FACULTY OF ENGINEERING OF THE UNIVERSITY OF PORTO

The Assessment of Corporate Social Responsibility in the Mining Sector using Data Envelopment Analysis

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A thesis submitted to the Faculdade de Engenharia da Universidade do Porto for the doctoral degree in Industrial Engineering and Management

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"Que ninguém se engane: só se consegue a simplicidade depois de muito trabalho"
—Clarice Lispector, escritora e jornalista

" Don't let anyone rob you of your imagination, your creativity, or your curiosity"
—Mae Jemison, physicist and astronaut

Declaration

- Chapter 3 is based on the paper “Expanded eco-efficiency assessment of large mining firms”, *Journal of Cleaner Production* (2017), 142(4), 2364–2373. The paper is co-authored with Ana S. Camanho and Andreia Zanella.

- Chapter 5 is based on the paper “‘The Assessment of Corporate Social Responsibility: the construction of an industry ranking and identification of potential for improvement.” Submitted for publication in the *European Journal of Operational Research*. The paper is co-authored with Ana S. Camanho and Andreia Zanella.

Abstract

This thesis focuses on the development of innovative models, based on optimization techniques, for quantifying Corporate Social Responsibility (CSR). The models proposed are based on Directional Distance Functions (DDFs) and Data Envelopment Analysis (DEA). The performance measures are built using quantifiable criteria, and reflect the three dimensions of the Triple Bottom Line (TBL), corresponding to Economic, Environmental and Social aspects of firms' activity. To ensure that all developments meet the needs of extractive industries from the primary sector, the three studies composing this thesis include applications of the methodologies developed to real data from large mining firms. The three main topics explored in this thesis are described in the following paragraphs.

The first topic concerns the relationship between the economic and environmental dimensions of CSR. This subject is addressed by proposing an expanded eco-efficiency model that takes into account conservation practices to be maximized (e.g., the support of protected areas) and environmental burdens to be reduced (e.g., CO_2 emissions). The model developed enables optimizing simultaneously the contraction of the total volume of the inputs consumed (e.g., water and energy) and the expansion of the proportion of renewable resources in the inputs composition. The distinction between desirable and undesirable inputs in a DEA framework is an innovative feature of the models presented. This allows accounting for the needs of future generations by promoting an increase in the proportion of renewable resources in the total level of resources consumed by firms.

The second topic concerns the development of an innovative procedure to evaluate the evolution of performance over time in the context of evaluations using composite indicators. It is focused on the evaluation of social performance using quantifiable criteria, examining in detail the social dimension of CSR. The Environmental and Economic dimensions of the TBL often overshadow the social dimension in the performance assessment of firms. The developments proposed in this thesis include a framework for the specification of indicators reflecting social burdens and benefits created by mining firms, based on international standards and sectorial guidelines. Reputation issues associated with firms' impact on society, including local employment and contribution to local economic development are nowadays considered critical, so the definition of appropriate key performance indicators (KPIs) to address this subject is an important contribution to the literature. This study develops a composite indicator, formulated with a DDF, to evaluate social performance. It can be used both for benchmarking comparisons among firms within an industry and to monitor the evolution of performance over time. This study also proposes new formulations of the Malmquist index that can be used with composite indicators estimated with particular directional vector. The formulation of the composite indicator proposed in this chapter overcomes the widely reported problems of infeasibilities corresponding to estimates of productivity change over time based on directional distance functions.

The third topic concerns the development of a composite indicator to quantify CSR. This thesis proposes an innovative approach to evaluate CRS under the firm and industry perspectives, which is organized in two-stages. The first stage is focused on the firm-level and second stage on the industry-level. The methodology adopted involves the estimation of a DDF model to obtain a composite indicator reflecting the overall performance at the firm-level and a goal programming model to rank the firms in the analysis at the industry-level. The firm-level analysis allows distinguishing the firms with best practices from those with potential for improvement. The industry-level analysis obtains a consensual and robust ranking of performance. The industry-level analysis also asserts if the CRS practices observed in efficient firms are aligned with the industry trends. This innovative methodology provides insights that enable firms classified as benchmarks at the firm-level to pursue an extra mile towards excellence, promoting realignments with the industry trends.

Overall, this study delivers advanced optimization models to quantify CSR that overcome the limitations of alternative approaches typically based in subjective judgments of firm's performance. The methodologies proposed in this thesis contributes to the performance assessment literature, especially in the field of corporate social responsibility. It also provides a detailed examination of the mining sector, which is

a relevant contribution given the controversial perception the importance of this sector to sustainable development by public opinion and administrative authorities. This thesis intended to reduce the lack of consensus regarding the selection of performance criteria for evaluating CSR of large extractive industries. Framed by the paradigm of pursuing a more sustainable world, this research focuses on the maximization of socio-environmental benefits and the minimization of socio-environmental burdens associated with mineral exploitation, without neglecting firms' financial sustainability. Finally, although the methodologies developed are illustrated in the context of mining firms, they can be easily adapted to the context of other sectors.

***keywords*:** Data Envelopment Analysis, Directional Distance Functions, Goal Programming, ranking methods, composite indicators, eco-efficiency, Corporate Social Responsibility, social performance, Malmquist index, efficiency analysis, productivity measurement.

Resumo

Esta tese enfoca o desenvolvimento de modelos inovadores, baseados em técnicas de otimização, para quantificação de Responsabilidade Socioambiental Corporativa (RSAC). Os modelos propostos são baseados em *Directional Distance Functions* (DDFs) e *Data Envelopment Analysis* (DEA). As medidas de desempenho são construídas usando critérios quantificáveis e refletem as três dimensões do *Triple Bottom Line* (TBL), correspondentes aos aspectos econômicos, ambientais e sociais da atividade das empresas. Para garantir que todos os desenvolvimentos atendam às necessidades das indústrias extrativistas, os três estudos que compõem esta tese incluem aplicações das metodologias desenvolvidas com dados reais de grandes empresas de mineração. Os três tópicos principais abordados nesta tese são descritos nos parágrafos seguintes.

O primeiro tópico diz respeito à relação entre as dimensões econômica e ambiental da RSAC. Este assunto é abordado propondo um modelo de eco-eficiência expandida que leva em consideração práticas de conservação a serem maximizadas (e.g., suporte a áreas protegidas) e fardos ambientais a serem reduzidos (e.g., emissões de CO_2). O modelo desenvolvido permite otimizar simultaneamente a contração do volume total dos *inputs* consumidos (e.g., água e energia) e a expansão da proporção de recursos renováveis na composição de *inputs*. A distinção entre *inputs* desejáveis e indesejáveis em um *framework* de DEA é uma característica inovadora dos modelos apresentados. Isso permite levar em consideração as necessidades das gerações futuras, promovendo um aumento na proporção de recursos renováveis no nível total de recursos consumidos pelas empresas.

O segundo tópico diz respeito ao desenvolvimento de um procedimento inovador para avaliar a evolução do desempenho ao longo do tempo no contexto de avaliações usando indicadores compósitos. O tópico está focado na avaliação do desempenho social utilizando critérios quantificáveis, examinando detalhadamente a dimensão social da RSAC. As dimensões ambientais e econômicas do TBL muitas vezes ofuscam a dimensão social na avaliação de desempenho das empresas. Os desenvolvimentos propostos nesta tese incluem um *framework* contendo indicadores que refletem os fardos e os benefícios sociais gerados pelas empresas de mineração, com base em normas internacionais e diretrizes setoriais. As questões de reputação associadas ao impacto das empresas na sociedade, incluindo o emprego local e a contribuição para o desenvolvimento econômico local, são hoje consideradas críticas, de modo que a definição de *Key Performance Indicators* (KPIs) adequados para abordar esse assunto é um importante contributo para a literatura. Este estudo constrói um indicador compósito formulado a partir de um modelo de DDF para avaliar o desempenho social. Ele pode ser usado tanto para *benchmarking* entre empresas dentro de uma indústria quanto para monitorar a evolução do desempenho ao longo do tempo. Este estudo também propõe novas formulações para o índice de Malmquist que podem ser usadas com estimativas de desempenho correspondentes a indicadores compósitos. Esta especificação do índice de Malmquist é nova e supera os problemas amplamente relatados de *infeasibility* correspondentes a estimativas de mudança de produtividade ao longo do tempo com base em *Directional Distance Functions*.

O terceiro tópico diz respeito ao desenvolvimento de um indicator compósito para quantificar a RSAC. Esta tese propõe uma abordagem inovadora para avaliar a RSAC sob a perspectiva da empresa e da indústria, que é organizada em duas etapas. A primeira etapa é focada no nível da firma e a segunda etapa no nível da indústria. A metodologia adotada envolve a estimativa de um modelo DDF para obter um indicator compósito refletindo o desempenho geral de empresa ao nível da firma e um modelo de *Goal Programming* para classificar as empresas durante a análise ao nível da indústria. A análise ao nível da firma permite distinguir as empresas com melhores práticas daquelas com potencial de melhoria. A análise ao nível da indústria obtém uma classificação de desempenho consensual e robusta. A análise ao nível da indústria também afirma se as práticas de RSAC observadas em empresas eficientes estão alinhadas com as tendências do setor. Esta metodologia inovadora fornece *insights* que permitem que as empresas classificadas como *benchmarks* no nível da firma percorram uma milha extra para a excelência, promovendo realinhamentos com as tendências da indústria.

No geral, este estudo apresenta modelos avançados de otimização para quantificar CSR que superam as limitações de abordagens alternativas tipicamente baseadas em julgamentos subjetivos de desempenho da empresa. As metodologias propostas nesta tese contribuem para a literatura de avaliação de desempenho, especialmente no campo da responsabilidade socioambiental corporativa. Elas também fornecem um exame detalhado do setor de mineração, que é um contributo relevante, dada a controversa percepção da importância desse setor para o desenvolvimento sustentável por parte da opinião pública e das autoridades administrativas. Esta tese tem como objetivo reduzir a falta de consenso quanto à seleção de critérios de desempenho para avaliação de RSAC de grandes indústrias extrativas. Enquadrada pelo paradigma da busca de um mundo mais sustentável, esta pesquisa centra-se na maximização dos benefícios econômicos, ambientais e sociais e na minimização dos fardos ambientais e sociais associados à exploração mineral, sem negligenciar a sustentabilidade financeira das empresas. Finalmente, embora a metodologia proposta seja ilustrada no contexto das empresas de mineração, ela pode ser generalizada para outros setores.

Palavras-chave: *Data Envelopment Analysis, Directional Distance Functions,Goal Programming, ranking methods*, indicadores compósitos, ecoeficiência, Responsabilidade Socioambiental Corporativa, performance social, índice de Malmquist, análise de eficência, avaliação da produtividade.

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Renata M.S. de Oliveira

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Acronyms

AIFR	All Injury Frequency Rate
ARM	African Rainbow Minerals
BoD	Benefit-of-the-Doubt
CI	Composite Indicator
CSP	Corporate Social Performance
CSR	Corporate Social Responsibility
CRS	Constant Returns to Scale
CSW	Common Set of Weights
DDF	Directional Distance Function
DEA	Data Envelopment Analysis
DJSI	Dow Jones Sustainability Index
DMU	Decision Making Unit
EBITDA	Earnings Before Interest, Taxes, Depreciation and Amortization
GHG	Greenhouse Gas
GP	Goal Programming
GRI	Global Reporting Initiative
ICMM	International Council of Mining and Metals
ILO	International Labour Organization
ISAE	International Standard on Assurance Engagements
ISO	International Organization for Standardization
LoOP	Law of One Price
MFI	Microfinance Institutions
MI	Malmquist Index
OECD	Organisation for Economic Co-operation and Development
OHSAS	Occupational Health and Safety Assessment Series
OSH	Organizational Safety and Health
SAI	Social Accountability International
SD	Sustainable Development
SRI	Socially Responsible Investments
TBL	Triple Bottom Line
UN	The United Nations
UNCTAD	United Nations Conference on Trade and Development
UNEP	United Nations Environment Programme
WBCSD	World Business Council of Sustainable Development

CHAPTER 1

Introduction

This chapter contextualizes the research topic investigated in this dissertation. Section 1.1 states the research motivation and the reasons for examining the mining sector. Section 1.2 discusses the multidimensional nature of Corporate Social Responsibility (CSR) and introduces the concepts underlying the constructs developed throughout this thesis. Section 1.3 discusses the main challenges associated with the evaluation of CSR. Next, section 1.4 discusses potential contributions of the mining industry to the global sustainable development agenda, following the recommendations of the International Council of Mining and Metals (ICMM) and the United Nations (UN). Section 1.5 presents the research objectives of the thesis. Finally, the thesis outline is described in section 1.6.

1.1 Motivation

The mining industry contributes to economic development worldwide through its wide ranging production chain, involving complex operations and a myriad of different products. The UN (2016) acknowledged this potential by declaring the mining industry as a core activity affecting sustainable development. To fulfill the sustainable development agenda, the firms in this sector must design and implement good organizational practices regarding environmental protection, decent work, business development, increased fiscal revenues, and infrastructure linkages.

Despite the potential economic and social benefits associated with mining, this industry has contributed historically to environmental and social conflicts. In this context, the effectiveness of corporate practices concerning the protection of the environment and the communities is often questioned. This has been aggravated in the past few years by the severe impacts generated by mining exploitation. Many of these impacts are reported in the literature, such as active exploitation in areas without social legitimacy, environmental imbalances, depletion of non-renewable resources, community disruptions, human rights violations, gender-based violence, contributions to increased risk for many health problems, tax evasion and corruption (Jenkins, 2004; Kumar and Nikhil, 2014; Mahdiloo et al., 2015; UN, 2016). In this context, cost-benefit analysis has often been used to outweigh the burdens imposed by large mining companies with the overall financial benefits generated. However, in recent years, this approach has been questioned by the civil society, changing the focus to a people-oriented sustainable development agenda of the 21^{st} century (e.g., UN, 2015b). Social issues became an additional point of pressure for the mining sector, in addition to economic and environmental topics.

In response to broad criticism, in the past few years the mining industry has started to dedicate considerable attention to Corporate Social Responsibility (CSR) worldwide, boosting efforts to amend the industry's reputation. Sharma and Bhatnagar (2015) enlist three main reasons that explain why achieving a more responsible status is highly desirable for mining firms. The first reason is public opinion regarding long-term commitment to responsible management of environmental and social goals (Solomon et al., 2006). The second reason is to become eligible for the list of Socially Responsible Investments (SRI) in the financial market (Sharma and Bhatnagar, 2015) where mining firms are often screened out. The third reason regards the constant challenge of maintaining the social license to operate, avoiding delays, interruptions or the closure of operations. The social and environmental drawbacks associated with the operations of mining sites have been extensively documented, including operational dust and noise, impacts and risks to groundwater, increased cost of living nearby exploited regions and inappropriate reclamation (Moffat and Zhang, 2014).

Evaluating firm's performance in what concerns the practical implementation of responsible practices can bring new insights on the path to be taken towards sustainable development. Therefore, to ensure that firms achieve the expected commitment to CSR, it is essential to properly monitor company actions according to a clearly defined construct of sustainability. Elkington (1997)'s construct, named Triple Bottom line (TBL), was chosen to fulfill this purpose as it became a milestone in the discussions on sustainable development. It has been acknowledged as the basis for most performance assessment frameworks in this field.

There is a range of management tools based on Elkington's dimensions dedicated to guiding organizations towards the implementation of the best practices of Corporate Social Responsibility. The most prominent Corporate Social Responsibility initiatives were reviewed in the study of Oliveira et al. (2016). The examination of these initiatives, also referred to as management tools, covered reporting guidelines, international standards, stock market indices, sector guidelines, and methodologies for the assessment of performance. The review inspired the work of this thesis, revealing opportunities for methodological developments in the field of CSR. The first insight gained from the review is that most of the performance assessment methodologies available in the literature are oriented towards the generation of economic wealth. Relatively few studies intended to support the reduction of the burdens imposed on society and ecosystems, in order to ensure compliance with legislation. The second insight is that the maximization of wealth and minimization of social and environmental burdens should be explored alongside the creation of social and environmental benefits. Although the fulfillment of the needs of future generations (e.g., environmental conservation and poverty eradication) is frequently stated in the sustainable development literature, there is a lack of consensus regarding the most suitable criteria (benefits and burdens) that could compose a quantifiable framework of performance assessment, especially regarding social themes (e.g., Cooper et al., 2006; Garcia-Castro et al., 2010; Orlitzky et al., 2003). The third insight is the absence of a consensual overall measure of CSR that takes into account burdens and benefits generated by firms. Finally, the fourth insight is the unavailability of performance assessment models that can represent different priorities regarding social, environmental and economic dimensions of firm activity.

The initial stages of the sustainable development discussions occurred during the 1960's, with more attention dedicated to the problems associated with wealth generation, risks to public health, and mitigation of environmental impacts. The focus on trade-offs in terms of economic and environmental dimensions of the TBL marked the beginning of the eco-efficiency analysis during the 1970s. In subsequent years, the social component of CSR gained notoriety and, since the 1990s, the three dimensions of the TBL are seen as inseparable. Their balance is required in order to ensure good performance in terms of CSR. As a consequence, the trade-offs among the three dimensions of the TBL dimensions are now well-established, and the pursuit of well-balanced performance in all dimensions is considered crucial.

This context motivated the research presented in this thesis, which is focused on the assessment of the CSR of large mining firms. This research assumes that Corporate Social Responsibility is attainable when the companies involved can consistently promote progress within the three dimensions of the TBL (economic, environmental and social), without compromising the needs of future generations. Therefore, the main premise of this work is that responsible wealth generation should occur in the presence of good practices of environmental protection and social cohesion. With this in focus, the research composing this doctoral thesis proposes frameworks and models to analyze performance from a "creation of benefits" perspective. All developments are supported with illustrative applications using real data from large mining firms.

1.2 The Concept of Corporate Social Responsibility

In recent history, the relationship between businesses and society has been described using a variety of terminologies. Since the 1800s, terms such as corporate citizenship, social responsibility, corporate social performance, among others, have emerged from wide-range discussions regarding how an organization's behavior affects the economy, public health, and the society at large. In this context, the term Corporate Social Responsibility (CSR) gained notoriety in the 1980s to describe how businesses could contribute to the achievement of a sustainable society. Despite the popularity of CSR and the vast body of research available in this field, there is no universal understanding of the meaning of CSR (Dahlsrud, 2008). A proper and stable definition for this term has been under debate since the late 19^{th} century. During the late 1800s, industries pressured by the labor movement raised concerns about the welfare of their employees. Among the social responsibility initiatives of that era, the following actions were especially popular: the construction of bathhouses, hospitals, and the fight against child labor (Carroll, 2009). At that time, another perspective sought to achieve social responsibility through philanthropic means to compensate society for the impact of the Industrial Revolution on public health.

Between the 1920s and the 1940s, the focus of CSR changed from philanthropy towards both the maximization of stockholder wealth and the creation of an equitable balance among the needs of customers, employees, and the community (Hay and Gray, 1974). Despite its roots dating back to the late 1800s and early 1900s, the shaping of CSR theories is often associated with the 1950s.

By then, the social responsibility of businesses focused on the maximization of honest profits and the creation of jobs for society (Bowen, 1953). The seminal work entitled "Social responsibilities of the businessman" (Bowen, 1953) coined the term Corporate Social Responsibility in the literature.

The period between 1954 and 1970 is referred to in the literature as the "awareness", which encompasses the recognition of the overall responsibility of business and its involvement in community affairs (Carroll, 2009). During the 1960s companies were required to focus on specific problems such as urban decay, discrimination and pollution. During this period, the book "Silent Spring" was released (Carson, 1962), representing a breaking point in the understanding of the interrelations among economic, social, and environmental dimensions.

The discussion about Corporate Social Responsibility (CSR) was globally extended during the 1970s and 1980s with special attention devoted to the environmental risks created by unsafe industrial practices of waste management. Carroll (1979) provided a major contribution to the development of the CSR concept by introducing a conceptual model of corporate social performance (CSP). For the author, "the social responsibility of business encompasses the economic, legal, ethical, and discretionary expectations that society has of organizations at a given point in time". CSP recommends the incorporation of the following four dimensions into businesses strategic plans: economic, legal, ethical, and discretionary. Also in this period, the concept of Sustainable Development (SD) emerged from the Brundtland Report in 1987. This report defined sustainable development as development that meets the needs of the present without compromising the needs of future generations (UN, 1987, p.37).

During the 1990s the concept of CSR evolved, creating a range of three-dimensional accounting frameworks. The Tripple Bottom Line (TBL), introduced by Elkington (1994, 1997), is considered the most prominent framework from that time. It states that the organization should achieve high-performance standards in all dimensions in order to be considered socially responsible. To this end, the following specific issues within each dimension must be taken into account:

- The economic dimension should comprise a firm's capacity to generate and share wealth.
- The environmental dimension should comprise the scope of the firm's impacts on ecosystems and environmental protection.
- The social dimension should comprise the firm's code of ethics and its relationship with the society at large.

During the 2000s, the focus of the discussions changed from the theoretical constructs of CSR to empirical initiatives, taking into account topics such as corporate citizenship and performance assessment. In this context, Aras and Crowther (2009) provided evidence of the inseparability of the three dimensions of the Triple Bottom Line to ensure the achievement of sustainable development. During this period, international initiatives emerged to provide guidance to large firms on how to report their efforts in this field (e.g., OECD, 2001; GRI, 2011). This panoply of initiatives contributed both to the increase of notoriety of this field, as well as to the diversity of definitions for the term. For instance, Dahlsrud (2008) identified 37 definitions of CSR between 1988 and 2003. By that time, it became evident that the concepts of sustainable development and Corporate Social Responsibility are strongly linked, despite the conceptual divergences.

In this thesis we adopted the widely accepted definition provided by the World Business Council for Sustainable Development (WBCSD), which describes Corporate Social Responsibility as follows:

> “[. . .] the continuing commitment by business to contribute to economic development while improving the quality of life of the workforce and their families as well as of the community and society at large". (WBCSD, 2011, p.3)

Regardless of the disagreements about the appropriate definition, CSR is often interpreted as the responsibility of businesses to successfully integrate economic, environmental and social issues into organizational practices (Belu and Manescu, 2013). Therefore, in order to be considered socially responsible, a firm should simultaneously achieve high-performance standards on the three dimensions of Corporate Social Responsibility.

1.3 Challenges for the Evaluation of CSR

There is a wide range of challenges to be addressed in the assessment of Corporate Social Responsibility. The first and most evident challenge is the complexity of the topic. The nature of CSR is multidimensional and multidisciplinary, which requires careful consideration of the performance criteria to be used for representing the three dimensions of the TBL. Note that the performance criteria representing the environmental and social dimensions are very likely to be of a qualitative nature.

The second challenge is the unavailability of a robust framework of indicators, simultaneously representing distinct elements of firm performance in the three dimensions of the TBL, such as value-added in the economic dimension, CO_2 emissions in the environmental dimension, and local development in the social dimension. The construction of a robust framework requires the analysis of the performance criteria recommended by international initiatives in the field of CSR and the identification of intersections.

The third challenge is that, regardless of their qualitative or quantitative nature, the numerous initiatives available have gaps of coverage, making them inappropriate for the assessment of overall performance. There is a variety of qualitative initiates, which branch into guidelines (e.g.10 principles ICMM), international standards (e.g., ISO26000:2010) and reporting guidelines (e.g., Global Reporting Initiative). These initiatives are often specialized in one or two dimensions of the TBL, and none is able to simultaneously cover all dimensions. Similarly, the criteria covered within each dimension are not consistent among the initiatives available. These qualitative initiatives recommend the integration of CSR in the strategy of the firms and the use of indicators to measure their performance.

In this context, the fourth challenge is that the qualitative nature of most frameworks associated with CSR does not allow a robust evaluation of overall firm performance in terms of Corporate Social Responsibility. The diversity of indicators recommended can represent an obstacle for seeing the “big picture”.

The fifth challenge regards the vague recommendation that businesses should perform above regulatory requirements. However, reference values for a minimum acceptable performance level are not established, and optimal performance standards for firm’s operations are not defined.

Regarding the quantitative approaches, there is a body of research focusing on the evaluation of CSR using a composite measure. In the context of quantitative assessments, the sixth challenge is that most of the quantitative methodologies available are based on the aggregation of indicators using a subjective system of weights (e.g., stock market indices for ranking socially responsible investments). The use of subjective weights can unduly emphasize some criteria that are not particularly important for a given firm or even for a particular sector. Another issue is that the subjective weights may not be representative of the trade-offs among the dimensions. For instance, the same system of values should not apply for schools and banks. Another issue that affects some of the methodologies currently available is that the indicators are in fact rates computed by a committee of experts. This is the case of the Dow Jones Sustainability Index (DJSI) (RobecoSAM, 2013) and other stock market indices. These indices are built upon the aggregation of rates, ranging from 0 to 100, based on qualitative evaluations. Therefore, these rating procedures carry a subjective component of expert perceptions of the businesses. The individual indicators (or rates) are then aggregated using a pre-selected set of weights, resulting in the construction of a composite index reflecting CSR.

As an alternative to the use of pre-selected systems of weights, other methodologies allow for choosing weights using optimization techniques. For instance, the Robust CSR index (Van den Bossche et al., 2010) and the strategic CSR index (Belu and Manescu, 2013) are based on Data Envelopment Analysis (DEA). Introduced by Charnes et al. (1978), DEA is a non-parametric assessment technique that has been used extensively to evaluate performance and to support benchmarking exercises among decision making units (DMUs). This technique can account for multiple inputs and outputs (or indicators) and uses linear programming to estimate weights. The use of DEA can be particularly beneficial for the assessment of CSR when the relative importance of the economic, environmental, and social dimensions is controversial, such that the appropriate set of weights is unknown. DEA estimates individual sets of weights for each decision Making Unit (DMU), which shows each unit under evaluation in the best possible light. The use of DEA also enables a direct comparison of homogeneous firms and the identification of best practices. DEA is a frontier method, which identifies the DMUs with best observed performance, corresponding to the anchor points that envelop the production possibility set. It also allows quantifying sub-optimal performances of non-frontier DMUs, based on their distances from the frontier. This procedure allows the estimation of the potential for improvement, which involves setting targets for the adjustments of input and output levels required to achieve the best-practice standards observed in peers.

The use of DEA for assessments involving sustainability can be traced back to the 1990s, when Färe et al. (1996) conducted an environmental assessment in the presence of undesirable outputs. Since then, the volume of research resorting to DEA to address various aspects of sustainability gained momentum, with a noticeable increase in recent years (e.g., Zhang et al., 2008; Gutiérrez-Nieto et al., 2009; Chen and Delmas, 2011; Picazo-Tadeo et al., 2012; Belu and Manescu, 2013; Mahlberg and Luptacik, 2014). The studies in this field often use standard DEA formulations, although some of the research in this field also involves the development of enhanced models to conduct the assessment (Zhou et al., 2018). These studies followed the "application driven theory" approach that has often directed performance assessment research in the DEA scientific field. Regardless of the sophistication of the models used, most of the empirical studies are often specialized in one or two dimensions of CSR (e.g., Picazo-Tadeo et al., 2012; Martínez-Campillo and Fernández-Santos, 2017). Research covering two dimensions of CSR often address eco-efficiency topics (linking the economic and environmental dimensions with a focus on undesirable outputs) or socio-economic efficiency analysis (linking the economic and social dimensions). Very few studies cover simultaneously three dimensions (e.g., Belu, 2009; Chen and Delmas, 2011). A common feature characterizing these studies is the use of ratings as indicators, inspired by qualitative assessments. Therefore, a final challenge for the assessment of CSR lies in the inexistence of a common theoretical basis for the assessment of CSR. The variety of quantitative and qualitative frameworks available in the literature reflect the lack of consensus both in the selection of the variables used as well as in the interpretation of the meaning of CSR.

To summarize, in recent years, the quantitative studies based on DEA mainly adopted on an environmental-economic perspective of CSR, with fewer studies focused on the socioeconomic perspective. In addition, research focusing on the three dimensions of CSR is skewed towards environmental issues. Therefore, the proposition of innovative methodologies of evaluation, considering the trade-offs among the dimensions of CSR and their characterization in quantitative terms remains a challenge. With this in focus, this thesis addresses the quantification of indicators of CSR and develops advanced DEA-based models for the assessment of Corporate Social Responsibility at firm and industry levels.

1.4 Main Recommendations for Sustainable Mining

1.4.1 ICMM 10 Principles

In 2003, the International Council of Mining and Metals (ICMM) released 10 principles for guiding mining companies towards Sustainable Development and Corporate Social Responsibility. The ICMM principles aimed to establish clearer performance criteria for evaluations in the mining and metals sector. In 2015, the 10 principles were updated and benchmarked against leading international standards to ensure robustness. The benchmarks include the Rio Declaration (UN, 1992), the Global Reporting Initiative (GRI, 2011), the UN Global Compact launched in 2000 (UN, 2015c), OECD Guidelines on Multinational Enterprises (OECD, 2011b), World Bank

Operational Guidelines (World Bank, 2011), OECD Convention on Combating Bribery (OECD, 2011a), the Voluntary Principles on Security and Human Rights (Foley Hoag, 2011), and ILO Conventions:C098 (ILO, 1949), C169 (ILO, 1989) and C176 (ILO, 98).

The original declaration of the 10 principles of ICMM provides the foundations for the research conducted in this doctoral research. They can be summarized as follows ICMM (2013):

- **Principle 1- Implement and maintain ethical business practices and sound systems of corporate governance**

  This principle stands for the establishment of an ethical code through which the company expresses its commitment to sustainable development, international regulations, and compliance with local legislation. Additionally, this principle foresees ethical relationships with governments and other stakeholders.

- **Principle 2 - Integrate sustainable development considerations within the corporate decision-making process**

  This principle defines that sustainable values must be integrated in all organizational levels of the company. According to the second principle, mining companies must invest in technology and innovation to improve social, environmental, and economic performance while enhancing shareholder value. The same values must be observed for all suppliers and partners in the company's value chain.

- **Principle 3 - Uphold fundamental human rights and respect cultures, customs, and values in dealings with employees and others who are affected by our activities**

  The third ICMM principle supports practices of decent work and the pursuit of certifications, such as OHSAS 18001. It also recommends minimizing involuntary resettlement of indigenous groups and fair compensation for adverse effects on the community, whenever they cannot be avoided. This principle also highlights the importance of respecting the culture and heritage of local communities as an important feature to minimize negative social impacts on traditional communities.

- **Principle 4 - Implement risk management strategies based on valid data and sound science**

  This principle requires stakeholder consultation during the decision-making process, especially on topics related to significant social, environmental, and economic impacts. Additionally, it discourses on effective procedures whenever the company incurs in situations of environmental risk and social risk.

- **Principle 5 - Seek continual improvement of our health and safety performance**

  The fifth principle requires the implementation of a management system for the continuous process improvement. The focus of this principle is to prevent situations that compromise the health and safety of both the company's internal public (employees and contractors) and its external public (community). Still, the fifth principle foresees the rehabilitation and reintegration of employees into operations after recovery from occupational illness and injuries.

- **Principle 6 - Seek continual improvement of our environmental performance**

  This principle establishes that a firm should broadly assess environmental impacts of operating systems, new exploration projects, and mining closures. It also recommends the implementation of a certified Environmental Management System (EMS), e.g. ISO 14000.

- **Principle 7 - Contribute to conservation of biodiversity and integrated approaches to land use planning**

  This principle concerns the respect for protected areas and scientific biodiversity conservation assessment. The seventh principle recommends the use of accurate environmental data to assess the company's actions to preserve environmental reserve areas.

- **Principle 8 - Facilitate and encourage responsible product design, use, re-use, recycling and disposal of our products**

  The eighth principle of ICMM establishes that the companies must invest on research to better understand the properties of metals and minerals, innovative technologies to minimize negative impacts of metallic and mineral products on human health and the environment, and increasing efficiency of the use of energy, natural resources and any other materials.

- **Principle 9 - Contribute to the social, economic and institutional development of the communities in which we operate**

  The penultimate principle establishes that the company must contribute to community sustainable development. Additionally, the firm must seek out opportunities to address and mitigate poverty.

- **Principle 10 - Implement effective and transparent engagement, communication, and independently verified reporting arrangements with our stakeholders**

  The last principle states that the company should report accurate and relevant information about its economic, social, and environmental performance. This principle also foresees the disclosure of strategic information for its stakeholders, which should be accomplished through public consultation.

The ICMM principles for mining align with the Triple Bottom Line, as they present specific performance guidelines for economic, environmental, and social dimensions. Furthermore, the three principles mention the need to integrate Sustainable Development values in the business model of the mining companies, which confirms that they should be seen as strategic issues. To enable a concise view of the principles, Table 1.1 provides a classification of the principles according to their affinity to the three TBL dimensions, with an additional category of "strategy and governance".

Table 1.1: Summary of the ICMM 10 Principles

Category	Principles
Strategy and governance	Principle 1 – Ethics towards society Principle 2 – Incorporation of SD values in the firm's strategy Principle 10 – Practices for reporting and achieving transparency
Economic	Principle 9 – Local development
Environmental	Principle 6 – Environmental performance Principle 7 – Land use and conservation Principle 8 – Fighting wastes
Social	Principle 3 – Communities and decent labor Principle 4 – Risk management Principle 5 – Safety and occupational hygiene

1.4.2 UN Recommendations for Sustainable Mining

In 2015 the 193 United Nations (UN) state members presented the 2030 Agenda for Sustainable Development and the Sustainable Development Goals (SDG) (UN, 2015b). This agenda represented a global action plan for economic development, social inclusion, and environmental sustainability. The SDG focus on the eradication of poverty and on the fight against climate change. This document recognizes that the eradication of poverty requires strategies for building economic growth and addressing social issues, including education, health, social protection and job opportunities, whilst tackling climate change and environmental protection. The SDG agenda is composed of 17 goals, 240 indicators, and 169 targets to be achieved by 2030.

Recognizing that the simultaneous achievement of broad-based economic development, sustainability and social protection is a bold objective, the UN foresees the need of cooperation and collaboration between the public and private sectors, including governments and non-governmental organizations. As a consequence, it becomes clear that all sectors and stakeholders should incorporate the SDG into their own practices and operations (UN, 2016, p.5). With this in focus, the extractive industries (e.g., mining and oil industries) were considered strategic sectors to enable the achievement of sustainable development, especially in developing countries.

Regarding the mining industry, the United Nations released a report entitled "Mapping Mining to the Sustainable Development Goals: An Atlas" (UN, 2016). This document focused on discussing potential contributions that the mining industry could provide to the achievement of the 17 SDG throughout the links within the production chain of mining and processing. The following paragraphs summarize the main recommendations of the UN's atlas for the mining sector.

- **Goal 1: End poverty in all its forms everywhere**

  Mining can contribute to SDG 1 for eradicating poverty with local job creation and development of local suppliers. Another facet associated with this goal is paying taxes and royalty so that public policies of social protection and economic development are financed (e.g., health, housing, education, and infrastructure).

- **Goal 2: End hunger, achieve food security and improved nutrition and promote sustainable agriculture**

Mining firms can support SDG 2 by becoming harm neutral to agriculture. Agriculture is the largest employer on the planet and the primary means of livelihood for poor rural households. This means that the reduction of environmental impacts of mining on the soil, water, and biodiversity is the main issue associated with agriculture.

- **Goal 3: Ensure healthy lives and promote well-being for all at all ages**

  The health risks associated with mining include occupational hazards and increased risk factors for public health, including particulate air pollution, tuberculosis caused by silica dust exposure, HIV/AIDS due to unsafe sex and prostitution in the mining sites, mental illness, substance abuse, domestic violence, and the prevalence of malaria in exploitation sites. Mining firms are often required to address these risk factors and encouraged to collaborate with governments to ensure the existence of health services next to exploited areas. This may involve the support of public health programs and the training of the community and employees to ensure safe workplaces.

- **Goal 4: Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all**

  This goal can be boosted by strengthening equitable access to work and education, especially for women and local communities. Scholarships programs and workforce training programs are suitable in this context.

- **Goal 5: Achieve gender equality and empower all women and girls**

  Mining firms should promote gender equality by ensuring gender parity and equal pay for equal work across all levels of the organization.

- **Goal 6: Ensure availability and sustainable management of water and sanitation for all**

  As a significant consumer of this natural resource, the mining industry should contribute to this goal by reducing its water footprint in quantity and quality, ensuring the shared use of water infrastructure, implementation of reuse policies, and collaboration with governments.

- **Goal 7: Ensure access to affordable, reliable, sustainable and modern energy for all**

  The consumption of energy in mining is massive. This industry must improve energy sustainability by adopting energy efficiency measures and increasing the use of renewable energy in power supplies. Mining can also provide power to under supplied areas by sharing its energy infrastructure. Other initiatives should comprise of supporting local energy initiatives and exploring co-financing partnerships.

