eff}} = \frac{\mathrm{ratio^{observed}}}{\mathrm{r^*_{./f}}} = \frac{\mathrm{ratio^{observed}}}{\mathrm{r^*_{x,y/f}}} \times \frac{\mathrm{r^*_{x,y/f}}}{\mathrm{r^*_{x/f}}} \times \frac{\mathrm{r^*_{x/f}}}{\mathrm{r^*_{./f}}} \tag{10}$$

The first ratio of this decomposition, $\frac{\mathrm{ratio^{observed}}}{\mathrm{r^*_{x,y/f}}}$, measures the eco-efficiency level when the inputs and the good output are held fixed. As explained above, it evaluates the presence of technical inefficiencies in the generation of detrimental output. This measure has been called the 'weak ratio efficiency' by Hampf and Rødseth (2014). The second component, the ratio $\frac{\mathrm{r^*_{x,y/f}}}{\mathrm{r^*_{x/f}}}$, refers to the possible increase in the eco-efficiency score when allowing flexibility regarding the level of good output. This ratio has been termed the 'allocative ratio efficiency'. The last component, $\frac{\mathrm{r^*_{x/f}}}{\mathrm{r^*_{./f}}}$, assesses the amount by which the eco-efficiency ratio can be improved (relative to $\mathrm{r^*_{x/f}}$) when the manager can freely decide the level of inputs in addition to the level of both good and bad outputs. Hampf and Rødseth (2014) refer to this third component as the 'input ratio efficiency'.

As regards the convergence or divergence of the different models mentioned in **Sub-section 2.1**, it can be demonstrated that, under the flexible assumption of free choice of all variables in the production technology (Assumption 3 above), all models except the by-production approach converge to the linear program of the case of undesirable outputs being treated as inputs.[5]

Shadow price computation

Trade-offs between the good and the bad outputs can also be given by shadow prices computed from the dual models. We rely here on the directional derivatives discussed in Rosen et al. (1998) and Chambers and Färe (2008) to estimate the values of the shadow prices of good and bad outputs. For example in the case of the by-production model extended with dependence constraints by Dakpo (2014), the eco-efficiency of the *n*-th DMU can be computed under the flexible assumption of free choice of all the variables as follows:

[5] Proofs are available from the authors on request.

$$
\begin{aligned}
&\min_{\alpha,\phi,\nu,\xi,x} \frac{\alpha}{\phi} \\
&s.t. \sum_{i=1}^{N} \nu_i X_{ik} \leq x_{nk} \quad k = 1, \dots, K \\
&\sum_{i=1}^{N} \nu_i Y_i \geq \phi y_n \\
&\sum_{i=1}^{N} \xi_i X_{ik} \geq x_{nk} \quad k = 1, \dots, K \\
&\sum_{i=1}^{N} \xi_i B_i \leq \alpha b_n \\
&\sum_{i=1}^{N} \nu_i X_{ik} = \sum_{i=1}^{N} \xi_i X_{ik} \qquad k = 1, \dots, K \\
&\sum_{i=1}^{N} \nu_i = 1 \, ; \, \sum_{i=1}^{N} \xi_i = 1 \\
&\nu_i, \xi_i \geq 0 \; (i = 1, \dots, N)
\end{aligned}
\tag{11}
$$

Linearising the model and taking the dual of it yield:

$$
\begin{aligned}
&\max_{W_{dx}, W_y, W_b, W_{1c}, W_{2c}} W_y \, . \, y_n \\
&s.t. \; W_y Y_i + \sum_{k=1}^{K} W_{dx_k} X_{ik} + W_{1c} \leq 0 \quad i = 1, \dots, N \\
&- \sum_{k=1}^{K} W_{dx_k} X_{ik} - W_b B_i + W_{2c} \leq 0 \quad i = 1, \dots, N \\
&-W_{1c} - W_{2c} \leq 0 \\
&W_b b_n \leq 1 \\
&W_y, W_b \geq 0 \\
&W_{dx}, W_{1c}, W_{2c} \quad \text{unrestricted}
\end{aligned}
\tag{12}
$$

where W_y and W_b are the shadow prices associated with the good output and the bad output, respectively. W_{dx_k} represents the dual variable associated with the dependence constraints. W_{1c} and W_{2c} represent the shadow prices of the convexity constraints of each sub-technology. From **(12)** and using the directional derivatives, the shadow prices of the good output and the bad output can be obtained.

For an efficient DMU_i which serves as a benchmark for DMU_n, the following condition is obtained:

$$-W_y y_i + W_b b_i = W_{1c} + W_{2c} \tag{13}$$

By differentiating **(13)** with respect to y_i and b_i, the trade-off (or the marginal relationship) between the good output and the bad output can be estimated using:

$$\frac{dy}{db} = \frac{W_b}{W_y} \tag{14}$$

2.3. Empirical studies of efficiency and pollution-generating technologies in agriculture: a review of the literature

Numerous studies have estimated the efficiency of farms in the presence of undesirable outputs. As can be seen from the studies listed in the **Annex**, most of the existing papers deal with nitrogen pollution arising from pig production. For instance Latruffe et al. (2013) estimated the technical efficiency of Hungarian pig producers accounting for the production of nitrogen in the manure. The authors assumed the strong disposability of nitrogen emissions and treated them as additional inputs. However, as mentioned above , this approach has been strongly criticised, in particular by Färe and Grosskopf (2003) and Färe and Grosskopf (2004b), as it is not in accordance with the reality of the production process. In addition, assuming strong disposability of bad outputs reflects situations where one can produce unlimited amounts of detrimental outputs with given quantities of inputs, which is technically impossible. As a solution to this shortcoming, for Dutch pig farms Oude Lansink and Reinhard (2004) developed a model that also treated bad outputs as inputs, but added the WDA of inputs. Using the WDA is common in studies considering bads as outputs. Another example is the work by Piot-Lepetit and Le Moing (2007), who considered nitrogen surplus as an output and assumed the WDA of nitrogen. However one can also mention the study by Yang et al. (2008) on pig producers in Taiwan, where the abated amount of bad outputs was included as a strongly disposable output.

By contrast to these studies and in the light of physical laws (based on thermodynamics), Coelli et al. (2007) applied the materials balance principles to the case of pig-finishing farms in Belgium. Based on the mass/energy balance equation, the authors estimated an iso-environmental cost line in a similar way to an iso-cost in a cost minimisation framework. They demonstrated that under the WDA a production system might not verify the mass/energy conservation property, which the authors assume to be inherent in all materials transformation processes. Yet their approach suffers from the failure to account for the presence of non-material inputs; these do not generate pollution and hence do not appear in the mass/energy conservation equation (Hoang and Rao, 2010).

Recognising the limits of the methods classically used (namely, bad outputs treated as inputs or the assumption of weak disposability), Asmild and Hougaard (2006) proposed a 'sort of data transformation' in the case of nutrient surpluses in pig farming in Denmark. Instead of using the nutrient (nitrate, potassium and phosphorous) surpluses as is widely done in the literature, the authors employed the nutrient removal by crops and considered it as a good output. Maximising this good output (under strong disposability assumptions) indirectly led to a minimisation of the nutrient surpluses. The model was set up as if the nutrient surpluses (which stemmed mainly from pig manure) were used as inputs in another production system (here represented by the production of crops).

Another strand of approach can be found in Picazo-Tadeo et al. (2011) and is based on the estimation of the frontier eco-efficiency (Kuosmanen and Kortelainen, 2005). This approach relies on estimating a ratio of economic outcomes (represented by value added or profit) to environmental pressures. However, in a dual perspective, the model considers undesirable outputs as inputs and thus faces the criticisms mentioned above. More recently, Serra et al. (2014) explored by-production technologies' modelling in the case of crop farm systems in Spain. Chambers et al. (2014) also relied on the by-production approach to compute the shadow prices of undesirable outputs in a state contingent situation (i.e. stochastic environment) for Catalan farms in Spain. Both studies used the by-production model proposed in Murty et al. (2012) and consequently maintained the independence among the different sub-technologies. We have found no applications to agriculture of the by-production model with the dependence constraints of Dakpo (2014), or the natural and managerial disposability concepts, or the weak G-disposability.

Finally, it should be stressed that only a few micro-economic studies in the agricultural sector have focused on the emissions of GHGs. In Kabata (2011) there is an application of the WDA to the case of crop and livestock production in the United States, where the bad outputs consist of methane and nitrous oxide emissions. Shortall and Barnes (2013) used a data transformation function (namely, an inverse function) to account for emissions of carbon dioxide, methane and nitrous oxide in the case of Scottish dairy farms. Toma et al. (2013) used two different models, the WDA and the eco-efficiency frontier estimation. Mohammadi et al. (2014) applied the joint Life Cycle Assessment (LCA)-DEA approach to GHG emissions in paddy rice farms in Iran.

3. Data and methodology

3.1. Data

The empirical application is undertaken on a sample of 1,292 farm-year observations surveyed in the period 1987 to 2013. The panel consists of 123 farms specialised in sheep meat production and located in the centre of France in grassland areas, including the plains and mountain areas. Several bookkeeping and production process characteristics are available in the database. Based on the literature on farms' technical efficiency (see, for example, the survey in Bravo-Ureta et al. (2007)), we retained four inputs: utilised land, farm labour, production related costs, and herd size. The production related costs consist of operating expenses and structural costs. Operating expenses, also called proportional costs, include all costs related to animal feeding, crop fertilisers, pesticides and all other costs directly associated with the presence of livestock (veterinary costs, mortality insurance, litter straw costs, marketing costs). Regarding the structural costs, these are mainly made up of mechanisation and building costs (depreciation, maintenance costs, expenses for fuels and lubricants, related insurances), as well as overheads (electricity, water, miscellaneous insurances). All costs are expressed in a constant currency (2005 Euros) to ensure relative quantity-based information. Utilised land is defined as the total number of hectares available to the producer for the sheep farming activity. This is essentially the main fodder area associated with the sheep livestock.[6] Labour is measured in terms of the number of full-time workers.

Regarding outputs, good output is defined as the net quantity of meat production expressed in kilograms of carcass,[7] and bad output is considered in terms of GHG emissions. The

[6] We did not include the land areas associated with the production of crops for animal feed because this is already accounted for in the costs.

[7] Net meat production refers to the fact that animal purchases have been removed from the gross production.

computations of the latter are based on the LCA methodology (Guinée et al., 2002). [8] The emissions of the three main GHGs generally considered in livestock farming (carbon dioxide, methane and nitrous oxide) were computed. The three gases were then summed based on the Global Warming Potential (GWP)[9] of methane and nitrous oxide relative to carbon dioxide. The bad output was thus computed as the total GHG emissions expressed in carbon dioxide equivalent. When applying the LCA we set the system boundary from the cradle to the farm gate, that is to say all upstream processes were considered up to the point where the meat production left the farm. It means that we did not take into account the flows associated with the processing (slaughtering and transformation) and marketing chains of the meat products. The main characteristics of the sample are summarised in **Table 1**.

Table 1: Summary statistics of the data used (1,292 farms over the period 1987-2013).

Variables	Mean	Standard deviation	Relative standard deviation	Minimum	Maximum
Utilised land (hectares)	74.4	35.1	0.47	12.4	257.0
Labour (full-time equivalents)	1.38	0.48	0.35	0.14	3.50
Production related costs (2005 Euros)	44,646	18,820	0.42	2,758	150,991
Herd size (livestock units)	76.9	31.5	0.41	10.9	200.0
Meat (kg of carcass)	9,434	4,482	0.47	565	30,314
Total GHG emissions (kg CO_2-eq)	340,713	142,515	0.42	35,195	1,048,134
Pollution intensity (kg CO_2-eq/kg meat)	38.8	12.0	0.31	19.8	132.7

Source: the authors

Notes: The livestock unit is a reference unit used for the aggregation of different types of animal on the basis of their nutritional or feed requirement. One livestock unit corresponds to one dairy cow which produces about 3,000 litres of milk per year. CO_2-eq: carbon dioxide equivalent. The relative standard deviation is computed as the ratio of the standard deviation to the mean.

On average, over the period of study 1987-2013, farms in our sample produced 9,434 kg of meat on a land area of 74.4 hectares with a herd size of 76.9 livestock units, which represents

[8] We have adapted the GES'TIM (Gac et al., 2011) and the Dia' terre® (ADEME, 2011) tools to our sample of French sheep meat farms. For our particular case study, more than 300 different variables (regarding the structure and the working processes involved in each farm) were required to conduct a meticulous LCA.

[9] The GWP is the warming effect relative to carbon dioxide over a period of 100 years. It is about 25 for methane and 298 for nitrous oxide.

about 440 productive ewes. Pollution intensity, which is measured as the ratio of the total GHG emissions to meat production, was on average 38.8 kg of carbon dioxide equivalent per kg of carcass. Methane was the most important GHG and accounted for more than 60% of the total emissions. The relative standard deviations, all greater than 0.30, show high variability in the data (Tufféry, 2011).

3.2. Models implemented to assess eco-efficiency

Based on the models reviewed in **Section 2**, nine models were implemented in our case study.

- **Simple model with no pollution in the technology**: this model, given by equation **(1)** but excluding b, implies free choice of good output and inputs. This pollution-free technology enables the potential operational efficiency of the DMU under evaluation to be calculated independently of the pollution generated. This operational efficiency is evaluated as the reciprocal of the potential increase of meat production given the free choice of inputs.
- **Simple model with no good output in the technology**: this model, given by equation **(1)** but excluding y, implies free choice of inputs and GHG emissions (the bad output). Under this technology the computed efficiency is simply the environmental efficiency independent of the production of good output (meat).
- **Model with pollution as input**: the classical model of the literature, described by equations **(2)**.
- **Model with WDA and uniform abatement factor**: another classical model, described by equations **(5)**.
- **Model with WDA and non-uniform abatement factor**: model introduced by Kuosmanen (2005), and described by equations **(5)** where θ is replaced by θ_i.
- **Model with weak G-disposability assumption**: model introduced by Hampf and Rødseth (2014), and described by equations **(6)**.
- **By-production model with independent sub-technologies**: model introduced by Murty et al. (2012), and described by equations **(7)**.
- **By-production model with interdependence constraint across sub-technologies**: model introduced by Dakpo (2014), and described by equations **(7)** and **(8)**.
- **Unified model under natural and managerial disposability**: model introduced by Sueyoshi et al. (2010), and described by equations **(9)**.

For the estimation, we consider here one single frontier which is estimated for the whole period (by pooling all observations together), that is to say we assume no technological change.

For all models, we compute and decompose the eco-efficiency based on equation **(10)**, and we calculate the shadow prices as explained in **Section 2.2**. This shadow price calculation is based on the use of the directional derivatives and in our case they are computed under the flexible assumption of free choice of all the variables in each model. In addition, we compute the optimal (that is, minimum) pollution intensity as the ratio of the GHG emissions to the meat production volume.

4. Results

4.1. Eco-efficiency and its components

The average eco-efficiencies and their components (equation **(10)**) and the pollution intensities, calculated for all nine models, are presented in **Table 2**.

Table 2: Eco-efficiencies for different models of pollution-generating technologies (sample averages over the period 1987-2013).