- **Goal 8: Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all**

  This goal can be supported by mining with the provision of decent work, the induction of indirect employment (e.g., new positions in local suppliers and subsidiaries), fomenting local economy and partnerships with local agents (e.g., local commerce chambers, business incubators).

- **Goal 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation**

  Basic services such as transport, water, energy, and Information and Communication Technology infrastructure are major requirements for sustainable development. In this sense, sharing the development and use of these infrastructures, especially in the least developed countries is a strong opportunity for the mining sector to expand access to critical services in the exploited regions.

- **Goal 10: Reduce inequality within and among countries**

  Socio-economic inequality is strongly associated with mining activities. This happens when local populations lack access to the basic infrastructure and economic opportunities brought by mining, despite significant overall improvements implemented by the companies. The mining industry can address this issue by collaborating with local entities in the fight against the marginalization of communities near mines.

- **Goal 11: Make cities and human settlements inclusive, safe, resilient and sustainable**

  Mining companies should contribute to sustainable cities by supporting the development of local infrastructure. This goal also covers topics such as responsible land use, implementation of cultural heritage plans, and reclamation of decommissioned mines into green spaces.

- **Goal 12: Ensure sustainable consumption and production patterns**

  The mining industry produces large volumes of waste as a by-product of its mining and processing activities. SDG 12 is particularly sensible to mining and it is critical to promote the reduction of hazardous waste, the increase of reuse, recycling and repurposing of raw materials, non-hazardous waste and products.

- **Goal 13: Take urgent action to combat climate change and its impacts**

  Climate change should be addressed by reducing the mining carbon footprint and integrating climate change measures into the business strategies.

- **Goal 14: Conserve and sustainably use the oceans, seas and marine resources for sustainable development**

  Mining impacts the ocean in a number of ways (e.g., shipping products, sub-sea shallow mining). SDG 14 can be supported by mapping environmental impacts in the oceans and mitigation strategies. Conservation practices regarding the oceans and seas are also highly desirable to achieve this goal.

- **Goal 15: Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss**

  The mining industry is often associated with the disruption of ecosystems that provide valuable environmental services to society. To address this issue and engage SDG 15, the mining sector should improve environmental impact assessment procedures, supporting projects to map and protect biodiversity, restoring habitats, and investing in R&D.

- **Goal 16: Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels**

  SDG16 should be supported by mining with the adoption of transparency practices, especially regarding the fight against illicit mining procedures, disclosure of operations reports, respecting human rights, and preventing conflicts with communities.

- **Goal 17: Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development**

  The achievement of SDG 17 in the mining sector involves partnering with governments in shared infrastructure arrangements or public-private partnerships. This goal also includes initiatives such as the diffusion of eco-friendly technologies and the disclosure of high-quality, timely and reliable data on the impact on local communities (e.g., income, gender, age, race, migratory status, employment levels).

The analysis of the potential contributions of mining to SDG implies that the operations of mining firms can generate benefits associated with the three dimensions of the triple bottom line (economic, environmental, and social). Among the benefits foreseen, it is worth noting direct and indirect job creation, economic growth in low-income countries, environmental protection, and equality seeking. On the other hand, this also implies that mining companies should reduce the burdens generated by their activity. For instance, the pressure for the reduction of waste and the reduction of water and energy use is highlighted, as well as the elimination of corruption, spills and unsafe practices at the workplace.

The 17 SDG were classified by the UN according to their relevance for the mining sector. The result is reported in Figure 1.1, where the horizontal axis includes three categories reflecting the relevance of the goals for the mining industry (i.e., indirect, moderately direct, and very direct). The vertical axis represents two categories, corresponding to the negative impacts of mining that should be mitigated and the positive impacts that should be enhanced.

The classification proposed in Figure 1.1 takes into account global expert opinions from industry, civil society, governments, academia, and financial institutions. However, this classification

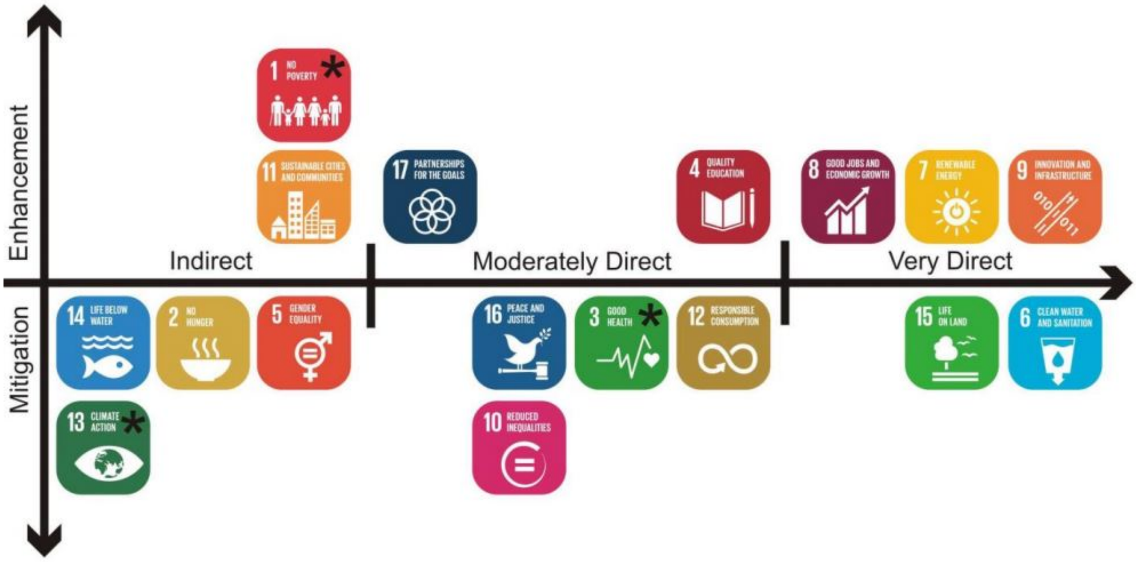

Figure 1.1: Indicative priorities of the SDG in the mining sector. From: UN (2015b)

implies that the SDG can be attained separately, refuting the premise of inseparability of the dimensions of sustainability defended in the literature (e.g., Elkington, 1997; Aras and Crowther, 2009; GRI, 2016).

In contraposition to the classification proposed by UN (2015b), the SDG are strongly interconnected and one goal cannot be ignored without compromising the achievement of others. For instance, the conservation of biodiversity (SDG 15) is only viable in the presence of integrated actions such as fighting climate change (SDG 13), the sustainable use of natural resources such as water (SDG 6), energy (SDG 7) and waste reduction (SDG 12). Similarly, taking SDG 1 as an example, the eradication of poverty is likely to be achieved simultaneously with several other goals, as it involves eliminating hunger and ensuring food security (SDG 2), good-health and well-being (SDG 3), equality (SDG 5 and SDG 10), and infrastructure (SDG 11).

1.5 Research Objectives

The main objective of this thesis is to develop innovative models, based on optimization techniques, for the quantification of Corporate Social Responsibility. This research intends to support assessments both at the firm and industry level. To ensure that all developments presented meet the needs of organizations, the studies are supported by illustrative applications using real data from large mining firms.

This thesis fits into the field of frontier methods, with a particular focus on the use of the Data Envelopment Analysis technique for the assessment of organizational performance. With this in focus, the next paragraphs describe the scientific contributions of this thesis to the performance assessment field.

The research begins by examining the eco-efficiency of firms from an innovative perspective. Classic eco-efficiency analysis addresses sustainability as a two dimensional problem that relates environmental burdens with the wealth generated by a firm. The expanded eco-efficiency measure introduced in this research extends this framework by taking into account environmental burdens, environmental benefits, and economic benefits. This investigation also developed an enhanced optimization model, based on Directional Distance Function (DDF) (Chambers et al., 1996a; Luenberger, 1992a,b) that enables the simultaneous optimization of the volumes of burdens produced during mineral exploitation and the shares of renewable resources used by mining. The exploration of scenarios reflecting different managerial preferences is also sought. To achieve the contributions intended for the first part of this doctoral research, the specific objectives set for the first part of this research are the following.

1. To provide an expanded view of the eco-efficiency of firms by constructing an enhanced assessment framework, considering both the benefits and burdens imposed on the environment by firms activity.

2. To develop an enhanced eco-efficiency assessment model based on Directional Distance Functions (DDFs) for incorporating alternative managerial preferences in the evaluation and exploration of distinct assessment scenarios.

3. To assess eco-efficiency taking into account the balance in the proportion of renewable resources consumed by firms, while attempting to reduce the burdens imposed on the environment.

The second part of this research includes methodological contributions with focus on the social dimension of the Triple Bottom Line, in the context of CSR evaluations. This research proposes a quantitative framework for the evaluation of social performance, which is often only addressed in qualitative frameworks. In this study, the analysis of social performance is dissociated from the economic dimension, in order to allow for an in depth study of this sustainability pillar and its evolution over time. An innovative composite indicator of social performance, based on DDFs, is introduced. One of the most innovative features in this part of the research is the introduction of exact relationships between the composite indicators (CIs) estimated with DDFs and radial efficiency measures. The equivalences demonstrated in this thesis enable the estimation of the Malmquist Index (MI) in evaluations involving CIs and, consequently, enable tracing of the evolution of the social performance of organizations over time. To deliver the contributions pursued in the second part of the research, the following specific objectives were set:

4. To develop a framework to evaluate social performance of mining firms according to quantifiable criteria, providing a more detailed analysis of the social dimension of the Triple Bottom Line. The framework should include both desirable and undesirable factors, corresponding to the social benefits and burdens generated by a firm.

5. To construct a composite indicator of social performance at the firm level, based on Directional Distance Functions. This aggregate performance measure should enable benchmarking comparisons under a variety of evaluation perspectives.

6. To enable the calculation of the Malmquist Index (MI) in the context of evaluations using composite indicators estimated using DDFs. This particular objective involves the deduction of the formulas that should be used for the computation of the MI for particular directional vectors underlying the construction of the CI.

The third part of this research involves the construction of a comprehensive framework for the evaluation of Corporate Social Responsibility (CSR) of large firms simultaneously considering the three pillars of the TBL. This framework involved the specification of an innovative composite indicator model, which can be estimated at two different levels of analysis (firm-level and industry-level). The firm-level analysis, grounded in the DDF technique, is used to obtain a relative measure of CSR in a benchmarking setting and guide performance improvement efforts. The industry-level analysis is based on the development of a Goal Programming model aimed at identifying a common set of weights for the indicators of CSR that can underlie the construction of an industry ranking. The integration between the DDF model and a Goal Programming model is an innovative feature of the methodology proposed. To attain the contributions sought in this part of the research, the specific objectives set are enlisted as follows.

7. To construct a comprehensive framework for evaluating Corporate Social Responsibility (CSR) of mining firms in accordance with the three dimensions of the Triple Bottom Line.

8. To propose a Composite Indicator (CI) that can be used to provide an overall (quantitative) measure of CSR at the firm level and an industry ranking of firms based on sectoral common grounds. This two-level analysis should resort to optimization techniques, avoiding the need to reach difficult consensus, based on expert opinion.

Note that all models developed in this research were built upon the the paradigm of versatility so that the methodologies presented can be can be easily generalized to organizations in other sectors.

1.6 Thesis Outline

This thesis is composed of six chapters. chapter 2 presents a brief overview of performance assessment techniques, with special attention devoted to Data Envelopment Analysis (DEA), Directional Distance Function (DDFs), and measures of productivity change. This thesis is a compilation document, composed of three papers corresponding to chapters 3, chapter 4, and chapter 5. The objectives of this doctoral research are attained in the papers compiled. Each paper contained in this collection presents a few methodological contributions to the field of performance assessment. The empirical support is presented in the illustrative applications using real data from large mining firms. Next, chapter 6 discusses the main conclusions of the research and presents the suggestions for future research.

The thesis outline is summarized in the next paragraphs.

Chapter 2 provides basic definitions of performance assessment, focusing on the use of Data Envelopment Analysis, Directional Distance Functions and productivity change indices. It includes a brief discussion of the performance assessment methods on which this thesis is based.

Chapter 3 provides an expanded view of the eco-efficiency of the firms by relating the economic dimension to the environmental dimension of Corporate Social Responsibility. Traditional eco-efficiency analysis evaluates companies by the ratio between the economic benefits and the environmental burdens produced by firm operations. The first contribution presented in this chapter is an enhanced framework that comprises a range of indicators corresponding to environmental burdens and benefits in the mining sector. The incorporation of environmental benefits in the assessment allowed for the exploration of potential improvements in good environmental practices (e.g., conservation and the use of renewable resources as inputs). The second contribution is the development of an enhanced optimization model, based on a Directional Distance Function. An innovative feature of the model is that, contrary to classic eco-efficiency models that are exclusively focused on adjustments to the magnitude of the indicators (volumes), the expanded eco-efficiency model also seeks for improvements in the balance between renewable and non-renewable resources (shares). The third and last contribution comprised in chapter 3 regards the specification of alternative directional vectors that allow for the incorporation of different managerial preferences in the model and exploration of distinct assessment scenarios. This chapter contains an empirical application to 25 large mining companies, in which different scenarios regarding managerial priorities for adjustments to the firms' economic and environmental indicators are explored.

Chapter 4 provides a closer view of the social dimension of CSR from a performance assessment perspective. The vast body of research focusing on CSR has dedicated more attention to the quantification of the environmental and economic themes than to social issues, often encapsulated in qualitative analysis. In this context, this study has three objectives. The first objective is to develop a framework for the quantification of the social performance of large firms, with a special focus on the mining sector. The second objective is to construct a composite indicator model, based on the Directional Distance Function suitable for benchmarking comparisons in the presence of indicators reflecting both burdens and benefits. The CI model should accommodate a variety of directional vectors reflecting different assessment perspectives. The third objective regards the estimation of the Malmquist Index for the evaluation of performance changes over time in the context involving composite indicators. The illustrative application provided in the last part of this chapter comprises a cross-sectional and longitudinal analysis of social performance of 24 large mining firms. The managerial implications are discussed, providing insights regarding potential improvements in the firm's social practices. The innovative firms in terms of the best social practices are also identified.

Chapter 5 presents a CI for the quantification of Corporate Social Responsibility. The proposed CI evaluates firms according to the three dimensions of the Triple Bottom Line (economic, environmental and social). The evaluation is conducted at two stages using optimization models. The initial stage corresponds to a firm-level analysis based on a Directional Distance Function model that estimates a relative measure of CSR. This model is particularly well-suited to guide performance improvement efforts. The firm-level analysis allows flexibility in the choice of weights and, consequently, admits the existence of different trade-offs across firms. Next, the industry-level analysis uses Goal Programming for estimating a Common Set of Weights (CSW), corresponding to identical trade-offs for all firms in the sector. The information obtained with the CSW is a consensual view of the industry allowing a robust ranking of firms. The methodology developed is illustrated using a sample of 24 large mining firms. The results obtained are discussed at the end of this chapter.

Chapter 6 presents the main conclusions of this thesis, including the contributions achieved and the research limitations. Insights extracted from the illustrative applications and directions for future research are also highlighted.

CHAPTER 2

The Assessment of Performance

The purpose of this chapter is to present an overview of the basic definitions underlying the assessment of performance. Special emphasis is placed on the presentation of Data Envelopment Analysis (DEA) and Directional Distance Functions (DDF) models. The construction of composite indicators and the evaluation of productivity change over time are also reviewed.

2.1 Introduction

The literature in the field of performance assessment is wide and multidisciplinary. Despite the effort made to provide a brief overview of this field, this chapter is focused on the evaluation of relative efficiency and productivity change over time using non-parametric frontier methods.

The efficiency measurement literature is strongly linked with productivity. Traditionally, the productivity of a unit (firm or nation) is expressed by the ratio between an output (y) (or an aggregation of outputs) and an input (x) (or to an aggregation of inputs) in a given production process. The productivity of a unit increases when the value of the ratio $\frac{y}{x}$ increases.

Productivity improvement is highly desirable, although it cannot be incremented indefinitely. The maximal achievable level of output obtained from a given set of inputs can be represented by a production frontier. In other words, the **technology of production** (Φ) or **production possibility set** (PPS) can be described as all feasible combinations of inputs $(x \in \Re^m_+)$ and outputs $(y \in \Re^s_+)$ for a certain production process. It is defined as shown in (2.1).

$$\Phi = \{(x, y) : x \text{ can produce } y\} \tag{2.1}$$

The estimation of the **frontier of the production possibility set** requires procedures that are strongly linked to economic theory. These procedures often involve the estimation of a production function, which is a mathematical representation of the relationship between inputs and outputs. It is defined as the maximum possible output obtained from a given set of inputs. The inputs may represent the factors of production (e.g., capital and labor), whilst the output is the result of firms' activities (Shephard, 1970).

Exact knowledge of the production function is not often available, so a range of methods have been proposed to estimate it. These methods involve empirical estimations of the location of the frontier that envelops the firms under assessment. In this context, deviations from the frontier are observed empirically. Despite the differences in the available methods, the frontier represents optimal levels of operation (efficiency) given the technology. One may be interested in evaluating the performance of a set of units, called **Decision Making Units** (DMUs), to compare their activity against a reference frontier. In this evaluation process, the units that do not achieve optimal levels are operating off the frontier of technology and located inside the production possibility set.

The degree of success in the transformation of inputs into outputs is called **Technical Efficiency**. It can be estimated by the comparison of the productivity level of a DMU against the maximal attainable productivity observed in a set of homogeneous units. The technical efficiency of a DMU can be estimated according to two perspectives: an input-oriented perspective and an output-oriented perspective. The input-oriented perspective regards the ability of a DMU to consume the minimum amount of input for the production of the current levels of output (minimize inputs while maintaining the outputs fixed). The output-oriented perspective regards the ability of a DMU to obtain the highest possible output given the current input levels (maximize the outputs while maintaining the inputs fixed).

Alternative definitions of technical efficiency were formulated in the 1950s by Debreu (1951), Farrell (1957) and Koopmans (1951). These are presented next.

Koopmans (1951) definition of **Technical Efficiency** states that a producer is technically efficient if an increase in an output requires a reduction in at least another output or an increase in at least one input, or if a reduction of an input requires an increase in at least another input or a reduction in at least one output (Koopmans, 1951).

According to Pareto (1906), efficiency is a state of allocation of resources in which it is impossible to make any individual better off without making at least one other individual worse off. This concept was used in the studies of economic efficiency and income distribution (Pareto, 1906).

Debreu (1951) proposed a radial measure of technical efficiency given by the maximum feasible radial reduction in all variable inputs given the output levels, or the maximum feasible radial expansion of all outputs given the input levels. The radial nature of the measure, involving equiproportional adjustments to inputs and outputs, implies that the estimation of efficiency is independent of the units of measurement.

Farrell (1957) revisited Koopmans' and Debreu's studies and introduced the notion of relative technical efficiency as the observed deviation from a frontier isoquant. For Farrell, technical efficiency should be estimated empirically through a comparison with the best observed practice in a reference set or comparison group, leading to a way of differentiating efficient from inefficient firms. Farrell's work implied that the technical efficiency measure is given by one minus the maximum equiproportionate (radial) reduction in all inputs that still allows the production of given outputs. A value of one indicates technical efficiency and a score less than unity indicates the severity of technical inefficiency (Fried et al., 2008, p.20).

Note that both Farrell's and Debreu's definitions describe radial measures of relative efficiency. For that reason, radial efficiency is also called in the literature Debreu-Farrell efficiency. Observe that the Debreu-Farrell radial efficiency measure disregards the possibility of non-radial adjustments (or slacks) to both input and output levels, while Pareto-Koopmans' efficiency takes these into account in the assessment of performance.

Ronald W. Shephard (Shephard, 1953) and Sten Malmquist (Malmquist, 1953) delivered important contributions to the field of efficiency and productivity analysis. They separately introduced the notion of distance functions as a tool for economics. Malmquist applied this notion to index number theory, whilst Shephard mainly used it for duality theory. The development of models of technology and distance functions provided the foundations for assessments involving multiple outputs and inputs. The work of Shephard enabled a complete characterization of the structure of a multi-input, multi-output production technology, and a reciprocal measure of the distance from each DMU to the efficient frontier (Johansen, 2011, p.16). Shephard distance functions are also the bases for the estimation of the Malmquist index of productivity and a range of other indices available in the literature (see.; Färe et al., 1989; Chambers et al., 1994).

2.2 Methods for the Assessment of Efficiency

The efficiency measurement methods based on the estimation of an efficient frontier evolved following two parallel lines: parametric and non-parametric approaches. These methods differ in the way the frontier is specified and estimated.

On the one hand, the parametric approach estimates the frontier using a function defined by a precise mathematical form (e.g., translog or Cobb-Douglas functions). This line of research requires an *a priori* specification of the functional form to represent the frontier. On the other hand, the non-parametric approach does not require defining a functional form for the frontier. Instead, the frontier is defined by a set of axioms that must be satisfied when setting the boundary of the PPS.

In the non-parametric approach, the most common method for the evaluation of efficiency is Data Envelopment Analysis (DEA). In the parametric approach, the method most frequently reported in the literature is Stochastic Frontier Analysis (SFA).

Both the parametric and the non-parametric approaches can be further divided into stochastic and deterministic approaches.

Stochastic approaches involve the estimation of the production frontier using statistical techniques. They involve the analysis of residuals between the observed DMUs and the line that defines the frontier. Deviations from the frontier can be distinguished between a non-normal residual corresponding to inefficiency and a normal residual corresponding to white noise or measurement error in the data.

Deterministic approaches rely on mathematical programming techniques for the estimation of the production frontier and assume that there is no random noise in the data. Consequently, the deviations from the frontier are interpreted exclusively as inefficiency.

This thesis follows the non-parametric research line and reports evaluations involving DEA-based models. Particularly, this dissertation is strongly related to Directional Distance Function models and, for that reason, the next sections present the main models for the estimation of efficiency.

2.2.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) enables the estimation of relative efficiency accounting for multiple inputs and outputs. It is based on a comparison among an homogeneous set of Decision Making Units. This method was introduced in the seventies by Charnes et al. (1978) in the paper entitled "Measuring the efficiency of decision making units". The authors operationalized the propositions of Farrell (1957) and formalized a linear programming problem that constitutes the basis of the non-parametric deterministic approach of performance assessment.

With the purpose of presenting the DEA formulations in an intuitive way, the starting point is the fractional model (Charnes et al., 1978) for the estimation of relative efficiency shown in (2.2). Consider a performance assessment of n DMUs ($j = 1,...,n$), each consuming inputs x_{ij} to produce outputs y_{rj}. The DMU under assessment is represented by k ($k = 1,...,n$) and it consumes inputs x_{ik} $(i = 1\ldots,m)$ to produce outputs y_{rk} $(r = 1\ldots,s)$.

The DEA fractional model:

$$\begin{aligned}
&\text{Max } e_k = \frac{\sum_{r=1}^{s} u_r\, y_{rk}}{\sum_{i=1}^{m} v_i\, x_{ik}} && \\
&s.t.\ \frac{\sum_{r=1}^{s} u_r\, y_{rj}}{\sum_{i=1}^{m} v_i\, x_{ij}} \leq 1 && j = 1,\ldots,n \\
&u_r \geq \varepsilon && r = 1,\ldots,s \\
&v_i \geq \varepsilon && i = 1,\ldots,m
\end{aligned} \tag{2.2}$$

The relative efficiency of DMU k is obtained from the objective function value of the fractional model shown in (2.2). The measure of relative efficiency involves a comparison of the ratio of weighted outputs to weighted inputs for the DMU under assessment with similar ratios estimated for all DMUs in the sample. The use of weights enables the aggregation of the multiple inputs and outputs to obtain a proxy measure of productivity, corresponding to a ratio of an "overall output" to an "overall input". For each DMU under assessment, an individual set of weights $(u_r$ and $v_i)$ is chosen with the purpose of evaluating its efficiency in the best possible light. This means that the ratio of weighted outputs to weighted inputs is maximized, subject to the constraints that all similar ratios estimated for other DMUs must be less than or equal to unity when evaluated with similar weights.

Note that the decision variables are the weights v_i and u_r and ε is a mathematical infinitesimal ensuring that the weights are strictly positive so that all inputs and outputs are taken into account in the evaluation.

The fractional model presented in (2.2) can be converted to linear-programming using alternative procedures, corresponding to the DEA input-oriented model (2.3) and the DEA output-oriented model (2.4). The formulations reported in (2.3) and (2.4) assume Constant Returns to Scale (CRS). Note that the input-oriented formulation involves a normalization that sets the denominator of the objective function of (2.2) equal to one while the numerator is maximized. In the output-oriented formulation, the normalization sets the numerator of the objective function of (2.2) equal to one while the denominator is minimized.

DEA input-oriented model under CRS (multiplier formulation):

$$\begin{aligned}
&\text{Max } e_k = \sum_{r=1}^{s} u_r\, y_{rk} \\
&s.t. \sum_{i=1}^{m} v_i\, x_{ik} = 1 \\
&\sum_{r=1}^{s} u_r\, y_{rj} - \sum_{i=1}^{m} v_i\, x_{ij} \leq 0 \quad j = 1,\ldots,n \\
&u_r \geq \varepsilon \qquad\qquad\qquad\qquad r = 1,\ldots,s \\
&v_i \geq \varepsilon \qquad\qquad\qquad\qquad i = 1,\ldots,m
\end{aligned} \tag{2.3}$$

DEA output-oriented model under CRS (multiplier formulation):

$$\begin{aligned}
&\text{Min } h_k = \sum_{i=1}^{m} v_i\, x_{ik} \\
&s.t. \sum_{r=1}^{s} u_r\, y_{rk} = 1 \\
&\sum_{r=1}^{s} u_r\, y_{rj} - \sum_{i=1}^{m} v_i\, x_{ij} \leq 0 \quad j = 1,\ldots,n \\
&u_r \geq \varepsilon \qquad\qquad\qquad\qquad r = 1,\ldots,s \\
&v_i \geq \varepsilon \qquad\qquad\qquad\qquad i = 1,\ldots,m
\end{aligned} \tag{2.4}$$

In formulations (2.3) and (2.4), the models seek for the maximization of the efficiency scores of the DMU k under assessment. In model (2.3), the relative efficiency score is given by e_k^*, and by $1/h_k^*$ in model (2.4). Note that the symbol * represents the optimal value of a variable. Models (2.3) and (2.4) provide identical optimal solutions ($e_k^* = 1/h_k^*$).

The value of the objective function ranges between 0 (worst) and 1 (best), so that if the DMU under assessment k is radially efficient, the score obtained equals one. Otherwise, it is considered inefficient. The linear programming problem is solved for each DMU so that each unit obtains an individual set of weights.

The multiplier DEA models (2.3) and (2.4) can be expressed in their dual form, called envelopment formulations, as reported in (2.5) and (2.6).

DEA input-oriented model under CRS (envelopment formulation):

$$
\begin{aligned}
&\text{Min } e_k = \delta_k - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) && && (2.5)\\
&s.t.\ \delta_k\, x_{ik} - \sum_{j=1}^{n} \lambda_j\, x_{ij} - s_i^- = 0 && i = 1,\ldots,m\\
&\sum_{j=1}^{n} \lambda_j\, y_{rj} - s_r^+ = y_{rk} && r = 1,\ldots,s\\
&\lambda_j \geq 0 && j = 1,\ldots,n\\
&s_i^- \geq 0 && i = 1,\ldots,m\\
&s_r^+ \geq 0 && r = 1,\ldots,s
\end{aligned}
$$

DEA output-oriented model under CRS (envelopment formulation):

$$
\begin{aligned}
&\text{Max } h_k = \theta_k + \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) && && (2.6)\\
&s.t.\ \sum_{j=1}^{n} \lambda_j\, x_{ij} + s_i^- = x_{ik} && i = 1,\ldots,m\\
&\theta_k\, y_{rk} - \sum_{j=1}^{n} \lambda_j\, y_{rj} + s_r^+ = 0 && r = 1,\ldots,s\\
&\lambda_j \geq 0 && j = 1,\ldots,n\\
&s_i^- \geq 0 && i = 1,\ldots,m\\
&s_r^+ \geq 0 && r = 1,\ldots,s
\end{aligned}
$$

In the input-oriented model (2.5), δ_k^* is the efficiency score of DMU k and it can also be interpreted as the factor by which the input levels of the DMU under assessment can be decreased radially (equiproportionally), while the outputs maintained at least the current levels. Similarly to the multiplier model (2.3), the value of the objective function ranges from 0 (worst) to 1 (best). A value of $\delta^* = 1$ means that the DMU k is radially efficient, but it is not efficient in Koopsman's sense. A DMU k is efficient in Koopman's sense if, and only if, the following conditions are satisfied:

- The radial efficiency score is 1
- There are no positive slacks values; i.e., $s_i^* = s_r^* = 0 \ \forall\, i, r$

The variables λ_j are the intensity variables and can be interpreted as the multipliers defining a point on the frontier estimated from the convex combination of other DMUs in the sample (peers). s_i^* and s_r^* are the slack variables transforming the constraints in equalities. These variables indicate the extent to which each input or output can be improved beyond the amount indicated by the radial factor δ_k^*. They are multiplied by the infinitesimal ε in the objective function to ensure that the slacks are only optimized on a second-stage, without affecting the efficiency scores.

For the output-oriented model shown in (2.6), the radial efficiency of DMU k is obtained as the inverse of $\theta_k^* (i.e., 1/\theta_k^*)$. This means that θ_k^* is the factor by which the outputs levels of the DMU under assessment can be increased equiproportionally, while keeping the inputs fixed. Therefore, DMU k is considered radially efficient when $\theta_k^* = 1$ and efficient in the Pareto-Koopmans' sense when $\theta_k^* = 1$ and $s_i^* = s_r^* = 0 \; \forall \; i, r$.

One should note that δ_k^* matches the Debreu-Farrell radial efficiency measure and θ_k^* matches the inverse of Debreu-Farrel radial efficiency measure.

The envelopment formulation of the DEA model also enables extracting further managerial information for benchmarking purposes. This feature is supported by the identification of peers for each inefficient DMU. These peers are the firms operating at the frontier, selected as a reference for the evaluation of DMU k in models (2.5) and (2.6). The inputs and outputs observed in the reference firms are used to build one composite DMU estimated from the linear combination of the inputs and outputs observed in the peers. The composite DMU uses the same or lower levels of input and produces equal or higher levels of output than DMU k. Therefore, when $\lambda_j > 0$ it means that DMU j is a peer to DMU k.

The linear combinations of the peers will indicate the targets for DMU k to reach efficient levels. The targets of the input-oriented model (2.5) are given by expression (2.7) and the targets of the output-oriented model (2.6) are given be expression (2.8).

$$\begin{cases} x_{ik}^{'} = \delta_k^* x_{ik} - s_i^* = \sum_{j=1}^{n} \lambda_j^* \, x_{ij} & i = 1, \ldots, m \\ y_{rk}^{'} = y_{rk} + s_r^* = \sum_{j=1}^{n} \lambda_j^* \, y_{rj} & r = 1, \ldots, s \end{cases} \tag{2.7}$$

$$\begin{cases} x_{ik}^{'} = x_{ik} - s_i^* = \sum_{j=1}^{n} \lambda_j^* \, x_{ij} & i = 1, \ldots, m \\ y_{rk}^{'} = \theta_k^* y_{rk} + s_r^* = \sum_{j=1}^{n} \lambda_j^* \, y_{rj} & r = 1, \ldots, s \end{cases} \tag{2.8}$$

The targets given expressions (2.7) and (2.8) represent the reference point in the frontier for the DMU k under assessment to become efficient.

2.2.2 DEA-based Composite Indicators

The composite indicators have become popular in recent years in a variety of fields such as Environmental Performance Index, Human Development Index, and Gender Gap Analysis. A composite indicator is an aggregation of a set of sub-indicators into a single measure. The composite indicator should ideally measure multidimensional concepts which cannot be captured by a single indicator (Nardo et al., 2008, p.13). CIs are intended to summarize into a single measure a range of different sub-indicators or criteria. In this context, the choice of appropriate weights reflecting the relative importance of the sub-indicators is an unsettled issue under debate among scholars and practitioners. The Organisation for Economic Co-operation and Development (OECD) (Nardo et al., 2008) recommends a range of techniques for the choice of appropriate weights in the construction of a composite indicator. OECD recommends the use of optimization techniques, namely DEA, appropriate for reducing subjectivity in the choice of weights.

The estimation of composite indicators based on DEA can be traced back to Cook and Kress (1990), who proposed a CI based on the aggregation of outputs assuming all DMUs are similar in terms of inputs. Therefore, the inputs are represented by a *dummy* variable equal to one, underlying the evaluation of every DMU. This *dummy* variable can be interpreted as a “helmsman” attempting to steer the DMUs toward the maximization of outputs. Cherchye et al. (2007) popularized the construction of composite indicators using DEA by proposing the use of formulation (2.9), known as “Benefit of the Doubt” (BoD).

$$\begin{aligned} CI = \max \sum_{r=1}^{s} u_r y_{rk} & \\ \text{s.t.} \sum_{r=1}^{s} u_r y_{rj} \leq 1 & \qquad j = 1,\ldots,n \\ u_r \geq \varepsilon, & \qquad r = 1,\ldots,s \end{aligned} \tag{2.9}$$

Formulation (2.9) is equivalent to the input-oriented model under CRS, with an unitary input assigned to the DMUs under assessment. y_r $(r = 1,\ldots,s)$ are the output indicators to be expanded. The weights u_r $(r = 1,\ldots,s)$ are the decision variables that give the highest objective function score (CI^*) for each DMU k assessed. The scores can range between 0 (worst) and 1 (best). This type of DEA-based CI is unit invariant, which makes the normalization constraint redundant (Cherchye et al., 2008). The applications of DEA based on this approach dedicate special attention to the selection of meaningful sub-indicators.

2.2.3 Directional Distance Functions

Chambers et al. (1996a), based on the Luenberger shortage function (Luenberger, 1992a,b), proposed a Directional Distance Function (DDF) that allows a DMU to scale inputs and outputs simultaneously along a path that is defined according to a directional vector g. The DDFs can be considered a generalization of Shephard (1970) input and output distance functions specification. Considering the production technology Φ defined in (2.1), the general form of the DDF is given by (2.10).

$$\vec{D}(x,y;g_x,g_y) = \max\ \{\beta : (x+\beta g_x,\ y+\beta g_y) \in \Phi\} \tag{2.10}$$

The directional vector $g = (g_x, g_y)$ can assume a variety of configurations. The components of the vector (g_x, g_y) indicate the direction of change for the inputs and outputs, respectively, reflecting alternative managerial objectives. For instance, the definition of the directional vector as $g =$

$(-x_,0)$ results in an input-oriented assessment, only involving reductions to inputs. Defining the directional vector as $g = (0, y)$ leads to an output-oriented assessment.

Another possibility is the specification of vector $g = (-x_,y)$, which allows the simultaneous radial reduction of inputs and increase of outputs in order to reach the frontier of the technology. When the components of the directional vector are equal to the values of the inputs and outputs observed in the decision making unit under assessment, it is possible to interpret the value of the Directional Distance Function as the proportional adjustments to inputs and outputs required to reach the frontier of the production possibility set. Another commonly used configuration of g is $g = (-1, 1)$, focusing on the reduction of the magnitude of the inputs usage and increase of output levels obtained.

The Directional Distance Function (2.10) can be estimated using a linear programming model, as shown in (2.11).

$$
\begin{aligned}
&\vec{D}(x,y;g_x,g_y) = \max \beta_k && \\
&s.t. \sum_{j=1}^{n} y_{rj}\, \lambda_j \geq y_{rk} + \beta_k g_y && r = 1,\ldots,s \\
&\sum_{j=1}^{n} x_{ij}\, \lambda_j \leq x_{ik} - \beta_k g_x && i = 1,\ldots,m \\
&\lambda_j \geq 0 && j = 1,\ldots,n
\end{aligned}
\tag{2.11}
$$

In (2.11), y_{rj} are the outputs generated and x_{ij} are the inputs consumed by DMU j. Similarly, y_{rk} and x_{ik} are the outputs and inputs observed in the DMU under assessment k. The variables λ_j are called intensity variables. They allow the specification of a point on the frontier of the PPS against which the DMU under assessment is compared, corresponding to a linear combination of other efficient DMUs used as peers.

The optimal value of β_k^* is the value of the DDF that can be interpreted as an inefficiency score. Therefore, a DMU is on the frontier of the PPS if $\beta_k^* = 0$, and positive values of β_k^* are associated with inefficient DMUs.

Chung et al. (1997) proposed the assessment of environmental performance using DDFs, taking into account the production of undesirable outputs (b). The technology defined for environmental performance assessments is given by (2.12).

$$
\vec{D}(x,y,b;g_x,g_y,g_b) = \max \{\beta : (x + \beta g_x, y + \beta g_y, b + \beta g_,) \in \Phi\} \tag{2.12}
$$

Chung et al. (1997) defined undesirable outputs (b) as by-products of a production process that cannot be reduced without reducing the levels of desirable outputs (y) or increasing the input consumption (x). As a consequence, the authors built a model to consider weakly disposable and null-jointness among desirable outputs and undesirable outputs.

The Directional Distance Function (2.12) in the presence of undesirable outputs can be estimated by solving the following linear programming problem (2.13), assuming constant returns to scale (Chambers et al., 1996a; Chung et al., 1997).

$$
\begin{aligned}
\vec{D}(x,y,b;g_x,g_y,g_b) \quad & = \max \beta_k \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ik} - \beta_k g_x \qquad i = 1,\dots,m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk} + \beta_k g_y \qquad r = 1,\dots,r \\
& \sum_{j=1}^{n} \lambda_j b_{qj} = b_{qk} - \beta_k g_b \qquad q = 1,\dots,h \\
& \lambda_j \geq 0 \qquad j = 1,\dots,n
\end{aligned}
\tag{2.13}
$$

In model (2.13), the factor β_k indicates the extent of the DMU's inefficiency. It corresponds to the maximal feasible contraction of inputs (x_{ik}), and undesirable outputs (b_{qk}) and expansion of outputs (y_{rk}) that can be achieved simultaneously. Therefore, DMU k is radially efficient when $\beta_k = 0$. Similarly to the DEA models presented in section 2.2.1, λ_j are the intensity variables representing the convex combination of the peers.

Note that the constraints specified for variables (b_q) are equalities representing the assumption of weak disposability and null-jointness inherent in environmental performance assessments.

The definitions regarding disposability depend on the assumptions underlying the models specified for evaluating a given production system. For instance, Färe et al. (1996) provided an empirical study proposing an environmental index for performance assessment and productivity analysis in power plants assuming weak disposability of air emissions as undesirable outputs. Another example is the work of Liu et al. (2010) describing a few practical situations with free disposability of undesirable outputs. For instance, electric generators often have pollution control systems, including equipment to reduce the undesirable output of sulfur dioxide (SO_2) resulting from the production process. As a consequence, SO_2 could be "freely" increased, at least to some extent, by shutting down these pollution control systems (Liu et al., 2010). Decisions regarding the disposability of variables is an issue often discussed in the literature (for further details see Kuosmanen and Podinovski, 2009; Yang and Pollitt, 2010; Podinovski and Kuosmanen, 2011).

2.3 Measures of Productivity Change

2.3.1 Malmquist Productivity Index

The Malmquist Index was introduced by Caves et al. (1982). These authors named it after Sten Malmquist, who had earlier proposed constructing input quantity indices as ratios of distance functions (Malmquist, 1953). The Malmquist Index was treated as a theoretical one until its enhancement by Färe et al. (1989), see Färe et al. (1992) and Fare et al. (1994) for further details on the Malmquist index.

Shephard (1953) and Malmquist (1953) separately introduced the distance functions as an apparatus for economics. Shephard mainly used it for duality theory, while Malmquist applied it to index number theory. To introduce the concept of distance functions, consider the technology of production Φ^t defined for period t (Φ_t) as shown in (2.14), with input $x^t \in \Re^m_+$ and outputs $y^t \in \Re^s_+$.

$$\Phi^t = \{(x^t, y^t) : x^t \text{ can produce } y^t\} \tag{2.14}$$

Based on the definitions of Shephard (1970) and Färe et al. (1985, 1992), the input distance function is defined in relation to the technology Φ^t as the maximal feasible contraction of x^t that enables producing y^t, as shown in (2.15).

$$D_i^t(x^t, y^t) = \max\{\delta : (\frac{x^t}{\delta}, y^t) \in \Phi^t\} \tag{2.15}$$

The input distance function (2.15) gives the reciprocal of the minimum factor $\frac{1}{\delta}$ by which the input vector x^t can be proportionally contracted while keeping the current level of the outputs. The input technical efficiency is therefore defined as $\frac{1}{Di(x,y)}$. Note that $D_i(x^t, y^t) \geq 1$ if and only if $(x^t, y^t) \in \Phi^t$. $D_i^t(x^t, y^t) = 1$ if and only if the point is located on the frontier of the technology.

The input-oriented Malmquist Index requires the specification of two within-period Shephard input distance functions: $D_i^{t+1}(x^{t+1}, y^{t+1})$. In addition, the MI also requires the specification of two mixed-period distance functions as shown in (2.16) and (2.17).

$$D_i^t(x^{t+1}, y^{t+1}) = \max\{\delta : (\frac{x^{t+1}}{\delta}, y^{t+1}) \in \Phi^t\} \tag{2.16}$$

$$D_i^{t+1}(x^t, y^t) = \max\{\delta : (\frac{x^t}{\delta}, y^t) \in \Phi^{t+1}\} \tag{2.17}$$

In the first mixed-period, the distance function measures the maximal proportional reduction to inputs required to make a DMU (x^{t+1}, y^{t+1}) in time period $t+1$, efficient in relation to technology Φ^t. The second mixed-period measures the maximal proportional reduction to inputs required to make a DMU (x^t, y^t) in time period t efficient in relation to technology Φ^{t+1}.

Caves et al. (1982) defined an input-based Malmquist Productivity Index relative to a single technology. The base technology can be Φ^t, defined for period t, as shown in shown in (2.18) or Φ^{t+1}, defined for period $t+1$, as shown in (2.19).

$$MI_i^t = \frac{D_i^t(x^t, y^t)}{D_i^t(x^{t+1}, y^{t+1})} \tag{2.18}$$

$$MI_i^{t+1} = \frac{D_i^{t+1}(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} \tag{2.19}$$

The values of MI_i^t and MI_i^{t+1} can be greater, equal or smaller than one. These values indicate respectively growth, stagnation or decline of productivity between periods t and $t+1$. The values of the MI_i calculated using expressions (2.18) and (2.19) can be different because their reference technologies may differ.

Färe et al. (1985) were the first to note that Shephard distance functions can be estimated using DEA models, assuming constant returns to scale. A few years later, Färe et al. (1992) defined an input-oriented productivity index based on the geometric mean of the two Malmquist indexes referring to the technology at time periods t (see expression (2.18)) and $t+1$ (see expression (2.19)). The geometric mean was proposed to avoid arbitrariness between the choice of base periods for the evaluation of productivity change.

The input-oriented Malmquist Index (Färe et al., 1992) can be estimated using expression (2.20).

$$MI_i^{t,t+1} = \left[\frac{D_i^t(x^t, y^t)}{D_i^t(x^{t+1}, y^{t+1})} \frac{D_i^{t+1}(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} \right]^{\frac{1}{2}} \tag{2.20}$$

Färe et al. (1992) highlighted that this index can be further decomposed into an efficiency change index ($EC_i^{t,t+1}$) and a technological change index ($TC_i^{t,t+1}$), such that $M_i^{t,t+1} = E_i^{t,t+1} \times T_i^{t,t+1}$. Enhancements in the efficiency change component are evidence of catching up to the frontier, while enhancements in the technological change component indicate frontier shift between t and $t+1$. The components are obtained by rewriting the index (2.20) as shown in (2.21) and (2.22):

$$EC_i^{t,t+1} = \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} \tag{2.21}$$

$$TC_i^{t,t+1} = \left[\frac{D_i^{t+1}(x^t, y^t)}{D_i^t(x^t, y^t)} \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^{t+1}, y^{t+1})} \right]^{\frac{1}{2}} \tag{2.22}$$

Similarly, the specification of the Shephard output distance functions (Shephard, 1970) is required to estimate an output-based Malmquist index (Färe et al., 1989). Expression (2.23) defines the Shephard output distance function in period t.

$$D_o^t(x^t, y^t) = \min\{\theta : (x^t, \frac{y^t}{\theta}) \in \Phi^t\} \tag{2.23}$$

The Shepard output distance function (2.23) gives the reciprocal of the maximum factor $\frac{1}{\theta}$ by which the output vector y^t can be proportionally expanded, given the input levels. Therefore, D_o^t corresponds to a radial efficiency measure. Note that $D_o^t(x,y) \leq 1$ if and only if $(x^t, y^t) \in \Phi^t$, and $D_o^t(x^t, y^t) = 1$ if and only if (x^t, y^t) is on the frontier of the technology.

The Shepard output distance functions for the mixed-periods are defined in (2.24) and (2.25).

$$D_o^t(x^{t+1}, y^{t+1}) = \min\{\theta : (x^{t+1}, \frac{y^{t+1}}{\theta}) \in \Phi^t\} \tag{2.24}$$

$$D_o^{t+1}(x^t, y^t) = \min\{\theta : (x^t, \frac{y^t}{\theta}) \in \Phi^{t+1}\} \tag{2.25}$$

The output-oriented Malmquist Index $(MI_o^{t,t+1})$ was proposed by Färe et al. (1989), as shown in (2.26).

$$MI_o^{t,t+1} = \left[\frac{D_o^t(x^{t+1},y^{t+1})}{D_o^t(x^t,y^t)} \frac{D_o^{t+1}(x^{t+1},y^{t+1})}{D_o^{t+1}(x^t,y^t)}\right]^{\frac{1}{2}} \tag{2.26}$$

The components of efficiency change and technological change, obtained by decomposing equation (2.26), are shown in (2.27) and (2.28).

$$EC_o^{t,t+1} = \frac{D_o^{t+1}(x^{t+1},y^{t+1})}{D_o^t(x^t,y^t)} \tag{2.27}$$

$$TC_o^{t,t+1} = \left[\frac{D_o^t(x^t,y^t)}{D_o^{t+1}(x^t,y^t)} \frac{D_o^t(x^{t+1},y^{t+1})}{D_o^{t+1}(x^{t+1},y^{t+1})}\right]^{\frac{1}{2}} \tag{2.28}$$

The values of $MI_i^{t,t+1}$, $MI_o^{t,t+1}$ and its components can be greater, equal or smaller than one. These values indicate respectively productivity growth, stagnation or decline between periods t and $t+1$. Improvements in the efficiency change component represent evidence of catching up to the frontier, while improvements in the technological change component are evidence of advances in the frontier position between the two time periods.

2.3.2 Luenberger Productivity Indicator

The Luenberger Productivity Indicator $(L^{t,t+1})$, proposed by Chambers (1996), is a distance-based measure used in the context of evaluations with DDF. This index was proposed after Luenberger (1992a,b) that developed the shortage function that allows for simultaneous contraction of inputs and expansion of outputs.

The Lunberger Productivity Indicator $(L^{t,t+1})$ is estimated using differences between Directional Distance Functions. The formulation of the Luenberger Productivity Indicator $(L^{t,t+1})$ is reported in (2.29).

$$\begin{aligned} L^{t,t+1} = \frac{1}{2}\big[&\vec{D}^{t+1}(x^t,y^t;g_x,g_y)-\vec{D}^{t+1}(x^{t+1},y^{t+1};g_x,g_y) \\ &+\vec{D}^t(x^t,y^t;g_x,g_y)-\vec{D}^t(x^{t+1},y^{t+1};g_x,g_y)\big] \end{aligned} \tag{2.29}$$

To avoid an arbitrary choice of base years, formulation (2.29) expresses an arithmetic mean of the differences evaluated for the base year t and the base year $t+1$. Note that model (2.11) can be used to estimate the Directional Distance Functions. This model must be adapted to consider single-period evaluations or mixed-period evaluations. The change in productivity can be interpreted as the change in the average distance between the original performance levels of the DMUs and their maximum performance levels in t and $t+1$.

Chambers et al. (1996b) and Färe and Grosskopf (2005) highlight that the Luenberger Indicator can be decomposed into two parts. The first component reflects the efficiency change over time $(LEC^{t,t+1})$, whilst the second component quantifies the technological change overtime $(LTC^{t,t+1})$.

The formulation of these components is reported in (2.30) and (2.31).

$$LEC^{t,t+1} = \vec{D}^{t}(x^{t},y^{t};g_x,g_y) - \vec{D}^{t+1}(x^{t+1},y^{t+1};g_x,g_y) \tag{2.30}$$

$$\begin{aligned} LTC^{t,t+1} = \tfrac{1}{2}\big[&\vec{D}^{t+1}(x^{t+1},y^{t+1};g_x,g_y) - \vec{D}^{t}(x^{t+1},y^{t+1};g_x,g_y) \\ &+ \vec{D}^{t+1}(x^{t},y^{t};g_x,g_y) - \vec{D}^{t}(x^{t},y^{t};g_x,g_y)\big] \end{aligned} \tag{2.31}$$

The Luenberger Indicator and its components can have strictly positive values $(L^{t,t+1} > 0)$ indicating productivity increase, negative values $(L^{t,t+1} < 0)$ indicating productivity decline and null values $(L^{t,t+1} = 0)$ indicating stagnation of productivity between the periods t and $t+1$.

Changes in efficiency $(LEC^{t,t+1})$ indicate whether the DMU under assessment has approached the frontier or moved away from it. Shifts in technology $(LTC^{t,t+1})$ indicate whether the frontier advanced or retreated between the periods analyzed.

2.4 Conclusions

This chapter provided an overview of the conceptual foundations for the assessment of performance. The standard DEA and DDF models were presented. In addition, the measures of productivity change estimated using DEA and DDF models were also reviewed.

CHAPTER 3

Expanded Eco-efficiency Assessment of Large Mining firms

Abstract Assessing eco-efficiency of companies is important to ensure the creation of wealth without compromising the needs of future generations. This work aims to extend the eco-efficiency concept by including in the assessment new features related to environmental benefits and environmental burdens. This concept is implemented using an innovative Directional Distance Function model, which searches for improvements in the magnitude of the indicators and in the composition of the resources consumed. This framework can help firms to become more sustainable by replacing non-renewable inputs with "greener" alternatives. We present an empirical application to large mining companies. Different scenarios regarding managerial priorities for adjustments to firms' economic and environmental indicators are explored. The results obtained and their managerial implications are discussed in the context of mining firms activity.

Keywords : Eco-efficiency, Directional Distance Function, Mining Companies, Renewable Resources.

3.1 Introduction

Minerals and metals are fundamental raw materials for contemporary society, as they are core supplies for supporting the life of humankind (ICMM, 2012b). These materials are crucial for several sectors, ranging from basic industries to the cosmetics industry. The high global demand for mineral commodities has led to the development of one of the most environmentally impactful economic activities on the planet: mining. However, unlike agriculture that allows one to choose what and where to produce, mining can only take place where minerals are available and can only be explored in economically viable conditions (Bell and Donnelly, 2006, p.12). The growing need for both metallic and non-metallic mineral resources has been especially propitious for the economic development of a few countries, including China, Australia, Brazil, Russia, Ukraine, South Africa and Canada. These countries own a significant proportion of the global mineral reserves, hosting the headquarters of the largest multinational mining companies(USGS, 2014).

According to Hartman and Mutmansky (2002, p.7-15), the industrial mining cycle consists of a broad macro process with five long-term stages, each with a strong impact on the environment. The stages of this process are Ore Prospection (2–3 years), Exploration (2–5 years); Development (2–5 years), Exploitation or Production (10–30 years) and Reclamation (1–10 years), when mines are shut down.

Industrial mining has recently garnered increased attention due to its vast environmental and social impacts (e.g.; Mahdiloo et al., 2015; Pimentel et al., 2015).Kumar and Nikhil (2014) state that these impacts potentially result in ecological imbalances such as contamination of the air, water or soil and the devastation of native forest or biomes. In addition, there are risks related to the depletion of natural resources, such as ore deposits, water, and fossil fuels.

Mining companies face unprecedented social pressure to state their commitment to seeking long-term competitive advantages through responsible management of environmental and social issues (Botin, 2009, p.2). In response, the relationship between the economic benefits produced and their social and environmental impacts is monitored by several initiatives (e.g., ICMM Principles, GRI Mining sectoral guidelines).

Scientific studies involving quantitative assessments of eco-efficiency in mining are also available in the literature (e.g.; van Berkel, 2007; Salmi, 2007; Wessman et al., 2014). Eco-efficiency is evaluated by the ratio of economic wealth to the environmental impacts of exploitation. Eco-efficiency traditionally involves an input–output analysis that seeks to explore the potential for reducing resources' consumption and environmental impacts, given the observed levels of turnover or profit (e.g.; Jasch, 2009; Zhang et al., 2008) However, the perspective of minimizing resources often ignores other important criteria of firms' environmental performance: the balance between the use of renewable resources (e.g., wind, solar energy or recycled materials) and non-renewable resources.

Enhancements on the earlier work by Oliveira et al. (2015) are introduced in this chapter, which aims to improve the eco-efficiency evaluation of firms by proposing several innovative features for the performance assessment. The first contribution of this study is to provide a comprehensive view of firm activity by using an enhanced range of indicators to assess eco-efficiency. In addition to the indicators traditionally used for this purpose, i.e., economic benefits (e.g., value-added) and environmental burdens (resources consumed and emissions of pollutants), indicators of environmental benefits were included (e.g., use of renewable resources and ecosystems' conservation initiatives). The second contribution is the development of an enhanced optimization model based on a directional distance function (DDF). Whilst previous eco-efficiency models sought exclusively for adjustments to the magnitude of the indicators (volumes), the new model proposed in this work pursues improvements in the balance between renewable and non-renewable resources (shares). The different specifications of the directional vector allow for the exploration of different scenarios reflecting the priorities for adjustments to the firms' benefits and burdens. In the empirical part of this study, the results obtained from an illustrative application of the new method are discussed.

This chapter is organized as follows. Section 3.2 presents a theoretical review of the eco-efficiency concept. It also explores the criteria defined by international standards and empirical studies on this topic. Section 3.3 presents the methodology adopted and the enhanced optimization model. Section 3.4 4 presents an illustrative application, including the indicators framework and the discussion of results for four scenarios. Section 3.5 concludes the paper by discussing the main contributions of this study and outlining future research opportunities.

3.2 Eco-efficiency Review

3.2.1 Evolution of the Concept

Discussions of eco-efficiency can be traced back to the 1970s when global discussions in the search for a healthy and productive environment gained momentum (Zhang et al., 2008). The first seminal publication is the "Declaration of the United Nations Conference on the Human Environment" (UNEP, 1972), which stated that protection and improvement of the human environment is a major issue for the well-being of peoples and economic development throughout the world. The seminal work of McIntyre and Thornton (1974), entitled"Environmental divergence: Air pollution in the USSR" was published shortly after. These authors discussed the environmental impact of urban welfare, generated by the commitment to economic development. Finally, the report "Canada as a Conserver Society" (SCC, 1977), pioneered the discussion on topics such as energy efficiency, conservation, the use of renewable resources and material flow analysis.

During the 1980s, the discussions on this theme mainly focused on the challenges faced by governments and society regarding the achievement of environmental quality. During this period, some of the most emblematic milestones on global environmental efficiency emerged. It is worth mentioning other seminal publications, such as the report "Our Common Future" (UN, 1987), the release of the first edition of the "Cleaner Production Program" in 1989 UN (2015d) and the release of "Environmental rationality"(Schaltegger and Sturm, 1990).

During the 1990s, the definition of eco-efficiency was first proposed by Schmidheiny (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" (WBCSD, 2000, p.9). This concept was popularized by the OCDE (1998) and was soon adopted in studies oriented to the quantitative assessment of environmental and economic performance. As a result, environmental efficiency and eco-efficiency issues began to figure prominently in the scientific fields of Sustainable Development and Business Management.

The World Business Council for Sustainable Development (WBCSD, 2000, p.15) has enriched the concept of Schmidheiny (1992) by describing eco-efficiency at the firm level as a business capability for keeping the business competitive (i.e., increase value), reducing material and energy requirements, minimizing the dispersion of toxic wastes and maximizing the sustainable use of renewable resource. We adopted the definition of the WBCSD, as it is considered the most comprehensive. To the best of our knowledge, this is the first study with all components of the WBCSD concept operationalized at the firm level.

3.2.2 Assessment Criteria and Indicators

For the United Nations Environment Program (UN, 2015d), the assessment of eco-efficiency can be conducted at the macro level (e.g., worldwide or country level), meso level (e.g., industry level) and micro level (e.g., product or company level), wherein the selected indicators vary depending on the level of detail. The main international sustainability guidelines focusing at the micro and meso levels were reviewed, including ISO (2003) and ISO (2012), WBCSD (2000), UNCTAD (2004), Council of the European Parliament (2004), GRI (2011), ICMM (2013). The purpose of this review is to identify common criteria recommended by these initiatives and their scope of application.

WBCSD proposes three assessment criteria from a competitiveness perspective. The first is minimizing the consumption of natural resources, including land, energy, water, and materials. The second is minimizing all dispersions on nature and fostering the sustainable use of renewable resources. The third is maximizing the products (or services) value by enhancing their durability, functionality, recyclability and flexibility.

ISO14045:2012 states two criteria for eco-efficiency assessments. The first criterion is environmental, which focuses on reducing air emissions and controlling waste. The second criterion is the product system value, which includes customer support and user-friendly functions (ISO, 2012, p.15- 22).

UNCTAD (2004) focuses on financial accounting, climate changes and avoiding natural resources depletion. It proposed minimizing the following pressures: water footprint, energy use, global warming, dispersions of ozone-depleting substances and waste.

The Council of the European Parliament (2004) discusses the “polluter pays” principle, which reinforces the corporation’s moral obligation to minimize environmental damage risks and avoid reputational complications for legal non-compliance.

GRI (2011) approach environmental performance according to ten criteria (materials, energy, water, biodiversity, emissions, effluents, waste, products and services, compliance and transport). Each criterion must be reported according to a specific set of indicators.

ICMM (2013) proposes three criteria related to eco-efficiency: seeking the continuous improvement of environmental performance, contributing to the conservation of biodiversity and development of integrated plans for land use, contributing to the social, economic and institutional development of communities nearby exploitation.

Based on these six initiatives and their associated indicators, five assessment criteria are proposed to serve as foundations for an enhanced eco-efficiency assessment of industries.

1. **Business competitiveness or wealth generation (Y)**: Describes the organization’s capability to generate wealth. It is usually represented by the following indicators: wealth generation (Y_1) (e.g., value-added, profit or return on investment) or production volume (Y_2). Given the current overcapacity in commodities production worldwide (including mining products), wealth indicators are more appropriate to represent the economic dimension of eco-efficiency of mining firms.

2. **Use of non-renewable resources (N)**: Encompasses the consumption of three input indicators: non-renewable energy (N_1), withdraw water (N_2) and other material requirements (N_3).

3. **Dispersions (D):** Refers to the emission of toxic particles and waste in the environment. Toxic dispersions have received great public attention since the 1960s due to their effect on climate change and the risks posed to human health and ecosystems in general.

   (a) Waste (D_1): Evaluates the amount of disposed material, including hazardous or non-hazardous substances.

   (b) Air emissions (D_2): Reflects the introduction of particles into the atmosphere. Indicators such as greenhouse gas (GHG) and Ozone Depleting Substances (ODS) emissions are included here.

   (c) Spills (D_3): Reflects the organizations' compliance with environmental legislation on oil and fuels spills.

   (d) Financial burdens for environmental damages (D_4): Reflects the "polluter pays" principle whereupon an organization whose activity has caused damage, or the imminent threat of damage, to the environmental is to be held financially liable.

4. **Sustainable use of renewable resources (R)**: Refers to avoiding depletion through the renewable use of energy (R_1), water (R_2) and materials (R_3).

5. **Conservation (C):** Reflects reclamation of exploited areas and the support of protected areas with high biodiversity. Conservation is a highly desirable practice to ensure the provision of resources for future generations. The indicators reflecting conservation are the protected areas supported (C_1) and environmental investments (C_2).

After identifying the main issues to be taken into account in eco-efficiency assessments, the empirical studies available in the literature were reviewed. We focused on studies at the firm or sectorial level, published between 1997 and 2015, and using Data Envelopment Analysis (DEA), Directional Distance Functions (DDF) or other quantitative methods used in the assessment. These approaches are based on the specification of weights for the aggregation of key performance indicators. Table 3.1 summarizes the indicators used in the studies reviewed and Table 3.2 explores the alignment among the indicators and the criteria proposed in this section. The studies cover different sectors, including agriculture, manufacturing, and energy.

Table 3.1: Indicators used in empirical studies.

Authors	Economic indicators	Indicators	Sector
Glauser and Müller (1997)	Net profit	Raw materials, end products, total waste before end-of-pipe treatment, valorised by-products, waste	Manufacturing
Dyckhoff and Allen (2001)	Production volume	Emissions (CO_2,$CFCl_3$,CF_2CL_2,CCL_4,$CHCl_3$)	Energy
De Koeijer et al. (2002)	Return above costs, production volume	Lutum content, mineral N soil, N fertilizer, N product, N surplus, herbicides, Env. impact herbicides	Agriculture
Hanssen et al. (2003)	Turnover	Material consumption waste (per type)	Packaging
Korhonen and Luptacik (2004)	Production volume	Emissions (NO_x, SO_2)	Energy
Kuosmanen and Kortelainen (2005)	Production volume	Fuel consumption, climate change, acidification, smog formation, dispersion of particle	Road transportation
Hua et al. (2007)	Production volume	Labour, Capital, BOD-Q, BOD	Manufacturing
Zhang et al. (2008)	Value-added	Water resource, raw mining resource, energy, dispersions (COD, NO_x,SO_2, soot, dust, solid waste)	Mining
Charmondusit and Keartpakpraek (2011)	Net sale, gross margin	Material flow, fossil fuel energy, withdraw water, hazardous waste	Petrochemical
Mahlberg and Sahoo (2011)	GDP	GHG, labor and capital	Supply Chain
Picazo-Tadeo et al. (2012)	Net incomes	Rates of erosion, pesticide risk, energy, CO_2 fixation	Agriculture
Zhou et al. (2012)	Production volume	CO_2 emissions	Energy
Beltrán-Esteve et al. (2013)	Value-added	Rates of erosion, pesticide risk, energy, CO_2 fixation, biodiversity	Agriculture
Koskela (2014)	Value-added	Emissions (NO_x, SO_2, COD, waste)	Energy
Arabi et al. (2015)	Production volume	NO_x, SO_2, CO_x emission, fuel consumption	Energy
Mahlberg and Luptacik (2014)	Final demand	Emissions, water, raw materials	Supply Chain
Mahdiloo et al. (2015)	Sales, ROA	CO_2, environmental R&D investments, energy consumption, amount of employees	Multi-sectorial (mining included)

Table 3.2: Criteria used in empirical studies.

Author	Criteria: Y		N				D				R		C	
	Y1	Y2	N1	N2	N3	D1	D2	D3	D4	R1	R2	R3	C1	C2
Glauser and Müller (1997)	x				x			x				x		
Dyckhoff and Allen (2001)		x					x							
De Koeijer et al. (2002)	x	x			x									
Hanssen et al. (2003)	x	x			x	x	x							
Korhonen and Luptacik (2004)		x							x					
Kuosmanen and Kortelainen (2005)		x	x		x	x	x							
Hua et al. (2007)		x			x	x								
Zhang et al. (2008)	x		x	x	x	x	x							
Charmondusit and Keartpakpraek (2011)	x		x	x	x	x								
Mahlberg and Sahoo (2011)	x													
Picazo-Tadeo et al. (2012)	x		x				x	x						
Zhou et al. (2012)		x					x							
Beltrán-Esteve et al. (2013)	x		x				x	x					x	
Koskela (2014)	x					x	x							
Arabi et al. (2015)		x					x							
Mahlberg and Luptacik (2014)		x		x	x		x							
Mahdiloo et al. (2015)	x		x				x							x

Regarding business competitiveness and wealth generation criteria (Y), all papers included indicators for this dimension in the eco-efficiency assessment. The value-added (Y_1) was selected in ten papers for representing the economic dimension while the volume of production (Y_2) was used in nine of the papers reviewed.

The indicators for non-renewable resources (N) have limited coverage in most papers. The consumption of raw materials (N_3) was often included in the input set of the eco-efficiency studies (considered in eight papers). Non-renewable energy consumption (N_1) was included in six papers, and water consumption (N_2) was included in three papers. The studies of Zhang et al. (2008) and Charmondusit and Keartpakpraek (2011) were the only ones including all indicators for group N.

Regarding dispersions (D), air emissions (D_2) were taken into account in most studies (11). Waste (D_1) was also frequently included in the assessments (six studies). Spills (D_3) were considered in three studies, but their magnitude was not taken into account. The financial burdens for environmental damages (D_4) were considered by only one author, but the amount of money involved was not reported.

The analyzed studies failed to account for the positive aspects of environmental policies, such as the use of renewable resources (R) and conservation (C). Glauser and Müller (1997) is the only eco-efficiency study accounting for firm policies regarding reused and recycled materials, Mahdiloo et al. (2015) is the only study covering environmental investments (C_2), and Beltrán-Esteve et al. (2013) is the only study including biodiversity conservation (C_1) in the assessment. One possible reason for the deprecation of criteria R and C is the fact that these indicators cannot fit the traditional perspective of minimization of ecological impacts within optimization models, as renewable resources and conservation efforts should be maximized. Ergo, the enhancement of eco-efficiency models to enable the incorporation of "desirable inputs", such as renewable resources or implementation of conservation policies, is an issue that deserves further research.

3.3 Methodology

3.3.1 Directional Distance Functions

Consider that the production technology Φ models the transformation of inputs, denoted by $x \in \Re^m_+$, into outputs, denoted by $y \in \Re^s_+$, as shown in (3.1). The production technology (T) consists of the set of all feasible input/output vectors for a certain production process.

$$\Phi = \{(x,y) : x \text{ can produce } y\} \tag{3.1}$$

The assessment of firms' performance involves a comparison between the location of the input/output vectors within the technology and its frontier, defining the best-practice standards.

Chambers et al. (1996a), based on Luenberger (1992a,b) shortage function, proposed a directional distance function that allows a producer to scale input and outputs simultaneously along a path that is defined according to a directional vector g. The general form of the directional distance function is presented in (3.2).

$$\vec{D}(x,y,g_x,g_y) = \max : \{\beta : (x+\beta g_x, y+\beta g_y) \in \Phi\} \tag{3.2}$$

Formulation (3.3) displays the standard formulation of a Directional Distance Function model. It resorts to linear programming to identify the optimum value of β for a firm k, leading to production on the frontier of the technology.

$$
\begin{aligned}
\max \quad & \beta_k && && (3.3)\\
\text{s.t.} \quad & \sum_j \lambda_j y_{rj} \geq y_{rk} + \beta_k g_{y_r} && r = 1, \ldots, s && (3.3a)\\
& \sum_j \lambda_j x_{ij} \leq x_{ik} - \beta_k g_{xi} && i = 1, \ldots, m && (3.3b)\\
& \lambda_j \geq 0 && j = 1, \ldots, n &&
\end{aligned}
$$

In model (3.3), y_{rj} are the outputs generated and x_{ij} are the inputs consumed by firm j. Similarly, y_{rj} and x_{ij} are the outputs and inputs observed in firm k under assessment. The components of the nonzero vector $g = (-g_{x_i}, g_{y_r})$ indicate the direction of the change for the inputs and outputs. Positive values for the components are associated with the expansion of outputs and negative values are associated with the contraction of inputs. The optimum value of β_k^* can be interpreted as the firms' scope for improvement (inefficiency or distance from the frontier). Positive values of β_k^* are associated with inefficient firms. The variables λ_j, in the left-hand side of the constraints (3.3a) and (3.3b), are called intensity variables, and can be interpreted as the multipliers defining a point on the frontier obtained as a linear combinations of other firms in the sample (called peers), against which firm k is compared when computing its inefficiency level β_k^*. A value of β_k^* equal to zero means that firm k is at the frontier, indicating that it is relatively efficient. For DEA-based studies, the notion of relative efficiency is as follows: "A Decision Making Unit decision (DMU) is rated as fully (100%) efficient in the basis of available evidence if and only if the performance of other DMUs does not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs" (Cooper et al., 2011, p.3).

The directional vector g can assume a variety of configurations. The most common specifications are directional vectors with unitary components, $g = (-1, 1)$, or with the components equal to the current value of the inputs and outputs for firm k under assessment $g = (-x_{ik}, y_{rk})$. The directional vector $g = (-1, 1)$ is more appropriate for situations with all inputs and outputs measured in the same units. In these cases, the value of β_k^* (inefficiency) can be interpreted as the amount of resources' overuse and outputs' underachievement for firm k under assessment, expressed in the units of measurement of each input and output. The directional vector $g = (-x_{ik}, y_{rk})$ has the advantage of allowing the interpretation of the value of β_k^* in terms of the proportional improvements to inputs and outputs required for firm k to achieve the frontier of the technology. This was the vector specified for our illustrative application to the evaluation of eco-efficiency of mining firms. If the decision maker (DM) desires to prioritize efforts to enhance the company's efficiency by searching for improvements in specific input and output dimensions, other directional vectors can be specified. For example, the directional vectors can have some components equal to zero, meaning that these dimensions are not the priority, such that emphasis is placed only on specific inputs and outputs. See Färe and Grosskopf (2010, 2004) for further considerations on this topic.

The pictorial interpretation of the value of β_k for the directional vector $g = (-x_{ik}, y_{rk})$ is shown in Fig.3.1. The simple example involves three firms with only one input and one output (see Table

3.3).

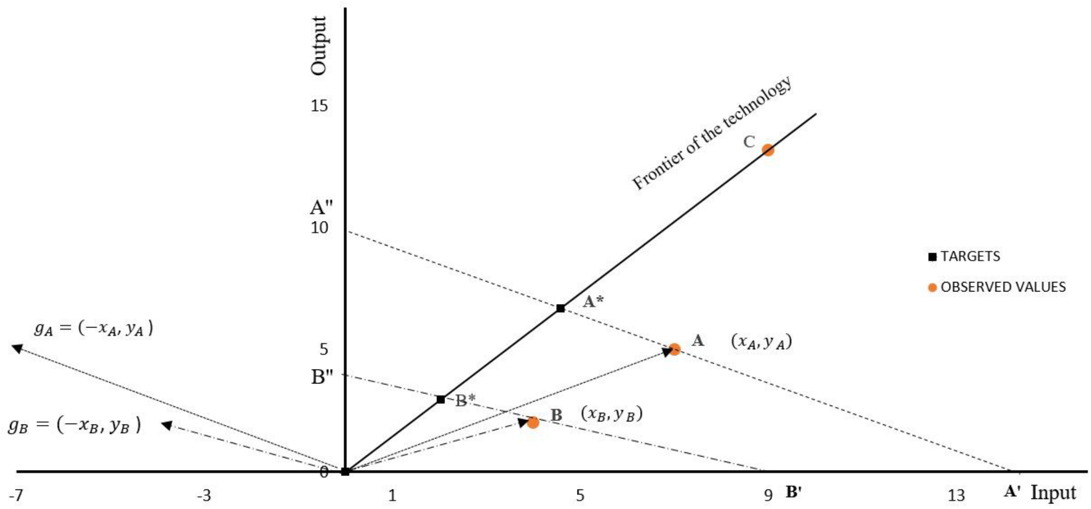

Figure 3.1: Representation of the frontier of technology.

Table 3.3: Data and results in the example

Firm	Observed input	Observed output	β_k^*	Target input	Target output	Peers (λ)
A	7	5	0.344	4.59	6.72	C(0.509)
B	4	2	0.492	2.03	2.98	C(0.226)
C	9	13.2	0	9	13.2	C(1)

Firm C operates on the frontier and has β_c equal to zero, meaning that it is relatively efficient. A has an inefficiency value of $\beta_A^* = 0.344$, representing the proportional improvement required on inputs and outputs for this DMU to reach the frontier. An efficient operations level for firm A implies an input level of $7 \times (1 - 0.344) = 4.59$ and an output level of $5 \times (1 + 0.344) = 6.72$. These are the targets for firm A, represented by A^* in Fig.3.1. The graphical interpretation of the value of β_A^* for firm A is the potential for equiproportional improvement for the input and output values, given by $\frac{\overline{AA^*}}{\overline{AA'}}$ (using as reference the input axis) or equivalently $\frac{\overline{AA^*}}{\overline{AA''}}$ (using as reference the output axis).