Models	Minimum pollution intensity (kg CO_2-eq/kg meat)	Eco-efficiency scores	Three sources of efficiency (equation (10))		
			Weak ratio efficiency $\frac{\text{ratio}^{\text{observed}}}{r^*_{x,y/f}}$	Allocative ratio efficiency $\frac{r^*_{x,y/f}}{r^*_{x/f}}$	Input ratio efficiency $\frac{r^*_{x/f}}{r^*_{./f}}$
Simple model with no pollution in the technology	34.6	0.311	The eco-efficiency score is the operational efficiency		
Simple model with no good output in the technology	37.7	0.125	The eco-efficiency score is the environmental efficiency		
Model with pollution as input	19.8	0.548	0.589	0.947	0.987
Model with WDA and uniform abatement factor	19.8	0.548	0.575	0.976	0.987
Model with WDA and non-uniform abatement factor	19.8	0.548	0.571	0.974	0.997
Model with weak G-disposability assumption	19.8	0.548	0.831	0.768	0.859
By-production model with independent sub-technologies	1.2	0.032	0.791	0.663	0.062
By-production model with interdependence constraint across sub-technologies	16.2	0.448	0.862	0.725	0.737
Unified model under natural and managerial disposability	19.81	0.548	0.876	0.801	0.790

Source: the authors

Notes: Pollution intensity is defined as the ratio of the total GHG emissions to meat production.

In the simple model with no pollution in the technology, where pollution is not an issue for the producers who can freely choose both the levels of input consumption and of good output, the sample average operational efficiency is 31.1% (score of 0.311). This indicates that, on average, farmers could improve their operational efficiency by 68.9% while fully ignoring the generation of GHG emissions. Similarly, in the simple model with no good output in the technology, the average environmental efficiency score is 12.5% (score of 0.125). This indicates that farmers could improve their environmental efficiency by 87.5% on average. A first conclusion arising from these two simple models is that, when independently evaluated, the improvement possibilities in terms of environmental efficiency are higher than those in terms of operational efficiency.

Regarding the other models, results in **Table 2** empirically confirm that all pollution-generating models, except the two approaches relying on by-production, converge to the same eco-efficiency score (0.548 on average) and the same pollution intensity (19.8 kg CO_2-eq/kg meat on average), similarly to the case when pollution is considered as input. These models suggest that farmers could increase their eco-efficiency by 45.2% on average. In other words, as the eco-efficiency is the ratio of the optimal pollution intensity to the observed pollution intensity, farmers could reduce their actual pollution intensity by 45.2%. A second convergence is observed for three models, namely the model with pollution as input, and the models with WDA with uniform or with non-uniform abatement factor. These models mainly underline the same source of inefficiency, namely the weak ratio efficiency, since the average scores for this component are lower than for the two other components. As explained earlier, this ratio accounts for the presence of technical inefficiencies in the pollution-generation process since it is computed assuming that the inputs and the good output are held fixed. The other two models with similar eco-efficiency scores and pollution intensity, that is, the model with weak G-disposability assumption and the unified model under natural and managerial disposability, are also close as regards the sources of eco-efficiency: the average scores for all three efficiency components are high and quite equivalently distributed among the different sources. All these models, (the WDA, the model assuming weak G-disposability and the unified model with natural and managerial disposability) converge to the same eco-efficiency score as when pollution is treated as an input. But, given the assumptions inherent in these approaches, they differ in terms of the weights given to the sources of eco-inefficiency.

The most pessimistic model in terms of eco-efficiency is the by-production model with independent sub-technologies, with an average score of 0.032, suggesting that about 97% of inefficiency is present in the sample. This result can be explained by the fact that the model separately optimises the operational efficiency (with the good output sub-frontier) and the environmental efficiency (with the bad output sub-frontier). As discussed earlier and seen in the first two rows of **Table 2**, when estimations are performed independently, the operational efficiency is 0.311 and the environmental efficiency is 0.125. The eco-efficiency score under the by-production model with independent sub-technologies is therefore simply the product of the operational efficiency and the environmental efficiency. One can also note from **Table 2**Table that the main source of inefficiency in this model is the input ratio inefficiency, which is greater than 93% (average score of 0.062).

By contrast, the by-production model with interdependence constraint across sub-technologies yields more realistic results, such as an average eco-efficiency of 44.8% (score of 0.448), and a more balanced distribution of the sources of inefficiency as in the case of the model with weak G-disposability assumption and the unified model natural and managerial disposability models. A closer look at the efficiency scores under each of the two sub-technologies indicates that the average operational efficiency score is 0.876 and the average environmental efficiency score is 0.620 (not shown in the table). In comparison to the results obtained from the simple models and displayed in the first two rows of **Table 2**, the introduction of the dependence constraint between the good and bad output frontiers in the by-production model provides higher average efficiency scores. One can also note that, for this by-production model with the interdependence constraint, on average the potential improvement is higher for environmental efficiency than operational efficiency, indicating that environmental inefficiency is the major contributor to eco-inefficiency.

4.2. Trade-offs between operational efficiency and environmental efficiency

The inclusion of the dependence constraints in Dakpo (2014)'s by-production model explicitly introduces some trade-offs between the operational efficiency and the environmental efficiency. As shown in **Table 3**, farm-year observations can be categorised into four groups depending on their improvement possibilities under this model:

1) The 'win-win' situation characterises farms that can simultaneously improve their operational and environmental performances. These farms are the ones which are operationally and environmentally inefficient. This concerns 59% of the observations in our sample.

2) For 'lose-win' farms, the winning potential is associated with improvement possibilities for environmentally inefficient farms. However, this is only possible at the cost of sacrificing some operational efficiency. Farms in this situation are environmentally inefficient

but operationally super-efficient (efficiency greater than one).[10] This echoes some economists' view that environment comes at a cost (Palmer et al., 1995). In our sample this concerns 32% of the observations.

3) The 'win-lose' farms are operationally inefficient (thereby with improvement possibilities in terms of operational efficiency) and environmentally super-efficient (thereby with only deterioration possibilities in terms of environmental efficiency). Only 9% of our sample's observations are classified in this group. This small number of super-efficient observations in terms of environmental efficiency may explain the lower level of environmental efficiency score in comparison to operational efficiency.

4) No farm is in a 'lose-lose' situation, where efficiency scores are greater than one (i.e. farms are super-efficient) both in terms of good output and of bad output. This is intuitive as, the eco-efficiency score being the product of the operational and the environmental efficiency scores, in a 'lose-lose' situation the eco-efficiency would be greater than one, which is not possible.

Table 3: Share of farm year observations (over the period 1987-2013) depending on the trade-offs between operational efficiency and environmental efficiency obtained in the case of the by-production model with interdependence constraint across sub-technologies.

	Environmental efficiency			
Operational efficiency		***Lose***	***Win***	Total
	Lose	0	*32%*	32%
	Win	*9%*	*59%*	68%
	Total	9%	91%	100%

Source: the authors

For all the other models the estimation of these trade-offs yields unsatisfactory results. For models that converge to the same results as that when bads are treated as inputs (namely, the models with WDA with uniform or with non-uniform abatement factor, the model with weak G-disposability assumption and the unified model under natural and managerial disposability), some observations are categorised in the 'lose-lose' category which is definitely counterintuitive.

[10] Super-efficient farms have efficiency scores above one. A super-efficient farm in terms of operational efficiency operates above its optimal scale and produces more meat. A super-efficient farm in terms of environmental efficiency uses less polluting inputs and generates less pollution than the optimal scale.

In the case of the classical by-production model as developed in Murty et al. (2012), the independence assumed between the two sub-technologies implies that all observations are mechanically categorised in the 'win-win' category.

4.3.Shadow prices

The shadow prices of the good output (W_y in equation **(13)**) and the bad output (W_b in equation **(13)**) as well as the trade-off calculated as $\frac{dy}{db} = \frac{W_b}{W_y}$ (equation **(14)**) are summarised in **Table 4**. For our case study, under the most flexible assumption of free choice of all the variables, the directional derivatives yield the same results for the minimum and the maximum.

Table 4: Shadow price values of good output and bad output for the different models (sample averages over the period 1987-2013).

Models	Shadow price for the good output	Shadow price for the bad output	Trade-off (bad output's shadow price / good output's shadow price)
Model with pollution as input **Model with WDA and uniform abatement factor** **Model with WDA and non-uniform abatement factor** **Model with weak G-disposability assumption** **Unified model under natural and managerial disposability**	7.047×10^{-5}	3.557×10^{-6}	0.050
By-production model with independent sub-technologies	4.130×10^{-6}	3.557×10^{-6}	0.861
By-production model with interdependence constraint across sub-technologies	5.761×10^{-5}	3.557×10^{-6}	0.062

Source: the authors

All the models yield similar shadow prices for the bad output (**Table 4**). Hence, the main difference across models in terms of trade-offs between the good output and the bad output stems from the difference in the shadow prices of the good output. Another observation is that the classical by-production model, as developed in Murty et al. (2012) and assuming independence between the different sub-technologies, highly overestimates the trade-off between the good output and the bad output in comparison to the other models. Again, the models based on the WDA, on the weak G-disposability, and on the natural and managerial disposability concepts, result in the same trade-off as for the case where pollution is treated as an additional input. The trade-off obtained from these models is 0.050, meaning that to produce 50 kg of meat, about 1,000 kg CO_2 equivalent of GHG emissions have to be generated. The trade-off for the case of the by-production with interdependence constraints across sub-technologies is higher by about 24%. It indicates that to produce 62 kg of meat, an eco-efficient farm needs to by-produce 1,000 kg CO_2 equivalent of GHG emissions.

Using these shadow prices and the sample's observed price for lamb meat production, we can assess an approximate price for the bad output represented here by the GHG emissions in CO_2 equivalent. For example in 2013, the average price of lamb meat was 6.48 Euros per kg for our sample. Based on this value, the shadow price of GHG emissions is calculated for each model and presented in **Table 5**.

Table 5: Shadow price of GHG emissions for the different models (sample averages over the period 1987-2013).

Models	Shadow price of GHG emissions (Euros per ton of CO_2 equivalent)
Model with pollution as input **Model with WDA and uniform abatement factor** **Model with WDA and non-uniform abatement factor** **Model with weak G-disposability assumption** **Unified model under natural and managerial disposability**	324
By-production model with independent sub-technologies	5,582
By-production model with interdependence constraint across sub-technologies	400

Source: the authors

The by-production model with independence of sub-technologies highly overestimates the GHG emissions' price in comparison to the other models (**Table 5**). When interdependence constraints are introduced, the average price falls from 5,582 to 400 Euros per ton of GHG generated. The latter is slightly greater than the one obtained from all models that converge to the case where bads are considered as inputs (namely 324 Euros). Except for the case of the by-production model with independent sub-technologies, the prices shown in **Table 5** are higher but in a similar range to those found in performance benchmarking and DEA literature. For example, Berre et al. (2012) assuming WDA, estimated the price of GHG emissions for a sample of milk producers in the French Reunion Island from the society point of view, and found a price of 229 Euros per ton of CO_2. More recently, Moore and Diaz (2015) found that the social cost of carbon could reach, depending on the gross domestic product (GDP), up to 220 US dollars (in

2015 currency) per ton of CO_2 in 2015. Njuki and Bravo-Ureta (2015), using a parametric output directional distance function (and the WDA), obtained for the United States' (US) dairy sector an average shadow price of GHG emissions of 485 US dollars (in 2012 currency). These prices, as well as the ones presented in **Table 5**, are however very high in comparison to the European Union allowances (EUA) carbon futures' prices from the European Climate Exchange (ECX) and reported in the literature (Nazifi, 2013; Zhu and Wei, 2013). Koch et al. (2014) for example reported that EUA carbon prices decreased from 30 to less than 5 Euros per ton of CO_2 between 2008 and 2014.

5. Conclusion

In this Chapter we investigate the eco-efficiency of sheep meat farms in grassland areas in France. This chapter contributes to the sparse literature on GHGs and efficiency in agriculture in several ways. First, we decomposed eco-efficiency into several components in order to assess the main sources of inefficiency. Second, we calculated the trade-offs between the good output (meat) and the bad output (GHG emissions) and we computed the shadow price of carbon. Third, we applied major non-parametric models of pollution-generating technologies available in the literature and compared the results obtained from them.

Although many of the models presented reach the same average optimal eco-efficiency score and trade-off between the good output and the bad output, they differ in their assumptions. From a theoretical perspective, models that consider pollution as an input, or as output under the WDA, produce arbitrary wrong trade-offs and do not capture the real nature of undesirable outputs. By contrast, the model assuming weak G-disposability and materials balance conditions is supposed to reflect the real production process by accounting for the laws of thermodynamics. However, in terms of results, this model also converges towards the one in which GHG emissions are treated as an input. To overcome the drawbacks of these models, some authors proposed relying on multiple frontiers. Sueyoshi and Goto (2011b) proposed a unification of operational and environmental efficiencies. However, in light of the results presented above, this interesting approach in fact collapses into the model where pollution is considered as an additional input, which is a refutable model. No such convergence is found for the models assuming by-production. Murty et al. (2012) were the first to develop a by-production model by assuming that the production process is made up of different sub-technologies, and the global technology is the intersection of the good and the bad outputs' respective sub-technologies. However, in the operationalisation of the approach, the authors assumed independence between both sub-frontiers. We have seen here that under this assumption inconsistent results are generated, such as extremely low eco-efficiency scores and an extremely high shadow price for carbon.

By contrast, the recent by-production model proposed in Dakpo (2014), which relies on interdependence constraints which link the use of inputs in both sub-frontiers, seems theoretically relevant and provides realistic results. The model shows an average eco-efficiency score of 0.448, with possible improvement in all three components. More precisely, the weak efficiency ratio, which captures technical inefficiency in the generation of bad output, is 0.862 on average. This indicates that, for fixed levels of inputs and good output, by removing inefficiencies farmers could decrease their pollution intensity by 13.8% in comparison to their actual levels. The allocative ratio efficiency, which compares the pollution intensity in the case where both good and bad outputs are endogenous in the model to the case where only the bad output's level is freely chosen, is 0.725 on average. This indicates that when the 13.8% of technical inefficiencies are removed, under free choice of both good output and bad output, farmers could still reduce their pollution intensity by 27.5%. The input ratio efficiency describes the most flexible situation of free choice of inputs, good output and bad outputs. This efficiency ratio is 0.737 on average, indicating that when both technical (13.8%) and allocative (27.5%) inefficiencies are removed, farmers can mitigate their pollution intensity by 26.3% when inputs are endogenously determined in the model in addition to good and bad outputs. The model also highlights that there is, on average, a higher improvement potential in terms of environmental efficiency than in terms of operational efficiency, since the two average scores are, respectively, 0.620 and 0.876. While this is an average picture, we also highlighted that, for 32% of the sample, improving environmental efficiency would result in deteriorating operational efficiency, but that for 59% of the sample both efficiencies can be improved simultaneously. The latter finding suggests that the Porter Hypothesis could hold for the sample considered (Porter and van der Linde, 1995b). Finally, we found that the average carbon price is 400 Euros per ton of GHG generated over the period considered, 1987-2013.

While from a methodological point of view we conclude that Dakpo (2014)'s model is a promising approach for assessing eco-efficiency in farming, from an empirical point of view the main conclusion is the presence of large inefficiencies in French sheep meat farms. One reason may be that there is no effective environmental regulation to control livestock farming's GHG emissions in France. One should also question whether sufficient cleaner production technologies or abatement options are available to such farms. Further research could therefore investigate the determinants of eco-efficiency. One limitation of our study is that we did not account for carbon sequestration in soils which is a specific feature of livestock farming as a potential abatement option. This aspect could be considered by further studies with available data on this issue. It can, for example, be explicitly modelled in the by-production technology.