3.3.2 The Expanded Eco-Efficiency Model

The assessment here proposed involves an optimization with two stages, whose formulation in shown in (3.4). The first stage seeks for performance improvements through the minimization of burdens (total amount of resources consumed and dispersions), and the maximization of benefits (conservation and wealth generation). The inclusion of the conservation criterion in the assessment is an innovative feature of model (3.4), which approaches a firm's commitment to the needs of future generations. This first stage is focused on determining the value of β_k (inefficiency or potential for improvement) for the inputs and outputs of the firm under assessment. The second stage explores improvement opportunities for balancing the proportion (ρ_{ik}) of renewable resources in the total amount of resource i $(i = 1,\ldots,I)$ consumed. This allows the firms to become more sustainable by replacing non-renewable resources with more sustainable alternatives. This second stage is another innovative feature of our eco-efficiency model, which intends to give credit to the sustainable use of renewable resources. If the companies do not have data concerning renewable and non-renewable amounts of the resources consumed, this second stage of assessment cannot be executed. Alternatively, the second stage can be conducted for a subset of resources with data available regarding renewable and non-renewable resources.

$$\max \beta_k + \varepsilon \sum_{i=1}^{I} S_i \tag{3.4}$$

$$\text{s.t.} \sum_j \lambda_j Y_{rj} \geq Y_{rk} + \beta_k \, g_{Y_r} \qquad r = 1,\ldots,R \tag{3.4a}$$

$$\sum_j \lambda_j C_{qj} \geq C_{qk} + \beta_k \, g_{C_q} \qquad q = 1,\ldots,Q \tag{3.4b}$$

$$\sum_j \lambda_j D_{lj} \leq D_{lk} - \beta_k \, g_{D_l} \qquad l = 1,\ldots,L \tag{3.4c}$$

$$\sum_j \lambda_j T_{ij} \leq T_{ik} - \beta_k \, g_{T_i} \qquad i = 1,\ldots,I \tag{3.4d}$$

$$\sum_j \lambda_j \rho_{ij} = \rho_{ik} + S_i \qquad i = 1,\ldots,I \tag{3.4e}$$

$$S_i,\ \beta_k,\ \lambda_j \geq 0$$

In (3.4) β_k is the eco-efficiency score for firm k under assessment. Y_{rj} are the economic benefits $(r = 1,\ldots,R)$ generated by firm $j (j = 1,\ldots,J)$, C_{qj} are conservation indicators $(q = 1,\ldots,Q)$ associated with firm j. D_{lj} are dispersion $(l = 1,\ldots,L)$. T_{ij} is the total amount of each resource $i(i = 1,\ldots,I)$, including both non-renewable inputs (N_{ij}) and renewable inputs (R_{ij}) $(T_{ij} = N_{ij} + R_{ij})$, consumed by j, such that $(T_{ij} = N_{ij} + R_{ij})$. ρ_{ij} is the proportion of each resource $i(i = 1,\ldots,I)$ that comes from renewable sources for j, i.e., $\rho_{ij} = \frac{R_{ij}}{T_{ij}}$. ρ_{ik} is the proportion of renewable resources in input i consumed by the firm k under assessment. In the environmental dimension, C_{qk} are the conservation indicators and D_{lk}, T_{ik} are respectively dispersion indicators and total resource use observed for firm k.

The directional vector $g = [g_{Y_r}, g_{C_q}, -g_{D_l}, -g_{T_i}]$ specifies the direction of the projection to the frontier used to derive the eco-efficiency score. Positive values mean that the indicators should be increased (constraints (3.4a) and (3.4b)), whereas negative values lead to reductions (constraints (3.4c) and (3.4d)).

Looking beyond the quantities of the resources consumed, constraint (3.4e) requires the assessed firms to manage the composition of the resources consumed. It implies that the firm under assessment must be compared to a point on the frontier with a balance between the renewable resources better than (or at least equal to) the original values observed in the firm under assessment. The search for improvement opportunities in the composition of inputs consumed is accomplished through the inclusion of slack variables (s_i) in constraint (3.4e), transforming it into an equality, whereas improvements in the original value of ρ_{ik} are guaranteed by searching for the maximization of slacks in the objective function. The slacks are multiplied by an infinitesimal (ε) to ensure that the search for a better value of ρ_{ik} is done only on a second stage, without affecting the optimal value of β_k. The slack is equal to the difference between the target proportion of renewable resources and the original proportion of renewable resources for firm k $(\sum_j \lambda_j \rho_{ij} - \rho_{ik})$. Positive slacks represent potential for improvement regarding the use of renewable resources.

3.4 Illustrative Application

3.4.1 Indicators Specified and Data Collection

The companies studied are affiliated to GRI and ICMM. The data sources for this article are the sustainability reports of mining companies and their financial statements. This information is in the public domain and is published voluntarily by companies on an annual basis.

To minimize unfairness and biases, we selected reports aligned with the GRI, which means they were subject to independent external assurance of information. GRI guidelines rely on certified offices to emit impartial conclusions on the quality of the information published on reports (for further details on external assurance procedures, see GRI (2013c)). One of the requirements for the reporting firms to obtain external assurance is to comply with international standards such as ISAE 3000 and AA1000AS.

Our illustrative application explored a sample of 25 large mining companies. Two main reasons guided our choice of firms. The first concerns the declaration of the complete core information and sector specific data regarding water, energy, land use (conservation), air emissions and waste generation. The second concerns the absence or minimal existence of missing data problems in the GRI database. The assessment focused on a cross-section assessment of performance for the year 2011, which is the year with the smallest number of missing values in the dataset. Performance changes over time can be a topic for future research as missing data problems currently existing in the database make this research line unviable.

The companies studied hold several mines around the world and usually own the entire mining production chain. The firms in the sample are not fully homogeneous, as their product mix, location and exploration sites may be different. For example, firms can be specialized on extracting a single type of ore or exploit several types of minerals. They may also face different challenges regarding natural conditions and economic context of the operation. However, all firms should observe the same international standards for environmental and economic performance, such that a benchmarking exercise can be an important contribution to promoting continuous performance improvements.

The framework proposed in this study represents the economic dimension by value-added (Y_1) and organizes the environmental dimension according to the framework of a balance sheet (Table 3.4). Balance sheets establish relations amongst indicators such as wealth generation, investments, expenses and obligations with third parties (Meigs et al., 1998).

Table 3.4: Expanded eco-efficiency framework.

Economic dimension	
Value-added (Y_1)	
Environmental dimension	
Benefits	**Burdens**
Use of renewable resources (R)	**Use of non-renewable resources (N)**
Renewable energy consumption (R_1)	Non-renewable energy consumption (N_1)
Recyled water consumption (R_2)	Withdraw water consumption (N_2)
Conservation (C)	**Dispersions (D)**
Environmental investments (C_1)	Waste (D_1)
Protected areas supported (C_2)	Air emissions (D_2)
	Spills (D_3)
	Environmental fines (D_4)

The environmental dimension is assessed on ten indicators, within four criteria: use of renewable resources (R), use of non-renewable resources (N), conservation (C) and dispersions (D). A noteworthy feature of mining lies on the usage of resources, both renewable and non-renewable, from categories R and N. In this sector, water ($R_{1,}$ N_1) and energy (R2, N2) consumption have the most severe consequences for the environment. Raw materials are considered immaterial for this sector, so they were disregarded from this framework. Regarding dispersions, waste (D_1) is a major issue in mining exploitation. The amount of mining waste generated depends on the quality of the extraction and transportation processes, as well as the ore contents in the soil. For ensuring data comparability across firms, this study considers only waste from packaging, raw and hazardous materials.

The zeros observed in the dataset used[1] (15.18%) were replaced by infinitesimal values ($\varepsilon = 0.0001$) to improve the discrimination of the model. There were missing data in two indicators of burdens (D_3, D_4) for five firms (2.2% of all dataset). These were replaced by the highest value observed in the corresponding variable to avoid undulling benefiting the DMUs for not having data available. The small sample size (25 companies) and the existence of missing data for five companies reinforces the need to interpret the results obtained with caution, considering the performance assessment as an illustrative exercise.

3.4.2 Specification of Scenarios with Directional Vectors

Model (3.4) can be specified with different directional vectors reflecting particular managerial scenarios defined a priori. Four scenarios were explored to illustrate some possibilities.

Scenario 1 investigates potential for simultaneous improvements in all economic and environmental dimensions (see indicators on Table 3.4). The directional vector for scenario 1 is $g_1 = \left[Y_{rk},\ C_{qk}\ , -D_{lk}, -T_{ik}\right]$. Scenario 2 explores improvements exclusively in the environmental dimension (indicators related to conservation, dispersions and use of renewable and non-renewable resources), given the observed level of economic benefits. The directional vector specified for this purpose was $g_2 = \left[0, C_{qk}\ , -D_{lk}, -T_{ik}\right]$. Scenario 3 seeks for the maximum reduction of dispersions and use of renewable and non-renewable resources, given the observed levels in the remaining indicators. The directional vector specified was $g_3 = [0, 0, -D_{lk}, -T_{ik}]$. Scenario 4 investigates opportunities to increase the indicators related to conservation efforts, given the observed levels in the remaining indicators. The directional vector used was $g_4 = \left[0, C_{qk}\ , 0, 0\right]$.

3.4.3 Discussion of Results

Table 3.5 reports the list of companies analysed and the results of the extended eco-efficiency assessment obtained using formulation (3.4). The results reported correspond to the specification of different scenarios, with 17 firms categorized as efficient. The remaining eight firms were classified as inefficient and ranked from best to worst, as shown in Table 5. For the 17 best performing

[1] Available from the authors upon request

companies, the model considers that there is no scope for improvement compared with the others companies of the sample. However, this classification as efficient is only a relative measure, which depends on the sample underlying the performance comparison. If the sample used for this benchmarking exercise was larger, it might be possible to obtain performance improvement targets for some of these companies. Note that the separation of companies in the sets of efficient and inefficient companies is an important feature of the DEA methodology, although for small sample sizes (as is the case of our empirical application), the discrimination power of the technique is reduced.

Table 3.5: Eco-efficiency scores.

Companies	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	β_k	Rank	β_k	Rank	β_k	Rank	β_k	Rank
Vale	0	—	0	—	0	—	0	—
Alcoa	0.450	4	0.459	4	0.621	4	1.768	5
Anglo American Ni	0	—	0	—	0	—	0	—
Rio Norte	0	—	0	—	0	—	0	—
Sama	0	—	0	—	0	—	0	—
Samarco	0.880	8	0.884	7	0.925	7	15.87	7
Votorantim	0	—	0	—	0	—	0	—
Alunorte Hydro	0.104	2	0.104	2	0.109	2	1.09	3
Kinross	0	—	0	—	0	—	0	—
Usiminas	0.229	3	0.23	3	0.291	3	0.598	2
Rio Tinto	0	—	0	—	0	—	0	—
Barrick	0	—	0	—	0	—	0	—
BHP Billiton	0	—	0	—	0	—	0	—
Glencore	0	—	0	—	0	—	0	—
Yamana	0.769	5	0.769	5	0.769	5	10.133	6
JX Nippon	0	—	0	—	0	—	0	—
Gold Fields	0.841	6	0.882	6	0.914	6	1.395	4
Mitsubishi Materials	0	—	0	—	0	—	0	—
Gold Corp	0	—	0	—	0	—	0	—
Teck	0	—	0	—	0	—	0	—
ARM	0.018	1	0.021	1	0.036	1	0.048	1
Codelco	0	—	0	—	0	—	0	—
Sumitomo	0.877	7	0.898	8	0.934	8	22.966	8
De Beers	0	—	0	—	0	—	0	—
Anglo American Pt	0	—	0	—	0	—	0	—

The classification of firms as efficient or inefficient is independent of the choice of the directional vector used for the assessment, but the eco-efficiency scores $\bar{\beta}_k$ are affected by the preferences specified in the directional vector.

The search for proportional improvements for all indicators (scenario 1) leads to an average eco-efficiency score of $\bar{\beta}_k$= 0.521. When exploring improvement only to the environmental dimension (scenario 2), the average eco-efficiency score increases slightly ($\bar{\beta}_k$= 0.531), meaning that the adjustments to environmental indicators should be more demanding when improvements to economic indicators are not required. Scenarios 3 and 4, where specific types of environmental indicators are required to improve, have average efficiency scores of 0.575 and 6.734, respectively. In particular, scenario 4 that explores exclusively conservation policies (C) corresponds to

Table 3.6: Targets and peers for Gold Fields.

Indicators	Observed	Targets			
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
Value-added (Y_1), mil.USD	3688	6790	—	—	—
Total energy consumption (T_1), Gj	5469784	869696	645435	470401	—
Total water consumption (T_2), mil.m^3	78269.45	12445	9236	6731	—
Environmental investments (C_1), mil.USD	0	0	0	—	0
Protected areas supported (C_2), ha	667	1246	1274	—	1621
Waste (D_1), tons	15×10^6	2.38×10^6	1.77×10^6	1.29×10^6	—
Air emissions (D_2), tons	5.30	0.8	0.6	0.5	—
Spills (D_3), m^3	47000	7473	5546	4042	—
Environmental fines (D_4), mil.USD	[a]	[a]	[a]	[a]	[a]
Peer (λ)		U16(0.014)	U16(0.000073)	U16(0.008)	U16(0.279)
		U18(0.160)	U18(0.164)	U18(0.087)	U18(0.208)

[a] Missing value.

the highest average improvement potential, meaning that the firms are quite heterogeneous in this criterion.

For each inefficient company, model (3.4) enables estimating targets for improvement and identifying the peers (companies with a similar profile) that a company with low performance should examine to learn with the examples of best practices. The potential managerial implications of this information are explored using Gold Fields Limited as an example (see Table 3.6). Gold Fields is a globally diversified producer of gold with eight operating mines in Australia, Ghana, Peru and South Africa. The annual production of this firm is approximately 2.2 million ounces (68.428 tons). Gold Fields declared as a strategic vision to enhance the environment in the areas exploited and limit the impact caused by mining.

DDF models such as (3.4) have often been used as a valuable tool for starting a benchmarking process. The expanded eco-efficiency model can be useful for identifying the best practice firms, and promote the adoption of their practices by other companies in the mining sector. For instance, this can help companies such as Gold Fields to mitigate inefficiencies by the implementation of better environmental practices observed in other companies. Gold Fields presents the highest volumes of waste generation in this sample. For reducing its dispersions, this firm could learn from its peers, particularly JX Nippon and Mitsubishi Materials.

The design of strategies to enhance the environmental performance of large mining companies also requires sharing best practices, which involves a qualitative benchmarking exercise following the quantitative analysis reported in this study. A successful coordinating of benchmarking efforts among companies requires overcoming a few challenges, related to time or financial constraints, staff resistance, or even low assimilation capability. See Freiling and Huth (2005) for further considerations.

Table 3.7 presents the results obtained by the second stage of the assessment. It presents a comparison of the original proportions of renewable energy and water and the target proportions obtained using (3.4). One should note that the improvements required to the share of renewable resources vary considerably among the companies analyzed.

Table 3.7: Targets for energy and water shares

Firms	Observed (%)		Targets (%)					
			Scenario 1		Scenario 2		Scenario 3	
	Renewable energy (þ1)	Recycled water (þ2)	Renewable energy (þ1)	Recycled water (þ2)	Renewable energy (þ1)	Recycled water (þ2)	Renewable energy (þ1)	Recycled water (þ2)
Alcoa	0	0	5.27	6.87	5.31	6.82	3.64	4.74
Samarco	0	7.07	8.00	8.28	8.27	7.85	0.50	7.07
Alunorte Hydro	0	25.03	0.37	25.03	0.37	25.03	0.37	25.03
Usiminas	49.82	19.72	53.97	34.73	53.99	34.62	49.82	32.00
Yamana	25.37	44.44	25.37	44.44	25.37	44.44	25.37	44.44
Gold Fields	0	0.04	0	16.68	0	15.82	0	9.06
ARM	0	0	43.08	27.51	43.18	27.56	42.31	27.01
Sumitomo	0	0	0.92	1.74	0.90	1.20	0.49	0.93
Average	9.40	12.04	17.12	20.66	17.17	20.42	15.31	18.79

The case of ARM should be highlighted. It exploits and processes a variety of ores and alloys: iron, manganese, copper, chrome, platinum, nickel, and coal. ARM possesses the highest potential for increasing the use of renewable resources in this sample, with the possibility of changing the proportion of renewable energy from zero to around 43%. The proportion of renewable water could change from zero to around 27%.

Figures 3.2 and 3.3 illustrate the targets for renewable resources, using scenario 2 as an example. They combine the magnitude of resources usage (T_{ik}) and the proportion of renewable resources (ρ_{ik}). The values were normalized to facilitate the comparison, taking as references the observed values of T_{ik} for each firm. The results indicate that for some companies the highest potential improvement concerns the magnitude of resources consumed (e.g., Gold Fields), whereas the most significant improvement for other firms concerns the proportion of renewable resources used (e.g., energy composition for ARM). Alunorte Hydro is an example of a firm with limited margins for improvement regarding both the magnitude of resources used and the proportion of renewable resources.

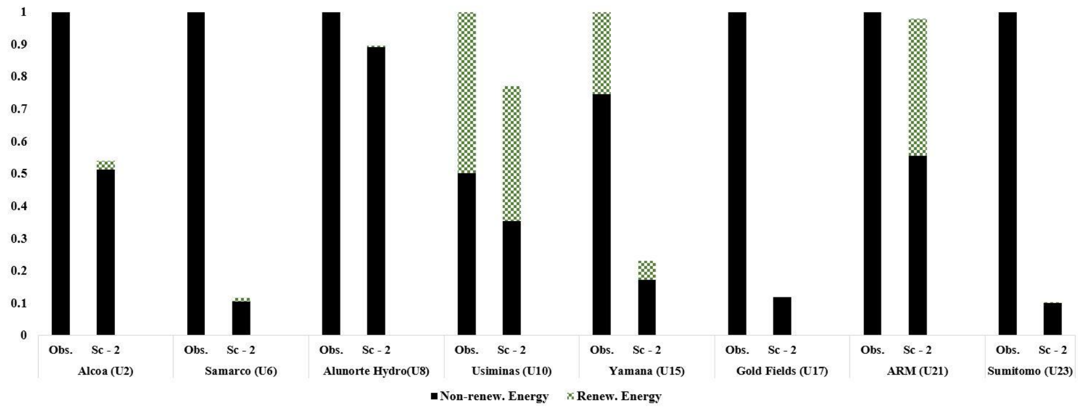

Figure 3.2: Combined targets for energy.

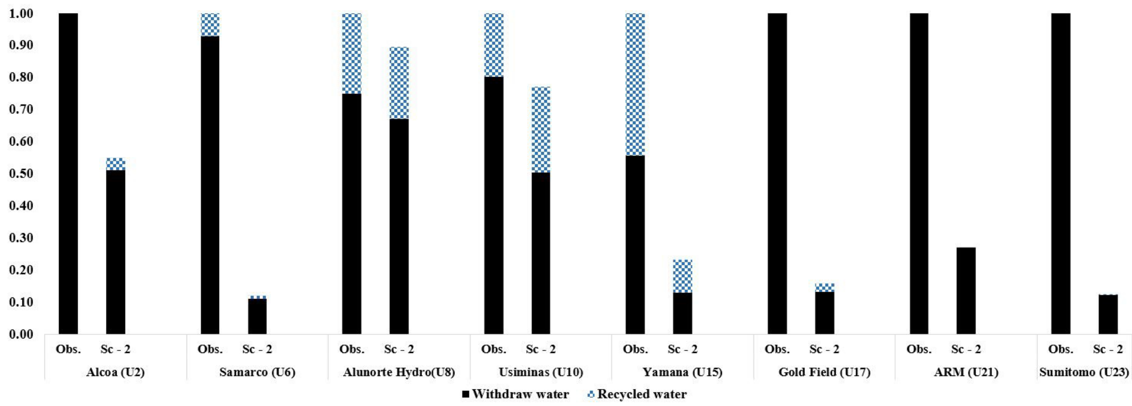

Figure 3.3: Combined targets for water.

Table 3.8 reports target values for energy (GJ) and water (million m^3). These targets were obtained based on information reported in Tables 6 and 7, using Gold Fields as an example.

Table 3.8: Water and energy targets for Gold Fields.

Gold Fields (U17)	Observed	Scenario 1	Scenario 2	Scenario 3
Total energy consumption (T_1)	5469784	869696	645435	470401
Non-renewable energy consumption (N_1)	5469784	869696	645435	470401
Renewable energy consumption (R_1)	0	0	0	0
Total water consumption (T_2)	78269.5	12445	9236	6731
Withdraw water consumption (N_2)	78236	10369	7775	6121
Recycled water consumption (R_2)	33.453	2076	1461	610

We can conclude with this example that the original level of water consumption (T_2) should be reduced by factor $\beta_{U17} = (0.882)$, and the proportion of recycled water should increase to the level suggested by ρ_2 (15.82%). Overall, the target for R_2 is obtained using the expression $T_2 \times (1 - \beta_{U17} \times \rho_2)$ (i.e., $78269.45 \times (1 - 0.882) \times 0.1582 = 1461$). Regarding energy consumption, the optimization model could not find potential improvements to the proportion of renewable energy (ρ_1) by comparison with other mining firms. Thus, the target for R_1 is obtained as $T_1 \times (1 - \beta_{U17}) \times \rho_1$, which in the case of this company is equal to zero $(i.e., 5469784 \times (1 - 0.882) \times 0)$.

3.5 Conclusions

This study proposed several enhancements to eco-efficiency assessments. The first enhancement is the unprecedented inclusion of the conservation criterion (C) in the evaluation, which allowed exploring the potential for strengthening good environmental practices. The second contribution lies on the development of an enhanced DDF model that optimizes the proportion of renewable resources used by firms. This new method for assessing the eco-efficiency can give credit to more eco-friendly balances in firms' input composition. To the best of our knowledge, this is the first attempt to optimize the nature of the inputs consumed by firms, promoting the substitution of non-renewable resources by more sustainable alternatives. The final contribution concerns the specification of multiple directional vectors that allow for incorporating alternative managerial preferences in the model and exploring distinct assessment scenarios. After the quantitative eco-efficiency analysis, based on optimization models, these firms should participate in collaborative benchmarking exercises, involving on-site visits to explore the practices implemented by peers.

The empirical part of this study is an illustrative application of the approach developed, based on the analysis of 25 mining companies. Due to the small sample size, the results obtained must be interpreted with caution. One of the major limitations of quantitative benchmarking studies is the unavailability of reliable and comparable data for companies within a sector, especially regarding environmental indicators. Sustainability reports following the GRI are a good starting point, although subjectivity in the reporting process is inevitable. In addition, as efficiency is a relative measure, the estimates obtained can change due to variations in the sample of companies included in the benchmarking analysis.

Future research foresees pursuing other real-life expanded eco-efficiency studies of industrial sectors, involving larger samples and refinements to the indicators analyzed. Another research opportunity concerns the analysis of the evolution of eco-efficiency over time.

CHAPTER 4

A Longitudinal Analysis of the Social Performance of Mining Firms

Abstract This study presents an innovative procedure to assess the evolution of the social performance of firms over time using Directional Distance Functions and the Malmquist index. In recent years, the social indicators of large corporations are increasingly being used to evaluate Corporate Social Responsibility. Reputation issues associated with the firms' impact on society, including local employment and contribution to local economic development are considered critical. This paper develops a composite indicator of social performance that can be used both for benchmarking comparisons among firms within an industry and to monitor the evolution of performance over time. Both desirable and undesirable factors can be taken into account in the performance evaluation. An illustrative application involving the assessment of 24 large mining firms in the years 2011 and 2012 is discussed. The specification of indicators reflecting social burdens and benefits of mining firms is based on international standards and guidelines for large corporations. The managerial implications of the results obtained are discussed.

Keywords: Data Envelopment Analysis, Directional Distance Functions, Composite indicators, Malmquist index, social performance, mining firms.

4.1 Introduction

The assessment of the social performance of large firms gained momentum in the 1950s, with the discussions on sustainable development following the release of the seminal work entitled "Social responsibilities of the businessman" (Bowen, 1953). In these broad discussions, themes such as human rights, decent work, local development and the protection of the environment have been recommended as fundamental values to be incorporated in businesses. A few years later, the book "Silent Spring" (Carson, 1962) represented a breakpoint in the understanding of the broader social purpose of firms. It established that firms' activity should encompass responsible behavior towards welfare generation and delivery of social benefits to local communities.

Within the literature dedicated to Corporate Social Responsibility (CSR), there is a body of research dedicated to the evaluation of firms' performance, encompassing a wide range of responsible practices. Although many organizations adopt the Triple Bottom Line (TBL) (Elkington, 1994) to evaluate performance with a broad perspective regarding the creation of value, the studies focusing on CSR have dedicated more attention to the quantification of the environmental and economic issues rather than social issues (Ayadi et al., 2015; Granderson, 2006). The work of Belu (2009) is one of the few exceptions that reported an evaluation of CSR taking into account the balance of social indicators (e.g., governance, human rights, and labor practices), environmental indicators (e.g., waste management) and financial indicators (e.g., revenue).

The social dimension is frequently associated with qualitative issues, such as ethics, human rights and impact on communities, which cannot be easily translated into measurable indicators. This qualitative character of social performance increases the difficulties inherent to the performance evaluation task. In particular, the specification of Key Performance Indicators (KIPs) and the evaluation of returns obtained from social initiatives is a very challenging endeavor. Despite these obstacles, a few scientific studies dedicated to this theme have identified positive relationships between CSR and corporate financial performance (Lee et al., 2013), as well as between CSR and corporate reputation (Weber, 2008).

Social performance has also become a subject of interest for administrative authorities, academia, and the society at large. Therefore, in recent years, firms have dedicated increased attention to the release of information on social actions in order to enhance reputation and market value. Transparency, accountability to society and the implementation of balanced policies promoting economic development and social welfare have become part of firms values, often emphasized in communication strategies.

This theme is prominent in what concerns international standards for the industry, such as the Global Reporting Initiative (GRI) (Kajüter, 2014) and norms by the International Organization for Standardization (e.g., ISO 26000) (ISO, 2010). The studies focused on the evaluation of social performance also gained notoriety amongst scholars. In this line of research, the incorporation of social value creation as a criterion for assessing the overall performance of organizations was explored in the context of social enterprises and hybrid organizations.

From a methodological perspective, the works resorting to Data Envelopment Analysis (DEA) to assess the socio-economic efficiency of organizations are worth noting (e.g.; Gutierrez-Goiria et al., 2017; San-Jose et al., 2014).

The study reported in this chapter has three main objectives. The first objective is to develop a framework based on Key Performance Indicators (KPIs) to assess the social performance of large mining firms according to quantifiable criteria. The framework proposed should take into account benefits and burdens generated by the operations of large corporations. The second objective is to construct an optimization model to estimate a robust composite indicator of social performance, based on a Directional Distance Function (DDF). The performance metric developed should be suitable for benchmarking studies within an industry, leading to the identification of targets and peers to guide performance improvements. The third objective regards enabling the estimation of performance change over time. This particular objective involves the calculation of the Malmquist index in the context of evaluations of performance using composite indicators estimated with DDFs. It requires the deduction of three formulas that should be used for the computation of the MI for particular directional vectors underlying the construction of the CI.

We use organizations in the mining sector to illustrate the methodology proposed and explore the managerial insights that it provides in a real-world context. Mineral exploitation is acknowledged as an industrial activity that can deliver economic and social benefits to low-income communities through local job creation and wealth generation. In many cases, the development and training of employees and local suppliers in new exploitation sites require assertive investments of mining companies. These are essential to respond to the pressures exerted by local and national authorities to promote social and economic development. Nevertheless, the contribution of mining firms to societal development is controversial. Firms practices often provide little evidence of their contribution to long-term benefit sharing and local development (Gilberthorpe and Banks, 2012), especially after the mining sites are closed. Kemp and Owen (2013) discuss additional mining-related burdens (e.g., land disputes, resettlements, environmental risks) that should be balanced by benefits to local communities (e.g.,conservation, local job creation, local development). Local authorities often exert pressure on companies in this sector to ensure their commitment to regional development.

This chapter is organized as follows. Section 4.2 provides a literature review of composite indicators, social performance studies using DEA, and international recommendations for firms social practices. Section 4.3 describes the methodology proposed for this study. Section 4.4 presents a small numerical example to illustrate the main features of the methodology developed. Section 4.5 contains an illustrative application involving the evaluation of 24 mining firms using real data. Section 4.6 concludes the chapter by highlighting the main contributions of the study and outlining future research opportunities.

4.2 Literature Review

4.2.1 Composite Indicators

Composite indicators (CIs) are obtained by the aggregation of a variety of individual sub-indicators into a single summary measure of performance. CIs can reflect multidimensional criteria in a summary measure of performance without significant loss of information. The main advantages of CI are the readiness to interpret complex performance results and to allow tracking performance progress over time (Nardo et al., 2008). In recent years, the literature on CIs became extensive, with applications in many different fields. Examples of internationally consolidated CIs include the Human Development Index (UNDP, 2016), the Environmental Performance Index (Hsu et al., 2016), and the Gender Gap Index (Schwab et al., 2016). These indices have been used for the evaluation of public policies both at national and international level.

In this context, the OECD (Nardo et al., 2008)) and the European Commission Joint Research Centre (Saisana and Tarantola, 2002) provide guidelines for the construction of composite indicators by reviewing a range of methods that can be used for this purpose. The use of Data Envelopment Analysis (DEA), introduced by Charnes et al. (1978), is recommended in both documents as a resourceful optimization technique for reducing subjectivity in the selection of the weights used for aggregating the indicators. One of the distinctive features of DEA is the specification of weights that are specific for each decision-making unit (DMU). This enables a flexible benchmarking exercise, highlighting the strengths and weaknesses of the units under assessment, as well as the identification of peers that can guide the implementation of policies for performance improvement.

The use of DEA-based models for constructing composite indicators can be traced back to Cook and Kress (1990) who conducted an empirical study in the context of aggregating votes for ranking purposes. Other studies followed this line of research, which consists of the formulation of DEA models without inputs. These can be used when the evaluation of performance moves away from the analysis of the efficiency of production processes, involving the transformation of inputs into outputs, and focuses instead on effectiveness in the achievements of the goals desired (Cooper et al., 2007, p.66).

There is a variety of studies reporting the construction of Composite Indicators using DEA, involving applications in different sectors. These include the assessment of mutual funds performance (Basso and Funari, 2001), the technology achievement index (Cherchye et al., 2008), the sustainable energy index (Hatefi and Torabi, 2010), the human development index (Despotis, 2005), quality of life (Morais and Camanho, 2011) and financial soundness of construction companies (Horta et al., 2012). All these studies evaluated the decision making units using a set of desirable output indicators and a *dummy* unitary input.

A more recent development in this literature allows the construction of composite indicators accommodating both desirable and undesirable outputs using a *dummy* unitary input, resorting to the use of Directional Distance Function (DDF) models. DDF models were introduced by Chambers et al. (1996a) and enable the simultaneous expansion of outputs and contraction of inputs according to the direction specified by a directional vector. Examples of this type of assessments include the evaluation of cities livability, including well-being and environmental impact (Zanella et al., 2014), the sustainability of Chinese regions (Zhang et al., 2014), the performance of national health services in Italy (Vidoli et al., 2014) and the performance of hydroelectric power plants in Brazil (Calabria et al., 2016).

4.2.2 Social Assessments using DEA

From a general standing point, the literature of quantitative social efficiency assessments is scarce and fuzzy. Therefore, *ah doc* definitions are proposed in individual studies, fitting the specific focus of the analysis reported. For instance, Lefeber and Vietorisz (2007) consider that social efficiency should compare social and environmental outcomes, given the economic resources available in the nations. At the firm level, Schaffel and La Rovere (2010) defined social efficiency as the ratio between a firm's value-added and its social impacts. This definition implies that it is desirable to minimize the social burdens and maximize social benefits, given the value-added produced by the firm. This approach clearly links the firm economic performance with social outcomes reflecting wealth distribution and the impact on society.

This section presents a review of studies focusing on social efficiency or social performance using Data Envelopment Analysis (DEA). Our literature survey included papers focusing on this topic, published between 2009 and 2017 in peer review journals listed by ISI Web of Science

(WOS). Studies on Corporate Social Performance (CSP), as a synonym for Corporate Social Responsibility (CSR), Corporate Sustainability and eco-efficiency that did not as primal focus the social dimension were disregarded.

Seven empirical studies focused on the social assessment with DEA were identified. Regarding conceptualization, there is neither a widely accepted definition of social efficiency nor a definition of social performance in the DEA literature. Gutiérrez-Nieto et al. (2009) proposed a definition of social efficiency for micro-finance institutions, based on the output-oriented concept of technical efficiency by Farrell (1957). It states that a firm can be considered socially efficient if it cannot increase its social and economic outputs without worsening the consumption of economic inputs. These authors defined social efficiency as the capacity to maximize wealth distribution and gender equity given the total assets and personnel available at the firm. González-Torre et al. (2017) defined social efficiency in the context of food banks as the capacity to maximize food distribution given the staff size available.

Despite the lack of convergence concerning the definitions, the papers make a distinction between two types of frameworks used for the empirical evaluations. The first type comprises studies taking into account inputs and outputs to evaluate social impacts. For instance, Gutierrez-Goiria et al. (2017) addressed social efficiency from the perspective of micro-finance institutions (MFI), relating inputs (e.g., external funding) and outputs (e.g., profit). The second type of framework uses the aggregation of Key Performance Indicators (KPI) to evaluate social impacts. The work of Reig-Martínez (2013) is an example of this type of assessment. The author estimated a Human Well-being Composite Index (WCI) to assess the social performance of countries in the European Economic Space, considering desirable KPIs (e.g., Gross Domestic Product per capita) and undesirable KPIs (e.g., Gender Gap Index).

Table 4.1 summarizes the criteria and indicators identified in the studies reviewed. Three criteria reflect economic goals (wealth distribution; cost and social profitability) and nine criteria reflect social goals (gender equity, local development, labor, poverty mitigation, human rights, non-discrimination, education, health, government effectiveness). The most prevalent social criteria, appearing in more than one study, are gender equity (3 papers), local development (3 papers), and human rights (2 papers). The most frequent economic criteria are wealth distribution (3 papers) and costs (2 papers). The remaining criteria appeared only once in the studies reviewed (non-discrimination, poverty mitigation, education, government effectiveness and social profitability).

Note that the social profitability criterion was used by San-Jose et al. (2014) to account for the banking profits distributed to stakeholders rather than to the shareholders. This criterion can be interpreted as a sub-category of wealth distribution. The criterion of wealth distribution was used by Gutiérrez-Nieto et al. (2009); Reig-Martínez (2013); Gutierrez-Goiria et al. (2017) to represent the distribution of wealth to ensure well-being and poverty mitigation.

Five studies conducted assessments focusing on both social and economic criteria. For instance, Martínez-Campillo and Fernández-Santos (2017) analyzed micro-finance institutions based on their capacity to promote local development given the operational costs incurred. Two studies focused exclusively on non-economic criteria (i.e., González-Torre et al., 2017; Agovino and

Rapposelli, 2017). Agovino and Rapposelli (2017) evaluated the social welfare of people with disabilities in the Italian labor market. However, the criteria covered in this study was quantified using hybrid socioeconomic indicators such as GDP per capita, unemployment rates, and poverty perceptions. The work of González-Torre et al. (2017) was the only study reviewed that addressed social criteria using exclusively non-economic indicators.

Table 4.1: Social criteria and indicators used by scholars

Authors	Sector	Criteria	Input (I) / Output (O) / Undesirable outputs (U)
Gutiérrez-Nieto et al. (2009)	Micro-finance	Gender equity, local development, wealth distribution, costs	Total Assets (I), Operating Cost (I), Number of employees (I), Number of active women borrowers (O), Indicator of benefit to the poorest (O), Gross loan portfolio (O), Financial revenue (O)
Reig-Martínez (2013)	Countries welfare	wealth distribution, gender gap, education, health, government effectiveness	Unitary input (I), GDP (O), Life Expectancy at Birth (O), Education (O), Government Effectiveness (O), Gini Coefficient (O), Global Gender Gap index (O)
San-Jose et al. (2014)	Banking	wealth distribution, labor, social profitability	Equity (I), Total assets (I), Deposits (I), Profits (O), Customer credit (O), Jobs (O), Social contribution (O), Loss (U), Risk (U)
Gutierrez-Goiria et al. (2017)	Micro-finance	Gender equity, local development, wealth distribution	Equity (I), External funding (I), Profit (O), Risk (O), Loans (O), Number of clients (O), Number of female borrowers (O), Economic Sustainability (O)
González-Torre et al. (2017)	Food banks	Poverty Mitigation, human rights (no hunger)	Bank age (I), volunteer staff size (I), permanent staff size (I), tons of food managed (O), number of recipients (O)
Agovino and Rapposelli (2017)	Regional Welfare	Human rights (labor), nondiscrimination	Bonding social capital (I), bridging social capital (I) and linking social capital (I), quality of work indicator (I), number of people with disabilities employed (O)
Martínez-Campillo and Fernández-Santos (2017)	Micro-finance (Credit cooperatives)	Local development, costs	Personal expenses (I), amortization (I), expenses (I), interest expenses (I), costumer socialization (O), financial inclusion (O)

From a modeling perspective, five papers evaluated social efficiency using an output-oriented perspective for exploring the potential for enhancing the social benefits (outputs) in three different sectors (micro-finance, banking and food banks). Two papers conducted performance assessments using a multi-method approach. Reig-Martínez (2013) proposed a country-level human well-being index by integrating standard DEA models and Compromise Programming. This approach enabled the evaluation and ranking of countries using a common set of weights. Agovino and Rapposelli (2017) integrated standard DEA models with cluster analysis to evaluate regional welfare in Italy.

Regarding the sector of application, despite the studies reviewed proposed quantifiable criteria and indicators suitable for country-level and firm-level evaluations, none of the empirical applications focused on industrial sectors. Nevertheless, some of the criteria identified should also be taken into account by responsible firms, irrespectively of the sector they operate (e.g., gender equity, local development, nondiscrimination). Other features of the frameworks reported in Table 4.1 are more applicable to country-level assessments (e.g., government effectiveness, financial inclusion).

The survey reported in this section has only identified empirical studies focusing on non-industrial entities. Consequently, most of the criteria and indicators reported in Table 4.1 are not applicable to the context of mining companies (e.g., loans, financial inclusion). To fill this gap of coverage, we reviewed eight international standards and guidelines containing recommendations on firms' social practices in order to identify social performance criteria applicable to the context of mining firms. The results of this analysis are discussed in the next section.

4.2.3 International Recommendations for Firms Social Practices

This subsection presents a survey of a variety of international standards and guidelines regarding firm's social practices. This review has the objective of identifying criteria that should underlie the evaluation of the social performance of large mining firms. Since the focus of the analysis is social performance, standards for environmental management and financial performance are not considered in this survey.

The criteria discussed in the following paragraphs are based on the recommendations of eight documents published by major international entities:

- Accountability 8000 (SA8000) (SAI, 2014)
- ISO 26000 - Social responsibility (ISO, 2010)
- OHSAS 18001 - Occupational Health and Safety Assessment Series (OHSAS, 2007)
- ILO-OSH 2001 - Guidelines on occupational safety and health management systems (ILO, 2001)
- ISO 45001 - Occupational health and safety (ISO, 2016)
- Global Reporting Initiative (GRI) standard 400 series by GRI (2016)
- OECD Guidelines for Multinational Enterprises (OECD, 2011b)
- United Nations global compact (UNGC) (UN, 2015a).

The first international standard reviewed is the Social Accountability 8000 (SA8000) by SAI (2014). It defines social performance focusing on the dimensions of decent work and occupational health. SA8000 is based on the principles of thirteen international human rights conventions, ten of which are conventions of the International Labour Organisation (ILO).

The second standard reviewed is ISO 26000:2010 (ISO, 2010), which provides guidance on how businesses and organizations can operate in a socially responsible way. These standards provide a general understanding of social responsibility by addressing seven core subjects: governance, human rights, labor practices, fair operation practices, consumer issues, community and the environment.

Three standards reviewed are related to occupational health and safety management system certifications. These are the OHSAS 18.001:2007 (OHSAS, 2007), the ILO-OSH 2001 (ILO,

2001) and the ISO 45001:2017 (ISO, 2016). ILO-OHS 2001 provides a framework for planning, implementing and evaluating the occupational hazards and risks to workers and contractors, proving guidance towards productivity improvements. ISO 45001 is more comprehensive than OHSAS 18.001 in what concerns the integration of Occupational Health and Safety standards at the strategic level.

The Global Reporting Initiative (GRI) standards (GRI, 2016) establish guidelines for economic, social and environmental reporting of organizations. The GRI Standards 400 series is composed of 18 standards exclusively dedicated to addressing social topics. These series contain in-depth detailed strategic recommendations for themes such as socioeconomic compliance, decent work and human rights, education and training, equal opportunity, supplier assessment and product responsibility.

The OECD Guidelines for Multinational Enterprises (OECD, 2011b) are international guidelines for large corporations. It proposes 15 principles for corporate ethical conduct with a focus on sustainable development, encompassing economic, environmental and social criteria. The principles described are mainly related to ethics, human rights, local hiring, local education, equal gender opportunities, environmental regulations, avoiding disputes against local communities and self-regulation practices.

The United Nations Global Compact (UNGC) of UN (2015a) provides ten principles to guide firms' operations according to fundamental values on human rights, labor, environment, and anti-corruption practices. These principles are derived from the Universal Declaration of Human Rights, the International Labour Organization's Declaration on Fundamental Principles and Rights at Work, the Rio Declaration on Environment and Development, and the United Nations Convention Against Corruption.

The documents analyzed report two qualitative criteria, seven quantitative criteria, and a wide range of further qualitative topics. The criteria are categorized according to the three dimensions of the triple bottom line, and an additional category of "strategy and governance". Regarding the quantitative criteria, five criteria focus on the social dimension, one criterion focuses on the environmental dimension and one criterion focuses on the economic dimension. The criteria identified as well as their coverage by standards and guidelines is reported in Table 4.2.

Table 4.2: Summary of social criteria considered in international standards

Category	Criteria	SA 8000	ISO 26000:2010	OHSAS 18001:2007	ILO-OSH 2001	ISO 45001:2017	GRI 400	OECD	UNGC
Strategy and governance	Human Rights	x	x	x	x	x	x	x	x
	Governance & Ethics	x	x	x	x	x	x	x	x
Social	Decent Work & OSH	x	x	x	x	x	x	x	x
	Equal Opportunities	x	x				x	x	x
	Community Support	x	x				x	x	x
	Local Development		x				x	x	x
	Education /training		x	x		x	x		
Environmental	Environmental Quality		x					x	x
Economic	Wealth Generation		x					x	x

In the category "strategy and governance", the criterion "Human Rights" regards incorporating, in the company's code of ethics, the respect for human rights and its reflection on all corporate actions. The criterion "Governance & Ethics" reflects the incorporation of responsible values in the firm's strategic planning. It is worth mentioning that both the criteria "Human Rights" and "Governance & Ethics" have qualitative nature.

Regarding the social dimension, the first quantitative criterion reported is "Decent work & Organizational Safety and Health (OSH)", reflecting policies focusing on employees' morale, well-being and safety.

The second quantitative criterion is 'Equal Opportunities", which evaluates policies for non-discrimination and gender balance. In industrial organizations, and in particular in extractive industries, these issues are critical, as considerable gender barriers are often observed (Keenan and Kemp, 2014). Other issues associated with this criteria regard religion, ethnicity and age.

The third quantitative criterion reported is "Community Support". It focuses on how the organizations address vulnerabilities that their operations may cause to surrounding areas. It can be related to environmental issues (e.g., quality of the air) or social issues (e.g., indigenous needs). This criterion also evaluates the existence of policies for local hiring and support of education programs to enhance the employability of inhabitants in the vicinity of firms' physical location.

The fourth social criterion regards "Local Development" practices for sharing long-term economic benefits at the local level, with a focus on avoiding local economic dependence of philanthropy. This criterion can encompass policies for local supplier assessment, local job creations, educational initiatives, infrastructure enhancements and poverty mitigation.

The fifth quantitative criterion evaluates "Education and Training". It is focused on organizational policies for education and training of firm employees at all levels, promoting sustainable development.

The criteria "Environmental Quality" and "Wealth Generation", which directly connect to the environmental and economic dimensions of the TBL, were mentioned in the documents reviewed. Although the standards and guidelines reviewed are focused on social performance, environmental and economic criteria are often associated with social issues. In the context of social performance, the "Environmental Quality" criterion discusses the reduction of emissions and waste management as a matter of public health.

The criterion "Wealth Generation" can be interpreted as an economic topic as much as a social or environmental topic. The measurement of wealth from a multidisciplinary perspective has been extensively documented in the literature (e.g. Schwartz, 1979; Cowell, 2000). Regarding the environmental impact of wealth inequality, poor communities are potentially more likely to be exposed to environmental toxins. Regarding the social feature of wealth distribution, the access to formal education is typically lower in poor communities than in wealthy groups. The distribution of wealth is expected to promote local development and reduce inequality. This criterion can encompass both economic sub-criteria (e.g., profit) and non-economic sub-criteria (e.g.,investments on education, gender balance and non-discrimination).

4.3 Methodology

This section introduces the methodology proposed to assess social performance at the firm level. The methodology starts with presenting the framework of KPIs used to reflect both social burdens and benefits related to mining firms operations (subsection 4.3.1). Next, it is presented a DDF-based model to estimate the composite indicator of social performance (subsection 4.3.2). The last part of the methodology presents a reformulation of the Malmquist index so that it can be calculated in the context of performance evaluations using CIs estimated with DDFs (subsection 4.3.3).

4.3.1 Framework for the Evaluation of Mining Firms

The selection of KPIs to compose the framework for the construction of a composite indicator of social performance of mining firms was based on the quantitative criteria used in previous studies available in the literature, the recommendations of international entities and the premise of the availability of reliable data in the public domain. The framework proposed reflects the firms' desirable (benefits) and undesirable (burdens) contributions to society based on the following criteria and indicators.

- **Criterion 1 - Education /training:**
  Investments in education per employee (Y_1)
- **Criterion 2 - Decent Work & OSH:**
  Employees' turnover ratio (B_1)
  All injury frequency rate (B_2)
- **Criterion 3 - Equal Opportunities (gender equality):**
  Female workforce ratio (Y_2)
- **Criterion 4 - Local Development:**
  Local hiring ratio (Y_3)
  Local purchase ratio (Y_4)

Note that these criteria correspond to those reported in Table 4.2 for the social dimension. The criterion "Community Support" was not covered due to unavailable quantitative data.

Table 4.3 summarizes the indicators proposed for the assessment conducted in this study according to their nature, i.e. desirable indicators representing benefits or undesirable indicators representing burdens. All KPIs are expressed in ratios to allow direct comparisons of social performance of mining firms, irrespectively of their size. The meaning of each KPI and its detailed description is presented in the next paragraphs.

The social benefits generated by a firm should reflect its efforts in promoting opportunities for employees to obtain decent work, equity, security and human dignity. The first indicator selected for our framework is "investments in education per employee" (Y_1), which is calculated as the ratio

Table 4.3: Framework for evaluating social performance

Desirable KPIs: Benefits (Y_r)	**Undesirable KPIs:Burdens** (B_i)
Investments in education per employee (Y_1)	
Female workforce ratio (Y_2)	Employees' turnover ratio (B_1)
Local hiring ratio (Y_3)	All injury frequency rate (B_2)
Local purchase ratio (Y_4)	

between the total investments on education and the total workforce. It reflects corporate practices towards fomenting in the workforce members and their families the development of lifelong technical, ethical and social skills to enhance employability (GRI, 2011; ISO, 2010). The second benefit indicator is "female workforce ratio (Y_2)". It is calculated as the percentage of women in the total workforce employed by the mining firm. The ideal value for this indicator, reflecting gender balance, is 0.5, meaning that the female workforce is balanced with the male workforce. Since it is estimated that only 7.9% of the global mining workforce is female (PWC, 2015), assume that the higher the value of this indicator the better, as values above the 50% threshold are unlikely to observe in this sector. This is a measure of consistency regarding the firms' gender equality policies. In addtion, research on occupational equality in mining confirms that good practices in this field can benefit the socio-economic development at the local-level (Abrahamsson et al., 2014; Keenan and Kemp, 2014).

Direct corporate contributions to the local development of mining sites are represented in the indicators "local hiring ratio" (Y_3) and "local purchase ratio" (Y_4). Local hiring ratios are calculated by the ratio between the number of employees and contractors belonging to local communities over the total workforce of the firm. Local purchase ratio is calculated by the ratio of expenses with materials purchased from local suppliers over the total expenses with suppliers.

Two indicators quantify the social burdens in the framework. The first burden is the "employees' turnover ratio" (B_1). The employees' turnover indicator is measured as the ratio between the number of employees fired or resigned and the annual average workforce. Higher values of this indicator are associated with job dissatisfaction and counterproductive work behavior, while lower values are associated with good relationships amongst employees and supervisors, job fulfillment and organizational commitment (Bryant and Allen, 2013; Fila et al., 2014).

The second burden indicator is "all injury frequency rate" (AIFR) (B_2). AIFR expresses the measure of all reportable injuries (lost time injuries, restricted work injuries, medical treatment cases and fatalities) divided per 200 thousand hours worked in a year. AIFR is considered the most reliable measure of the overall safety environment of an organization (Baker et al., 2001; Harris, 2016). Lower values of injury increase the morale of the workforce and indicate good practices on Decent Work & OSH (GRI, 2013a).

4.3.2 Cross-sectional Evaluation using Composite Indicators

4.3.2.1 Directional Distance Functions

Chambers et al. (1996a), based on the Luenberger shortage function (Luenberger, 1992a,b), developed a Directional Distance Function (DDF) model that allows a producer to scale inputs and outputs simultaneously along a path that is defined according to a directional vector g.

Consider that a production technology, here defined by Φ, that transforms inputs $x \in \Re_{+}^{m}$ into outputs $y \in \Re_{+}^{s}$ under constant returns to scale, as shown in (4.1). The production possibility set (PPS) comprises the set of all feasible input and output vectors that belong to Φ.

$$\Phi = \{(x, y) : x \text{ can produce } y\} \tag{4.1}$$

Considering the production technology Φ defined in (4.1), the general form of the Directional Distance Function is presented in (4.2).

$$\vec{D}(x, y; g_x, g_y) = \max\,\{\beta : (x + \beta g_x,\ y + \beta g_y) \in \Phi\} \tag{4.2}$$

The directional vector $g = (g_x, g_y)$ can assume a variety of configurations. The components of the vector (g_x, g_y) indicate the direction of change for the inputs and outputs, respectively, reflecting alternative managerial objectives. For instance, $g = (-x, y)$ allows the simultaneous radial reduction of inputs and increase of outputs in order to achieve the frontier of the technology. Other possibilities include the definition of the directional vector as $g = (-x, 0)$ resulting in an input-oriented assessment, only involving reductions to inputs. Defining the directional vector as $g = (0, y)$ leads to an output-oriented assessment. When the components of the directional vector are equal to the values of the inputs and outputs observed in the decision making unit under assessment, it is possible to interpret the value of the Directional Distance Function as the proportional adjustments to inputs or outputs required to reach the frontier of the production possibility set. Another commonly used configuration of the directional vector is $g = (-1, 1)$, particularly interesting when all inputs and outputs are measured in the same units, as in this case the value of β can be interpreted as the magnitude of waste that could be avoided by efficient operation, correcting both input and output slacks.

Chambers et al. (1996a) showed that the DDF (4.2) can be estimated using a linear programming model, as shown in (4.3).

$$
\begin{aligned}
&\vec{D}(x,y;g_x,g_y) = \max \beta_k && && (4.3)\\
&s.t. \sum_{j=1}^{n} y_{rj}\, \lambda_j \geq y_{rk} + \beta_k g_y && r = 1,\ldots,s\\
&\sum_{j=1}^{n} x_{ij}\, \lambda_j \leq x_{ik} - \beta_k g_x && i = 1,\ldots,m\\
&\lambda_j \geq 0 && j = 1,\ldots,n
\end{aligned}
$$

In (4.3), y_{rj} are the outputs generated and x_{ij} are the inputs consumed by DMU j. Similarly, y_{rk} and x_{ik} are the outputs and inputs observed in the DMU k under assessment. The variables λ_j are called intensity variables. They allow the specification of a point on the frontier of the Production Possibility Set (PPS) against which the DMU under assessment is compared, corresponding to a linear combination of other efficient DMUs located on the best-practice frontier and used as peers.

The optimal value of β_k^* corresponds to the value of the Directional Distance Function, which can be interpreted as an inefficiency score. A DMU is on the frontier of the PPS if $\beta_k^* = 0$, whilst positive values of β_k^* are associated with inefficient DMUs.

4.3.2.2 Specification of Composite Indicators Based on Directional Distance Functions

This section presents the formulation of a composite indicator (CI) based on a Directional Distance Function model. Recall that a composite indicator consists of a particular case of the Directional Distance Function model, with a single *dummy* input (with a unitary value for all DMUs) and multiple outputs corresponding to performance indicators. These indicators can be classified into two types: burdens of firms' activity (corresponding to indicators that should be reduced) and benefits of firms' activity (corresponding to indicators that should be increased). The resulting formulation of a composite indicator can thus be envisioned as a partition of the traditional inputs of the DDF formulation (x_{ij}) in model (4.3) in two classes of variables: a *dummy* input equal to one and the burdens resulting from the firms activity (B_{ij}), which should be reduced. According to Koopmans (1951), the *dummy* variable works as a "helmsman" attempting to steer the DMUs towards better performance. The outputs corresponding to the benefits of firms activity, denoted by Y_{rj}, should be increased. The composite indicator can be estimated using the linear programming model shown in (4.4).

$$
\begin{aligned}
\mathrm{CI}(1,B,Y;g_1,g_B,g_Y) = \max \quad & \beta_k \\
\text{s.t.} \quad & \sum_j \lambda_j \leq 1 - \beta_k g_1 \\
& \sum_j \lambda_j B_{ij} \leq B_{ik} - \beta_k g_B \quad i = 1,\ldots,m \\
& \sum_j \lambda_j Y_{rj} \geq Y_{rk} + \beta_k g_Y \quad r = 1,\ldots,r \\
& \lambda_j \geq 0
\end{aligned}
\tag{4.4}
$$

Formulation (4.4) will be used to estimate the composite indicator of social performance in the empirical application reported in this chapter. Note that formulation (4.4) estimates a frontier that passes through the origin and delineates extensions parallel to the axes at infinity.

In formulation (4.4), the directional vector $g = (g_1, g_B, g_Y)$ defines the path of improvement underlying the performance evaluation. For example, the equivalent to an output-oriented assessment corresponds to the specification of the directional vector $g = (0,0,Y)$, and the equivalent to an input-oriented assessment corresponds to the specification of the directional vector $g = (-1,-B,0)$. For these specifications of the directional vector, it is possible to find an exact equivalence between the inefficiency estimate provided by the Directional Distance Function model (4.4) and the Shepard input and output distance functions or a radial efficiency score (see Fare and Grosskopf, 2000).

It is also possible to consider other specifications of the directional vector, including simultaneous adjustments to all indicators considered in the performance assessment or only to some indicators. The specification of $g = (0,-B,Y)$ is particularly interesting to support benchmarking procedures and target estimation with composite indicators. The estimation of targets, corresponding to points located on the efficient subset of the PPS, is facilitated by the inclusion of slack variables (s_i^- and s_r^+) in formulation (4.4). As a result, the formulation of a composite indicator for target setting purposes is shown in (4.5).

$$
\mathrm{CI}(1,B,Y;g_1,g_B,g_Y) = \quad \max \beta_k + \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{4.5}
$$

$$
\text{s.t.} \quad \sum_j \lambda_j \leq 1 \tag{4.5a}
$$

$$
\sum_j \lambda_j B_{ij} = B_{ik} - \beta_k g_B - s_i^- \qquad i = 1,\ldots,m \tag{4.5b}
$$

$$
\sum_j \lambda_j Y_{rj} = Y_{rk} + \beta_k g_Y + s_r^+ \qquad r = 1,\ldots,s \tag{4.5c}
$$

$$
\lambda_j \geq 0
$$

$$
s_i^- \geq 0
$$

$$
s_r^+ \geq 0
$$

Formulation (4.5) involves an optimization with two stages. The first stage seeks for the estimation of a radial score (β_k^*) corresponding to the composite indicator score. It reflects the inefficiency of DMU k under assessment. This score can also be interpreted as the proportional factor by which the burdens (B_i) can be contracted and the benefits (Y_r) can be expanded for DMU k, maintaining the value of the *dummy* variable fixed (equal to one). The second stage seeks for the maximum non-radial improvement in each indicator. This is implemented by the inclusion of the slack variables s_i^- and s_r^+ in the objective function and constraints (4.5b) and (4.5c). These slacks are multiplied by an infinitesimal (ε) to ensure they do not affect the optimal value of β_k^*, corresponding to the composite indicator.

4.3.3 Evaluation of Performance Change Over Time with the MI

4.3.3.1 Specification of the Malmquist Productivity Index with Shephard Distance Functions and Radial Efficiency Measures

The Malmquist index (MI), introduced by Caves et al. (1982) and developed by Färe et al. (1989, 1992) is used to evaluate productivity change over time. As originally presented by Färe et al. (1989) (see also Färe et al., 1992; Fare et al., 1994), it relies on ratios of Shephard distance functions. The Malmquist can be either input-oriented or output-oriented, depending on the orientation chosen for the Shepard distance functions underlying the computation of the Malmquist index.

Shephard Distance Functions and Radial Efficiency Measures

Following the definitions of Shephard (1970), the input distance function is defined in relation to the technology Φ as shown in (4.6).

$$D_i(x,y) = \max\{\delta : (\frac{x}{\delta}, y) \in \Phi\} \tag{4.6}$$

The input distance function (4.6) gives the reciprocal of the minimum factor $\frac{1}{\delta}$ by which the input vector x can be proportionally contracted whilst keeping the current level of the outputs. $D_i(x,y) \geq 1$ for all input-output combinations that belong to technology Φ. $D_i(x,y) = 1$ if and only if the point is located on the frontier of the technology.

Färe et al. (1985) were the first to note that Shephard distance functions can be estimated using DEA models. The DEA model that can be used to estimate the Shephard input distance function, assuming constant returns to scale and an input orientation, is shown in (4.7).

$$
\begin{aligned}
E(x,y) &= \text{Min } \delta \\
s.t. \sum_{j=1}^{n} y_{rj}\, \lambda_j &\geq y_{rk} \quad r = 1,\ldots,s \\
\sum_{j=1}^{n} x_{ij}\, \lambda_j &\leq \delta x_{ik} \quad i = 1,\ldots,m \\
\lambda_j &\geq 0 \quad j = 1,\ldots,n
\end{aligned}
\tag{4.7}
$$

The optimum value of δ^* is the radial efficiency score of the DMU under assessment (k), which can also be interpreted as the maximum factor by which the input levels of DMU$_k$ can be radially contracted, whilst the outputs are kept at their current level. A DMU is considered radially efficient if $\delta^* = 1$. Values of δ lower than one are evidence of the existence of inefficiency. The variables λ_j are intensity variables, corresponding to the coefficients of the linear combination of peer DMUs that define the point on the frontier used to estimate the radial distance between the DMU k under assessment and the frontier.

Färe et al. (1985) showed that the Shephard input distance function (4.6) is equal to the inverse of the radial efficiency score (4.7), assuming constant returns to scale, as stated in (4.8).

$$
D_i(x,y) = \frac{1}{E(x,y)} \tag{4.8}
$$

Is is also possible to specify a Shephard output distance function as shown in (4.9).

$$
D_o(x,y) = \min\{\theta : (x, \frac{y}{\theta}) \in \Phi\} \tag{4.9}
$$

This function gives the reciprocal of the maximum factor $\frac{1}{\theta}$ by which the output vector y can be proportionally expanded, whilst the inputs are kept at their current level. $D_o(x,y) \leq 1$ for all input-output combinations that belong to technology Φ. $D_o(x,y) = 1$ if and only if the point is located on the frontier of the technology.

The output-oriented DEA model, assuming constant returns to scale, which can be used to estimate the output distance function, is shown in (4.10).

$$
\begin{aligned}
\frac{1}{E(x,y)} &= \text{Max } \theta \\
s.t. \sum_{j=1}^{n} y_{rj}\, \lambda_j &\geq \theta y_{rk} \quad r = 1,\ldots,s \\
\sum_{j=1}^{n} x_{ij}\, \lambda_j &\leq x_{ik} \quad i = 1,\ldots,m \\
\lambda_j &\geq 0 \quad j = 1,\ldots,n
\end{aligned}
\tag{4.10}
$$

In the DEA model (4.10) a DMU is considered radially efficient if and only if the optimal value of θ^* is equal to one. Values greater than one reflect evidence of the existence of inefficiency.

Färe et al. (1985) showed that the Shephard output distance function (4.9) is equal to the radial efficiency score (4.10), assuming constant returns to scale, as stated in (4.11).

$$D_o(x,y) = E(x,y) \tag{4.11}$$

In addition, Färe et al. (1985) also showed also that under constant return to scale $D_o(x,y) = \frac{1}{D_i(x,y)}$.

Formulation of the Malmquist Index with Shephard Distance Functions

The Malmquist index requires the estimation of two within-period Shephard distance functions and two mixed-period Shephard distance functions, whose definition is provided as follows. Consider two different time periods defined by t and $t+1$. The technology of production can be defined in relation to t and $t+1$ (Φ^t and Φ^{t+1}). The DMUs can also be observed in period t and $t+1$, i.e. (x^t, y^t) and (x^{t+1}, y^{t+1}). Therefore, the two within-period distance functions are represented by $D_i^t(x^t, y^t)$ and $D_i^{t+1}(x^{t+1}, y^{t+1})$, while the two mixed-period distance functions are represented by $D_i^t(x^{t+1}, y^{t+1})$ and $D_i^{t+1}(x^t, y^t)$.

Note that the period inside brackets indicates the year of the DMU under assessment and the period in the superscript indicates the year used for the construction of the production possibility set. For instance, $D_i^{t+1}(x^t, y^t)$ means that the DMU in t is evaluated against the frontier of $t+1$

Following Färe et al. (1992), the input-oriented MI is obtained using expression (4.12).

$$MI_i^{t,t+1} = \left[\frac{D_i^t(x^t, y^t)}{D_i^t(x^{t+1}, y^{t+1})} \frac{D_i^{t+1}(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} \right]^{\frac{1}{2}} \tag{4.12}$$

Formulation (4.12) is a geometric mean of two indices of Caves et al. (1982), reflecting the productivity change between t and $t+1$ for the input-output combinations (x^t, y^t) and (x^{t+1}, y^{t+1}). The difference between the two ratios inside brackets is the reference technology used to estimate productivity change. Whilst the first evaluates productivity change in relation to Φ^t, the second ratio evaluates change using as reference Φ^{t+1}. In order to avoid an arbitrary choice between the base years, formulation (4.12) is the geometric mean of the two ratios inside brackets.

Färe et al. (1992) showed that the MI can be decomposed in two sub-indices. The first measures efficiency change (EC) between the two time periods (4.13) and the second measures technological change (TC) between the two time periods (4.14). EC compares the distance to the frontier t of the DMU in t, compared with the distance to the frontier $t+1$ of the DMU in $t+1$. TC compares the distance between the best practice frontiers in t and $t+1$, evaluated at the input-output mix of the DMU in t and in $t+1$.

$$EC_i^{t,t+1} = \frac{D_i^t(x^t, y^t)}{D_i^{t+1}(x^{t+1}, y^{t+1})} \tag{4.13}$$

$$TC_i^{t,t+1} = \left[\frac{D_i^{t+1}(x^t, y^t)}{D_i^t(x^t, y^t)} \frac{D_i^{t+1}(x^{t+1}, y^{t+1})}{D_i^t(x^{t+1}, y^{t+1})} \right]^{\frac{1}{2}} \tag{4.14}$$

The product of the two components results in the Malmquist index.

$$MI_i^{t,t+1} = EC_i^{t,t+1} \times TC_t^{t,t+1} \tag{4.15}$$

The values of $MI_i^{t,t+1}$ and its components can be greater, equal or smaller than one. These values indicate respectively productivity growth, stagnation or decline between periods t and $t+1$. Improvements in the efficiency change component represent evidence of catching up to the frontier, while improvements in the technological change component are evidence of advances in the frontier position between the two time periods.

Similarly, the output-oriented Malmquist index (Färe et al., 1989), is defined as shown in formulation (4.16). The efficiency change and the technological change components are shown in (4.17) e (4.18).

$$MI_o^{t,t+1} = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \tag{4.16}$$

$$EC_o^{t,t+1} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \tag{4.17}$$

$$TC_o^{t,t+1} = \left[\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \right]^{\frac{1}{2}} \tag{4.18}$$

The values of $MI_o^{t,t+1}$ and its components can be greater, equal or smaller than one. These values indicate respectively productivity growth, stagnation or decline between periods t and $t+1$.

To identify which DMUs are shifting the frontier over time Fare et al. (1994) proposed a combined analysis of the technological change component of the MI with the two Shephard output distance functions evaluated for the DMU in $t+1$. The values of these three measures combined allow one to identify evidence of innovation. The conditions to be fulfilled by the innovators are the following:

- $TC^{t,t+1}$ >1, representing evidence of technological improvement, meaning that the frontier in $t+1$ envelops the frontier in t for the geometric average of the two estimates involving the location of the firm in t and t+1.
- $D_o^{t+1}(x^{t+1}, y^{t+1}) = 1$ or equivalently $E^{t+1}(x^{t+1}, y^{t+1}) = 1$, meaning that the DMU is located on the frontier of $t+1$.
- $D_o^t(x^{t+1}, y^{t+1}) > 1$ or equivalently $E^t(x^{t+1}, y^{t+1}) > 1$, meaning that the DMU in $t+1$ is outside the PPS of the previous period t.

Therefore, a firm is considered an innovator as it shifts the boundaries of PPS between t and $t+1$, and is located on the best-practice frontier in $t+1$.

Formulation of the MI with Efficiency Measures

Using the equivalences between the Shepard input distance function and the radial efficiency measure (4.8), the input-oriented Malmquist index (4.12) can also be rewritten in terms of efficiency estimates as shown in (4.19).

$$MI^{t,t+1} = \left[\frac{E^t(x^{t+1},y^{t+1})}{E^t(x^t,y^t)} \frac{E^{t+1}(x^{t+1},y^{t+1})}{E^{t+1}(x^t,y^t)} \right]^{\frac{1}{2}} \tag{4.19}$$

Similarly, using the equivalences between the Shepard output distance function and the radial efficiency measure (4.11), the output-oriented Malmquist index (4.16) can be expressed in terms of efficiency scores as shown in (4.19).

The efficiency change component and the technological change component are estimated as shown in (4.20) and (4.21).

$$EC^{t,t+1} = \frac{E^{t+1}(x^{t+1},y^{t+1})}{E^t(x^t,y^t)} \tag{4.20}$$

$$TC^{t,t+1} = \left[\frac{E^t(x^t,y^t)}{E^{t+1}(x^t,y^t)} \frac{E^t(x^{t+1},y^{t+1})}{E^{t+1}(x^{t+1},y^{t+1})} \right]^{\frac{1}{2}} \tag{4.21}$$

4.3.3.2 Specification of the MI with Directional Distance Functions

Exact Equivalences Between the Directional Distance Function and Radial Efficiency Measures

Fare and Grosskopf (2000) described exact relationships between the Shephard input and output distance functions and the Directional Distance Functions, for particular specifications of the directional vector.

Consider the Directional Distance Function model, as shown in (4.3). If the directional vector involves the simultaneous reduction of all inputs, along with a direction whose components are equal to the output levels observed in the DMU under assessment, such that $g = (g_x, g_y) = (-x, 0)$, the following relationship holds (Fare and Grosskopf, 2000).

$$\vec{D}(x,y;-x,0) = 1 - \frac{1}{D_i(x,y)} \tag{4.22}$$

From expression (4.8) it follows that:

$$\vec{D}(x,y;-x,0) = 1 - E(x,y) \tag{4.23}$$

Rearranging the terms in expression (4.23), we obtain an equivalent expression in terms of $E(x,y)$.

$$E(x,y) = 1 - \vec{D}(x,y;-x,0) \tag{4.24}$$

If the directional vector involves the simultaneous expansion of all outputs, along with a direction whose components are equal to the input levels observed in the DMU under assessment, such that $g=(g_x,g_y)=(0,y)$, the following relationship holds (Fare and Grosskopf, 2000).

$$\vec{D}(x,y;0,y)=\frac{1}{D_o(x,y)}-1 \tag{4.25}$$

From expression (4.11) it follows that:

$$\vec{D}(x,y;0,y)=\frac{1}{E(x,y)}-1 \tag{4.26}$$

Rearranging the terms in expression (4.26), we obtain an equivalent expression in terms of $E(x,y)$.

$$E(x,y)=\frac{1}{1+\vec{D}(x,y;0,y)} \tag{4.27}$$

Boussemart et al. (2003) provided an exact equivalence between the radial efficiency score $E(x,y)$ and the Directional Distance Function with a directional vector $g=(-x,y)$, as shown in formulation (4.28).

$$E(x,y)=\frac{1-\vec{D}(x,y;-x,y)}{1+\vec{D}(x,y;-x,y)} \tag{4.28}$$

Note that the equivalences (4.24), (4.27) and (4.28) hold for three configurations of the directional vector, as follows: $g=(-x,0)$, corresponding to the reduction of all inputs, given the output levels; $g=(0,y)$, corresponding to the expansion of all outputs, given the input levels; $g=(-x,y)$, corresponding to the simultaneous improvement of all inputs and all outputs, respectively.

Formulation of the MI with DDFs

Given the equivalences between the efficiency measures and the Directional Distance Function, valid for particular specifications of the directional vector, it is possible to estimate the Malmquist index using the value of Directional Distance Functions.

The formulation of the Malmquist index depends on the path defined by the directional vector, so three different formulations of the MI will be presented, for the particular directional vectors: $g=(-x,0)$, $g=(0,y)$ and $g=(-x,y)$.

Starting from expression (4.19) and using equivalence (4.24) for vector $g=(-x,0)$, the Malmquist index is defined as follows:

$$MI^{t,t+1}=\left[\frac{1-\vec{D^t}(x^{t+1},y^{t+1};-x^{t+1},0)}{1-\vec{D^t}(x^t,y^t;-x^t,0)}\;\frac{1-\vec{D^{t+1}}(x^{t+1},y^{t+1};-x^{t+1},0)}{1-\vec{D^{t+1}}(x^t,y^t;-x^t,0)}\right]^{\frac{1}{2}} \tag{4.29}$$

Alternatively, starting from expression (4.19) and using equivalence (4.27) for vector $g = (0, y)$, the Malmquist index is defined as follows:

$$MI^{t,t+1} = \left[\frac{\frac{1}{1+\vec{D}^t(x^{t+1},y^{t+1};0,y^{t+1})}}{\frac{1}{1+\vec{D}^t(x^t,y^t;0,y^t)}} \; \frac{\frac{1}{1+\vec{D}^{t+1}(x^{t+1},y^{t+1};0,y^{t+1})}}{\frac{1}{1+\vec{D}^{t+1}(x^t,y^t;0,y^t)}} \right]^{\frac{1}{2}} \tag{4.30}$$

This expression simplifies as follows:

$$MI^{t,t+1} = \left[\frac{1+\vec{D}^t(x^t,y^t;0,y^t)}{1+\vec{D}^t(x^{t+1},y^{t+1};0,y^{t+1})} \; \frac{1+\vec{D}^{t+1}(x^t,y^t;0,y^t)}{1+\vec{D}^{t+1}(x^{t+1},y^{t+1};0,y^{t+1})} \right]^{\frac{1}{2}} \tag{4.31}$$

Finally, starting from expression (4.19), and using equivalence (4.28) for vector $g = (-x, y)$, the Malmquist index is defined as follows:

$$MI^{t,t+1} = \left[\frac{\frac{1-\vec{D}^t(x^{t+1},y^{t+1};-x^{t+1},y^{t+1})}{1+\vec{D}^t(x^{t+1},y^{t+1};-x^{t+1},y^{t+1})}}{\frac{1-\vec{D}^t(x^t,y^t;-x^t,y^t)}{1+\vec{D}^t(x^t,y^t;-x^t,y^t)}} \; \frac{\frac{1-\vec{D}^{t+1}(x^{t+1},y^{t+1};-x^{t+1},y^{t+1})}{1+\vec{D}^{t+1}(x^{t+1},y^{t+1};-x^{t+1},y^{t+1})}}{\frac{1-\vec{D}^{t+1}(x^t,y^t;-x^t,y^t)}{1+\vec{D}^{t+1}(x^t,y^t;-x^t,y^t)}} \right]^{\frac{1}{2}} \tag{4.32}$$

Formulation of the MI with Composite Indicators

For performance evaluations involving composite indicators estimated with Directional Distance Functions, as formulated in (4.4), the Malmquist index shown in (4.29), (4.31) and (4.32) can be adapted in a straightforward manner using the directional vectors $g = (-1, -B, 0)$, $g = (0, 0, Y)$ and $g = (-1, -B, Y)$.