Annex: Applications of efficiency calculation accounting for bad outputs in agriculture

Authors	Decision Making Units	Country	Bad outputs	Bad outputs treated as:	Assumptions regarding bad outputs
Ball et al. (2001)	48 States	United States	Nitrogen and pesticide surpluses, pesticide toxicity on human health and fish	Outputs	Weak disposability assumption (directional distance function)
Shaik and Perrin (2001)	Nebraska State	Nebraska	Nitrate pollution and pesticide environmental impact	Outputs	Weak disposability assumption (hyperbolic efficiency measure)
Shaik et al. (2002)	Nebraska State	Nebraska	Nitrogen pollution (surpluses)	Outputs and inputs	Two models: 1)weak disposability of bad outputs, 2) strong disposability of bad outputs treated as inputs
Ball et al. (2004)	48 States	United States	Risk to human health and aquatic life of pesticide runoff and leaching	Inputs	Strong disposability assumption
Oude Lansink and Reinhard (2004)	Pig producers	The Netherlands	Phosphorus surplus and ammonia emissions	Inputs	Weakly disposable inputs
Asmild and Hougaard (2006)	Pig producers	Denmark	Nutrient removal (nitrate, potassium and phosphorus)	Outputs	Strong disposability assumption (transformation of nutrient surpluses into nutrient removal)
Coelli et al. (2007)	Pig producers	Belgium	Phosphorus emissions	Residuals	Materials balance principles
Piot-Lepetit and Le Moing (2007), and Piot-Lepetit (2010)	Pig producers	France	Nitrogen surplus	Outputs	Weak disposability assumption (directional distance function)
Yang et al. (2008)	Pig producers	Taiwan	Wastewater (biochemical oxygen demand - BOD, chemical oxygen demand -COD, suspended solid -SS)	Outputs	Assume the presence of abatement technologies and consider the abated bad outputs as strongly disposable
Azad and Ancev (2010)	Irrigated agricultural enterprises	17 natural resource management regions in Australia	Ecologically weighted water withdrawal index and salinity impact	Outputs	Weak disposability assumption
Hoang and Rao (2010)	29 countries	OECD countries	Balance of cumulative energy	Residuals	Materials balance principles
Arandia and Aldanondo-Ochoa (2011)	Crop farmers and vineyards	Spain	Nitrogen surplus and pesticide impacts	Outputs	Weak disposability without the equality constraints

Authors	Decision Making Units	Country	Bad outputs	Bad outputs treated as:	Assumptions regarding bad outputs
Hoang and Coelli (2011)	30 countries	OECD countries	Nitrogen and phosphorus surpluses	Residuals	Material balance principles
Iribarren et al. (2011)	Dairy farms	Spain	Methane, ammonia, nitrous oxide, wastewater,	Not incorporated in the model	LCA+DEA methodology
Kabata (2011)	Crop/livestock production; data for States	United States	Methane and nitrous oxide gas	Outputs	Weak disposability assumption (hyperbolic efficiency measure, directional distance function)
Picazo-Tadeo et al. (2011)	Rain-fed agricultural systems (crop producers)	Spain	Specialisation (tendency towards monoculture), nitrogen and phosphorus balance, pesticide risk, energy balance (energy ratio of inputs on outputs)	Inputs	Strong disposability assumption (use of eco-efficiency model)
Ramilan et al. (2011)	Virtual dairy farms	New Zealand	Nitrogen discharge	Outputs	Weak disposability assumption
Berre et al. (2012)	Dairy farms	Reunion Island (France)	Nitrogen surplus	Outputs	Weak disposability assumption (directional distance function with heterogeneity in abatement factors)
Picazo-Tadeo et al. (2012)	Olive-growing producers	Spain	Soil erosion, pesticide risks on biodiversity, energy balance	Inputs	Strong disposability assumption (use of eco-efficiency model)
Skevas et al. (2012)	Specialised arable farms	The Netherlands	Pesticide impacts on water organisms and biological controllers	Outputs and inputs	Weak disposability of undesirable inputs/outputs in a dynamic perspective (non-radial directional distance function)
Thanh Nguyen et al. (2012)	Rice farms	South Korea	Eutrophication (Nutrients balance, N and P)	Residuals	Material balance principles
Beltrán-Esteve et al. (2013)	Rain-fed olive farms	Spain	Pressures on environmental resources and biodiversity (soil erosion and energy used)	Inputs	Eco-efficiency model (strong disposability) adapted to the case of meta-frontier
Hoang and Nguyen (2013)	Rice producers	South Korea	Nitrogen and phosphorus surpluses	Residuals	Materials balance principles (mass balance equation and iso-environmental cost line)

Authors	Decision Making Units	Country	Bad outputs	Bad outputs treated as:	Assumptions regarding bad outputs
Falavigna et al. (2013)	102 provinces	Italy	Nitric acid emissions	Outputs	Weak disposability assumption (directional output distance function)
Kuosmanen and Kuosmanen (2013)	Whole country	Finland	Nitrogen and phosphorus surpluses	Residuals	Dynamic materials balance conditions
Latruffe et al. (2013)	Pig producers	Hungary	Nitrogen produced	Inputs	Strong disposability assumption
Nin-Pratt (2013)	Livestock farms	142 countries	Nitrogen surplus	Residuals	Materials balance principles (mass balance equation and iso-environmental cost line)
Shortall and Barnes (2013)	Dairy farms	Scotland	Carbon dioxide, methane, nitrous oxide	Outputs	Strong disposability (inverse data transformation function)
Toma et al. (2013)	Dairy farms	Scotland	GHG emissions and nitrogen surpluses	Outputs and inputs	Two models: 1) weak disposability assumption of bad outputs, 2) eco-efficiency model (strong disposability)
Aldanondo-Ochoa et al. (2014)	Vineyard farms	Spain	Nitrogen surplus and pesticides toxicity	Inputs	Strong disposability assumption
David Berre et al. (2014)	Dairy farms	Reunion Island (France)	GHG emissions and nitrogen surplus	Outputs	Weak disposability assumption with non-uniform abatement factor
Chambers et al. (2014)	Cereals, oilseeds, protein crops farms	Spain (Catalan farmers)	Nitrogen and pesticide pollution	By-products	Cost disposability (by-production modelling)
Mohammadi et al. (2014)	Paddy rice farmers	Iran	GHG emissions (carbon dioxide, methane, nitrous oxide, ammonia, nitrates), phosphorus emissions in water	Not incorporated in the model	LCA+DEA methodology
Serra et al. (2014)	Crop farms	Spain	Nitrogen and pesticide pollution, damages to human health	By-products	Cost disposability (by-production modelling)
Vlontzos et al. (2014)	25 countries	European states	Carbon dioxide emissions and nutrient surpluses (nitrogen and phosphorous)	Outputs	Weak disposability assumption (use of a non-radial approach by including slacks in all variables except for bad outputs)

Authors	Decision Making Units	Country	Bad outputs	Bad outputs treated as:	Assumptions regarding bad outputs
Guesmi and Serra (2015)	Cereals, oilseeds, protein crops farms	Spain (Catalan farmers)	Pesticide pollution	Residuals/by-products	Two models accounting for risk: 1) materials balance principles, 2) cost disposability (by-production modelling)
Pérez Urdiales et al. (2015)	50 dairy farms	Spain (Region of Asturias)	Nutrient balances and GHG emissions	Inputs	Strong disposability assumption (use of eco-efficiency model)

Note: In the case of the study of Arandia and Aldanondo-Ochoa (2011) the model is simply equivalent to the case where undesirable outputs are treated as inputs.

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Chapter 4. Investments and dynamic eco-efficiency under the by-production of undesirable output: a non-parametric framework[1]

[1] This chapter has been written in collaboration with Alfons Oude Lansink (Business Economics group of Wageningen University, the Netherlands).

1. Introduction

Productive entities evolve in a competitive world where decisions made today will inevitably affect their future outcomes. They are confronted with price fluctuations, consumer demands, evolution towards environmentally friendly products, technological change, and policy reforms. All this requires Decision Making Units (DMUs) to adjust to these changes in their environment (Gardebroek, 2004). An important feature of these adjustments is materialized through investment strategies aiming at firms' structural change. As pointed out in many studies, the presence of quasi-fixed inputs or "imperfectly variable" inputs that can be stored or accumulated like capital prevents from instantaneous adjustments (Eisner et al., 1963; Lucas, 1967; Gould, 1968; Cooper and Haltiwanger, 2006). Silva and Stefanou (2003) refer to this situation as the presence of "sluggish" adjustments in some production factors within a productive entity. Since some inputs have their effects spread over time, in some sense DMUs operate in a dynamic environment. The foundation of dynamic economic analysis is then grounded on this distinction between variable and storable (quasi-fixed) inputs which also implies to make the separation between short and long runs (Caputo, 2005; Stefanou, 2009).

In performance benchmarking and production frontier estimation, mainly, applications restrict themselves to static evaluation which assumes that producers instantaneously adjust (as opposed to gradual adjustment) (Nemoto and Goto, 2003), or time comparison of static technologies (Färe and Grosskopf, 1997),[2] and thus omit all the dynamic aspects that impose linkages between past, present and future decisions. In the neoclassic theory, the adjustment cost model is a well-known and developed strategy to cope with dynamic aspects in the presence of quasi-fixed inputs. The logic behind the idea is that investments in capital inputs generate some adjustment costs. These costs can be internal (learning effects or retraining, reorganization of production processes, installation costs, administrative costs, search costs, etc.) or external (market forces…),[3] and are assumed to increase with the levels of investments. The presence of "costs of adjustment can explain why firms tend to conduct investments in smaller proportions, spread over time, rather than to adjust to new conditions instantaneously" (Oude Lansink et al. (2001)). Generally these costs are incorporated in the producer objective function (as an intertemporal value function: cost minimization, revenue and profit maximization) in terms of

[2] As presented by these authors (Färe and Grosskopf, 1997) the time comparison of static technologies can be based on the estimation of the Malmquist productivity index.

[3] In this work we assume that adjustment costs are internal to the production system. However the developments in this chapter can be easily extended to the presence of external adjustment costs.

physical output losses or in value terms i.e. some share of the output can be transformed into capital. Thereby, investments can be viewed as associated to forgone present outputs but for higher future outputs levels. However as underlined in Kapelko et al. (2014) "adjustment costs are not observed, but are implicit in higher costs of inputs and lower revenues of output. In the presence of adjustment costs in quasi-fixed factors of production, static measures do not correctly reflect inefficiency". In the same vein according to Nemoto and Goto (1999) in the presence of quasi-fixed inputs, a static measure of efficiency will lead to biased estimations where allocative efficiency is overestimated.

Besides, sustainable production behaviour is crucial to overcome environmental challenges and in situation of scarce resources competition. For policy makers, efforts must be undertaken by firms to internalize the production of environmentally detrimental outputs which can no longer be ignored by managers. In the same line, the International Resource Panel has recommended a two-ways strategy based on the concept of decoupling: first "using less resources per unit of economic output" and second "reducing the environmental impact of any resources that are used…" (Fischer-Kowalski and Swilling, 2011). The double objective of economic and environmental efficiency associated to this new defy has then led to the proposition of eco-efficiency tools for DMUs benchmarking. In the non-parametric framework of Data Envelopment Analysis (DEA), many approaches have been proposed (Hailu and Veeman, 2001b; Färe et al., 2005; Sahoo et al., 2011; Murty et al., 2012) to assess the technical and environmental efficiency of production units. However less has been done to understand the effects of the inclusion of undesirable outputs in the production technology modelling, on the dynamic optimal paths framework. In addition, the advent of more environmental regulations will set pressure on firms' managers and require some short and long term adjustments.

Given these realities of dynamic production process and eco-efficiency importance, our aim in this chapter is to propose a theoretical framework to assess the efficiency of DMUs regarding their adjustment paths in the presence of quasi-fixed inputs and undesirable outputs. To this aim we propose to measure the dynamic eco-efficiency which is defined here using the directional distance function (DDF) developed by (Chambers et al., 1996). For comparison purpose, the dynamic technical eco-efficiency is computed and analyzed along with the static measure. We also rely on DEA techniques and propose a variation of the by-production model (Førsund, 2009; Murty et al., 2012; Dakpo, 2014) which is based on the idea that a pollution-generating technology cannot be represented by a single reduced form and thus requires using different sub-technologies i.e. one for good output production and another for bad output generation. The benefit of this approach over the other models existing in the literature (like the ones that treat pollution as inputs or as outputs under the weak disposability assumption) is the explicit representation of the different processes involved in a production system. Moreover, the by-production provides with the right trade-offs between the different variables involved. All these eco-efficiency measures are computed for a sample of French suckler cow farms located in grassland areas (Massif Central) over the period 1978-2013.

2. Dynamic efficiency measurement in the literature

Literature on adjustment cost models where investments (disinvestments) may generate some costs related to installation (uninstallation) of the purchase capital, has been existing for decades (Treadway, 1969, 1970; Epstein, 1981; Luh and Stefanou, 1993; Abel et al., 1995; Luh and Stefanou, 1996; Oude Lansink and Stefanou, 1997; Gardebroek and Oude Lansink, 2004). For instance in the situation of investment, to set up new equipment might require some labour to be diverted from the production of the output to the installation of the new facilities (learning behaviours…). These “internal costs” arising from the adjustment to new investments can then be expressed in terms of output losses. A necessary property for internal adjustment costs is that they increase with the level of investment, as previously said. However the additional levels of capital inputs through new investment give the possibility of future outputs increase. In the production theory the presence of internal adjustments costs is captured by adding some regularity conditions about the negative marginal productivities of the production function in its investment variables. As stressed in Sengupta (1995) adjustments costs specify “an optimal learning behaviour by firms or DMUs i.e. they learn to adapt their short run behaviour to their optimal dynamic trajectories”.

In efficiency evaluation, Sengupta (1995) introduced the first order conditions of the dynamic optimization in the DEA framework. Another approach to account for the dynamic connections exploit the advantage of network modelling as in Färe and Grosskopf (1996) where some storable inputs and intermediate outputs used or produced in one period serve as inputs for the next period. Färe and Grosskopf (1997) applied the dynamic network approach for the analysis of the performance difference between rich and poor countries in order to evidence convergence issues as posited in the neoclassical growth model. In their network framework an intermediate output (investment) is considered to make the interconnection between the different periods of time. In the same line Nemoto and Goto (1999) developed a new approach similar to the network framework where they made the distinction between initial capital which is an input and final capital considered as output for each period of time (Sueyoshi and Sekitani (2005) proposed an extension of this model by incorporating returns to scale assumptions.