Formulation (4.33) of the MI is suitable for evaluations involving CIs with the directional vector $g = (-1, -B, 0)$, which is a straightforward adaptation of (4.29).

$$MI^{t,t+1} = \left[\frac{1-\vec{CI}^t(1,B^{t+1},Y^{t+1};-1,-B^{t+1},0^{t+1})}{1-\vec{CI}^t(1,B^t,Y^t;-1,-B^t,0^t)} \; \frac{1-\vec{CI}^{t+1}(1,B^{t+1},Y^{t+1};-1,-B^{t+1},0^{t+1})}{1-\vec{CI}^{t+1}(1,B^t,Y^t;-1,-B^t,0^t)} \right]^{\frac{1}{2}} \tag{4.33}$$

Similarly, formulation (4.34) calculated a MI index for evaluations involving CIs with the directional vector $g = (0, 0, Y)$:

$$MI^{t,t+1} = \left[\frac{1+\vec{CI}^t(1,B^t,Y^t;0,0,Y^t)}{1+\vec{CI}^t(1,B^{t+1},Y^{t+1};0,0,Y^{t+1})} \; \frac{1+\vec{CI}^{t+1}(1,B^t,Y^t;0,0,Y^t)}{1+\vec{CI}^{t+1}(1,B^{t+1},Y^{t+1};0,0,Y^{t+1})} \right]^{\frac{1}{2}} \tag{4.34}$$

Formulation (4.35) calculates a MI based on CIs with the directional vector $g = (-1, -B, Y)$. This is a straightforward adaptation (4.32):

$$MI^{t,t+1} = \left[\frac{\frac{1-\vec{CI}^t(1,B^{t+1},Y^{t+1};-1,-B^{t+1},Y^{t+1})}{1+\vec{CI}^t(1,B^{t+1},Y^{t+1};-1,-B^{t+1},Y^{t+1})}}{\frac{1-\vec{CI}^t(1,B^t,Y^t;-1,-B^t,Y^t)}{1+\vec{CI}^t(1,B^t,Y^t;-1,-B^t,Y^t)}} \; \frac{\frac{1-\vec{CI}^{t+1}(1,B^{t+1},Y^{t+1};-1,-B^{t+1},Y^{t+1})}{1+\vec{CI}^{t+1}(1,B^{t+1},Y^{t+1};-1,-B^{t+1},Y^{t+1})}}{\frac{1-\vec{CI}^{t+1}(1,B^t,Y^t;-1,-B^t,Y^t)}{1+\vec{CI}^{t+1}(1,B^t,Y^t;-1,-B^t,Y^t)}} \right]^{\frac{1}{2}} \tag{4.35}$$

Formulation (4.34) of the Malmquist index will be used in the empirical part of this paper to evaluate the evolution of social performance over time. It has the advantage of avoiding the occurrence of infeasibility in the estimation of productivity change over time, which is a common problem reported in evaluations of productivity change over time with the Directional Distance Functions, even for models assuming CRS. It also allows the direct use of the composite indicator score to estimate the evolution of performance over time and a straightforward interpretation of the meaning of the MI score, representing the proportional improvement in productivity levels between t and t+1.

4.4 Small Example

This small example has the objective to illustrate the estimation of productivity change over time using composite indicators formulated with Directional Distance Functions. We intend to show that the MI score, assuming CRS, can be obtained using the original input and output values of a firm's activity in the traditional DEA framework or using the CI formulation using a Directional Distance Function. The results are the same for all formulations of the MI presented in the previous section.

- (4.12) with Shephard input distance functions
- (4.16) with Shephard output distance functions
- (4.19) with radial efficiency scores
- (4.33) with CI estimated using DDFs and directional vector $g = (-1, -B, 0)$
- (4.34) with CI estimated using DDFs and directional vector $g = (0, 0, Y)$
- (4.35) with CI estimated using DDFs and directional vector $g = (-1, -B, Y)$

Suppose a decision maker wishes to assess a set of DMUs in a DEA framework with two inputs, x_1 representing the number of employees and x_2 representing energy consumption, and one output, y_1 representing the revenue obtained. The dataset used as an example comprises periods t and $t+1$, as reported in Table 4.4.

Table 4.4: Data for the small illustrative example with the DEA framework

	Period t			Period $t+1$		
DMUS	x_1^t	x_2^t	y_1^t	x_1^{t+1}	x_2^{t+1}	y_1^{t+1}
A	4	2	4	5	2	7
B	3	6	9	3	7	12
C	3	6.9	7.5	2.8	8.4	9.8
D	4	4	4	3	2	9
E	2	1	3	3	2	4.5
F	2	3	3	2	3	3

Using the data reported in Table 4.4, the standard DEA input-oriented model (4.7) can be used to estimate an input Malmquist index $(M_i^{t,t+1})$ using expression (4.19) based on efficiency scores or expression (4.12) based on Shephard input distance functions. Note that expression (4.8) states the equivalence between the DEA radial efficiency score and the Shephard input distance function. The results obtained are reported in Table 4.5.

Table 4.5: Input oriented assessment of productivity change using DEA

	DEA CRS input oriented model				Input Sherphard distance function				Malmquist index
DMUS	$E^t(t)$	$E^{t+t}(t+1)$	$E^t(t+1)$	$E^{t+1}(t)$	$D_i^t(t)$	$D_i^{t+1}(t+1)$	$D_i^t(t+1)$	$D_i^{t+1}(t)$	$M_i^{t,t+1}$ obtained with (4.19) or (4.12)
A	0.667	0.778	1.167	0.444	1.500	1.286	2.250	0.857	1.750
B	1	1	1.333	0.789	1	1	1.267	0.750	1.300
C	0.8333	0.876	0.817	0.667	1.2	1.143	1.124	1.5	0.8816
D	0.5	1	1.800	0.313	2	1	3.200	0.556	3.394
E	1	0.5	0.900	0.667	1	2	1.500	1.111	0.822
F	0.600	0.429	0.600	0.429	1.667	2.333	2.333	1.667	1

The Malmquist index could alternatively be estimated using an output-oriented DEA model (4.10). In this case, the MI could be obtained using (4.16) or (4.19). The results obtained are reported in Table 4.6.

Table 4.6: Output oriented assessment of productivity change using DEA

	DEA CRS output oriented model				Output Sherphard distance function				Malmquist Index
DMUS	$\frac{1}{E^t(t)}$	$\frac{1}{E^{t+1}(t+1)}$	$\frac{1}{E^t(t+1)}$	$\frac{1}{E^{t+1}(t)}$	$D_o^t(t)$	$D_o^{t+1}(t+1)$	$D_o^t(t+1)$	$D_o^{t+1}(t)$	$M_o^{t,t+1}$ obtained with (4.19) or (4.16)
A	1.500	1.286	2.250	0.857	0.667	0.778	1.167	0.444	1.750
B	1	1	1.267	0.750	1	1	1.333	0.789	1.300
C	1.2	1.143	1.124	1.5	0.8333	0.876	0.817	0.667	0.8816
D	2	1	3.200	0.556	0.5	1	1.800	0.313	3.394
E	1	2	1.500	1.111	1	0.5	0.900	0.667	0.822
F	1.667	2.333	2.333	1.667	0.600	0.429	0.600	0.429	1

One can conduct an assessment equivalent to the previous analysis based on the CI paradigm. In this context, instead of observing the transformation of inputs into outputs, we may define KPIs for the evaluation of performance. In this illustrative example, the first KPI represents energy consumption per employee $(B_1 = \frac{x_2}{x_1})$ and the second KPI represents revenue per employee $(Y_1 = \frac{y_1}{x_1})$. The assessment also takes into account a *dummy* input equal to one for all DMUs to enable the construction of the CI. The resulting dataset is reported in Table 4.7 and can be considered an equivalent representation of DMUs A to F presented in Table 4.4.

Table 4.7: Data for the small example with CI framework

	Period t			Period $t+1$		
DMUS	$dummy^t$	B^t	Y^t	$dummy^{t+1}$	B^{t+1}	Y^{t+1}
A	1	0.5	1	1	0.4	1.4
B	1	2	3	1	2.333	4
C	1	2.3	2.5	1	3.0	3.5
D	1	1	1	1	0.667	3
E	1	0.5	1.5	1	0.667	1.5
F	1	1.5	1.5	1	1.5	1.5

The Malmquist index score can be estimated using the composite indicator scores computed with model (4.4) using the dataset reported in Table 4.7. The results obtained for the directional vectors $g = (-1, -B, 0)$, $g = (0, 0, Y)$ and $g = (-1, -B, Y)$ are reported in Table 4.8.

Table 4.8: Results of the CI model and MI obtained from (4.33), (4.34), and (4.35)

	Model (4.4) with $g = (-1, -B, 0)$				Model (4.4) with $g = (0, 0, Y)$				Model (4.4) with $g = (-1, -B, Y)$				Malmquist index
DMU	$CI^t(t)$	$CI^{t+1}(t+1)$	$CI^t(t+1)$	$CI^{t+1}(t)$	$CI^t(t)$	$CI^{t+1}(t+1)$	$CI^t(t+1)$	$CI^{t+1}(t)$	$CI^t(t)$	$CI^{t+1}(t+1)$	$CI^t(t+1)$	$CI^{t+1}(t)$	$MI^{t,t+1}$
A	0.333	0.222	-0.167	0.556	0.5	0.286	-0.143	1.25	0.2	0.125	-0.077	0.385	1.750
B	0	0	-0.333	0.211	0	0	-0.25	0.267	0	0	-0.143	0.118	1.300
C	0.833	0.874	0.667	0.817	0.833	0.874	0.667	0.817	0.833	0.875	0.817	0.667	0.8816
D	0.5	0	-0.8	0.688	1	0	-0.444	2.2	0.333	0	-0.286	0.524	3.394
E	0	0.5	0.1	0.333	0	1	0.111	0.5	0	0.333	0.053	0.2	0.822
F	0.4	0.571	0.4	0.571	0.667	1.333	0.667	1.33	0.25	0.4	0.25	0.4	1

Note that the value of the CI changes according to the directional vector chosen. The within-periods scores correspond to different estimates of inefficiency, which depend on the direction specified for g. However, a unique efficiency measure $E(x,y)$ can be estimated using the exact equivalences between a radial efficiency score and DDF score for particular specifications of vector g. Expression (4.24) can be used to convert the CI score estimated with $g = (-1, -B, 0)$ into an equivalent radial efficiency score. Similarly, expression (4.27) is applicable when $g = (0, 0, Y)$, and expression (4.28) can be used when the $g = (-1, -B, Y)$.

Taking DMU A in period t as example, the radial efficiency score of $E^t_A(x^t, y^t) = 0.667$ as follows:

- For $g = (-1, -B, 0)$, expression (4.24) gives:

$$E^t_A(x^t, y^t) = 1 - CI^t(t) = 1 - 0.333 = 0.667$$

- For $g = (0, 0, Y)$, expression (4.27) gives:

$$E^t_A(x^t, y^t) = \frac{1}{1 + CI^t(t)} = \frac{1}{1 + 0.5} = 0.667$$

- For $g = (-1, -B, Y)$, expression (4.28) gives:

$$E^t_A(x^t, y^t) = \frac{1 - CI^t(t)}{1 + CI^t(t)} = \frac{1 - 0.2}{1 + 0.2} = 0.667$$

Similarly, depending on the direction of g, the Malmquist index can be estimated from the CI values using expressions (4.33), (4.34) and (4.35).

Taking DMU A as an example, the MI is estimated as follows of equations (4.29), (4.30), and (4.32).

- For $g = (-1, -B, 0)$, expression (4.33) gives:

$$MI^{t,t+1}_A = \left[\frac{1 - CI^t(t+1)}{1 - CI^t(t)} \times \frac{1 - CI^{t+1}(t+1)}{1 - CI^{t+1}(t)} \right]^{\frac{1}{2}} = \left[\frac{1 + 0.667}{1 - 0.333} \times \frac{1 - 0.222}{1 - 0.556} \right]^{\frac{1}{2}} = 1.75$$

- For $g = (0,0,Y)$, expression (4.34) gives:

$$MI_A^{t,t+1} = \left[\frac{1+CI^t(t)}{1+CI^t(t+1)} \times \frac{1+CI^{t+1}(t)}{1+CI^{t+1}(t+1)}\right]^{\frac{1}{2}} = \left[\frac{1+0.5}{1-0.143} \times \frac{1+1.25}{1+0.286}\right]^{\frac{1}{2}} = 1.75$$

- For $g = (-1,-B,Y)$, expression (4.35) gives:

$$MI^{t,t+1} = \left[\frac{\frac{1-CI^t(t+1)}{1+CI^t(t+1)}}{\frac{1-CI^t(t)}{1+CI^t(t)}} \times \frac{\frac{1-CI^{t+t1}(t+1)}{1+CI^{t+t1}(t+1)}}{\frac{1-CI^{t+1}(t)}{1+CI^{t+1}(t)}}\right]^{\frac{1}{2}} = \left[\frac{\frac{1+0.077}{1-0.077}}{\frac{1-0.2}{1+0.2}} \times \frac{\frac{1-0.125}{1+0.125}}{\frac{1-0.385}{1+0.385}}\right]^{\frac{1}{2}} = 1.75$$

Figure 4.1 depicts the shape of the frontier of technology for periods t and $t+1$ with the horizontal axis representing $\frac{B}{dummy}$ (or $\frac{x_2}{x_1}$) and the vertical axis representing $\frac{Y}{dummy}$ (or $\frac{y_1}{x_1}$). The frontier is the same, irrespectively of the model used for its estimation, which can be a standard DEA model with data from Table 4.4. A feature worth noting is the shape of the frontier, passing through the origin and with a horizontal line extending $B(t)$ and $B(t+1)$ to infinity parallel to the horizontal axis in period t and $t+1$, respectively. This particular shape of the frontier prevents the occurrence of infeasibility in the estimation the mixed-period scores $CI^t(t+1)$ and $CI^{t+1}(t)$, ensuring that no infeasibilities will occur in the computation of the MI.

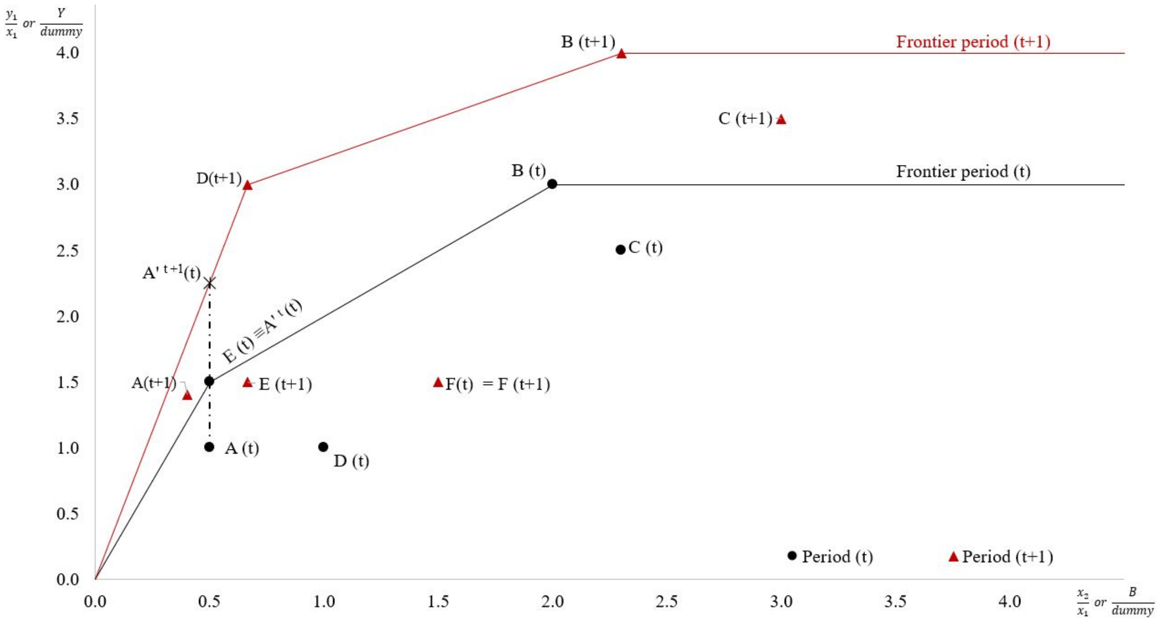

Figure 4.1: Illustration of the frontier shape.

In this normalized space used to visualize the PPS, a feature worth noting is that the projections on the frontier underlining the computation of the CIs and the MI are the same, irrespectively of the directional vector used for the evaluation of performance.

Taking the DMU A in period t as an example, represented by point $A(t)$ in the graph, there is a vertical line segment connecting $A(t)$ to the reference points in the frontier used for the estimation of the within-period composite indicator $CI^t(t)$ and the mixed-period composite indicator $CI^{t+1}(t)$. The first point, $A'^t(t)$ represents the radial target for $A(t)$ on the frontier in t. The second point, $A'^{t+1}(t)$, represents the radial target of $A(t)$ on the frontier in $t+1$. The estimation of the radial targets $A''(t)$ and $A'^{t+1}(t)$ considering the three directional vectors $g = (-1, B, 0)$, $g = (0, 0, Y)$, and $g = (-1, B, Y)$ are reported in Table 4.9.

Table 4.9: Estimation of projections on the frontier

within-period t (t)						
	Radial targets				Representation in the x-axis	Representation in the y-axis
directional vector	$CI^t(t)$	$dummy'^t(t)$	$B'^t(t)$	$Y'^t(t)$	$\frac{B'^t(t)}{dummy'^t(t)}$	$\frac{Y'^t(t)}{dummy'^t(t)}$
$g = (-1, -B, 0)$	0.333	0.667	0.333	1	$\frac{0.333}{0.667} = 0.5$	$\frac{1}{0.667} = 1.5$
$g = (0, 0, Y)$	0.5	1	0.5	1.5	$\frac{0.5}{1} = 0.5$	$\frac{1.5}{1} = 1.5$
$g = (-1, -B, Y)$	0.2	0.8	0.4	1.2	$\frac{0.4}{0.8} = 0.5$	$\frac{1.2}{0.8} = 1.5$
Cross period t+1 (t)						
	Radial targets				Representation in the x-axis	Representation in the y-axis
directional vector	$CI^{t+1}(t)$	$dummy'^{t+1}(t)$	$B'^{t+1}(t)$	$Y'^{t+1}(t)$	$\frac{B'^{t+1}(t)}{dummy'^{t+1}(t)}$	$\frac{Y'^{t+1}(t)}{dummy'^{t+1}(t)}$
$g = (-1, B, 0)$	0.556	0.444	0.222	1	$\frac{0.222}{0.444} = 0.5$	$\frac{1}{0.444} = 2.25$
$g = (0, 0, Y)$	1.25	1	0.5	2.25	$\frac{0.5}{1} = 0.5$	$\frac{2.25}{1} = 2.25$
$g = (-1, -B, Y)$	0.385	0.615	0.3075	1.385	$\frac{0.3075}{0.615} = 0.5$	$\frac{1.385}{0.615} = 2.25$

The procedures for obtaining the normalized representation of the targets illustrated in Figure 4.1 are also reported in Table 4.9. In these three cases, the projections on the frontier in t and $t+1$ are vertically aligned with $A(t)$, all rendering the same point $A'^t(t) = (0.5, 1.5)$ in the within-period assessment and point $A'^{t+1}(t) = (0.5, 2.25)$ in the mixed-period assessment, irrespectively of the directional vector used. Finally, it is note worthy that the same projections would be obtained using either the input or the output oriented DEA models. This feature underlines the theoretical equivalences between the models that lead to a unique estimate of the productivity change captured by the MI.

4.5 Illustrative Application

4.5.1 Data Collection

This section reports the study of 24 mining firms affiliated to GRI and the ICMM. Our data sources are the firms' sustainability reports and annual statements. To ensure the reliability of the reported information, the GRI guidelines require firms to comply with international standards, such as ISAE 3000 and AA1000AS. In addition, certified offices have to issue an impartial opinion about the quality of the information published in reports (GRI, 2013). This external assurance of information motivated our choice of the included in this study.

The sample includes both state-owned businesses and private corporations exploiting several mines around the world. The companies exploit a diversified portfolio of minerals, under a variety of social and natural local conditions. Notwithstanding their contextual particularities, all firms should comply with legislation on labor practices and with the international standards of ethical behavior.

For this illustrative application, we focused on reports published after 2013, whose data regards the years 2011 and 2012. The data collected is shown in Table 4.10 and Table 4.11. The KPIs selected reflect the framework discussed in the methodological section, as enlisted below.

- Benefits
  - Investments in education per employee (Y_1)
  - Female workforce ratio (Y_2)
  - Local Hiring ratio (Y_3)
  - Local Purchase ratio (Y_4)
- Burdens
  - Employees' turnover ratio (B_1)
  - All injury frequency rate (AIFR) (B_2)

The indicator "investments in education per employee" (Y_1) was obtained by the dividing the total amount of investments dedicated to employees' education and training in hundred million USD to the total workforce reported. The indicator "female workforce ratio" (Y_2) was the result of the division of the number of female employees and contractors in the firm by the total workforce. The "local hiring ratio" (Y_3) is the percentage of employees and contractors locally hired in the firm's workforce and the "local purchase ratio" (Y_4) is the percentage of materials and services locally purchased in the total volumes of purchases in million USD. The first burden indicator "employees' turnover rate" (B_1) was directly obtained from GRI reports, without any further calculations. The second burden indicator "AIFR" (B_4), here reported in observations by 2000 hours, was calculated for most firms based on the related indicators available in the reports.

In Table 4.10 and Table 4.11, indicators are marked the symbol "♠" correspond to missing values in the original indicator that were replaced by values reported in previous periods (2010-2011). When data on previous periods were not available, missing values were replaced by the worst value of each indicator observed in the same year. The cases are marked with the symbol "*".

In the dataset of 2011, three firms (U06, U20 and U22) reported extreme values for indicators Y_1, Y_2 and B_1, respectively. In year 2012 two firms (U03 and U24) reported extreme values for Y_1 and Y_2, respectively. These values are unrealistic so they were treated as inaccurate values. The extreme values were replaced by values closer to the central tendency of the sample. The approach followed consisted of replacing extreme values of benefit indicators by the mean $(\overline{Y_r})$ plus three times the standard deviation SD_{Y_r}. The same rationale applied to burden indicators, that were replaced by $\overline{B_i} + 3SD_{B_i}$ reported with extreme values. This procedure was adopted as well for extreme values observed in the sample of 2012, respectively Y_1 (U03) and Y_2 (U24).

Table 4.10: Dataset for 2011

Firm	**Unit**	B_1	B_2	Y_1	Y_2	Y_3	Y_4
Vale	U01	5	330	0.007	10.016	44	86
Alcoa	U02	12	372	7.7364	14.9829	0.03	25.9938
Anglo American Ni	U03	12	922♠	0.2676	18.8983	67	15
Rio Norte	U04	7.8	176	0.007*	7.2925	87	59.75
Sama	U05	2♠	1007	0.1151	4.0071	0.03	100
Samarco	U06	3	49	27.1488♦	12.9716	0.03	40.1
Votorantim	U07	21	520	0.007*	10.9387	0.03*	0.1
Norsk Hydro	U08	7	370	0.007*	19	0.03*	0.01
Kinross	U09	11.4	86	0.007*	11.3281	99	69
Rio Tinto	U10	41♠	144	0.0425	6.4006	43	100
Barrick	U11	9	92	0.0073	5	95.5 ♠	0.1
BHP Billiton	U12	10.47	500	0.0424	6	58	25
Glencore	U13	3.6	900	0.007*	9	0.03	0.1
Yamana	U14	6	544	0.0973	1	75♠	93.7
JX Nippon	U15	12	27	0.007*	12.7611	22.7474	0.1
Gold Fields	U16	10.72	1049	0.084	8	0.03	47
Mitsubishi Materials	U17	4	61	0.007*	1.3323	79♠	0.1
Gold Corp	U18	11	182	0.0331	5.6865	62♠	0.1*
Teck	U19	7	145	0.0383♠	17	54♠	0.1*
ARM	U20	4.8	43	0.0544	41.3815♦	65	40
Codelco	U21	3.6	3.3	0.007*	7.7	3.6	91
Sumitomo	U22	67.9431 ♦	1049	0.0073	22.5757	0.03	41
De Beers	U23	14♠	15♠	0.0817	23.1	86.9	51
Anglo American Pt	U24	7.08	410.8	0.0396	26	3.9985	95
Average		12.2255	374.8792	1.4941	12.5989	39.4161	40.8477
St.dev. (*SD*)		14.2700	361.2805	5.6854	9.1931	37.1777	37.8744

♠ Missing data replaced by the values observed in the previous year
*Missing values replaced by the worst observation of 2011
♦ Outliers replaced by $\overline{Y_r} + 3SD_{Y_r}$ or $\overline{B_i} + 3SD_{B_i}$

Table 4.11: Dataset for 2012

Firm	Unit	B_1	B_2	Y_1	Y_2	Y_3	Y_4
Vale	U01	5.1	280	0.0073	10.0205	44	87
Alcoa	U02	11	351	0.9469	9.9877	80	30.3575
Anglo American Ni	U03	9	0.09	9.6720♦	34.695	43.5	10.2
Rio Norte	U04	7	198	0.079	7.2917	89	50
Sama	U05	1.38	229	0.1061	4.4554	17	100
Samarco	U06	3.8	65	0.1080♠	12.793	63	37
Votorantim	U07	31.5	722	0.0073*	13	0.4*	65
Norsk Hydro	U08	10	410	0.0073*	18	0.4*	0
Kinross	U09	5.4	20	0.0073	11	77	69♠
Rio Tinto	U10	703	67	0.0425	6.4006	55	87
Barrick	U11	3.6	92	0.102	25	95.5	87
BHP Billiton	U12	8.83	470	0.0072	4.746	54	87
Glencore	U13	15.2	900♠	0.022	6.0225	0.4	0.1*
Yamana	U14	6	544	0.0073*	9	75♠	88
JX Nippon	U15	13.2897	26	0.0073*	1	97.4652	0.1*
Gold Fields	U16	7.89	684	0.0073*	13.027	0.4*	68
Mitsubishi Materials	U17	4.6	63	0.0183	12	51	0.1*
Gold Corp	U18	12	165	0.0065	1.2452	62♠	48
Teck	U19	6	133	0.0311	6.3654	71.4418	0.1*
ARM	U20	1.9	40	0.0345	13	65♠	50
Codelco	U21	1	3.3♠	0.1634	8.3333	99.72	87
Sumitomo	U22	260	0.0975	0.0073*	7.7	0.4269	48
De Beers	U23	516	48	0.0073*	19.5474	81.2	68
Anglo American Pt	U24	730	537.8	0.0817	54.0833 ♦	4.7269	94
Average		98.8954	252.0120	0.4786	12.8631	51.1492	52.5403
St.dev. (*SD*)		221.5023	264.8512	1.9674	11.5174	34.9327	35.1457

♠ Missing data replaced by the values observed in the previous year
*Missing values replaced by the worst observation of 2012
♦ Outliers replaced by $\overline{Y_r} + 3SD_{Y_r}$ or $\overline{B_i} + 3SD_{B_i}$

4.5.2 Cross-sectional Evaluation of Mining Firms in 2012

This section illustrates the benchmarking evaluation of mining firms in 2012. The direction chosen for the construction of the composite indicator is $g = (0, -B, Y)$ to explore the potential for improvement in burdens and benefits, while the *dummy* variable is fixed at one. The specification of this vector in formulation (4.5) enable the analysis of both the potential for equiportional improvements of the indicators (β_k) in the first stage of the optimization and the maximization of slacks in the second stage of optimization.

The CI scores obtained are reported in Table 4.12. Six firms were evaluated as efficient $(CI = 0)$ and 18 firms were classified as inefficient. The average value of the composite indicator is $\overline{CI_k} = 0.2651$. This value represents an estimate of the average potential for proportional improvement in the firms, indicating that benefit indicators could be increased by an average factor of 26.51% and burden indicators could be reduced by the same average factor.

Table 4.12 also reports the peers and lambda values (λ_j) for the inefficient firms. Five out of six efficient firms are used as peers for the other firms in the sample. Codelco (U21) is the benchmark for 14 firms, Barrick (U11) is the benchmark for 13 firms, both Anglo American Ni (U3) and Sama (U5) are benchmarks for 6 firms, and Anglo American Pt (U24) is the benchmark for 2 firms.

Table 4.13 reports the slacks estimated during the second stage of optimization. These variables enable exploring the maximum potential for improvement (both radial and non-radial) for the 18 inefficient firms. Note that none of the six efficient firms has positive slacks, meaning that they are strongly efficient.

Table 4.12: CI scores for 2012 data, with $g = (0, -B, -Y)$

Firm	DMU	CI	Peer (λ)					
Vale	U01	0.09113	U5	(0.6099)	U11	(0.297923)	U21	(0.092156)
Alcoa	U02	0.1738	U3	(0.1000)	U11	(0.0452)	U21	(0.8547)
A. American Ni	U03	0						
Rio Norte	U04	0.1204	U21	(1000)				
Sama	U05	0						
Samarco	U06	0.3332	U03	(0.0444)	U11	(0.4530)	U21	(0.5025)
Votorantim	U07	0.4116	U05	(0.354248)	U11	(0.6241)	U24	(0.0216)
Norsk Hydro	U08	0.5142	U03	(0.2328)	U11	(0.7671)		
Kinross	U09	0.1741	U03	(0.0778)	U11	(0.1518)	U21	(0.7703)
Rio Tinto	U10	0.0403	U05	(0.2702)	U21	(0.729754)		
Barrick	U11	0						
BHP Billiton	U12	0.0752	U05	(0.5035)	U21	(0.4964)		
Glencore	U13	0.9021	U11	(0.1873)	U21	(0.8126)		
Yamana	U14	0.02813	U05	(0.2673)	U11	(0.1174)	U21	(0.6152)
JX Nippon	U15	0.02313	U21					
Gold Fields	U16	0.3496	U05	(0.3656)	U11	(0.6311)	U24	(0.0032)
Mitsubishi Materials	U17	0.4154	U03	(0.0872)	U11	(0.3811)	U21	(0.5316)
Gold Corp	U18	0.6083						
Teck	U19	0.3939	U11	(0.03235	U21	(0.9676)		
ARM	U20	0.0437	U11	(0.3141)	U21	(0.6858)		
Codelco	U21	0						
Sumitomo	U22	0						
De Beers	U23	0.0735	U03	(0.1822)	U11	(0.4707)	U21	(0.3469)
A. American Pt	U24	0						
CI		0.2651						
St.dev.(SD)		0.2404						

Table 4.13: Slacks estimated with model (4.5)

Firm	DMU	s_1^-	s_2^-	s_1^+	s_2^+	s_3^+	s_4^+
Vale	U01	2.6288	87.0964	0.1024	0	0	0
Alcoa	U02	7.1701	283.0048	0	0	0	43.6819
A. American.Ni	U03	0	0	0	0	0	0
Rio Norte	U04	5.1568	170.8510	0.07448	0.1626	0	30.9775
Sama	U05	0	0	0	0	0	0
Samarco	U06	0	0	0.4143	0	11.3136	34.2539
Votorantim	U07	0	274.6152	0.0931	0	65.1624	0
Norsk Hydro	U08	0	128.5416	2.3193	0	82.7881	69.1050
Kinross	U09	2.4416	0	0.8859	0	4.2883	0
Rio Tinto	U10	673.5090	0	0.1038	0.6255	20.1442	0
Barrick	U11	0	0	0	0	0	0
BHP Billiton	U12	6.9741	317.6740	0.12672	1.2769	0	0
Glencore	U13	0	68.1319	0.1097	0	98.1686	86.8097
Yamana	U14	4.4243	454.6428	0.1334	0	0	0
JX Nippon	U15	11.9825	22.0984	0.1558	7.3098	0	86.8976
Gold Fields	U16	0	301.3129	0.0939	0	65.9649	0
Mitsubishi Materials	U17	0	0	0.9439	0	21.0186	80.1578
Gold Corp	U18	3.6993	61.3161	0.1533	6.33055	0	9.7974
Teck	U19	2.5524	74.4407	0.1178	0	0	86.8606
ARM	U20	0	7.0827	0.1073	0	30.5485	34.8110
Codelco	U21	0	0	0	0	0	0
Sumitomo	U22	0	0	0	0	0	0
De Beers	U23	474.3733	0	1.8601	0	0.3142	0
A. American Pt	U24	0	0	0	0	0	0

Table 4.14 reports the calculation of targets for the 18 inefficient firms.

Table 4.14: Targets for 2012

Firm	DMU	B_1'	B_2'	Y_1'	Y_2'	Y_3'	Y_4'
Vale	U01	2.0063	167.3850	0.1100	10.9331	48.0100	94.9289
Alcoa	U02	1.9179	6.9890	1.1115	11.7239	93.9045	79.3163
A. American Ni	U03	-	-	-	-	-	-
Rio Norte	U04	1	3.3	0.163	8.333	99.72	87
Sama	U05	-	-	-	-	-	-
Samarco	U06	2.5337	43.3397	0.55836	17.0560	95.3074	83.5836
Votorantim	U07	18.5332	150.1793	0.1029	18.3513	65.7271	91.7567
Norsk Hydro	U08	4.8571	70.6024	2.3299	27.2570	83.3938	69.1202
Kinross	U09	2.0176	16.5160	0.8942	12.9161	94.7014	81.0194
Rio Tinto	U10	1.1026	64.2944	0.1475	7.2849	77.3652	90.5131
Barrick	U11	-	-	-	-	-	-
BHP Billiton	U12	1.1913	116.9592	0.1342	6.3800	58.0634	93.5466
Glencore	U13	1.4870	19.9142	0.1515	11.4548	98.9295	87
Yamana	U14	1.4068	74.0542	0.1405	9.2531	77.1097	90.4754
JX Nippon	U15	1	3.3	0.163	8.333	99.72	87
Gold Fields	U16	5.1313	143.5300	0.1033	17.5818	66.5048	91.7758
Mitsubishi Materials	U17	2.6889	36.8266	0.9693	16.9853	93.2065	80.2994
Gold Corp	U18	1	3.3	0.163	8.333	99.72	87
Teck	U19	1.0841	6.1696	0.1610	8.8722	99.5834	87
ARM	U20	1.8168	31.1661	0.1438	13.5691	98.3942	87
Codelco	U21	-	-	-	-	-	-
Sumitomo	U22	-	-	-	-	-	-
De Beers	U23	3.6822	44.4702	1.8676	20.9844	87.4853	7342
A. American Pt	U24	-	-	-	-	-	-

This benchmarking procedure can provide insights for the improvement of social practices of the mining firms. To illustrate the learning potential of good practices amongst firms, take as an example the South African multinational firm African Rainbow Minerals (U20). African Rainbow Minerals (ARM) is a leading South African multinational mining company. It holds the entire production chain in the exploitation and processing of a diversified portfolio of ores in South Africa, Zambia, and Malaysia, with emphasis on Iron, Nickel and Gold investments.

ARM has a *CI* score equal to 0.0437, signaling potential for improvement in social practices. This could be achieved by the observation of best practices in its peers, Barrick (U11) and Codelco (U21). The first peer, Codelco (U21), is a Chilean state-owned company with operations in two countries in South America. This firm is specialized in the exploration and processing of copper and its by-products. The second peer, Barrick (U11), is a Canadian multinational, holding core operations with Gold and Copper in 10 countries, including USA, Saudi Arabia, and Australia.

Figure 4.2 portrays a comparison between ARM its benchmark firms (peers) for each indicator. The x-axis in the graph represents the values of the indicators representing burdens (B_i) and benefits (Y_r). To facilitate the visualization, the indicator “investments on education per employee” (Y_1) is reported in thousands of USD dollars per employee. The percentage indicators are reported in their original scale, and the indicator “All injury frequency rate” (B_2) is re-scaled by diving by 100.

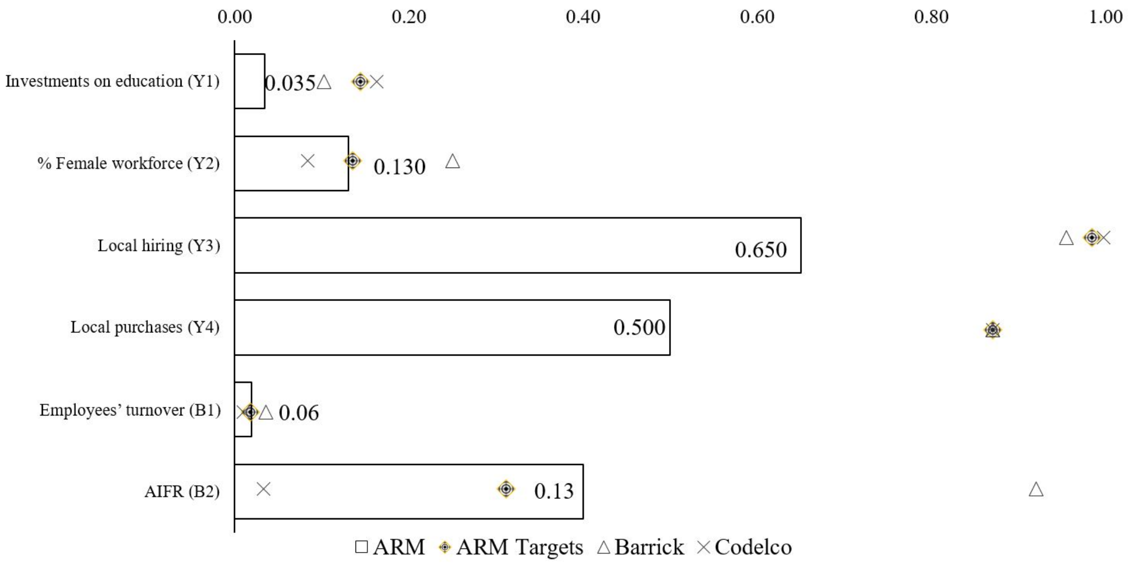

Figure 4.2: Illustration of benchmarking analysis.