Another example of this model can also be found in Sanei et al. (2008)). À la difference of Färe and Grosskopf (1997), the objective function is based on an intertemporal cost minimization function.[4] Nemoto and Goto (1999) also demonstrated the link between their approach and the dynamic optimal solution of adjustment costs models and the Hamilton-Jacobi-Bellman condition. Later Nemoto and Goto (2003) argued that the network modelling developed by Färe and Grosskopf (1996) does not "explicitly state the conditions for the optimal paths of adjustment that play a central role in investment theory." Nemoto and Goto (2003) also proposed a decomposition of the overall cost efficiency into a dynamic and static efficiency components, the latter being decomposed into static technical (radial) and allocative efficiency. However, Ouellette and Yan (2008) recently argued that the approach developed in Nemoto and Goto (1999, 2003) produces an overestimation of efficiency because of an inadequate representation of the technology set notably in the presence of disinvestments where the restriction of the end of period capital does not hold. Ouellette and Yan (2008) proposed a new approach that imposes symmetry between investment and disinvestment (same shadow price). These latter authors also argued that the constraints burden in Nemoto and Goto (1999, 2003) 's approach can create some numerical issues.[5] Besides, their model supposes that every decision is taken in the first period i.e. what has been planned for the other period is supposed to be realized, showing then the uselessness of the information of the future periods. Other studies which used the network framework to account for the dynamic aspects involved in a production system can be found in Emrouznejad and Thanassoulis (2005); Chen (2009); Chen and van Dalen (2010); Kao (2013).[6]

From another perspective Silva and Stefanou (2003) have provided some non-parametric tests of the consistency of data to an intertemporal dynamic cost minimization under an adjustment cost model. Their model which extends the non-parametric revealed preference static dual cost approach developed in Varian (1984) by including dynamic aspects, requires the estimation of some shadow values for quasi-fixed inputs.[7] Silva and Stefanou (2007) using the

[4] In Färe and Grosskopf (1997) the objective function is the maximization of the sum over time of the radial output efficiency corresponding to each year.

[5] Furthermore, the dynamic model developed in Nemoto and Goto (1999, 2003) requires a balanced panel dataset and also the assumption of finite period of time for the optimization.

[6] An application of the network structure to the case of undesirable outputs which are considered as intermediate outputs can be found in Skevas et al. (2012).

[7] Silva and Stefanou (2003) offered to use non-parametric regression and kernel estimation for the estimation of these shadow costs.

non-parametric framework developed in Silva and Stefanou (2003) proposed an estimation of the technical (hyperbolic), allocative and economic (cost) efficiency for the short and long run[8] terms. They also propose to bound the true efficiency scores by computing a lower and an upper limits using the theory developed in Silva and Stefanou (2003).[9] Contrarily to Ouellette and Yan (2008), Silva and Stefanou (2007) considered that investments are irreversible (i.e. disinvestments are not allowed in the model). In Silva and Stefanou (2007) two strategies were proposed to estimate the shadow value associated to the quasi-fixed inputs. Depending on the model to estimate (technical, allocative or cost efficiency), the estimation of the shadow price can be based on the linear complementarity problem which is based on Kuhn-Tucker conditions (Al-Khayyal, 1987; Al-Khayyal, 1989). However the shadow value estimation "requires information on the behavioural shadow value of the quasi-fixed factors. The behavioural shadow value of the quasi-fixed factors… is estimated using the kernel estimation method and the symmetric of the marginal cost of adjustment evaluated at the observed gross investment vector" (Silva and Stefanou, 2007). Kapelko et al. (2014) have also proposed a new strategy to derive the shadow value of the quasi-fixed inputs, which requires a quadratic specification of the optimal value function.

Oude Lansink and Silva (2006) extended the approach of Silva and Stefanou (2003) to measure the short and long run input dynamic efficiency using the DDF (developed in Chambers et al. (1996) in a static framework). Recall that as previously mentioned the short run efficiency is related to the inefficiency associated to the variable inputs and the long run efficiency is the one linked to both variable inputs and quasi-fixed input investments. Besides using the duality theory established in Chambers et al. (1998) between the DDF technology and profit maximization, Oude Lansink and Silva (2006) provided the calculus of the short and long run

[8] For instance the short run technical efficiency only seeks for the reduction in variable inputs while the long run technical efficiency associates to this reduction in variable inputs an increase in investment levels.

[9] Silva and Stefanou (2003) proposed to build inner and outer bounds for the technology. The inner bound is computed as the set of DMUs obtained by convexifying the monotonic hull (input sets) defined by the variable inputs and the investments for all observations that produce more outputs and use less quasi-fixed inputs. This inner bound relates the non-parametric tests presented by the authors to the DEA. As for the outer bound of the technology, it is defined, using the properties expressed in Varian (1984), as the set of observations for which the associated costs of variable inputs and investments (using the shadow value of capital) based on the prices of a specific DMU_i are greater or equal to the costs of this specific DMU_i. In the same time all the observations used to build the outer technology must produce more outputs and use less quasi-fixed inputs than the specific DMU_i whose prices are used.

dynamic cost efficiency decomposition starting from the input DDF. More discussion of the dynamic DDF can also be found in Silva and Lansink (2013). Kapelko et al. (2012) extended the dynamic DDF to the Luenberger productivity index.

All the previous approaches have been developed in the non-parametric framework. But recently Serra et al. (2011) have extended the use the dynamic DDF to the parametric case. In this parametric framework another strategy to account for the dynamic technical efficiency has been employed in some studies by using lag structures to capture the changes in the technical efficiency (Ahn and Sickles, 2000; Tsionas, 2006; Emvalomatis et al., 2011). However as argued in Serra et al. (2011) these studies are not based on a structural representation of the production technology. Besides, in the early seventies it has been argued that the use of lag structures in empirical economics studies "is astounding, but, what is more remarkable, is the virtual lack of theoretical justification for the lag structures, superimposed on basically static models" (Nerlove, 1972). Still in this parametric formulation, an exception can be found in Rungsuriyawiboon and Stefanou (2007) which generalized the static shadow cost approach to the dynamic duality of the intertemporal cost minimization to derive behavioural equations. Using this dynamic duality these latter authors derived variable inputs and net investment demand. Hence technical and allocative efficiencies can be computed.[10] Rungsuriyawiboon and Stefanou (2007) also accounted for the disembodied technological change in a similar way as in Howard and Shumway (1988). Rungsuriyawiboon and Stefanou (2008) have extended the approach in Rungsuriyawiboon and Stefanou (2007) to include total factor productivity measurement and decomposition. Oude Lansink et al. (2015) have also proposed to measure dynamic productivity using a parametric estimation of the primal/dual Luenberger indicator. An extended literature review of dynamic efficiency measurement in non-parametric framework can be seen in (Fallah-Fini et al., 2014).

3. Dynamic aspects in pollution-generating technologies

Formally, let $v(t)$ represent a vector of variable inputs ($v \in \mathbb{R}_+^K$), $f(t)$ a vector of initial quasi-fixed inputs ($f \in \mathbb{R}_+^L$), $i(t)$ a vector of gross investment ($i \in \mathbb{R}_+^L$),[11] $y(t)$ a vector of good outputs ($y \in \mathbb{R}_+^Q$), $b(t)$ the vector of bad outputs ($b \in \mathbb{R}_+^R$) and N the number of DMUs, and t the time variable. As previously explained the representation of pollution-generating technology here is based on the by-production model (Førsund, 2009; Murty et al., 2012; Dakpo, 2014). The

[10] Besides, the authors (Rungsuriyawiboon and Stefanou, 2007) imposed a quadratic functional form (with symmetry) for the estimation of the behavioural value function.

[11] Investment can be zero for some of the quasi-fixed inputs.

approach adopted in this chapter is the by-production approach extended with some dependence constraints developed in Dakpo (2014) and where all inputs are considered in both sub-technologies (no inputs separation is operated as recommended in Murty et al. (2012)). The dynamic production technology $\Psi(t)$ can be represented by the intersection of two dynamic sub-technologies, one for good outputs and the second for bad outputs:

$$\Psi(t) = \Psi_g(t) \cap \Psi_b(t) \tag{1}$$

where

$$\Psi_g(t) = \left[\, (v(t), i(t), y(t), b(t)) \colon \big(v(t), i(t)\big) \text{ can produce } y(t) \text{ given } f(t)\right] \tag{2}$$

and

$$\Psi_b(t) = \left[\, \big(v(t), i(t), y(t), b(t)\big) \colon v(t) \text{ can generate } b(t) \text{ given } f(t)\right] \tag{3}$$

Properties of $\boldsymbol{\Psi_g(t)}$ (Silva and Stefanou, 2003; Silva and Oude Lansink, 2013)

G1 No free lunch and inactivity

G2 Inputs essentiality and attainability

G3 Non-emptiness and closeness

G4 Boundedness

G5 Positive monotonicity in $v(t)$: if $v(t) \in \Psi_g(t)$ and $v'(t) \geq v(t)$ then $v'(t) \in \Psi_g(t)$

G6 Negative monotonicity in $i(t)$: if $i(t) \in \Psi_g(t)$ and $i'(t) \leq i(t)$ then $i'(t) \in \Psi_g(t)$[12]

G7 Free disposability of good outputs: if $y(t) \in \Psi_g(t)$ and $y'(t) \leq y(t)$ then $y'(t) \in \Psi_g(t)$

G8 Reverse nestedness in $f(t)$: if $f(t) \in \Psi_g(t)$ and $f'(t) \geq f(t)$ then $f'(t) \in \Psi_g(t)$

G9 Convexity in $\big(v(t), i(t), f(t), y(t)\big)$

[12] Property G6 along with the convexity implies the presence of adjustment costs.

Given these different properties and assuming variable returns to scale (VRS), the good output sub-technology can be written as:

$$\Psi_g(t) = [(v(t), i(t), f(t), y(t), b(t) : \; y_o(t) \leq \sum_{n=1}^{N} \mu_n^g \, y_n(t) \, , v_o(t) \geq \sum_{n=1}^{N} \mu_n^g \, v_n(t) \, ,$$

$$i_o(t) - \delta f_o(t) \leq \sum_{n=1}^{N} \mu_n^g \left(i_n(t) - \delta f_n(t)\right), \sum_{n=1}^{N} \mu_n^g = 1 \, , \forall n] \tag{4}$$

where δ is the depreciation rate vector associated to quasi-fixed input f.

Properties of $\Psi_b(t)$

The main property relative to pollution-generating technologies is the cost disposability as expressed in Murty et al. (2012). This property expresses the fact that given a fixed level of inputs, there is a minimal amount of pollution that can be jointly-produced by the technology. Of course poor management can create some inefficiency in the production that could yield more than this minimal level of undesirable outputs. We can then express the main following postulates which are polar opposite of the ones associated to the good output technology $\Psi_g(t)$:

B1 Negative monotonicity in $v(t)$: if $v(t) \in \Psi_b(t)$ and $v'(t) \leq v(t)$ then $v'(t) \in \Psi_b(t)$

B2 Positive monotonicity in $i(t)$: if $i(t) \in \Psi_b(t)$ and $i'(t) \geq i(t)$ then $i'(t) \in \Psi_b(t)$

B3 Negative monotonicity in $f(t)$: if $f(t) \in \Psi_b(t)$ and $f'(t) \leq f(t)$ then $f'(t) \in \Psi_b(t)$

B4 Positive monotonicity in $b(t)$: if $b(t) \in \Psi_b(t)$ and $b'(t) \geq b(t)$ then $b'(t) \in \Psi_b(t)$

B5 Convexity in $\left(v(t), i(t), f(t), b(t)\right)$

The bad outputs sub-technology can be represented under VRS by:

$$\Psi_b(t) = [\left(v(t), i(t), f(t), y(t), b(t)\right) : \; b_o(t) \geq \sum_{n=1}^{N} \mu_n^b \, b_n(t) \, , v_o(t) \leq \sum_{n=1}^{N} \mu_n^b \, v_n(t) \, ,$$

$$i_o(t) - \delta f_o(t) \geq \sum_{n=1}^{N} \mu_n^b \left(i_n(t) - \delta f_n(t)\right), \sum_{n=1}^{N} \mu_n^b = 1 \, , \forall n] \tag{5}$$

To properly represent the by-production model, we need to consider two different intensity variables, one associated to each sub-technology (μ_n^g, μ_n^b). Following Murty et al. (2012) the overall technology $\Psi(t)$ can be represented by:

$$\Psi(t) = \Big[\big(v(t), i(t), f(t), y(t), b(t)\big) : \; y_o(t) \leq \sum_{n=1}^{N} \mu_n^g \, y_n(t) \, , v_o(t) \geq \sum_{n=1}^{N} \mu_n^g \, v_n(t) \, ,$$

$$i_o(t) - \delta f_o(t) \leq \sum_{n=1}^{N} \mu_n^g \big(i_n(t) - \delta f_n(t)\big) , \sum_{n=1}^{N} \mu_n^g = 1 \, , b_o(t) \geq \sum_{n=1}^{N} \mu_n^b \, b_n(t) \, , \tag{6}$$

$$v_o(t) \leq \sum_{n=1}^{N} \mu_n^b \, v_n(t) \, , i_o(t) - \delta f_o(t) \geq \sum_{n=1}^{N} \mu_n^b \big(i_n(t) - \delta f_n(t)\big) , \sum_{n=1}^{N} \mu_n^b = 1\Big]$$

However, as argued in Dakpo (2014) the model as displayed in **(6)** assumes the independence of the two sub-technologies $\Psi_g(t), \Psi_b(t)$. Dakpo (2014) then recommended to introduce some interdependence constraints that link the different sub-technologies. An adaptation to the presence of adjustment costs due to investment in quasi-fixed inputs is proposed here through the following additional constraints:

$$\sum_{n=1}^{N} \mu_n^g \, v_n(t) = \sum_{n=1}^{N} \mu_n^b \, v_n(t)$$

$$\sum_{n=1}^{N} \mu_n^g \big(i_n(t) - \delta f_n(t)\big) = \sum_{n=1}^{N} \mu_n^b \big(i_n(t) - \delta f_n(t)\big) \tag{7}$$

The idea behind the constraints expressed in **(7)** is that to link the different sub-processes of a production system one has to equalize the optimal values of the common variables involved in the different sub-systems. Dakpo (2014) refers to these constraints as the factor bands concepts which involve a relation between input variables independently of the levels of either the good or the bad outputs (Frisch, 1965; Førsund, 2009).

4. Dynamic vs. static eco-efficiency estimation

The dynamic eco-efficiency is based on the use of the DDF (Chambers et al., 1998). A general representation of the non-radial form of the dynamic DDF is summarized in **(8)**:

$$
\begin{aligned}
\vec{D}_t^{dyn}\left(v(t), i(t), f(t), y(t), b(t); \vec{g}_y, \vec{g}_b, \vec{g}_v, \vec{g}_i\right) &= \max_{\beta,\mu^g,\mu^b} \frac{1}{N_{\vec{g}}}[\beta_y + \beta_b + \beta_v + \beta_i] \\
s.t. \quad y_o(t) + \beta_y \vec{g}_y &\leq \sum_{n=1}^{N} \mu_n^g \, y_n(t) \\
v_o(t) - \beta_v \vec{g}_v &\geq \sum_{n=1}^{N} \mu_n^g \, v_n(t) \\
i_o(t) + \beta_i \vec{g}_i - \delta f_o(t) &\leq \sum_{n=1}^{N} \mu_n^g \left(i_n(t) - \delta f_n(t)\right) \\
b_o(t) - \beta_b \vec{g}_b &\geq \sum_{n=1}^{N} \mu_n^b \, b_n(t) \\
v_o(t) - \beta_v \vec{g}_v &\leq \sum_{n=1}^{N} \mu_n^b \, v_n(t) \\
i_o(t) + \beta_i \vec{g}_i - \delta f_o(t) &\geq \sum_{n=1}^{N} \mu_n^b \left(i_n(t) - \delta f_n(t)\right) \\
\sum_{n=1}^{N} \mu_n^g \, v_n(t) &= \sum_{n=1}^{N} \mu_n^b \, v_n(t) \\
\sum_{n=1}^{N} \mu_n^g \left(i_n(t) - \delta f_n(t)\right) &= \sum_{n=1}^{N} \mu_n^b \left(i_n(t) - \delta f_n(t)\right) \\
\sum_{n=1}^{N} \mu_n^g = 1 \quad &; \quad \sum_{n=1}^{N} \mu_n^b = 1
\end{aligned}
\tag{8}
$$

where $N_{\vec{g}}$ represents the number of decision variables in the objective function. Furthermore for the comparison purpose, a static technology is also built. In this situation one has to remove the investment variables from the model. Since under the static technology, the quasi-fixed inputs are assumed to be adjusted instantaneously, the objective function of the DDF can also include

β_f, the inefficiency associated to the quasi fixed inputs f. A general formulation of the static DDF can be found in **(9)**:

$$
\begin{aligned}
&\vec{D}_t^{static}\left(v(t), f(t), y(t), b(t); \vec{g}_y, \vec{g}_b, \vec{g}_v, \vec{g}_f\right) = \max_{\beta, \mu^g, \mu^b} \frac{1}{N_{\vec{g}}} [\beta_y + \beta_b + \beta_v + \beta_f] \\
&s.t. \quad y_o(t) + \beta_y \vec{g}_y \leq \sum_{n=1}^{N} \mu_n^g \, y_n(t) \\
&v_o(t) - \beta_v \vec{g}_v \geq \sum_{n=1}^{N} \mu_n^g \, v_n(t) \\
&f_o(t) - \beta_f \vec{g}_f \geq \sum_{n=1}^{N} \mu_n^g \, f_n(t) \\
&b_o(t) - \beta_b \vec{g}_b \geq \sum_{n=1}^{N} \mu_n^b \, b_n(t) \\
&v_o(t) - \beta_v \vec{g}_v \leq \sum_{n=1}^{N} \mu_n^b \, v_n(t) \\
&f_o(t) - \beta_f \vec{g}_f \leq \sum_{n=1}^{N} \mu_n^b \, f_n(t) \\
&\sum_{n=1}^{N} \mu_n^g \, v_n(t) = \sum_{n=1}^{N} \mu_n^b \, v_n(t) \\
&\sum_{n=1}^{N} \mu_n^g \, f_n(t) = \sum_{n=1}^{N} \mu_n^b \, f_n(t) \\
&\sum_{n=1}^{N} \mu_n^g = 1 \;\; ; \;\; \sum_{n=1}^{N} \mu_n^b = 1
\end{aligned}
\tag{9}
$$

Another important difference between the static evaluation and the dynamic one is that here in model **(9)** the quasi-fixed inputs are treated in the same way as variable inputs to materialize the instantaneous adjustments.

5. Empirical application

The empirical application is conducted on a sample of specialized suckler cow farms located in France (Massif Central and its northern periphery). The farm data are provided by the survey team within the livestock economic unit of the French National Institute of Agricultural Research (INRA) located in Clermont-Ferrand-Theix. In total the sample contains 3,142 farm-year observations covering the period 1978-2013, with an average of 87 farms per year. In total 170 different farms have been surveyed over the period of study. The panel is unbalanced due to new comers and departures. Over the 36 years of the period of analysis, farms stay on average a little more than 25 years in the sample. To better capture the dynamics, one frontier should be estimated per year i.e. 36 different temporal frontiers. However, the non-parametric DEA is well known for its sensitivity to the curse of dimensionality which produces many efficient DMUs when the number of variables is large (Cooper et al., 2007). The presence of the curse of dimensionality suppresses the discriminatory power of the DEA which has very slow convergence rate (Daraio and Simar, 2007a). To overcome this situation we decide to split the sample into three periods of twelve years each (1978-1989, 1990-2001, and 2002-2013). Besides, another benefit of time pooling is to provide smooth efficiency scores exempt from high inter-annual variability. Based on this time separation we consider two variable inputs, one quasi-fixed input, one good output and one undesirable output. Land measured in hectares and labour measured in annual working units are considered as fixed inputs. The fixity of labour is based on the fact that most of the farm workers are family members. The quasi-fixed input is associated to the capital stock of machinery and equipment, buildings and land improvements, all measured in 2005 constant prices. The two variable inputs are intermediate consumption and livestock units. Intermediate consumption, also measured in constant prices of 2005 is the aggregation of different operational expenses and structural costs (feed costs, veterinary, insurances, miscellaneous supplies, taxes, other breeding costs, seeds, fertilizers, pesticides, fuels and lubricants, maintenance costs, overheads…). As regard livestock, contrarily to some studies (Silva and Stefanou, 2007; Oude Lansink et al., 2015) that treat this variable as a quasi-fixed factor, in this study we set livestock as a variable input given the time-range of twelve years considered. The herd size is expressed in livestock units which represent a reference unit used for the aggregation of different types of animal on the basis of their nutritional or feed requirement. One livestock unit is equivalent to one dairy cow which produces about 3,000 litres of milk per year. The good output is the total kilograms of live meat produced on the farm. It is the only good output considered given that all the other variables are related to this only production. The bad output variable is the estimated greenhouse gas (GHG) emissions associated to the whole farm activity using life cycle assessment (LCA). For some inputs these GHG emissions encompass all the flows associated to these inputs from the cradle to the farm gate boundary. Three GHG are considered, methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2), but these three gases are aggregated using their global warming potential in comparison to the basis of carbon dioxide, i.e. the total gross GHG emissions are expressed in carbon dioxide equivalent.

As previously discussed the dynamics are captured by the levels of investments/disinvestments which generate some adjustment costs. However as argued in Ouellette and Yan (2008) a particular care of disinvestments is required. For simplicity reasons, we decide to conduct our empirical application after excluding observations with negative investments. Observations in this category represent less than 2% of the initial sample size. Besides, in their managing strategies, many farms can decide to not invest at all in quasi-fixed inputs. Recalling that the aim of this chapter is to investigate how relevant considering dynamic aspects can be while assessing eco-efficiency, our computations should be based on those observations with minimum levels of investments and thereby can exhibit adjustment costs. For this reason, we have also excluded all observations with almost zero amounts of investments. The sample size then reduces to 2,791 observations. The investments are also expressed in constant currency (2005 Euros). The descriptive statistics of the variables used for our analysis can be found in **Table 1**.

The investment variable is affected by a large heterogeneity (coefficient of variation greater than one) which might simply reflect the different behaviour of farmers in terms of capital acquisition. For example many farms instead of buying their own equipment, rely on farm machinery lease (contracting services) from machinery cooperatives. Thus a farmer can borrow specific equipment (tractors….) from a cooperative, but in return he is charged with a small price depending in most case on the time and the surfaces. Therefore many farmers with this opportunity choose to invest very little in quasi-fixed inputs. This strategy can partly explain the high heterogeneity for this variable. In 2007 the investments reached on average their highest levels. This specific year follows the 2006 implementation of the decoupled Single Farm Payment (SFP) of the Common Agricultural Policy (CAP) in France, after the 2003 Luxemburg reform. This suggests that the SFP scheme has provided greater financial ability to farmers who can therefore invest more. Investments in machinery and equipment represent the biggest part of the total investments with about 74%; it is followed by investments in buildings which weight about 18% and land improvements which constitute around 8%.

Table 1: Summary statistics of the pooled sample (average over the period 1978-2013).

Variables	Mean ($\bar{x}$)	Standard deviation (Sd)	Relative standard deviation ($Sd/\bar{x}$)	Minimum	Maximum
Utilised land (hectares)	106.5	49.0	0.5	26.4	442.2
Labour (full-time equivalent)	1.7	0.6	0.3	0.3	4.6
Intermediate consumption (thousands 2005 Euros)	51.9	31.6	0.6	8.7	285.1
Herd size (livestock units)	131.9	64.9	0.5	29.9	457.0
Opening capital (thousands 2005 Euros)	94.3	57.5	0.6	6.4	443.4
Investments (thousands 2005 Euros)	18.3	21.0	1.2	0.1	230.7
Meat (tons of live weight)	39.6	22.1	0.6	5.9	173.9
Total GHG emissions (tons of CO_2-eq)	581.3	311.3	0.5	113.0	2,592.0
Pollution intensity (kg CO_2-eq/kg meat)	15.0	2.2	0.2	9.7	32.3
Number of farms	2,791	-	-	-	-

Source: authors based on data from the Livestock Farming Economics Laboratory (INRA/EGEE/UMRH, Theix, France)

6. Results

Following Chung et al. (1997), we retain the directional vectors which are the observed values corresponding to the DMU under evaluation for all the variables except investments i.e. $\vec{g}_y = y_o$, $\vec{g}_b = b_o$, $\vec{g}_v = v_o$, $\vec{g}_f = f_o$. For these variables the DDF provides an inefficiency score that can be easily converted into an efficiency score and interpreted as a Farrell measure. Given the high heterogeneity in the investment variable we use a directional vector equivalent to 20% of the capital stock i.e. $\vec{g}_i = 0.2 \times f_o$. The inefficiency score obtained should be interpreted given this particular vector. In models **(8)** and **(9)** no fixed inputs are considered, but in this empirical application land and labour are treated as fixed inputs. These two variables are introduced in the models but no inefficiency is associated to them because of their fixity. All the computations are realized using the R software (R Core Team, 2013). **Table 2** and **Table 3** respectively present the results of the dynamic and static inefficiency scores for the different periods analysed. We also display the inefficiency associated to each variable.

The comparison of the two tables provides some interesting points of interpretations. For example we can see that the inefficiency associated to the variable inputs namely intermediate consumption and herd size are higher in the static dimension. Actually under the static hypothesis the inefficiency associated to these variable inputs is almost twice as large as the dynamic eco-inefficiency. Intermediate consumption and herd size can be respectively decreased overall by 7.6% and 2.4% under dynamic considerations while they can be reduced by 16.5% and 10% under static treatment of the technology. This means that when we account for dynamic aspects in the eco-efficiency evaluation, suckler cow farms better use their variable inputs.

For meat production, the situation is different. The results show that when correctly adjusting on their optimal paths, the potential increase in the quantity of meat production is higher than in the case of static (instantaneous) adjustments. More explicitly, under the dynamic technology the meat production can be increased by almost 2.4% while under the static technology this increase is only 1.3%. When accounting for the changes in quasi-fixed inputs, producers can produce more meat by fully taking advantage of the investments potential in comparison to the static case.

For GHG emissions, it goes in the opposite direction i.e. under dynamic aspects consideration the inefficiency is lower than in the case of static measures. When considering dynamic measures, the levels of GHG can be reduced by 6.2% and this reduction potential rises to 17.3% under the static assessment. Actually this result is quite understandable given that under the sub-technology that generates bad output in model **(8)**, gross investments could act like an abatement output. In this case of suckler cow it might mean that investments in quasi-fixed inputs that occurred over the period of study embedded cleaner technologies that require less highly-polluting variable inputs, hence the higher efficiency in GHG emissions and variable inputs in comparison to the static case.

Again, the huge heterogeneity in the investment variable is clearly translated in the performance evaluation by the explosive levels of the inefficiency scores associated to this adjustment variable (average scores between 3 and 5 over the different periods). The presence of farms that invest very few and some which invest too much can explain the tremendous levels of inefficiencies associated to the adjustment variables. However this inefficiency can be tampered by splitting the sample based on the ratio of investment per capital stock. Using quantile distribution we split the sample into three groups depending on the investment share (% of investment in the opening capital). The results (see tables in **Annex**) reveal that the heterogeneity in the measurement of inefficiency associated to the adjustment variable can be reduced. For example this inefficiency score falls to almost 0.195 for farmers who invest less than

8% in proportion to their capital stock. Although the inefficiency scores are still high (especially for farmers who invest more than 22%), by accounting for the different strategies of farmers in terms of investments, the heterogeneity can be partly captured. Nevertheless this situation might point out serious issues associated to investments in agriculture in general and to our case of suckler cow farms specifically in France. The large room of potential improvement in investment management deserves to deeply analyse the determinants of farmer decisions in terms of investments. In both the static and dynamic cases, the highest inefficiencies are associated to the quasi-fixed inputs or investments in those inputs.

Table 2: Dynamic eco-inefficiency scores: averages over different periods (1978-1989, 1990-2001, and 2002-2013).

Inefficiencies per period and variable	1978-1989	1990-2001	2002-2013	Whole period
Intermediate consumption	0.080	0.063	0.088	0.076
Herd size	0.031	0.024	0.018	0.024
Investments	4.605	4.407	3.101	4.061
Meat	0.027	0.018	0.026	0.023
GHG emissions	0.066	0.054	0.066	0.062
Average inefficiency	0.962	0.913	0.660	0.849

Source: authors' own computations

Table 3: Static eco-inefficiency scores: averages over different periods (1978-1989, 1990-2001, and 2002-2013).

Inefficiencies per period and variable	1978-1989	1990-2001	2002-2013	Whole period
Intermediate consumption	0.179	0.161	0.156	0.165
Herd size	0.080	0.114	0.107	0.100
Opening capital	0.467	0.376	0.396	0.413
Meat	0.014	0.009	0.015	0.013
GHG emissions	0.156	0.186	0.178	0.173
Average inefficiency	0.179	0.169	0.170	0.173

Source: authors' own computations

Overall, the results show that the inefficiency of the inputs and GHG emissions are lower in the dynamic case than in the static case. Hence, using the dynamic approach would attribute inefficiency to investments rather than to the inputs and GHG emissions. This could indicate that the static approach incorrectly attributes inefficiency to the use of inputs and GHG emissions.

In terms of evolution, we can also observe some contrasted results between the dynamic and static frameworks. For example in the dynamic analysis, the efficiency in herd size management improves while in the static case we can observe a small drop in the middle period (1990-2001). In terms of intermediate consumption, under the static technology we record an efficiency improvement. In the dynamic case this efficiency reaches a peak in the period 1990-2001 and drop in the last period (2002-2013). In both cases, as regard the operational efficiency related to meat production, the period 1990-2001 appears to be the glory days before the efficiency drops in the last period. In the dynamic analysis, the environmental efficiency associated to GHG emissions rises till the middle period (1990-2001) before the drop recorded in the last time range. It is the reverse tendency under the static technology where the environmental efficiency drops in the middle period before the last period improvement. Overall there is an improvement tendency of average eco-efficiency under the dynamic and static framework. However it is worth noting that the two eco-efficiency scores cannot be directly compared given the different modelling specifications (we use a directional vector of $0.2 \times$ value of capital stock to the investments and a different vector for the capital stock in the static case)[13].

7. Conclusion

In this chapter we proposed an adaption of the by-production model (Murty et al., 2012; Dakpo, 2014) to account for adjustment costs in the presence of undesirable outputs. We measured and discussed the dynamic eco-efficiency in comparison to a model that does not assume the presence of adjustments (static technology).