Concerning the indicators of social benefits, insights regarding best practices in terms of "investments in education per employee" (Y_1) can be provided both by Barrick and Codelco. Barrick shows good practices in the field of gender balance, with one of the best levels of the "female workforce ratio" (Y_2) observed in the sample. Both Coldeco and Barrick can provide good examples of local development practices, both in terms of "local hiring ratio" (Y_3) and "local purchase ratio" (Y_4). The social burdens of "employees' turnover ratio" (B_1) and "all injury frequency rate" (B_2) can be reduced by learning practices from Codelco, whose levels in these indicators are close to zero.

4.5.3 Evolution of Social Performance Over Time

This section describes the analysis of the social performance of firms in the biennium 2011-2012. We will use the directional vector $g = (0,0,Y)$ for this analysis, although the vectors $g = (-1,B,0)$ and $g = (-1,B,Y)$ could also have been used, leading to the same results of the Malmquist index. The results obtained for the composite indicators $CI^t(t)$, $CI^{t+1}(t+1)$, $CI^t(t+1)$, and $CI^{t+1}(t)$ are reported in Table 4.15.

The Malmquist index $(MI^{t,t+1})$ was calculated using expression (4.34). Both the efficiency change $(EC^{t,t+1})$ and the technological change $(TC^{t,t+1})$ components are reported in Table 4.16.

Table 4.15: CI scores with vector $g = (0,0,Y)$ used for the calculation of $MI^{t,t+1}$

Firm	DMU	$CI^t(t)$	$CI^{t+1}(t+1)$	$CI^t(t+1)$	$CI^{t+1}(t)$
Vale	U01	0.002835383	0.091137698	-0.0080032	0.102843553
Alcoa	U02	0.733536657	0.173806677	0.181268056	0.024134586
A.American Ni	U03	0.263193572	0	-0.99720802	0.367996967
Rio Norte	U04	0	0.120449438	-0.04723529	0.14613525
Sama	U05	0	0	-0.60833363	-083584
Samarco	U06	0	0.533882407	-0.15485796	-0.88177233
Votorantim	U07	2.782886918	0.417856933	0.48767864	2.20117791
Norsk Hydro	U08	1.177947368	0.928993913	1.298944444	0.637066277
Kinross	U09	0	0.192779261	-0.42746345	-037616
Rio Tinto	U10	0	0.042172755	-0.04325431	-0.04943371
Barrick	U11	0	0	-0.53562005	0.044188482
BHP Billiton	U12	0.6704208	0.075248397	0.083962852	0.710875237
Glencore	U13	2.448416667	4.789060224	5.854782484	1.777777778
Yamana	U14	0	0.028130428	-0.04180438	-0.02668664
JX Nippon	U15	1.424160668	0.023136511	-0.09512936	1.520556433
Gold Fields	U16	1.063891012	0.350914754	0.422555638	0.971598441
Mitsubishi M.	U17	0	0.810458097	0.457828489	0.262278481
Gold Corp	U18	0.585030835	0.608387097	0.527775227	0.605145159
Teck	U19	0.472571602	0.393906573	0.169883531	0.582881228
ARM	U20	0	0.084795858	-0.62063931	-0.40611649
Codelco	U21	0	0	-0.92145847	-0.04395604
Sumitomo	U22	0.544193482	0	-0.97030303	0.389034816
De Beers	U23	0	0.086093309	-0.06128688	-0.10364577
A. American Pt	U24	0	0	-0.34600596	-0.0763272
$\overline{CI}$		0.50705	0.40630043	0.150253169	0.364772517
St.dev. (SD)		0.78117	0.971656559	1.328115873	0.692809132

Table 4.16: Social performance change over time

DMU	Firms	$MI^{t,t+1}$	$EC^{t,t+1}$	$TC^{t,t+1}$
U01	Vale	1.0108	0.9191	1.0998
U02	Alcoa	1.1315	1.4769	0.7662
U03	A.American Ni ⋆	24.8784	1.2632	19.6948
U04	Rio Norte	1.0362	0.8925	1.1610
U05	Sama⋆	1.5972	1.0000	1.5972
U06	Samarco	0.3020	0.6519	0.4632
U07	Votorantim	2.3960	2.6680	0.8981
U08	Norsk Hydro	0.8967	1.1291	0.7942
U09	Kinross	1.2099	0.8384	1.4431
U10	Rio Tinto	0.9764	0.9595	1.0176
U11	Barrick⋆	1.4995	1.0000	1.4995
U12	BHP Billiton	1.5659	1.5535	1.0080
U13	Glencore	0.4913	0.5957	0.8248
U14	Yamana	0.9940	0.9726	1.0219
U15	JX Nippon	2.5690	2.3693	1.0843
U16	Gold Fields	1.4551	1.5278	0.9525
U17	Mitsubishi Materials	0.6916	0.5523	1.2520
U18	Gold Corp	1.0175	0.9855	1.0325
U19	Teck	1.1956	1.0564	1.1317
U20	ARM	1.2013	0.9218	1.3032
U21	Codelco⋆	3.4889	1.0000	3.4889
U22	Sumitomo ⋆	8.4987	1.5442	5.5036
U23	De Beers	0.9376	0.9207	1.0184
U24	A. American Pt ⋆	1.1884	1.0000	1.1884
Average		2.5929	1.1583	2.1352
St.dev.(SD)		5.0143	0.5021	3.8816

The average score of performance change ($\overline{MI}^{t,t+1}$) is equal to 2.59, indicating improvements in social performance between 2011 and 2012. This results from the combined effect of efficiency improvements ($E^{t,t+1} > 1$), meaning that on average inefficient firms are closer to the frontier in 2012 than in 2011, and technological improvements ($TC^{t,t+1} > 1$), representing shifts in the frontier towards higher productivity levels between 2011 and 2012.

Three firms in the sample exhibit outstanding performance progress (Anglo American Ni, Sumitomo and Codelco) with a MI score well above the sample average. In particular, Anglo American Ni has a MI score equal to 24.8784, which is worth highlighting. The decomposition of the MI for this company indicates that the main source of performance improvement is the technological change component ($TC^{t,t+1}$), signaling advances in the frontier in the biennium analyzed. The efficiency change component shows an improvement aligned with the sample average.

Despite the overall improvement observed in the sample, seven firms show evidence of deterioration of performance: Samarco (U06), Norksh Hydro (U08), Rio Tinto (U10), Glencore (U13), Yamana (U14), Mitsubishi Materials (U17) and De Beers (U23). Some firms in this subgroup failed to catch up with the frontier even when it retreated. This is the case of Samarco (U06) and Glencore (U13). In the latter firm, the efficiency change component decreased by a factor of 59% while the technological change component decreased by a factor of 82%.

Next, we will explore innovation aspects for the firms evaluated. This analysis requires the evaluation of the innovation conditions of Fare et al. (1994):

- $TC^{t,t+1}$ >1
- $D_o^{t+1}(x^{t+1}, y^{t+1}) = 1$ or equivalently $E^{t+1}(x^{t+1}, y^{t+1}) = 1$
- $D_o^{t}(x^{t+1}, y^{t+1}) > 1$ or equivalently $E^{t}(x^{t+1}, y^{t+1}) > 1$

Note that the efficiency scores can be obtained from the Directional Distance Function values with $g = (0, 0, Y)$ using expression (4.27). The radial efficiency scores obtained are reported in Table 4.17.

Table 4.17: Efficiency scores required for the evaluation of innovation of mining firms

Firms	DMU	$E^{t+1}(x^{t+1},y^{t+1})$	$E^{t}(x^{t+1},y^{t+1})$
Vale	U01	0.916474613	1.008067768
Alcoa	U02	0.851929044	0.846547907
A.American Ni $\star$	U03	1	358.1687548
Rio Norte	U04	0.892498997	1.049577078
Sama $\star$	U05	1	2.553193423
Samarco	U06	0.651940459	1.183233057
Votorantim	U07	0.705289777	0.672188182
Norsk Hydro	U08	0.518404954	0.434982238
Kinross	U09	0.838378091	1.746613382
Rio Tinto	U10	0.959533815	1.04520983
Barrick $\star$	U11	1	2.153409078
BHP Billiton	U12	0.930017662	0.92254084
Glencore	U13	0.172739609	0.14588355
Yamana	U14	0.972639242	1.043628231
JX Nippon	U15	0.977386682	1.105130342
Gold Fields	U16	0.740239158	0.702960203
Mitsubishi M.	U17	0.552346393	0.685951748
Gold Corp	U18	0.621740874	0.654546547
Teck	U19	0.717408196	0.854785945
ARM	U20	0.921832428	2.636013763
Codelco $\star$	U21	1	12.73211765
Sumitomo $\star$	U22	1	33.67346904
De Beers	U23	0.920731204	1.065288189
A. American Pt $\star$	U24	1	1.529065922
Average $\overline{E}(x,y)$		0.8275638	17.85888161
St.dev.(SD)		0.202921079	71.28645771

The combined analysis of the scores reported in Tables 4.16 and 4.17 enables the identification of six innovative firms in the sense of Fare et al. (1994). These firms are A. American Ni, Sama, Barrick, Codelco, Sumitomo and A. American Pt, all signaled with the symbol $\star$ in Tables 4.16 and 4.17.

The identification of innovative firms in terms of social performance enables one to trace which firms promote the betterment of social practices in the controversial mining sector.

Next, we provide a brief overview of the mains features of these companies.

Anglo American Ni is a centenary multinational with South African roots. It extracts and processes two-thirds of the total production of nickel and ferronickel in the world. This company holds multiple nickel mines in Brazil.

The second most innovative firm is the Japanese Sumitomo Metal Mining (SMM), which explores gold, nickel and non-metallic minerals in four continents.

The third innovative company is Codelco, which operates in Chile and Brazil with focus on nickel, gold, and silver.

The forth innovative firm is the Brazilian Sama, one of the global leaders in the production of asbestos and chrysotile.

The fifth firm is Anglo American Platinum, based in the Southern African region. It has one of the most diversified portfolios of ores in the sample (cobalt, copper, gold, iridium, nickel, osmium, palladium, platinum, rhodium, and ruthenium).

Finally, Barrick Gold Corporation is a Canadian multinational with operations in the three Americas, Africa, Oceania and Asia. Barrick exploits and processes gold and copper.

The indicators of these six innovative firms in 2011 and 2012 and the gain between 2011 and 2012 are reported in Table 4.18.

Table 4.18: Shift in the indicators of innovative firms

DMU	Data	Employees' turnover rate	AIFR	$ education per employee	%female workforce	%Local Hiring	%Local Purchases
		B_1	B_2	Y_1	Y_2	Y_3	Y_4
Anglo American Ni (U03)	Observed (2011)	12	n.a	0.268	18.898	67	15
	Observed (2012)	9	0.09	n.a	34.695	43.5	10.2
	Shift 2011-2012	-25%	n.a	n.a	84%	-35%	-32%
Sama (U05)	Observed (2011)	n.a	1007	0.115	4.007	0.03	100
	Observed (2012)	1.4	229	0.106	4.455	17	100
	Shift 2011-2012	n.a	-77%	-8%	11%	56567%	0%
Barrick (U11)	Observed (2011)	9	92	0.0073	5	n.a	0.1
	Observed (2012)	3.6	92.0	0.102	25	95.5	87
	Shift 2011-2012	-60%	0%	1297%	400%	n.a	86900%
Codelco (U21)	Observed (2011)	3.6	3.3	n.a	7.7	3.6	91
	Observed (2012)	1	n.a	0.163	8.333	99.72	87
	Shift 2011-2012	-72%	n.a	n.a	8%	2670%	-4%
Sumitomo (U22)	Observed (2011)	n.a.	1049	0.007	22.576	0.03	41
	Observed (2012)	260	0.1	n.a	7.7	0.427	48
	Shift 2011-2012	n.a.	-100%	n.a	-66%	1323%	17%
Anglo American Pt (U24)	Observed (2011)	7.08	410.8	0.04	26.0	3.999	95
	Observed (2012)	730	537.8	0.082	n.a	4.727	94
	Shift 2011-2012	10211%	31%	106%	n.a	18%	-1.1%

Taking Anglo American Ni (U03) as an example, we can see that this firm fulfilled the conditions required to be considered innovator by enhancing the "% female workforce" by approximately 1.84 times to improve gender balance amongst employees and contractors. Despite the undesirable results observed in the local development practices (local hiring and local purchases both decreased approximately 30%), this firm succeeded in the reduction of the burden "employees' turnover rate" by 25%.

Looking at each indicator individually, we can see that the most remarkable reduction in indicator of "employees' turnover rate" is observable in Codelco. Reductions in the indicator of "AIFR" were observable in two firms. The first firm is Sama (U05), that reduced by three times the occurrence of injuries and the second is Sumitomo (U21), whose levels of injuries dropped to virtually zero in the last period. Notorious improvement in the indicator of "$ education per employee" was observed in Barrick (U11) and Anglo American Pt (U24). The levels of "$ education per employee" in Barrick is more than 10 times higher in 2012 that it was in the previous year. Anglo American Pt managed to double the levels of this indicator between 2011 and 2012. The enhancement of "% female workforce " was lead by Barrick (U11), which quadrupled the percentage of the female population in the firm's body of work. The indicator " % local hiring" is a highlight in the company Sama (U05) that has been able to increase its local hiring by 56 times. Finally, the indicator "% local purchases" decreased in most of the innovators (A. American Ni, Codelco and A. American Pt), but had a distinguished improvement in Barrick.

Figure 4.3 provides the visualization of the evolution of firms' social performance over time. This graph depicts in the X-axis the efficiency scores $E^{t+1}(x^{t+1}, y^{t+1})$ reflecting the performance assessment of the 24 mining firms in the year 2012. The Y-axis depicts the Malmquist index ($MI^{t,t+1}$) reflecting the changes in social performance in the biennium analyzed (2011-2012). A horizontal segment crosses the Y-axis at $MI^{t,t+1} = 1$ and a vertical segment crosses the X-axis at the median of the efficiency scores in the sample.

Figure 4.3 is divided into four quadrants, representing different profiles of firms: QI: "shining stars",Q II: "rising stars", QIII: "firms on red alert", and Q IV:"Falling stars". The use of quadrants in a matrix representation of performance can be traced back to previous DEA studies, including Boussofiane et al. (1991); Camanho and Dyson (1999); Vaz and Camanho (2012).

The first group in QI comprises the firms with the best performance in the sample, with both high performance in the final year and a positive trend in the evolution over time. Nine firms are comprised in the first quadrant: the six innovative firms of the sample (marked with a star $\star$) as well as BHP Billiton (U12), JX Nippon (U15) and ARM (U20). Note that the value of the MI for U22 and U03 is very high so the Y-axis has a discontinuity after 4.00 to allow visualization of these firms.

Quadrant QII, corresponding to the "Rising stars", comprises eight firms: Vale (U01), Alcoa (U02), Rio Norte (U04), Votorantim (U07), Kinross (U09), Gold Fields (U16), Gold Corp (U18) and Teck (U19). This quadrant encompasses firms placed behind the top performance of the sample, but that improved their social performance over time. For instance, Votorantim (U07) had a MI equal to 2.39 signaling social performance improvement, but its efficiency level in 2012 is only 70.5%.

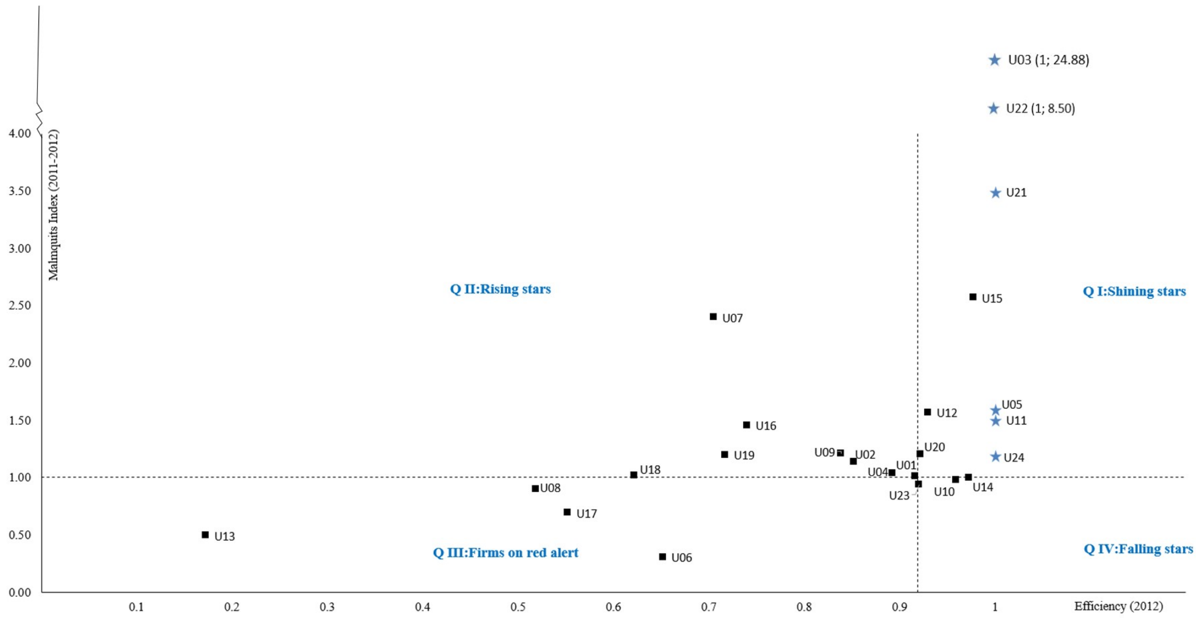

Figure 4.3: Evolution of social performance over time (2011,2012).

Quadrant QIII, corresponding to the "firms on red alert", lodges four firms: Norksh Hydro (U08), Mitsubishi Materials (U17), Glencore (U13) and Samarco (U06). This group comprised the firms that declined their social performance between 2011 and 2012 and have poor social performance in the last period considered. Glencore and Samarco showed evidence of decline both in the efficiency change component and in the technological change component. Norksh Hydro and Mitisubish Materials showed decline only in one of the components of the MI. Taking Mitsubishi Materials (U17) as an example, this firm showed decline in the efficiency change component (approximately 55.23% in 2012), while the technological change component was enhanced to a factor of 125.20%.

The last quadrant, QIV "falling stars" includes the firms that, despite the decline in social performance between 2011 and 2012, are still able to exhibit good performance in the final year. Three firms are located in this quadrant: Rio Tinto (U10), Yamana (U14), De Beers (U23). Note that MI values close to unity observed for the firms in this quadrant indicate that the decline in performance was smooth, suggesting stagnation rather than a negative trend in performance over time.

4.6 Conclusions

This study proposed an innovative methodology to quantify the social performance of large firms and track its evolution over time. This chapter developed a framework for the selection of Key Performance Indicators reflecting the recommendations of major international entities. The methodology discussed in this chapter involved the construction of a CI, based on a DDF model, capable of supporting both benchmarking comparisons and the estimation of the Malmquist Productivity index in the context with both desirable and undesirable KPIs.

The procedure proposed for the calculation of the MI using CI scores represents the major innovative feature of this study. The developments discussed in the methodology section enabled the estimation of the MI using three particular directional vectors, equivalent to an input-oriented directional vector, an output-oriented directional vector and a directional vector involving adjustments to all dimensions simultaneously. Another worth noting feature of the CI model developed is that, in the longitudinal analysis, it prevents the occurrence of infeasibility in the estimation of mixed-period Directional Distance Functions.

Concerning the empirical application of this methodology to large companies in the mining sector, the main contributions are as follows. The first contribution is the identification of KPIs available in companies' reports with external assurance that can be used for the assessment of social performance in the mining sector. The second contribution is the categorization of firms according to their social performance in a given moment of time, as well as the trend in the evolution of performance over time. The third contribution is the identification of innovative firms. The last contribution concerns the definition of targets for improvements resulting from a benchmarking approach. This benchmarking exercise can be valuable in helping firms to reach higher standards of social performance in the future.

A limitation of this study concerns the collection of reliable and updated information on indicators related to firms' social impact on society. The main sources of information available are sustainability reports voluntarily issued by firms. Due to the lack of available data, the framework proposed did not support the examination of social performance based on other indicators of firms' impact on local communities (e.g.; quality of life nearby mining sites, land disputes, disputes on water use).

As future research, extensions of this study can include the expansion of the sample to allow a broader analysis of social performance of firms. In addition, since environmental and economic issues can create social conflicts, a longitudinal analysis considering a CI of Corporate Social Responsibility could complement the performance evaluation of firms in the mining industry.

CHAPTER 5

The Assessment of Corporate Social Responsibility: Construction of an Industry Ranking and Identification of Potential for Improvement

Abstract This chapter proposes an innovative composite indicator to evaluate Corporate Social Responsibility (CSR). The methodology used involves three stages. First, the criteria and indicators that appropriately reflect CSR are identified, considering in particular the case of mining firms. All dimensions of the Triple Bottom Line (economic, environmental and social) are taken into account in the assessment of firms' performance. Then, an optimization model, grounded in the Data Envelopment Analysis technique, is used to obtain a relative measure of CSR achievements and guide performance improvement efforts at the firm level. This model allows distinguishing the firms with best practices from those with potential for improvement. Finally, a Goal Programming model is proposed to identify a Common Set of Weights for the indicators of CSR that can underlie the construction of an industry ranking. The advantage of this method is that the weights are endogenously determined resorting to optimization, in order to show the firms in the industry in the best possible light whilst respecting the trade-offs observed at the frontier of technology. An illustrative application of the method proposed is presented at the end of the paper. The results and their managerial implications are discussed with the objective of promoting the discussion and awareness of this topic among decision makers and the society in general, supporting the sustainable development of industrial activities.

Keywords : Data Envelopment Analysis, Directional Distance Functions, composite indicators, Goal Programming, Common Set of Weights.

5.1 Introduction

The mining industry has a highly complex production chain. The International Council of Mining and Metals (ICMM, 2012a) describes an extensive list of stakeholders in some way affected by this industry: investors, suppliers, employees, contractors, government, indigenous peoples, mining affected communities, civil society organizations, trade unions and final customers. These stakeholders exert pressure on the mining corporations attempting to promote economic and social benefits at local and global levels, without compromising the needs of future generations.

The mineral exploitation as an economic activity faces strict legislation due to its social and environmental impacts. Firms' operations and processing activities often involve the use of hazardous chemicals, posing risks to both the safety and health of employees and to the environment. In recent years, the pressure for mining firms to guarantee a responsible behavior through the implantation of Corporate Social Responsibility (CSR) practices has increased. To address this issue, prominent international standards, such as ISO (2010), strongly require that the evaluation of Corporate Social Responsibility (CSR) is conducted through a comprehensive and consensual framework that takes into account the firms' performances in three dimensions: economic, environmental and social.

The economic performance of a company should reflect the wealth generated and its long-run distribution viability. In the environmental dimension, the performance should take into consideration the impact of the firm on the planet, with emphasis on the renewable use of natural resources and the dispersion of waste. The social performance should consider the firm's practices of decent work and the contribution to local development. Despite the prominence of this theme in organization management and performance assessment fields, the quantification of firm's social performance remains a challenge and requires special attention (Branco and Rodrigues, 2006). Another challenge is the lack consensus in the literature regarding the specification of appropriate models and selection of indicators to evaluate CSR (e.g., Cooper et al., 2006; Garcia-Castro et al., 2010; Orlitzky et al., 2003; Surroca et al., 2010; Waddock and Graves, 1997; Williams and Barrett, 2000).

The methodology proposed in this study focuses on a consensual evaluation firms' CSR and the identification of potential performance improvements. The first procedure involves the specification of criteria and indicators to evaluate CSR of firms, with special attention to the criteria associated with the mining sector. Next, a firm-level analysis of CSR is carried on by using a benefit of doubt approach to conduct the benchmarking exercise, where each firm can choose the weights that show it in the best possible light when constructing the composite indicator of CSR. The composite indicator reveals the potential for improvement of each firm, taking into account its profile in terms of strengths and weaknesses. A Directional Distance Function model (Chambers et al., 1996a) is used for this purpose. Lastly, an industry-level analysis is conducted for the construction of a ranking of CSR for firms. It is based on the use of a Goal Programming model for the estimation of a consensual set of common weights. These weights show the firms in the sector in the best possible light, whilst respecting the trade-offs observed at the industry frontier of technology. The methodology proposed is illustrated in the context of the evaluation of mining firms, but it can be generalized to other contexts.

The main contributions of this work are as follows. The first contribution is the proposal of a comprehensive framework for the selection of criteria and indicators to evaluate CSR of mining firms. The second contribution is the ability to quantify the concept of CSR, reflecting the relative performance of organizations recurring to optimization techniques. The integration of DEA-based models and Goal Programming for this purpose is unprecedented. The third contribution is the ability to guide improvements of CSR, both at the firm level (through the identification of benchmark firms) and at the industry level (through the ranking of firms with a Common Set of Weights, reflecting the industry perspective).

This chapter is organized as follows. Section 5.2 presents the alternative definitions of CSR available in the literature and reviews the evaluation approaches used in previous research. Section 5.3 presents the methodology underlying our study. This section also contains a small illustrative example for depicting the approach proposed. Section 5.4 contains an illustrative application with the evaluation of 24 mining firms, discussing the results obtained and their managerial implications. Section 5.5 concludes the paper by highlighting the main contributions of the study and outlining future research opportunities.

5.2 Corporate Social Responsibility

5.2.1 Definitions of Corporate Social Responsibility

Corporate Social Responsibility (CSR) is a dynamic concept, for which many definitions have been proposed since the beginning of the last century. Before the 1960s, the social responsibility of a business consisted of guaranteeing profits to its investors and generating jobs for society. The seminal work entitled "Social responsibilities of the businessman" (Bowen, 1953), coined the term Corporate Social Responsibility in the literature. According to Bowen (1953), CSR refers to corporate obligations to pursue policies and lines of actions with value to society, with focus on pursuing honest profits. This early perspective of CSR is comparable with the definition of social responsibility proposed by the economist Milton Friedman, which defined the firm's responsibility as follows:

> "(...) there is one and only one social responsibility of business – to use its resources and engage in activities designed to increase its profits so long as it stays within the rules of the game, which is to say, engages in open and free competition, without deception or fraud" (Friedman, 2002, p.133).

After the year 1962, a major change of perspective occurred concerning the role of organizations in the economy and the society. The book Silent Spring was released in 1962 (Carson, 1962) and has represented a break-point in the understanding of the interrelations among economic, social and environmental dimensions. This publication also contributed to the popularization of discussions about the negative impact of industry and agriculture on global welfare.

The discussion about Corporate Social Responsibility (CSR) was globally extended during the 1970s and 1980s with the argument that governments should be responsible for promoting economic development without compromising the environment. Some international events corroborated this global trend, including the United Nations Conference on the Human Environment, which brought together representatives from 113 nations in Stockholm in 1972, and the First World Climate Change Conference in Geneva in 1979. As a result of that global discussion, in 1987 the concept of Sustainable Development (SD) emerged from the Brundtland Report:

> "Sustainable development is a development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (UN, 1987, p.37).

In recent years, it became evident that the concept of sustainable development was built from the pressures of society and academia on both governments and companies to assume greater responsibilities with the environment and public health. This explains why Sustainable Development and Corporate Social Responsibility are associated in the 21st-century literature. However, CSR is not a direct equivalent of the term sustainable development. In fact, the former consists of a deployment of the latter but applied exclusively to organizations. The World Business Council for Sustainable Development (WBCSD) defines Corporate Social Responsibility as follows:

> "[. . .] the continuing commitment by business to contribute to economic development while improving the quality of life of the workforce and their families as well as of the community and society at large" (WBCSD, 2011, p.3).

To achieve the social commitments required for CSR, it is essential to plan and monitor properly companies' actions. In this context, authors like Carroll (1979) and Elkington (1994) are two of the most notorious theorists in this area. Carroll first proposed a three-dimensional conceptual model incorporating innovative aspects in the assessment of CSR, such as ethical issues and discretionary components. Years later, Elkington (1994) developed an accounting framework named Triple Bottom Line (TBL). According to Elkington's proposition, this framework defines three dimensions of organizational performance: economic, environmental and social. These are often referred in the literature as the 3 P's, which correspond to People, Planet and Profits (Elkington, 1997). The TBL establishes that the organization should achieve high-performance standards in all dimensions to be considered socially responsible.

5.2.2 Review of CSR Evaluation Procedures

There is a considerable body of research on quantitative and qualitative approaches to guide firms towards CSR. Amongst these initiatives, three broad groups gained prominence in recent years.

The first group comprises the management and reporting guidelines. In this area it is noteworthy the 10 ICMM principles (ICMM, 2011), the global reporting initiative (GRI, 2013a,b,d), the OECD Guidelines (OECD, 2008) and the UN Global Compact (United Nations, 2014).

The second group is related to international standards, such as ISO 26000 (ISO, 2010), ISO 14001 (ISO, 2014), OHSAS 18000 (Louette, 2007), AA1000AS (AccountAbility, 2008) and SA 8000 (SAI, 2008). Both the guidelines and the international standards evaluate CSR through the use of a vast number of indicators (e.g., GHG emissions, energy sourcing, job creation). However, the plurality of measures tends to be an obstacle for a broader interpretation of organizational outcomes.

To address this issue, a third group of initiatives emerged from the literature, which consists in the construction of composite indicators (CIs). The CIs aggregate a range of individual indicators, representing several performance dimensions into a single measure. Some of these composite indicators are oriented to stock market rating, such as the Dow Jones Sustainability Index (RobecoSAM, 2013, 2014). The stock exchange indicators assess the CSR of firms with a set of weights defined by expert's opinions. However, they usually provide limited access to the public on the criteria and indicators used. Nardo et al. (2008) prepared an OECD report dedicated to the construction of composite indicators, which presents several guidelines for the treatment of data and methodological approaches for weighting and aggregating indicators. In this report, the Data Envelopment Analysis (DEA) technique is recommended as a possible solution to avoid arbitrary weighting systems in the formulations of CIs. The weights selected with DEA are specific for each firm. This allows flexibility to show each firm under the best possible light, recurring to optimization techniques.

Only a few empirical studies were dedicated to the use of DEA for the assessment of CSR. The studies that can be highlighted include Belu and Manescu (2013), focusing on the development of a Corporate Social Responsibility (CSR) index, and Belu (2009) proposing a ranking of sustainable firms adopting an economic perspective.

The flexibility in the choice of weights recurring to optimization is a distinctive feature of DEA-based models. These models have the advantage of providing a categorization of firms, distinguishing between efficient and inefficient decision-making units (DMUs). Nevertheless, refinements in the modeling are often required to increase the discrimination among the efficient DMUs or to allow a full ranking of firms based on common grounds. This problem is more prominent in small sets of DMUs with a relatively high number of indicators to be taken into account. In these cases, the "curse of dimensionality" often leads to the classification of a large number of firms as efficient, which may in some cases be due to a judicious choice of weights. To overcome these problems, the literature recommends the identification of a Common Set of Weights to increase the discrimination among efficient DMUs (Despotis, 2005; Portela et al., 2011; Zhou et al., 2007). Roll et al. (1991) first introduced this notion, using weight restrictions in DEA-based models for obtaining common weights. A few years later, Despotis (2002) proposed an approach to identify DMUs that maintained their full efficiency scores under a common weighting structure. These DMUs, called globally efficient, were identified with Goal Programming in a post-DEA stage. Another prominent approach using common weights is the law of one price (LoOP) in DEA (Kuosmanen et al., 2006). The LoOP method addressed the relation between industry-level and firm-level cost efficiency measures to obtain consensual multipliers for assessing the efficiency of the firm. Several empirical studies used DEA-based models to identify a Common Set of Weights. The pioneering study of Cook et al. (1991) proposed one of the earliest applications using common weights for ranking highway maintenance patrols according to a consensual reference point. Other studies with applications in diverse fields followed, including the assessment of power plants (Cook and Zhu, 2007) and urban quality of life (Morais and Camanho, 2011).

5.3 Methodology

5.3.1 Identification of Indicators for CSR Assessment

The selection of the indicators for the evaluation of CRS of mining firms described in this study considered several aspects. The first one concerns being trustworthy to the WBCSD's definition of CSR. The second aspect is to ensure that the indicators selected are comprehensive and cover the main performance criteria recommended in the literature for the evaluation of mining companies. The last aspect concerns the availability of data in the public domain.

Table 5.1 summarizes the dimensions and indicators proposed for the assessment of CSR of mining companies. All indicators are expressed in ratios to allow direct comparisons among large and small firms. The detailed description of each indicator and the rationale for its selection is provided in the next paragraphs.

Table 5.1: Indicators considered in the assessment framework

Dimensions	Indicators
Economic	EBITDA margin (y_1)
Environmental	Proportion of renewable energy use (y_2)
	Proportion of renewable water use (y_3)
	Waste production ratio (b_1)
	Air emissions ratio (b_2)
Social	Local hiring rate (y_4)
	Local purchase rate (y_5)
	Employees' turnover rate,(b_3)
	All injury frequency rate (b_4)

The economic dimension of CSR focuses on the firms' continuing commitment to long-run economic viability. This dimension is represented in the framework proposed by the indicator EBITDA Margin (y_1). We calculated this indicator dividing the firm's earning before tax depreciation and amortization (EBITDA) by the firm's total revenue (Weber et al., 2008).

Four indicators represent the environmental dimension of CSR. There are two indicators depicting environmental benefits, which are the "proportion of renewable energy use" (y_2) and the "proportion of renewable water use" (y_3). These indicators allow one to monitor the firms' long-term commitment to future generations through promoting the sustainable use of natural resources. Avoiding the depletion of natural resources is a very important issue in the mining sector (Kumar and Nikhil, 2014). Most studies dedicated to environmental issues focused on the quantification of impacts, rather than the assessment of environmental benefits. In this context, the work of Glauser and Müller (1997) in the pharmaceutic sector is seminal, as it focused on the reuse and recycling of resources in order to reduce waste generation. We followed this line of research and defined some of the environmental indicators as benefits. The proportion of renewable energy use (y_2) was calculated as the ratio of the renewable energy consumption to the total amount of energy consumed during exploitation and processing ores. A similar procedure was conducted for obtaining the proportion of renewable water use (y_3). The indicators used to reflect environmental burdens are waste production ratio (b_1) and air emissions ratio (b_2). These two indicators represent the most important environmental issues for the mining and minerals industry (Azapagic, 2004). This is because the extraction and processing of ores can cause severe ecological imbalances, such as the contamination of air, water and land, as well as habitat disturbances for wildlife and marine ecosystems. Kumar and Nikhil (2014) highlight another concern, which is the acid mine drainage generation due to mineral exploitation. To ensure data comparability across firms, the waste information considers only the values associated with packaging, and waste originated from raw and hazardous materials. The value of waste produced is reported in tons and the air emissions are reported in tons of CO_2. These indicators were converted to ratios (b_1 and b_2) by dividing the tons produced by the firm's total energy consumption. These ratios reflect the environmental impacts imposed on the planet per unit of energy (Terajoule) used in the exploitation and transformation of ores by mining companies.

Four indicators represent the social dimension in this framework. Long-term contributions to the local development of regions hosting mining operations are reflected in the following benefit indicators: "local hiring rate" (y_4) and "local purchase rate" (y_5). The effects of the mining industry on employment levels and the contribution of firms to sustainable development at the local level is a prominent theme that can be traced back to Watkins (1963, 1977). This topic has been revisited repeatedly in a number of empirical studies (e.g., Black et al., 2005; Fleming and Measham, 2014; Marchand, 2012; Moretti, 2010; Watkin, 2007; Marchand, 2012). In addition, local hiring practices can also express the firm's policies regarding the qualification of local labor and is calculated by the ratio between the number of employees and contractors belonging to local communities over the total workforce of the firm. Regarding social burdens, the following indicators were conscripted: "employees' turnover rate" (b_3) and "all injury frequency rate" (AIFR) (b_4). These cover the mid-term corporate engagement towards quality of life of the workforce. The employees' turnover indicator is measured through the ratio between the number of employees fired or resigned and the annual average workforce. Fila et al. (2014) associate high employee turnover rates with negative factors, such as job dissatisfaction and counterproductive work behaviors. Lower rates for this indicator are strongly associated with job fulfillment and organizational commitment, in addition to a positive relationship with co-workers or supervisors and also with clear opportunities for growth (Bryant and Allen, 2013). The indicator AIFR reports the measure of all reportable injuries (i.e., lost time injuries, restricted work injuries, medical treatment cases and fatalities) divided per 200000 hours worked in a year. AIFR is considered the most reliable measure of the overall safety environment of an organization, possessing a broad range of applications, including the mining sector (Baker et al., 2001; Harris, 2016). Lower values of injury rates explicit the companies' performance regarding decent work practices (GRI, 2013a) and implies a high morale among employees.