The application performed on a sample of suckler cow farms showed the importance of considering the presence of quasi-fixed inputs and adjustment costs occurring with investments in those inputs. Our analysis revealed very high inefficiency in investments for the farmers under

[13] For instance under the period 1978 to 1989 investments can be increased by $4.605 \times 2 \times$ value of capital stock in that period. In the static case capital stock can be reduced by 46.7% over the same period of study. Hence the interpretation of the capital stock inefficiency is entirely different

analysis. However these high levels can be explained by the large heterogeneities between farmers in light of their investment levels. This situation might require a further analysis specifically by constructing some groups with more homogenous levels of investments. Besides, when the sample is split on the basis of investments' share in the capital stock the inefficiency decreases.

Important differences subsist between the static and the dynamic analysis, stressing in the same line as many of the studies aforementioned that in the presence of adjustment costs, not accounting for them can produce misleading results. Finally, this work can be extended to productivity analysis and certainly on the dual models estimation.

Annex: Dynamic and static eco-efficiency scores under different investment ratios

Table 3: Dynamic eco-inefficiency scores under different ratio of investment to capital: averages over the period 1978-2013.

Inefficiencies per ratio of investment to capital and variable	Less than 8%	Between 8% and 22%	More than 22%
Intermediate consumption	0.202	0.180	0.041
Herd size	0.139	0.060	0.019
Investments	0.195	0.571	4.986
Meat	0.015	0.031	0.027
GHG emissions	0.220	0.144	0.058
Average inefficiency	0.154	0.197	1.026
Number of observations	953	896	942

Source: the authors' computations

Table 4: Static eco-inefficiency scores under different ratio of investment to capital: averages over the period 1978-2013.

Inefficiencies per ratio of investment to capital and variable	Less than 8%	Between 8% and 22%	More than 22%
Intermediate consumption	0.174	0.156	0.163
Herd size	0.128	0.119	0.080
Opening capital	0.445	0.364	0.422
Meat	0.015	0.018	0.010
GHG emissions	0.196	0.197	0.154
Average inefficiency	0.191	0.171	0.166
Number of observations	953	896	942

Source: authors' own computations

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Chapter 5. General Discussion

1. Introduction

The question of the internalisation of negative environmental externalities has triggered many developments in the economic literature. In this context, the overall objective of this PhD was to provide a framework devoted to the analysis of undesirable outputs in production technologies modelling. This final chapter discusses the main findings of the PhD. To this aim we organise this discussion around four points. Firstly, we position the research questions addressed in this dissertation within some existing frameworks for analysing environmental impacts; secondly, we recall the main results obtained; thirdly, we list a number of theoretical, methodological and empirical limits associated to this work; and fourthly, we open a discussion on possible paths of future research for further improvements.

2. Environmental impacts' analysis frameworks in the literature

The economic literature has offered several analysis frameworks for the appraisal of environmental impacts.[1] For example, computer-based models can be used which, through simulations, estimate the marginal abatement cost (MAC) of reduction of detrimental outputs in the long run, consistent with climate change policy targets (Kuik et al., 2009).[2] In other words, these models evaluate the cost-effectiveness of reducing negative environmental impacts and analyse the efficiency of mitigation technologies and climate change policies. The models in this category can be split into different classes: supply-side microeconomic models, engineering cost approaches, and general or partial equilibrium analyses (more details about these different models can be found in Vermont and De Cara (2010)).[3] MAC approaches have received increased attention in various sectors including agriculture (Bockel et al., 2012). Their shortcomings include negative abatement costs and intertemporal issues (Kesicki, 2010; Kesicki and Strachan, 2011; Vogt-Schilb and Hallegatte, 2011; Kesicki and Ekins, 2012).

Another framework of analysis considers the problem the other way round, by focusing on payments for environmental services (PES), that is to say financial compensations for

[1] We discuss only some of them but many other frameworks are available in the literature, for example cost-benefit analysis, economics of laws and the associated carbon markets…

[2] The MAC is the additional cost a producer is willing to pay to achieve the reduction of one more unit of pollution.

[3] These approaches have been applied to the agricultural sector in many studies (De Cara et al., 2005; Hediger, 2006; Povellato et al., 2007; Golub et al., 2009; De Cara and Jayet, 2011; Moran et al., 2011; Lengers and Britz, 2012).

preserving ecosystems. Ecosystems provide a broad range of services to human societies such as provisioning services (food, water and other raw materials supply…), regulating services (air and water purification, carbon storage, erosion prevention, soil formation, extreme events regulation…), supporting services (habitats for species, maintenance of genetic diversity…) and cultural services (tourism…) (Daily et al., 1997; Millennium Ecosystem Assessment, 2005).[4] According to Costanza et al. (2014) those services "contribute more than twice as much to human well-being as global GDP" (GDP: Gross Domestic Product). Actually Costanza et al. (1997) estimated the average minimum value of 17 different ecosystem services and found that this value can be equivalent to 1.8 time the current Gross National Product (GNP).The desire to preserve those benefits has given rise to the new paradigm of PES. As clarified in Wunder (2005)[5] PES are consistent over five criteria: i-) they are voluntary transactions where, ii-) a well-defined environmental service (ES) is bought, iii-) by an ES buyer, iv-) from an ES provider, v-) if and only if the ES provider secures ES provision. As pointed out by this author, the main environmental services on which the debate has concentrated are carbon sequestration in soils, biodiversity protection, watershed protection, and landscape beauty. Contrarily to the principle of polluter-payer, the PES are grounded on the beneficiary-payer idea (Engel et al., 2008). PES can then be viewed as a win-win solution in which policies compensate some agents for taking actions that increase the provision of ecosystem services (Jack et al., 2008). PES can also be viewed as market-based mechanisms that provide incentives to some economic agents to produce more environmental services. For long PES have been designed and implemented for the cases of forest management, biodiversity conservation, or watershed management (Dutilly-Diane et al., 2007). In the livestock sector case, PES are considered as relevant tools for environmental management and for providing additional revenues to farmers (Silvestri et al., 2012). It has been even argued that PES can be an interesting tool in poverty alleviation (Barrett et al., 2005; Pagiola et al., 2005). Yet some challenges still have to be met in designing and implementing PES (George et al., 2009; Muradian et al., 2013). For example, it may be problematic to attach prices to non-market goods.

A third framework of analysis considers the relation between environmental quality and economic growth (or development). The studies that fall into this category analyse the existence of the Environmental Kuznet Curve (EKC) which is an inverse U-shaped relation between

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[4] One can refer to http://www.teebweb.org/resources/ecosystem-services/ for more examples of services. Besides a discussion on the ecosystem services provided by agriculture can be found in Power (2010).

[5] More details about the principles of PES can be found in Wunder (2015).

environmental degradation and per capita income.[6] This specific shape illustrates an increase in environmental degradation in the early stages of economic growth, and a decrease beyond a threshold level of income per capita (Grossman and Krueger, 1991). For the proponents of this approach, "there is clear evidence that, although economic growth usually leads to environmental deterioration in the early stages of the process, in the end the best and probably the only-way to attain a decent environment in most countries is to become rich" (Beckerman, 1992). Thereby, environmental quality becomes a luxury good beyond high levels of income, while below these levels it can be considered as a normal good (Yandle et al., 2004).[7] From another perspective, the EKC is viewed as another way to express the "stages of economic growth" (see Rostow (1959)), where the transition from agricultural-based activities to heavy industries increases levels of pollution, and then the shift from an industry-based economy to an economy of services and industries with high technological value, pollutes less (Moomaw and Unruh, 1997). In summary the EKC theory posits the simple idea that the poor have to become rich in order to care about the environment. This clearly states the existence of an environmental path dependency where there is no room for managerial actions in the earlier stages of economic growth. It is as if the world is ruled by a "big economic law" and there is no way to escape. Given the time requirements for each stage of economic growth, there is still a long way to go. For that matter, the existence of an EKC and the associated apparent rigidity to this theory certainly implies different kinds of instruments for mitigating environmental damages. Nevertheless, many studies question the existence of the EKC (Stern and Common, 2001; Nektarios, 2009; Choumert et al., 2013). For example, Copeland and Taylor (2003) indicated that "our review of both the theoretical and empirical work on the EKC leads us to be skeptical about the existence of a simple and predictable relationship between pollution and per capita income". And even though the EKC might still appear in some situations, "we should be wary of concluding that economic growth alone will result in environmental improvements" Harris and Roach (2013 p412).

As a solution to the controversial EKC, Stern (2004) proposed to use "a new generation of decomposition and efficient frontier models [which] can help disentangle the true relations between development and the environment and may lead to the demise of the classic EKC". This

[6] The EKC is fully derived from early works of the economist Simon Kuznet who showed the existence of an inverse U-shaped relationship between income inequality and economic growth in the 1950s.

[7] As defined in Harris and Roach (2013 p410), a normal good is the one for which "people will seek to 'purchase' more of it as their income increase", while for a luxury good the "spending on it increases disproportionately as income grows".

relates to another framework of analysis, which uses performance benchmarking techniques, and in particular estimation for a neo-classical production technology. These methods provide efficiency scores for agents, which are useful for monitoring and analysing the evolution and the effectiveness of policies. The major interest of the methods relying on the estimation of production frontiers is their ability to assess the available potential wiggle room to firms' managers, by comparing their firms to other productive units. In the case of undesirable outputs' generation, the production technology is modelled by including these outputs under different possible assumptions (Reinhard and Thijssen, 2000; Korhonen and Luptacik, 2004; Barnes et al., 2009; Murty et al., 2012; Chambers et al., 2014; Mahlberg and Luptacik, 2014; Sueyoshi and Wang, 2014). In these models environmental technical efficiency, eco-efficiency or eco-innovation can be assessed using activity analysis on a homogenous group of producers.

This PhD falls into the latter framework of analysis with a particular focus on non-parametric methods, represented by Data Envelopment Analysis (DEA), mainly based on linear programming techniques. As pointed out in Chapter 1, two paradigms exist in the field of frontier estimation, DEA and the parametric Stochastic Frontier Analysis (SFA). We relied in this PhD on the non-parametric approaches because of the many developments that have occurred in this domain given its modelling flexibility. Another reason is that parametric approaches impose a priori a functional form for the production function, and as underlined in Silva and Stefanou (2003) "characterization of the production structure may be different across functional forms and, consequently, policy implications derived from empirical studies on the production structure can vary. The vulnerability of the empirical results to the ad hoc specification of the technology motivates investigation into a free-functional form methodology."

The generalisation of the DEA framework in the research field of performance measurement (Lee et al., 2014; Lampe and Hilgers, 2015) and its enlargement to account for undesirable outputs (Scheel, 2001) constitute the basis of this PhD. The overall objective of the PhD was to provide a critical review of the developments in the area of modelling pollution-generation technologies, and thereby propose a new approach, compare it empirically to the existing ones and extend it through a dynamic eco-efficiency analysis considering investment strategies of Decision Making Units (DMUs).

In the next sections we discuss the main findings that have been achieved during the PhD, several limits of the work, and suggestions for future research.

3. Synthesis of main findings

This PhD dissertation is organised into four research chapters, each one addressing one research question. Here we present a summary of answer to each question.

Research question 1:

What are the strengths and weaknesses of the existing approaches aiming at modelling pollution-generating technologies in performance benchmarking within the non-parametric DEA framework?

To answer this question, we undertook in Chapter 1 a critical review of methods integrating environmental aspects into productive efficiency (in the non-parametric framework). We have described and discussed the limits associated to the commonly used weak disposability assumption (WDA). We also reviewed recent developments around the inclusion of undesirable outputs in production technology modelling, like the materials balance principles and the weak G-disposability, the by-production modelling and the cost disposability assumption, as well as the unified model under natural and managerial disposability concepts. The limits inherent to each of these new developments were also discussed.

Let's recall that the WDA posits that it is costly to reduce pollution, and any action aimed at reducing the levels of bad outputs will also inevitably imply a proportional reduction of good outputs. For long and still nowadays, the WDA has been employed for eco-efficiency assessment in the empirical literature. However, several arguments and theoretical demonstrations have challenged the approach. Among those criticisms one can name the inconsistent trade-offs between bad outputs and inputs that generate them, as demonstrated in Murty et al. (2012); the possibility of negative shadow prices (Chen, 2014); and the violation of the laws of thermodynamics (Coelli et al., 2007). All these drawbacks question the results obtained from models based on the WDA. As underlined in Rødseth (2014) an explicit inclusion of pollution control activities can make the WDA consistent with the physical constraints. Actually under the WDA it is implicitly assumed that inputs can be diverted from the production of good outputs to the abatement of pollution (Färe et al., 1989; Färe et al., 2005). But this amount of pollution control is not directly incorporated to the model. The WDA works like a black box where some operations happen "behind the scene" (Rødseth, 2014). Besides, the WDA requires the existence of potential inputs that can be allocable to cleaning activities. In the case where these inputs are not present in the technology the WDA can generate misleading results.

As a solution, Hampf and Rødseth (2014) have developed the weak G-disposability assumption which relies on the materials balance principles (MBP) and therefore is in accordance with the laws of thermodynamics. However, as we argued in Chapter 1, this approach lacks flexibility. For instance the direction for the reduction of the bad output is highly constrained if one wants to maintain the MBP. Besides, under the dual approach some counterintuitive results are generated, such as the fact that the use of additional inputs generates extra revenues to the firm, while in reality input consumption incurs costs. Finally, as underlined in Murty et al. (2012 p124) the "mass-energy accounting identity" used in this approach does not properly represent "nature's pollution generating technology".

Following these criticisms, new ways of modelling pollution-generating technologies have emerged. They rely on the separation of the overall production system into two distinct processes or sub-technologies: one that produces good outputs and one that generates bad outputs. Among these new models we can find the unified model under natural and managerial disposability of Sueyoshi et al. (2010). Natural disposability reflects the possibility of reducing pollution by simply decreasing the consumption of inputs that generate the pollution, while managerial disposability requires the firm's restructuring or the use of cleaner inputs (so that bad outputs' use can be decreased but good output production can be maintained or even increased). In their unification strategy, Sueyoshi et al. (2010) offer to separate input slacks into two exclusive categories: positive ones (i.e. their levels should be increased; thus they represent input shortfalls) and negative ones (i.e. their levels should be decreased; thus they represent input excesses). Nevertheless, despite the interesting logic behind these disposability concepts, the exclusivity feature of the input slacks makes the model equivalent to the incorrect model where bad outputs are treated like inputs, when the slacks are negative. When the slacks are positive, the model converges to the equally incorrect model where inputs are equivalent to good outputs, both produced by the bad outputs. In this area of multiple frontier estimation we also mentioned the promising by-production model of Murty et al. (2012). The difference with the model of Sueyoshi et al. (2010) is that Murty et al. (2012) have explicitly represented two different technologies by using two separate intensity variables. However, in their non-parametric implementation of the model, the authors maintained independence between the two production processes, with an efficiency score being evaluated by assigning a weight of 50% to each objective (objectives of operational performance and of environmental performance). As we argued in Chapter 1, in practice this can lead to inconsistent optimal levels of inputs identified under each separate sub-technology.

It is worth underlining here the criticism formulated by Rødseth (2014) towards some recent developments like the by-production approach (Førsund, 2009; Murty et al., 2012). According to this author (Rødseth, 2014) all these developments impose some "arbitrary disposability assumption" and a priori specific relationships between inputs, good and bad outputs. For instance, in their by-production approach Murty et al. (2012) assumed that some resources can be allocated between the production of good outputs and the abatement of pollution. According to (Rødseth, 2014), given these specifications those models are not "suitable for the purpose of empirical testing of whether certain inputs (...) play a role in pollution control"(Rødseth, 2014). The idea defended by this author is that in the absence of inputs allocable to pollution control, the efficiency measure obtained in a classical model where undesirable outputs are not considered, should be the same as in a model that includes pollution. To test this idea, Rødseth (2014) proposed a model that does not directly include undesirable outputs but that uses the abatement output as a contextual (exogenous) variable which can be used to build "group output sets". The empirical results obtained in the associated paper effectively confirmed that there is no difference between the model that considers pollution control and the classic technology that does not, in the situation where there are no inputs allocable to pollution control. However we do not agree with the criticisms of the by-production approach made by Rødseth (2014). In Murty et al. (2012)'s model (expressed in equations (12) in their paper), the abatement output (related to bad output removal) is treated as another freely disposable good output but without maintaining the convexity assumption on its side. This reminds the selected proportionality concept discussed in Podinovski (2004) to model hybrid returns to scale where some inputs/outputs sets might be consistent to the proportionate increase and decrease of the constant returns to scale while other sets might not. Besides, Rødseth (2014) does not empirically compare his model to the by-production one because the latter would be unsuitable to test this assumption. We would like to stress here that the philosophy behind the by-production approach is that each activity in a production system can be represented by a specific technology. In the case where pollution control can be considered as a separate activity, the by-production model offers the possibility to build an entire sub-technology for pollution control with its associated inputs. Given these flexibilities, it appears to us that the by-production model can also be used to assess the impact of an input on pollution control. Moreover, we believe that the analyses undertaken by Rødseth (2014) raise a practical concern. In the empirical application the author considers different models, one with labour and another without. It is worth stressing that this kind of comparison can also be misleading in the case labour is a crucial input in the production system. Therefore the production technology considered is incomplete.

Finally, this chapter showed that all the existing models of pollution-generating technologies have pros and cons. However, the severity of the limits associated to some approaches requires that some models should be discarded. In terms of future perspectives, we argued that new developments should take advantage of multiple technologies and especially the by-production approach, and proposed new formulations that can overcome the related drawbacks.

Research question 2:

Which new theoretical model for eco-efficiency evaluation can be formulated in the non-parametric DEA framework, given the pros and cons of the existing approaches?

The main conclusion of Chapter 1 was that the by-production approach developed in Murty et al. (2012) fails to provide a unified framework of the different processes involved in the overall technology. In that chapter we also argued that the axiomatisation of the by-production approach discussed in Murty (2012) provides strong theoretical background for this approach. Based on this observation, Chapter 2 was devoted to provide a new formulation of the by-production model, which incorporates some dependence constraints that link both sub-technologies (the one that produces good outputs and the one that generates undesirable outputs). The improvement that I introduced here is based on the factor bands concept which describes the relation between inputs in an overall technology independently from the amount of outputs.[8] For this new formulation of the by-production model, the interconnection constraints are related to the equality between the optimal levels of inputs in each sub-technology. These constraints, that I added to the classic Murty et al. (2012) model, implicitly assume the existence of trade-offs between the production of good outputs and the generation of bad outputs. Using a numerical application (with virtual data) I showed that there is a difference between the two by-production models, and the extent of this difference depends on the assumption regarding the (free or not) choice of the different variables (restrictive assumption of fixed levels of inputs vs. flexible case of free choice of input quantities).

[8] In relation to the criticism of Rødseth (2014) discussed above, I would like to stress that I do impose some a priori relationship between inputs. However, epistemologically speaking I believe that this is how it should happen in economics research: we posit some ideas and some assumptions that must then be theoretically and empirically validated.

Research question 3:

What lessons from an empirical comparison of pollution-generating technologies within the non-parametric DEA framework, in terms of convergence analysis and trade-offs for French livestock grazing systems?

Following the first two research questions, Chapter 3 aimed at providing a technical and empirical discussion on the convergence or divergence of existing pollution-generation technologies modelling in the case of DEA framework, including my new approach namely the by-production approach with some dependence constraints. This chapter also provided a trade-off analysis in the case of GHG emissions in French sheep meat farms.

The analysis was based on the objective of eco-efficiency maximisation. The eco-efficiency was defined here as the good output intensity, which is simply the ratio of a good output per unit of a bad output. The eco-efficiency score is obtained by comparing the optimal ratios provided by the models and the actual observed ratio. Following the work of Hampf and Rødseth (2014), we computed eco-efficiency under three different assumptions: i-) inputs and good output are held fixed; bad outputs are endogenous; ii-) only inputs are fixed; good and bad outputs are endogenous; iii-) all the variables are endogenously determined. We assumed that the eco-efficiency score is computed under the third assumption. The score can then be decomposed into different sources (weak efficiency ratio associated to the first assumption; allocative efficiency ratio related to the second assumption; and input efficiency ratio bounded to the third assumption).

The empirical application used a network of sheep meat farms located in grassland areas in France for the period 1987 to 2013. Four inputs, namely land (in hectares), labour (in full-time equivalents), flock size (in livestock units) and production related costs (in 2005 Euros) were used in the technology that produces meat (in kilograms of carcass) and generates GHG emissions (in kilograms of carbon dioxide equivalent).

The eco-efficiency computed under the flexible assumption of endogenous levels of all inputs and outputs (assumption iii-)) revealed that the model under WDA, the weak G-disposability model and the unified model under natural and managerial disposability converged to the same results as in the case where undesirable outputs are treated as inputs. Let's stress here again that this way of modelling pollution-generating technologies is not correct. Besides, we found that the by-production model as proposed in Murty et al. (2012), that is to say assuming independence between the different sub-technologies, highly overestimated the overall inefficiency in comparison to the other approaches. However, when some dependence constraints were introduced, the model seemed to yield more acceptable results. Furthermore, an analysis of the trade-offs between operational and environmental performances showed that some farms can exhibit a win-win situation, i.e. there is room for improving both operational and environmental efficiencies. Other farms fell into the win-lost or the lost-win categories, i.e. one of the efficiency must be sacrificed to improve the other one and reach eco-efficiency. Under my new formulation of the by-production model with interlinked sub-technologies, the shadow price of GHG emissions for an eco-efficient farm was found to be on average 400 Euros per ton of GHG emitted (in carbon dioxide equivalent).

Research question 4:

How do dynamic aspects associated to the nature of investments in quasi-fixed inputs, matter in eco-efficiency appraisal within the non-parametric DEA framework?

This last research question was discussed in Chapter 4 by assessing the importance of considering dynamic aspects in eco-efficiency measurement. These dynamic aspects relate to the theory of adjustment costs in the presence of quasi-fixed inputs (Caputo, 2005). We argued in this chapter that for the traditional efficiency analysis (i.e. without bad outputs), it has been demonstrated that accounting for dynamic aspect matters (Stefanou, 2009). We therefore extended these aspects to the case of inclusion of undesirable outputs. We grounded our analysis on my by-production approach with interconnected sub-technologies.

An empirical analysis was carried out with a sample of suckler cow farms located in grassland areas in France for the period 1978-2013. Quasi-fixed inputs in this case were considered to be machineries, buildings, land improvements, while the adjustment variable was represented by the investment in these inputs. Land and labour were considered as fixed inputs. Intermediate consumption, that is to say annual expenses in consumables, was one of the variable inputs. Herd size was also considered as a variable input given that the analysis was conducted on three different periods of 12 years each. Total live meat production was the good output while the bad output was the level of GHG emissions. For comparison purpose we computed the eco-efficiency score under a static framework. The results highlighted the importance of considering dynamic aspects in eco-efficiency appraisal. We also presented the inefficiency scores associated to each input and output. Under both dynamic and static technologies, the lowest inefficiency was recorded for the good output production, i.e. during the period considered suckler cow farmers have performed better as regard meat production than other variables. Besides, the high heterogeneity in investment decisions was reflected in the high inefficiency scores associated to this variable. This also contributes to explain the higher overall eco-inefficiency under the dynamic framework.

4. Limits of the work

Limits of the work carried out in this PhD relate to theoretical, methodological and empirical aspects.

Firstly, theoretical shortcomings relate to my by-production extension, which includes some dependence constraints in the overall technology in order to link the good and the bad outputs' sub-technologies. A first question that immediately arises is why Murty et al. (2012) in their formulation did not underline this interdependence necessity. In the theoretical description of the technology they argued that the overall technology is the intersection of two sub-technologies, but in the DEA framework they maintained independence between those sub-technologies. Is there a sound reason for doing so, that would call into question my interdependence extension? One explanation for this puzzling situation in Murty et al. (2012) may relate to the data, I showed that under the assumption of fixed levels of inputs, my extension of the by-production model and the original version of Murty et al. (2012) do not really differ. But I also argued that the extent of the discrepancy between both approaches depends on the data under analysis and the levels of inefficiency present in the inputs' use. Besides, in Chapter 3 using sheep meat farms data and assuming free choice of input levels, we showed that the independence maintained by Murty et al. (2012) is highly problematic to evaluate eco-efficiency. This interdependence omission in their model may be due to the database used for the empirical application and the hypotheses used. Nevertheless, I believe that, theoretically, independence between the two sub-technologies should not be maintained. In light of this discussion, I recommend that my model extension, which was applied here to one type of database (livestock farms), should be applied to other databases from different areas, and sensibility analyses are required. More numerous empirical analyses can probably point out the differences between my formulation and the one from Murty et al. (2012). A last but not least point of discussion about my extension of the by-production approach, is related to the use of factor bands which is a relation between the inputs independently from the levels of outputs. The related question is, if it is possible to use product couplings (i.e. relations between outputs, independently from the input levels), will the eco-efficiency scores be comparable to the case of factor bands? Obviously, the expected answer to this question is yes.

In terms of the methodology employed, we can underline the potential limit in the literature review. Indeed, in Chapter 1 we undertook a critical review of the literature in eco-efficiency measurement using DEA. To gather the literature, we relied on several research engines like Google Scholar, Web of Science, and Scopus. Since we are never safe from omissions, we hope that we accounted for the relevant papers in this area. Some studies (Yang and Meho, 2006; Archambault et al., 2009; Franceschet, 2010) have nevertheless pointed out that the combination of these three research engines should result in a good cover of the literature on a specific topic, leaving little chance to leave something important behind.

Other limits are related to the methodological and empirical aspects dealing with GHG emissions' measurement.

Actually, one important limit to mention relate to the background work done in view of the empirical applications performed in this PhD dissertation. As mentioned in the general introduction of the dissertation, LCA was used to compute GHG emissions used in this research, a task that was complex and cumbersome but that allows using quantitative data in the PhD empirical analyses. However, the use of LCA to compute GHG emissions might not be exempt from computing errors, as well as from flaws in the survey data used. Such errors may affect the relative levels of GHG emissions across farms, and hence the relative levels of eco-efficiency or the belonging to the various win/lost categories. Another shortcoming relating to the use of LCA is that the perimeter boundary was limited to the cradle to the farm gate, i.e. we excluded all the flows that occur beyond the farms (in transformation and distribution processes). Based on that, our analysis can be qualified as partial. This partial characteristic may affect the relative environmental impacts between, for example, breeders and breeder-fatteners. The former sell young animals which are fattened in other (fattening) farms, while the latter rear animals and also fatten them on the farm. The environmental impacts related to each phase of the animal growing may be different. By including these two types of farms in our empirical analysis imply that we do not account for the potential impacts that breeding farms transfer to fattening farms. This situation may occur for the particular case of suckler cow farms. For sheep meat farms, this situation simply reflects two different strategies: farms that sell light lambs to slaughtering houses and farms that produce fattened lambs. Both types of sheep meat farms can however be compared on the same basis, namely the quantity of meat production.

Besides, we should also stress the fact that the main interest of this PhD was to provide tools to account for global warming in performance measurement, and thereby the analyses are all based on GHG emissions. However, in livestock farming or other agricultural sectors, other environmental impacts can be also at stake, like water pollution, pesticide toxicity, eutrophication, nitrification… LCA can also be used to estimate those impacts, and our analysis based on GHG emissions can be replicated to assess them.

Another shortcoming, still relating to empirical aspects, deal with the two databases used for the empirical applications in the PhD. Firstly, each database includes only a sample of farms of the region considered. Hence, if one wants to draw more general conclusions or recommendations, the representativeness of the samples has to be assessed first. Secondly, the panels of farms used are unbalanced because of retirements and new entries, implying a potential selection bias. This change in the farms constituting the sample each year means that changes in efficiency from year to year may not be due to a reduction of efficiency per se, but only to a change of the sample. Thirdly, despite the richness of the two databases, the number of yearly observations is too small to conduct a year-based analysis.[9] Thus, in Chapter 3 we pooled all the observations and constructed a unique frontier for all years. The limit of this strategy is that we did not account for the possibility of technological change to be present over the period.

Other limits of the PhD are mentioned in the next section simultaneously to suggestions to overcome them.

5. Suggestions for future research

In the field of performance benchmarking in general and in the case of eco-efficiency evaluation specifically, many questions are still not clearly answered. From a political point of view, one of the most relevant questions is related to the impact of the different regulations on technical efficiency and eco-efficiency of DMUs. The overall effects of regulations (especially environmental regulations) have been investigated along two different paths: i-) the traditional economic approach that indicates that environmental regulations impose additional costs to firms which see their profits reduced; ii-) the controversial path that is grounded on the idea that well-designed regulations can create sufficient incentives so that perpetual innovation process engaged by firms might outweigh the costs associated to the regulation. This last strand of thought is well known as the Porter Hypothesis (Porter and van der Linde, 1995b). Like the EKC, the Porter Hypothesis is largely debated in the literature (Harris and Roach, 2013).[10] For the specific case of agriculture, one issue is to understand the role of CAP subsidies on the performance of farmers and particularly their eco-efficiency. CAP subsidies include payments not related to environment (payments within the first pillar of the CAP), and payments for rural development (within the second pillar of the CAP). Among the latter are agri-environmental

[9] There are around 48 observations per year in the sheep meat database and about 87 for suckler cow farms.

[10] Some studies evidence the Porter Hypothesis (Wagner, 2003) while others do not (Lanoie et al., 2011).

schemes, which are in some sense a payment for the potential environmental services agriculture can provide. It is therefore legitimate to assess whether such schemes have eventually helped farms increase their level of environmental services. For this, assessing the effects of such subsidies on farms' eco-efficiency would contribute to this question. This however is barely done in the literature. What is mainly discussed in this literature is the role of subsidies on farms' technical efficiency. The answer to this question has generated ambiguous results both theoretically and empirically (Minviel and Latruffe, 2014). Technically, in the non-parametric framework one research direction is to develop an adaption of my new by-production model with dependence constraints, to the conditional efficiency measurement as initially discussed in Cazals et al. (2002); Daraio and Simar (2005, 2007b) and further extended in De Witte and Kortelainen (2013). Other directions like semi-parametric estimation (Sun and Kumbhakar, 2013) or semi-parametric conditional analysis (Minviel and De Witte, 2014) can also be relevant strategies.

Empirically, my by-production model with interconnected sub-technologies can provide answers to three specific questions: i-) what is the cost or benefit of including undesirable outputs in production modelling? This can be assessed through the analysis of shadow values associated to the dependence constraints; ii-) what is the shadow cost of the undesirable output? This cost can also be obtained by the estimation of the dual model; iii-) what are the efficiency levels: eco-efficiency, operational and environmental performance? In Chapter 3 part of questions ii-) and iii-) were explored. We did not provide an answer to question in i-), which might be relevant for policy-makers. Besides, although we showed in Chapter 3 that some farms can exhibit a win-win situation, we did not provide a direct investigation of the validity of the Porter Hypothesis. Firstly, our decomposition did not account for the current regulations (namely CAP subsidies), and we did not provide any discussion on the possible incentives for farms to be in this win-win situation. As argued in the literature, the firm's innovation implied by the Porter Hypothesis as a technological response to environmental regulations, should be examined through technological change assessment. Thereby, eco-efficiency should be examined over a long period of time, accounting for shifts in the frontier over time. Another research direction relates to eco-productivity decomposition using Malmquist or Luenberger indexes (Mahlberg et al., 2011; Mahlberg and Sahoo, 2011; Zhang and Choi, 2014).[11]

[11] The analysis of eco-productivity can also be extended to account for adjustment costs both in primal and dual approaches.

A further issue that could be examined is the link between eco-efficiency and decoupling, a concept defined by the Organisation for Economic Cooperation and Development (OECD) as "breaking the link between environmental bad and economic goods" (OECD, 2002). Another definition can be found, namely "breaking the correlation between increased economic activity and similar increases in environmental impacts" (Harris and Roach, 2013 p414).[12] This concept was initially applied to analyse countries' evolution towards sustainable development (Van der Voet et al., 2005). It can be extended to the analysis of individual productive units. Here also environmental innovation should be accounted for (Popp et al., 2010).

A further suggestion of research is to characterise farms depending on their eco-efficiency, in terms of farm size, structure and management (e.g. cropland and grassland) and managers' characteristics. An "optimal" farm may be identified for a specific area. In addition, investigating the exogenous determinants of eco-efficiency can help design support measures such as subsidies or insurance schemes. We mentioned above policy regulations. However, other exogenous factors may affect the level of eco-efficiency as well as the trade-offs (that is to say the belonging to a specific win/lost category). These factors include economic conditions (price levels and variability, input availability), as well as soil and climatic conditions. In theory, unfavourable economic or soil-climatic conditions may force farms to change their input use strategy, resulting in a change in eco-efficiency. The idea would be to assess empirically whether the change in eco-efficiency is substantial, or whether some farms can adapt so that their eco-efficiency is maintained.

In Chapter 4 results regarding dynamic measurement of eco-efficiency when accounting for adjustment possibilities, revealed that the large heterogeneity existing between farmers in terms of investment strategies clearly affect the efficiency scores derived from the model. Actually in France, farmers join massively cooperatives for the use of agricultural equipment (Cuma[13]). There are 13,000 Cuma in France and one of two farmers is member (225,000 farmers are involved in this kind of cooperative). A Cuma gathers farmers to buy agricultural equipment together, to obtain specific subsidies, to improve their competitiveness and to organise their work for higher efficiency. Given this situation, comparing farmers that are part of a Cuma and therefore have lower levels of own investments but higher levels of variable costs, to farmers who possess their own equipment, can be irrelevant. In the same line, some farmers simply delegate the work to private companies or other third parties (such as other farmers who own specific

[12] One can also refer to these authors (Harris and Roach, 2013) for the definition of absolute and relative decoupling.

[13] *Coopératives d'Utilisation de Matériel Agricole* in French.

equipment; this is contractual work, see Dupraz and Latruffe (2015)).[14] Such type of workforce is not accounted in labour but in production costs. It is thus important to propose a new framework of analysis that can account for this heterogeneity.

As previously mentioned, given their nature methane emissions are in some sense "incompressible" because associated to animal physiology (namely enteric fermentation, (Martin et al., 2010)). Actually it is possible to modify the levels of enteric fermentation through modification of the animals' diets. As demonstrated in some studies (Giger-Reverdin et al., 2003; Doreau et al., 2011), specific dietary composition can help mitigate the levels of enteric methane emissions without affecting the levels of meat or milk produced by the animal. But in our analysis, when using the LCA we did not account for this situation (mainly because of the lack of data), that is why we posit that methane is in some sense "incompressible". Given this fact, further analysis can be undertaken to assess the variability in eco-efficiency measurement. For instance, methane emissions can be simply removed from the analysis or considered as a fixed gas, depending on the assumption related to the inputs. The conclusion of such analysis can be very important given that methane is the biggest contributor to GHG emissions in the animal rearing sector. Preliminary results of such analysis assuming separability between the different GHG emissions on our sheep meat database, reveal that when we exclude methane from the analysis, eco-efficiency decreases by almost 19% on average (under my by-production approach with dependence constraints).[15] Still in this line of assessing the variability of eco-efficiency, it is also possible to separate the three GHGs (CO_2, CH_4 and N_2O) and evaluate their individual contribution to eco-efficiency. Further, another type of separation could consider the nature of the GHGs, i.e. they could be split into direct and indirect emissions. This could help assess where farmers should place their mitigation efforts.

As estimated in many studies, mitigation of GHG emissions in agriculture can be increased through carbon sequestration in soils (Solomon et al., 2007). This particularly matters for livestock systems in grassland areas. As pointed in Soussana et al. (2010), soil carbon can be increased through some practices like conservation tillage, and grassland and herd management. It is thus relevant to assess farms' eco-efficiency, not only accounting for their level of GHG emitted, but also accounting for their potential of carbon sequestration in soils. However, the computation of carbon sequestration is very challenging given the number of factors

[14] Entreprises de Travaux Agricoles (ETA) in French.

[15] These results will be presented at the International Conference of Agricultural Economists (ICAE) in Milan, Italy (8-14th August 2015).

(management practices, soils' microbiology...) that need to be considered. More simply, the Joint Research Center (JRC) in Ispra (Italy) has recommended using the values of 0.87 ton CO_2 equivalent per hectare and per year as a potential carbon sequestration for permanent grasslands, 0.42 ton CO_2 equivalent for cultivated grasslands, and -2.16[16] tons CO_2 equivalent for croplands (Leip et al., 2010). One can also use a more robust approach that relies on exponential equations which describe the amount of carbon sunk with time and also the quantity destocked due to tillage or other land management (Soussana et al., 2004). We adapted this latter approach to our two databases by accounting for the different nature of grasslands and croplands, and also the possible rotation schemes in different areas. Preliminary results reveal that carbon sequestration can be an important part of pollution intensity. For instance in our suckler cow farms' database it represents on average 1.9 kg of CO_2 equivalent per live kg of meat, i.e. about 12.5% of the gross pollution intensity. In our sheep meat farms' database carbon sequestration is on average 2.6 kg of CO_2 equivalent per live kg of meat, i.e. about 15% of the gross pollution intensity.

In benchmarking analysis two modelling strategies are possible: one can consider net GHG emissions, or one can simply consider carbon sequestration as another good output that needs to be increased. In the latter case, the by-production approach offers several possibilities to account for it. Firstly, we can still consider two sub-technologies and simply add carbon sequestration to the list of the good outputs under the associated sub-technology. Secondly, we can consider that carbon sequestration in soils is involved a different process than the one that generates meat. We can currently model three sub-technologies instead of two (by accounting for the existing connections between all the processes involved). Thirdly, we can consider that carbon sequestration, in addition to being a good output, is also an abatement output which can be explicitly introduced in both the good and the bad outputs' sub-technologies. Under these different possibilities one can easily compute an eco-efficiency score by using directional distance functions. In terms of policy regulations, it could be relevant to design a PES measure associated to carbon sequestration. This would be highly appropriate for livestock farming which is part of the rare human activities beneficial to carbon sequestration in soils. Dual approaches can be very helpful in deriving shadow values associated to non-market goods like carbon sinks. In this line, many other positive externalities from agriculture can be analysed (such as maintenance of rural landscapes and other environmental services).

[16] This is equivalent to carbon destock.

All the analyses conducted in this PhD are based on individual observations (farms). It could also make sense to provide an analysis in light of regional stakes. This would imply the move from the individual level to the regional one, and accounting for the interactions between these two levels. This situation is relevant for instance in the case of optimal allocation of emissions' tradable permits, or in the case of resource allocations.

A salient question that arises while working with different production systems like in this PhD research (sheep meat vs. suckler cows) is the comparison between these types of production. The tools presented in this dissertation can help provide a comparative analysis of eco-efficiency between sheep meat and suckler cow farmers.[17]

Finally, as specified in the general introduction of this PhD disseration, sustainability not only covers economic and environmental aspects, but also social issues. In the case of agriculture many problems can be analysed in this frame: labour arduousness, farmers' isolation, health issues associated to the use of toxic products, and the key role played by agricultural activities for the viability of rural disadvantaged areas. All these aspects deserve a closer look with respect to eco-efficiency including non-market goods.

[17] In this context, we are currently working on exploratory and econometric analysis that can help understand the main factors that explaining the potential difference between the two production systems (sheep meat and suckler cow farms). Identifying these factors can also be relevant for future policy design.

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Conclusion

It is difficult to imagine that all DMUs will one day not pollute at all. Hence, one question that can be asked is: how can DMUs efficiently pollute? However, efficiently polluting is not the panacea. While defining sustainable development, a point of interest is the intergenerational equity which imposes to shift our short-sighted production modes to new ones. As underlined by the American economist Rifkin (2011) in his book, the world needs a “third industrial revolution” that will take advantage of new communication technologies and renewable energy regimes. Maybe somewhere on earth a revolution is underway.

Meanwhile, the use of performance benchmarking techniques and, in the case of this PhD the use of Data Envelopment Analysis (DEA) in particular, helps assess eco-efficiency of productive units and determine the strategies (opportunities and current technologies) that pollute less. As regard agriculture and particularly livestock products, as stressed by the Food and Agriculture Organisation (FAO), the demand in these goods will seriously increase, and in developing countries it is expected that this demand for animal products will double by 2030 (Bruinsma, 2003). The environmental impacts of this increasing demand will also amplify (Bailey et al., 2014). In terms of meat consumption, in the leading position one can find the United States with about 120 kg per person and per year, while for Europeans it is a little more than 76 kg per person and per year, in Asia 31 kg per person and per year with huge disparities between countries, and finally in Africa this supply falls a little below 18 kg per person per year (Schwarzera et al., 2012). According to many scientists, to prevent dramatic environmental impacts that will exacerbate climate change, the average consumption of meat should not exceed 71-90 grams per day (i.e. 26-33 kg per person and per year) in order to keep the greenhouse gas (GHG) emissions to their 2000 levels and given the projected world population of 9 billion people in 2050 (McMichael et al., 2007; Barclay, 2011). To meet these challenges, apart from changes in consumption patterns, some technological improvements are required. Many mitigation tools have been discussed in the literature for the case of agriculture (Smith et al., 2008; Gill et al., 2010; Lesschen et al., 2011; O’Mara, 2011; Verchot, 2014). These mitigation tools fall into three categories: tools that help reduce emissions levels; tools that help enhance pollution removals; and tools that help prevent or avoid emissions. It is worth noting that the impacts of these tools vary depending on the local conditions, the regions and other characteristics of the case studies.

In this line of assessment of mitigation potentials, the developments carried out in this PhD showed that many developments have occurred in the past decades, but that there is still room for improvements in terms of modelling pollution-generating technologies. I hope that the formulation of my new approach in this field will trigger further discussion in this area, especially on how different mitigation tools can be evaluated. Furthermore, I expect that my approach is a promising avenue for the agricultural economics literature, for example in the assessment of operational and environmental performance in the case of GHG emissions. As explained in Chapter 2, this approach relies on the explicit representation of all the processes involved in a production system such as a farm. Inputs generating the GHG emissions are also those used for producing the agricultural output. Linking the two sub-technologies (agricultural output production and GHG generation) is therefore necessary. This latter point is one of the major contributions of this PhD.

This PhD dissertation largely discusses theoretical and methodological challenges and potential improvements, but is not devoted to design new policy tools for accounting for the presence of negative externalities like GHG emissions. But as mentioned above regarding the objectives of the PhD, this work provides knowledge and tools that are helpful in formulating new policies. Besides, each of the research question addressed in this PhD dissertation sheds light on some generic policy implications. For instance the conclusions of Chapter 1 shows that all the existing approaches in modelling pollution-generating technologies have limits, implying that the results obtained previously with all the models discussed in that part should be taken with caution. Even though the discussion in that chapter sticks to theoretical and methodological points of view, it does not mean that the empirical results provided by these models should not be deeply analysed and confronted to expert knowledge. Chapter 3 notably showed some substantial differences in terms of eco-efficiency results between the models.

In Chapter 2 I discussed the importance of considering that all the production processes are interconnected and should not be considered independently. In particular, the dual of the model can be used to evaluate the cost or gain related to the integration of undesirable outputs' generation by the managers in their strategies. One could then assess how an environmental regulation may affect productivity, in a beneficial or detrimental way. For instance, when it is expected that some regulations would decrease the profits of DMUs, one can imagine a sort of transfer (subsidies) from the government to DMUs, so as to compensate managers for their loss. In the case that those regulations can positively affect the economic returns of the DMUs, a tax could be applied to internalise environmental impacts.

In Chapter 3 the empirical comparison of the different models including my new formulation of the by-production model, provides an interesting policy tool as regard GHG emissions in French sheep meat farms. This comparison confirms that some of the existing models produce in some way unreliable information on eco-efficiency assessment. For the particular case of study of this PhD (GHG on sheep meat farms in French grassland areas), my by-production approach with dependence constraints seems to outperform the aforementioned approaches. A further positive point is that abatement outputs can be explicitly incorporated in the production processes. The results pointed out that in French sheep meat farms there can be a necessary trade-off between operational and environmental performances as a response to the existence of GHG emissions. Furthermore, under specific assumptions many farms can experience a win-win opportunity à la Porter, that is to say the implementation of specific regulations could enhance both economic and environmental performances. The design of new policies dealing with environmental stakes could make use of these results. For instance the categorisation of farmers in "win-win", "win-lost" or "lost-win" groups depending on whether they could improve their operational efficiency or their environmental efficiency or both, can feed debates on the design of agri-environmental measures. Some of them could for example be based on the characteristics of the farmers involved in each group. In summary, these results can constitute a first step in the perspectives of future "greening" reforms of the CAP. In addition, the analysis of the shadow price associated to GHG emissions provides the virtual cost associated to one ton of GHG generated for an optimal eco-efficient farm. This cost was found to be 400 Euros for our case study. This can be a starting point for discussions on a potential carbon tax. In this area of policy design, many simulation and predictive models can use eco-efficiency results and compare scenarios with various combinations of policy measures.

Chapter 4 builds on an approach that considers the presence of quasi-fixed inputs that cannot be instantaneously adjusted and which imply the presence of adjustment costs. This chapter extends this approach to the case of undesirable outputs. The empirical results associated to the sample of suckler cow farms revealed high levels of inefficiency in terms of investment (which is the adjustment variable in this dynamic framework), which exacerbate the eco-inefficiency scores. However, we argued that this is a reflection of the heterogeneity in terms of farmers' investment decision. This observation might revive the debate about investment subsidies and their effect on farmers' decision to invest and with which amount.

To contribute even more to debates on tools and indicators that are useful for environmental measures in livestock farming, we intend, in the short run after this PhD, to undertake an analysis of the factors that influence the eco-efficiency levels in both sheep meat and suckler cow farms considered in this PhD research. This can contribute to identifying greening strategies, a relevant information for the future CAP.

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