5.3.2 Benchmarking CSR Adopting the Firms' Perspective

In order to evaluate the firms' performance on CSR issues and promote improvements by learning from other companies in the industry, we developed a benchmarking procedure based on a Directional Distance Function (DDF) model. This involved the construction of a composite indicator, accommodating in this evaluation model both desirable and undesirable factors. To facilitate the interpretation of the results and the implementation of best-practices sharing efforts, the composite indicator was designed in such a way that it could reflect the potential for improvement in all CSR dimensions in proportional terms. DDF models were proposed by Chambers et al. (1996a) and allow a simultaneous expansion of outputs and contraction of inputs through a directional vector. Chung et al. (1997) enhanced the DDF approach by proposing a formulation that allows the inclusion of undesirable factors, whose production should be reduced. Zanella et al. (2015) proposed a formulation for the construction of composite indicators using Directional Distance Functions in the presence of indicators expressed in ratios, allowing for the incorporation of both desirable and undesirable indicators. The model of Zanella et al. (2015) is shown in (5.1). It assesses each DMU highlighting its strengths through an optimized selection of weights. The solution of this problem finds the value of β for a firm k using linear programming. In the context of this study, the value of β_k reflects the CSR of the firm under assessment.

$$
\begin{aligned}
\max \quad & \beta_k \\
\text{s.t.} \quad & \sum_j \lambda_j y_{rj} \geq y_{rk} + \beta_k g_{y_r} \qquad r = 1,\dots,r \\
& \sum_j \lambda_j b_{ij} \leq b_{ik} - \beta_k g_{bi} \qquad i = 1,\dots,m \\
& \sum_j \lambda_j = 1 \qquad\qquad\qquad j = 1,\dots,n \\
& \lambda_j \geq 0
\end{aligned}
\tag{5.1}
$$

In model (5.1), y_{rj} are the benefits (desirable factors) $(r = 1,\dots,s)$ generated and b_{ij} are the burdens (undesirable factors) $(i = 1,\dots,m)$ imposed by DMU j on society. Similarly, y_{rk} and b_{ik} are the benefits $r = 1,\dots,s)$ and burdens $(i = 1,\dots,m)$ observed in firm k under assessment. The directional vector $g = (g_{y_r}, -g_{b_i})$ indicates the direction of change for the burdens and benefits. Positive values for the components reflect the desire to expand benefits whilst negative values reflect the intention to contract burdens. Values of β_k^* equal to zero mean that firm k has the best value of CSR observed in the sample under assessment. Positive values of β_k^* indicate potential for improvement in CSR indicators. λ_j are the intensity variables, and can be interpreted as the multipliers defining a point on the frontier obtained as a linear combination of other firms in the set (peers), against which firm k is compared for computing its performance.

In this study, the directional vector g is specified as being equal to the observed value of the burdens and benefits for firm k under assessment $g = (y_{rk}, -b_{ik})$. This specification of vector g allows the interpretation of the value of β_k^* in terms of the proportional improvements to benefits and burdens required for firm k to achieve the frontier of the technology.

Model (5.2) is the dual of model (5.1). Therefore, the optimal value of the objective function in models (5.1) and (5.2) is identical, meaning that both formulations can be used to estimate the composite indicator reflecting each firm's relative performance. This formulation focuses on the identification of optimal weights for the indicators.

$$\min \quad -\sum_{r=1}^{s} u_r\, y_{rk} + \sum_{i=1}^{m} p_i b_{ik} + c \tag{5.2}$$

$$\text{s.t.} \quad \sum_{r=1}^{s} u_r g_{y_r} + \sum_{i=1}^{m} p_i g_{b_i} = 1 \tag{5.2a}$$

$$-\sum_{r=1}^{s} u_r y_{rj} + \sum_{i=1}^{m} p_i b_{ij} + c \geq 0 \qquad j = 1,\dots,n$$

$$u_r, p_i \geq 0\ \forall r\ \forall i$$

$$c \in \mathbb{R}$$

In the multiplier model (5.2), the weights u_r and p_i are the decision variables associated to the benefits $(r = 1,\dots,s)$ and burdens $(i = 1,\dots,m)$ of the firm under assessment (k). Similarly to the envelopment formulation (5.1), the objective function of model (5.2) reports to the maximal feasible improvement to the desirable and undesirable factors that can be achieved simultaneously.

During the evaluation, each DMU is assigned a set of optimized weights, which guarantees that k receives the best possible score. As model (5.2) is run individually to evaluate each DMU in the sample, the optimal weights can differ among DMUs.

This flexibility in the choice of weights can be seen as a strength of the method, as it allows showing the DEA in the best possible light, respecting its operating profile in the search for appropriate peers and directions for improvement in the performance assessment exercise. However, this flexibility also has some weaknesses, as it can allow certain indicators to be ignored during the assessment. This would correspond to the assignment of a null value to some of the weights for a given DMU.

One way to overcome this limitation is the inclusion of weight restrictions in the model formulation. In the context of the construction of composite indicators using Directional Distance Function models, Zanella et al. (2015) proposed an enhanced formulation of weight restriction in the form of Assurance Regions type I (Thompson et al., 1990). This formulation enables expressing the relative importance of the indicators in percentage terms. In this study, we adopted this formulation of weight restrictions, reproduced in (5.3), to avoid having indicators ignored in the assessment by the assignment of null values to the weights.

$$\begin{cases} \frac{u_r \overline{y_r}}{\sum_{r=1}^{s} u_r \overline{y_r} + \sum_{i=1}^{m} p_i \overline{b_i}} \geq LB_r, & r = 1,\dots,s \\ \frac{p_i \overline{b_i}}{\sum_{r=1}^{s} u_r \overline{y_r} + \sum_{i=1}^{m} p_i \overline{b_i}} \geq LB_i, & i = 1,\dots,m \end{cases} \tag{5.3}$$

In the restrictions shown in (5.3), $\overline{y_r}$ $(r = 1,\dots,s)$ are the benefits and $\overline{b}_i$ $(i = 1,\dots,m)$ burdens of an "artificial" DMU representing the average values of the indicators in the sample analyzed. The advantage of this formulation is that the bounds imposed to the weight restrictions LB_r and LB_i can be expressed as percentages and become independent of the units of measurement of the original indicators. Note that this is possible because the left hand side of inequalities (5.3) is a ratio of virtual weights (i.e., the product of raw weights with the value of the indicators corresponding to the "artificial" DMUs).

One limitation associated with the construction of composite indicators using firm-specific weights is that the resulting performance measure is not appropriate for the construction of rankings. Robust rankings involve a comparison of firms in an industry according to common grounds, meaning that the importance attributed to each indicator should be consensual within the sector. The ranking of firms is addressed in the next section and involves the estimation of a Common Set of Weights.

5.3.3 Evaluation of CSR with an Industry Perspective

The objective of this section is the identification of a Common Set of Weights (CSW) that can be used to rank the firms in an industry. These weights should reflect a consensual view of the industry performance. The values of the common weights are obtained by minimizing the deviations from the original weights estimated from the firm's perspective, as described in the previous section. The goal-programming model used for this purpose is specified in (5.4).

$$\min \quad \sum_{j}^{n} d_j \tag{5.4}$$

$$\text{s.t.} \quad -\sum_{r=1}^{s} u_r^{CW} y_{rj} + \sum_{i=1}^{m} p_i^{CW} b_{ij} - d_j = \beta_j^* \qquad j = 1,\ldots,n \tag{5.4a}$$

$$u_r^{CW}, p_i^{CW}, d_j \geq 0 \qquad \forall r\, \forall i\, \forall j$$

Model (5.4) is run for all DMUs simultaneously and aims to minimize the sum of the deviations from the original scores (β_j^*) obtained for each DMU j using model (5.1). y_{jr} are the benefits generated and b_{ij} are all burdens imposed to society by firm j. The single weights u_r^{CW} ($r = 1,\ldots,s$) and p_i^{CW} ($i = 1,\ldots,m$) are the decision variables of the model. Constraint (5.4a) is the primary goal, which aims to obtain a Common Set of Weights to assess all DMUs j that minimizes non-negative deviations (d_j) from the original performance score $\left(\beta_j^*\right)$ estimated using model (5.2). Model (5.4) admits exclusively non-negative deviations from the goal to ensure that the Common Set of Weights will derive a feasible set of weights that does not represent for any of the DMUs under evaluation a comparison with a point beyond the production possibility set (i.e., the set of weights cannot result in an evaluation of performance leading to a better score than the one obtained using model (5.2)).

Model (5.4) intends to derive a Common Set of Weights reflecting the relative importance of the benefit and burden indicators that should underlie the construction of the industry ranking. However, the ordering of the DMUs must be based on relative performance measures, and in all cases, the reference must be a facet of on the frontier for which the set of weights leads to a performance score equal to one. Note that the normalizing constraint of model (5.2) is $\sum_{r=1}^{s} u_r g_{y_{rk}} + \sum_{i=1}^{m} p_i g_{b_{ik}} = 1$, and this normalisation is also required for the estimation of the new composite indicator value (β_j^{rank}) of each DMU j used for ranking purposes. Accordingly, for each DMU j, the weights must satisfy $\sum_{r=1}^{s} u_{rj}^{rank} g_{y_{rj}} + \sum_{i=1}^{m} p_{ij}^{rank} g_{b_{ij}} = 1$, whilst respecting the information on the relative values of weights obtained using the Goal Programming model.

The system of equations ranging from (5.5a) to (5.5c) can be used to obtain the weights corresponding to the variables u_{rj}^{rank} and p_{ij}^{rank}, required for estimating the new composite indicator of each DMU j underlying the construction of the industry ranking.

$$\begin{cases} \sum_{r=1}^{s} u_{rj}^{rank} y_{rj} + \sum_{i=1}^{m} p_{ij}^{rank} b_{ij} = 1 & & (5.5a) \\ \dfrac{u_{rj}^{rank}}{u_{1j}^{rank}} = \dfrac{u_r^{CW}}{u_1^{CW}} & r = 2, \ldots s & (5.5b) \\ \dfrac{p_{ij}^{rank}}{u_{1j}^{rank}} = \dfrac{p_i^{CW}}{u_1^{CW}} & i = 1, \ldots m & (5.5c) \end{cases}$$

In the system of equations (5.5a) to (5.5c), one of the indicators underlying the assessment (either a benefit or a burden), must be selected as the reference to be included in the denominator of the expressions (5.5b) and (5.5c). Expression (5.5b) specified as reference the weight u_r^{CW}. This choice does not affect the identification of the solution obtained for the variables u_{rj}^{rank} and p_{ij}^{rank} of this system. The equations (5.5b) and (5.5c) can be linearized to obtain the equivalent linear system reported in (5.6b) and (5.6c).

$$\begin{cases} \sum_{r=1}^{s} u_{rj}^{rank} y_{rj} + \sum_{i=1}^{m} p_{ij}^{rank} b_{ij} = 1 & & (5.6a) \\ u_{rj}^{rank} u_1^{CW} - u_r^{CW} u_{1j}^{rank} = 0 & r = 2, \ldots s & (5.6b) \\ p_{ij}^{rank} u_1^{CW} - p_i^{CW} u_{1j}^{rank} = 0 & i = 1, \ldots m & (5.6c) \end{cases}$$

The solution of this system, which is solved for each DMU j, respects the consensual trade-offs estimated with the Goal Programming model for the industry. The new composite indicator for Corporate Social Responsibility of each DMU j is then obtained as the value of β_j^{rank}, computed using expression (5.7). The new values of the composite indicator β_j^{rank} allow ranking the DMUs in the industry based on common grounds.

$$\beta_j^{rank} = -\sum_{r=1}^{s} u_{rj}^{rank} y_{rj} + \sum_{i=1}^{m} p_{ij}^{rank} b_{ij} \tag{5.7}$$

5.3.4 A Small Illustrative Example

To depict graphically the methodology proposed, consider a set of seven DMUs whose evaluation should focus on two indicators, one representing a benefit (y_1) and the other representing a burden (b_1). Table 5.2 reports the values of these indicators for all DMUs. Table 2 also shows the results of the benchmarking model focusing on the firm perspective, using the multiplier formulation presented in (5.2), with a directional vector equal to the values of the benefit and burden observed at each DMU under evaluation.

Table 5.2: Indicators and results of model (5.2)

DMU	Indicator		Results				
	b_1	y_1	β_k^*	c	p_1	u_1	$\frac{u_1}{p_1}$
A	4	4	0	-0.4286	0.1786	0.0714	0.4
B	6	9	0	-0.2500	0.1042	0.0417	0.4
C	9	12.5	0	1	0	0.08	$+\infty$
D	5	1.7	0.2	-0.8	0.2	0	0
E	5.3	5.5	0.0933	-0.3200	0.1333	0.053	0.4
F	12	11.5	0.0870	0.0870	0	0.0870	$+\infty$
G	9	9	0.1795	0.1026	0.0598	0.0513	0.8571

Figure 5.1 illustrates the production possibility set (PPS), as well as the targets levels corresponding to the projections of inefficient DMUs on the frontier of technology. Firms A, B, and C are operating on the frontier ($\beta_k^*=0$), which means that these companies cannot improve the value of the benefit indicator (y_1) without worsening the value of the burden (b_1). Firms D, E, F and G have potential for improvement, as they are operating inside the production possibility set. The values of β_k^* express the DMUs' potential for simultaneous improvement for indicators b_1 and y_1.

The ratio between the weights obtained at the optimal solution to model (5.2), reflects, for each inefficient DMU under assessment, the trade-off between the indicators y_1 and b_1 at the facet of the frontier against which the DMU is assessed. For instance, DMU E, with a ratio between weights $\frac{u_{1E}}{p_{1E}}=0.4$, is projected to the facet of the frontier corresponding to segment $[AB]$, and DMU G with a ratio between weights $\frac{u_{1G}}{p_{1G}}=0.8571$ is projected to the facet of the frontier corresponding to segment $[BC]$. These segments are represented by the dotted lines in Figure 5.1. Note that the trade-off of segment $[AB]$ is 0.4 and the trade-off of segment $[BC]$ is 0.857. In the cases of DMUs A, B and C there are multiple optimal solutions, such that the ratio between weights for DMU A can be in the range $\frac{u_{1A}}{p_{1A}}\in[0,0.4]$, for DMU B $\frac{u_{1B}}{p_{1B}}\in[0.4,\ 0.857]$, and for DMU C $\frac{u_{1C}}{p_{1C}}\in[0.857,\ +\infty[$.

The subsequent stage aims to obtain a Common Set of Weights reflecting the industry performance. Regarding the results of the Goal Programming model (5.4), the objective function value $(\sum_j^n d_j)$ is equal to 0.326, and the optimal solution for the Common Set of Weights is $p_1^{CW}=0.0597$ and $u_1^{CW}=0.0398$. Note that the relative value of weights is $\frac{u_1^{CW}}{p_1^{CW}}=\frac{0.0398}{0.0597}=0.667$, corresponding to the industry trade-off. For ranking the firms, the trade-off information is used to obtain specific weights for each DMU. These weights are used to estimate a new composite indicator for each DMU, consistent with the requirements that should be fulfilled when constructing a ranking. This implies that the ranking should be done based on the distance to a common facet of the frontier, whose slope is defined by the trade-offs identified by the Goal Programming model. For this distance to be correctly estimated, the weights assigned to each DMU for the construction of the new composite indicator must satisfy the normalization constraint (second line) included in model (5.2). These DMU specific weights (u_{1j}^{rank} and p_{1j}^{rank}) are obtained solving the system of equations

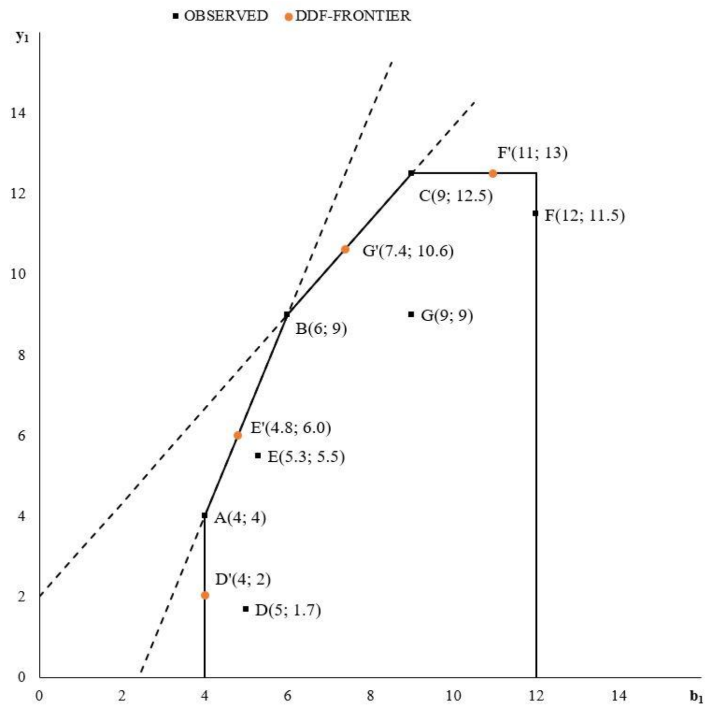

Figure 5.1: Production Possibility Set obtained using model (5.2).

shown in (5.8) for each DMU j. Note that the first restriction relates to satisfying the normalization constraint, and the second restriction imposes equal trade-offs for all DMUs when defining the facet of the frontier underlying the construction of the industry ranking.

$$\begin{cases} u_{1j}^{rank} \times y_{1j} + p_{1j}^{rank} \times b_{1j} & = 1 \\ p_{1j}^{rank} \times u_1^{CW} - p_1^{CW} \times u_{1j}^{rank} & = 0 \end{cases} \tag{5.8}$$

The solution of this system for DMU B is illustrated below:

$$\begin{cases} u_{1j}^{rank} \times y_{1B} + p_{1j}^{rank} \times b_{1B} & = 1 \\ p_{1B}^{rank} \times u_1^{CW} - p_1^{CW} \times u_{1B}^{rank} & = 0 \end{cases} \tag{5.9}$$

$$\begin{cases} u_{1B}^{rank} \times 9 + p_{1B}^{rank} \times 6 & = 1 \\ p_{1B}^{rank} \times 0.0398 - 0.0597 \times u_{1B}^{rank} & = 0 \end{cases}$$

$$\begin{cases} u_{1B}^{rank} & = 0.0556 \\ p_{1B}^{rank} & = 0.0833 \end{cases}$$

After finding the solution of the system (5.8) for each DMU under assessment, the composite indicator scores that can be used to obtain the industry ranking are computed using expression (5.7). This expression estimated for DMU B is shown below:

$$\beta_B^{rank} = -u_{1B}^{rank} y_{1B} + p_{1B}^{rank} b_{1B} = -0.0556 \times 9 + 0.0833 \times 6 = 0 \tag{5.10}$$

The results obtained for all DMUs are shown in Table 5.3. Note that the discrimination among DMUs increased when the composite indicator is estimated using the procedure based on a Common Set of Weights. Furthermore, this procedure also ensures that at least one DMU in the sample analyzed operates on the industry single trade-off frontier (with $\beta_j^{rank} = 0$). DMU B was the only firm that maintained its original score, being evaluated as the DMU with the best performance in the industry. The remaining six units in the set operate off the single trade-off industry frontier.

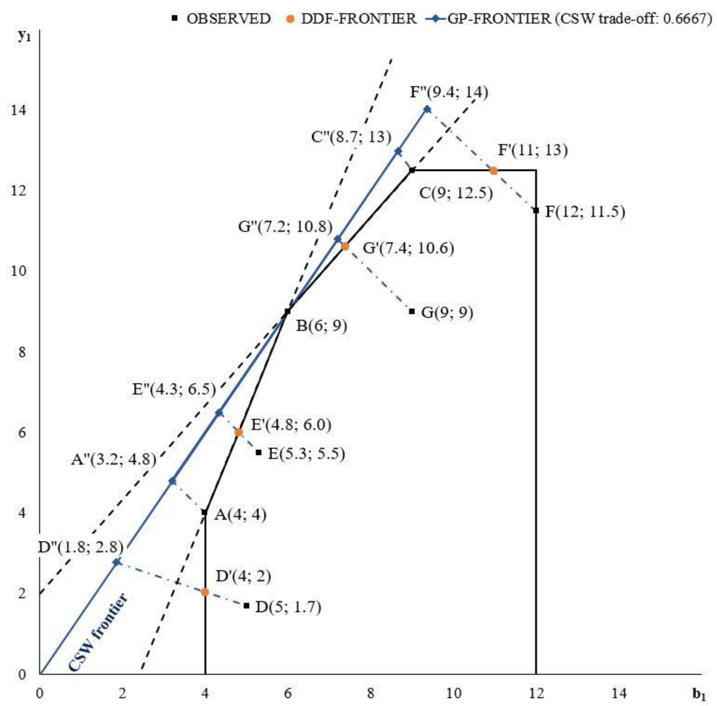

Figure 5.2: Representation of the industry frontier estimated with common trade-offs.

Table 5.3: Performance assessment with the industry perspective

DMU	p_i^{rank}	u_r^{rank}	β_k^*	Rank	Projections	
					$b''_{1j} = b_{1j} \times (1-\beta_j^{rank})$	$y''_{1j} = y_{1j} \times (1+\beta_j^{rank})$
A	0.15	0.1	0.2	4	3.2	4.8
B	0.0833	0.0556	0	1	6	9
C	0.0577	0.0385	0.0385	2	8.6538	12.9808
D	0.163	0.1087	0.6304	7	1.8478	2.7717
E	0.1115	0.0743	0.1822	3	4.3346	6.5019
F	0.0508	0.0339	0.2203	6	9.3559	14.0339
G	0.0667	0.0444	0.2	5	7.2	10.8

Figure 5.2 depicts the projections for all DMUs on the industry frontier, corresponding to the values reported in the last two columns of Table 5.3. Note that the industry trade-off (0.667) represents an intermediate trade-off between those of segments $[AB]$ and $[BC]$, which is represented in Figure 5.2 by the segment labeled CSW frontier. This new segment can be interpreted as the industry frontier.

5.4 Illustrative Application: Evaluation of Mining Firms

5.4.1 Data Gathering

In this illustrative application, we studied 24 large mining firms affiliated to GRI and ICMM. The data sources used to compose our datasets were the firms' sustainability reports and financial statements. The GRI guidelines require firms to comply with international standards, such as ISAE 3000 and AA1000AS. In addition, certified offices have to issue an impartial opinion about the quality of the information published on reports (GRI, 2013a). This external assurance of information enhances the reliability of data made available to the public, and this motivated our option to restrict the analysis only to large mining firms affiliated to the GRI initiative.

The firms studied exploit several mines around the world, totalizing 43 countries. They exploit a diversified portfolio of minerals, under a variety of particular natural local conditions. Regardless the heterogeneity that naturally exists among firms, all of them must comply with the international standards regarding environmental, social and economic performance.

The data collection, reported in Tables 5.4 and 5.5, focused on reports published in 2014, whose data refers to the year 2012 (these reports are published with a time lag of two years). Thus, the reference year used in our study is 2012. All benefits in Tables 5.4 and 5.5 are expressed in percentage (y_1 to y_5), as well as the burdens b_1, b_2 and b_3. The indicator AIFR (b_4) is expressed in number of reportable injuries per 2000 hours worked in a year.

Regarding the benefits indicators, the economic information on EBITDA margin (y_1) reported the negative values of -0.0072 (U05) and -0.0235 (U24). These values were replaced by a positive infinitesimal number in the dataset (0.001), to satisfy the requirements for the use of a Directional Distance Function model. The GRI guidelines report environmental data in quantities for all firms. Most firms reported their renewable energy and total energy use in Gigajoules (Gj), Terajoules (Tj) or megawatts hour (MWh). The ratio indicator proportion of renewable energy use (y_2) was calculated after the necessary conversions to Tj. The total consumption of water and the renewable water use were reported in million m^3 or gallons, which allowed the calculation of the proportion of renewable water use (y_3). Regarding the social benefits, the local hiring rates (y_4) were reported in percentage for all observations. The local purchases rates (y_5) were reported in percentage for most firms. Only three firms reported raw data on employment, which allowed the calculation of the ratios required for our analysis.

Table 5.4: Dataset of benefits

Firm	y_1	y_2	y_3	y_4	y_5
Vale (U01)	32.4349	16.6667	76.1686	44.0000	87.0000
Alcoa (U02)	7.9391	0.001**	41.1765	80.0000	30.3575
Anglo American Ni(U03)	1.4655	99.4711	44.7514	43.5000	10.2000
Rio Norte (U04)	16.6069	0.0134	75.5350	89.0000	50.0000
Sama (U05)	0.001+	0.2659	0.8977	17.0000	100.0000
Samarco (U06)	46.5991	71.4286	4.7117	63.0000	37.0000
Votorantim (U07)	14.5957	99.8576	22.1754	0.4000	65.0000
Norksh Hydro (U08)	9.9064	68.4932	0.001**	0.4000	0.0100
Kinross (U09)	46.1544	0.001**	47.8992	77.0000	69.0000
Rio Tinto (U10)	20.5427	67.0000	41.1765	55.0000	87.0000
Barrick (U11)	8.3917	14.4425	0.0127	95.5000	87.0000
BHP Billiton (U12)	32.1502	29.0847	0.0244	54.0000	87.0000
Glencore (U13)	1.4009	8.4007	52.1815	0.4000	0.1000
Yamana (U14)	54.8339	31.0000	80.4744	75.0000	88.0000
JX Nippon (U15)	11.4254	0.0004	37.4433	97.4652	0.1000
Gold Fields (U16)	29.1534	0.0006	48.7021	0.4000	68.0000
Mitsubishi Materials (U17)	0.1111	0.001**	0.0966	51.0000	0.1000
Gold Corp(U18)	55.7498	0.0122	72.5402	62.0000	48.0000
Teck (U19)	30.9174	19.6371	57.6714	71.4418	0.1000
ARM(U20)	2.5742	0.001**	0.001**	65.0000	50.0000
Codelco (U21)	0.0619	52.3551	75.1217	99.7200	87.0000
Sumitomo (U22)	14.8050	0.001**	0.001**	0.4269	48.0000
De Beers (U23)	24.2771	30.0236	37.6453	81.2000	68.0000
Anglo American Pt (U24)	0.001+	0.001**	59.4940	4.7269	94.0000
Average	19.2623	25.3397	36.4958	51.14920	52.5403
St.dev. (SD_{y_r})	17.6722	32.3586	28.7984	34.19722	34.4057

$^{+}$Negative values replaced by 0.001 **Zero values replaced by 0.001

For the collection of burden indicators, the volumes of waste production (tons) and the air emissions (CO_2 equivalent) were converted into ratios by diving these values by the total energy consumption (Tj), resulting in the indicators waste production ratio (b_1) and air emissions ratio (b_2). Seven firms (U04, U05, U08, U14, U16, U22 and U24) reported very extreme values in at least one of these indicators of environmental burdens. These values were treated as inaccurate values, and were replaced by values closer to the central tendency of the sample, representing the mean ($\bar{x}_{b_i}$) plus three times de standard deviation (SD_{b_i}) of the sample for variable ($\bar{x}_{b_i} + 3SD_{b_i}$), which was calculated after the removal of the original very extreme observations from the sample.

Table 5.5: Dataset of burdens

Firm	b_1	b_2	b_3	b_4
Vale (U01)	49.7222	25.8426	5.1000	280.0000
Alcoa (U02)	14.8701	535.7346	11.0000	351.0000
Anglo American Ni (U03)	19.6108	30.9816	9.0000	0.0900
Rio Norte (U04)	70.7670	3545.0682$^\diamondsuit$	7.0000	198.0000
Sama (U05)	79.9804$^\diamondsuit$	3545.0682$^\diamondsuit$	1.3800	229.0000
Samarco (U06)	0.001**	1004.5489	3.8000	65.0000
Votorantim (U07)	0.0002	1595.7239	31.5000	722.0000
Norksh Hydro (U08)	79.9804$^\diamondsuit$	3545.0682$^\diamondsuit$	10.0000	410.0000
Kinross (U09)	0.0015	735.4419	5.4000	20.0000
Rio Tinto (U10)	0.0382	12.4032	703.0000	67.0000
Barrick (U11)	0.0143	0.0096	3.6000	92.0000
BHP Billiton (U12)	3.2542	1430.5085	8.8300	470.0000
Glencore (U13)	8.3755	7.0039	15.2000	900.0000*
Yamana (U14)	79.9804$^\diamondsuit$	3545.0682$^\diamondsuit$	6.0000	544.0000
JX Nippon (U15)	4.7153	3129.4635	13.2897	26.0000
Gold Fields (U16)	79.9804$^\diamondsuit$	3545.0682$^\diamondsuit$	7.8900	684.0000
Mitsubishi Materials (U17)	3.4965	1888.4445	4.6000	63.0000
Gold Corp(U18)	8.0127	1094.9091	12.0000	165.0000
Teck (U19)	0.001**	0.0521	6.0000	133.0000
ARM (U20)	0.0004	1944.7700	1.9000	40.0000
Codelco (U21)	57.8698	1184.6497	1.0000	3.3000*
Sumitomo (U22)	79.9804$^\diamondsuit$	811.2575	260.0000	0.0975
De Beers (U23)	1.2624	1260.8353	516.0000	48.0000
Anglo American Pt (U24)	79.9804$^\diamondsuit$	3545.0682$^\diamondsuit$	730.0000	537.8000
Average	13.4451	927.3656	98.8954	252.0119
St.dev. (*SD*)	22.1784	872.5675	216.8386	259.2748

* Missing data replaced by the values observed in the previous year
** Zero values replaced by 0.001
$^\diamondsuit$ Outliers replaced by $\bar{x}_{b_i} + 3SD_{b_i}$

The employees' turnover rate (b_3) was directly obtained from GRI reports, without any calculations. The values for AIFR (b_4) were calculated for most firms based on the related indicators available in the reports. This indicator b_4 had missing values in firms U13 and U21. To replace the missing values of social indicators, we used the values reported for these indicators in previous periods (2010 or 2011). All missing values were substituted following this procedure.

5.4.2 Discussion of Results

5.4.2.1 Firm-level Analysis

The firm-level analysis started by the specification of the minimum importance that should be assigned to each indicator in the optimization model. The bound of the virtual weights intended to ensure that all indicators are considered in the construction of the composite indicator score. We conducted a sensitivity analysis of the results for different lower bounds (LB), with values ranging from 0.5% to 5%. Table 5.6 reports the results of the sensitivity analysis conducted with the composite indicator model (5.2) with the addition of the weight restrictions formulated in (5.3). The results reveal a gradual increase of the average composite indicator scores ($\overline{\beta_k^*}$) as the value of the LB increases. We selected a value of the LB equal to 1.5% for our assessment, as it enabled a good balance between ensuring that none of the indicators is ignored by the assignment of a null weight, and avoiding significant changes to the composite indicator score β_k^*. Table 5.6 shows that the average value of the composite indicator ($\overline{\beta_k^*}$) is quite stable for weight bounds of magnitude around 1.5%. In particular, the average score of β_k^* for the weight threshold of 1.5% is approximately 2.4 times larger than the score of the unbounded model.

Table 5.6: Sensitivity analysis

LB (%)	Firms with best scores	β_k^* min	β_k^* max	$\overline{\beta_k^*}$	$SD_{\beta_k^*}$
unbounded	17	0.0	0.3312	0.0492	0.1056
0.5	15	0.0	0.5361	0.0781	0.1473
1.0	15	0.0	0.6536	0.1037	0.1809
1.5	15	0.0	0.6937	0.1168	0.1988
2.0	13	0.0	0.7343	0.1302	0.1302
2.5	13	0.0	0.7758	0.1447	0.2288
3.0	12	0.0	0.8177	0.1593	0.2427
3.5	12	0.0	0.8582	0.1744	0.2558
4.0	12	0.0	0.8981	0.1895	0.2688
5.0	11	0.0	0.9777	0.2204	0.2941

Table 5.7 reports the results obtained for the assessment at firm level, including the scores of the composite indicator β_k^* in the second column. This value of β_k^* the can be interpreted as expressing the potential for performance improvement of each firm. The third column reports the peers for inefficient firms and the intensity variables (λ_j) associated with each peer. The fourth column in Table 5.7 reports the frequency each efficient firm was used as a peer by inefficient firms. The results obtained with model (5.2), corresponding to the multiplier formulation of the DDF model, are reported in Table 5.8.

Table 5.7: Results of the firm-level analysis (LB=1.5%)

Firm	β_k^*	Peer (λ)	Freq. as peer
Vale (U01)	0		2
Alcoa (U02)	0.1110	U09 (0.3255) U11 (0.2571) U19 (0.1771) U21 (0.2404)	
Anglo American Ni (U03)	0		2
Rio Norte (U04)	0.0533	U14 (0.3718) U21 (0.6282)	
Sama (U05)	0		1
Samarco (U06)	0		1
Votorantim (U07)	0		1
Norksh Hydro (U08)	0.4322	U03 (0.5295) U06 (0.1441) U07 (0.3264)	
Kinross (U09)	0		4
Rio Tinto (U10)	0		
Barrick (U11)	0		4
BHP Billiton (U12)	0		1
Glencore (U13)	0.2428	U01 (0.1398) U18 (0.0804) U19 (0.7798)	
Yamana (U14)	0		2
JX Nippon (U15)	0		2
Gold Fields (U16)	0.3338	U01 (0.7128) U12 (0.0552) U14 (0.2319)	
Mitsubishi Materials (U17)	0.6937	U09 (0.6975) U11 (0.2407) U15 (0.0294) U21 (0.0323)	
Gold Corp(U18)	0		1
Teck (U19)	0		2
ARM (U20)	0.3359	U09 (0.6165) U11 (0.2492) U15 (0.1340) U21 (0.0002)	
Codelco (U21)	0		5
Sumitomo (U22)	0.5117	U03 (0.1118) U09 (0.6930) U11 (0.1952)	
De Beers (U23)	0		
Anglo American Pt (U24)	0.0885	U05 (0.2523) U21 (0.7477)	
β_k^*	0.1168		
$SD_{\beta_k^*}$	0.1988		

To illustrate the lessons that can be learned from the application of this benchmarking methodology, we take the firm ARM (U20) as an example. African Rainbow Minerals (ARM) is a leading South African multinational mining company that holds the entire production chain in the exploitation and the processing of a diversified portfolio of ores (Fe, Mg, Cr, Au, Pt, Cu, Ni and coal) in South Africa, Zambia, and Malaysia, with emphasis on Iron, Nickel and Gold investments. The evaluation of ARM indicates that this firm has potential for improving its practices in CSR. The sharing of good practices could be guided by leading firms in the sector, identified as peers for ARM, namely Kinross (U09), Barrick (U11), JX Nippon (U15) and Codelco (U21).

For illustration purposes, we explore improvement opportunities mirrored in the CSR practices from the four peers of ARM (Kinross Gold, Barrick Gold Corporation, JX Nippon Mining and Metals and Codelco). Kinross (U09) is a Canadian multinational that exploits and processes gold mining in United States, Brazil, Chile, Ghana, Mauritania, and Russia. Barrick (U11) is also a Canadian multinational, whose core operations are associated with Gold and Copper in 10 countries, including USA, Saudi Arabia, and Australia. JX Nippon is a multinational japonese company, with focus on the exploitation, processing and recycling of non-ferrous metals (mostly cooper, silver and gold). JX Nippon operates on mines located in Japan and East Asia (Twain, Singapore, China). Codelco (U21) is a Chilean state-owned company with operations in South America (Chile and Brazil), specialized in the exploration and processing of copper and its by-products.

Table 5.8: Results from model (5.2) and WR (5.3) (LB=1.5%)

Companies	β_k^*	Benefits					Burdens			
		u_1	u_2	u_3	u_4	u_5	p_1	p_2	p_3	p_4
Vale (U01)	0	0.00048	0.00036	0.00061	0.00018	0.01001	0.00084	0.00001	0.00009	0.00004
Alcoa (U02)	0.1110	0.00059	0.00045	0.00383	0.00895	0.00022	0.00499	0.00005	0.00012	0.00005
Anglo American Ni(U03)	0	0.00022	0.00989	0.00012	0.00008	0.00008	0.00032	0.00001	0.00004	0.00002
Rio Norte (U04)	0.0533	0.00039	0.00030	0.01177	0.00015	0.00014	0.00056	0.00001	0.00008	0.00008
Sama (U05)	0	0.00043	0.00033	0.00023	0.00016	0.00892	0.00062	0.00001	0.00008	0.00011
Samarco (U06)	0	0.00060	0.01264	0.00032	0.00023	0.00022	0.01905	0.00001	0.00012	0.00050
Votorantim (U07)	0	0.00072	0.00576	0.01235	0.00027	0.00107	0.01470	0.00002	0.00022	0.00006
N. Hydro (U08)	0.4322	0.00683	0.01143	0.00030	0.00021	0.00021	0.00082	0.00001	0.00247	0.00004
Kinross (U09)	0	0.01346	0.00036	0.00025	0.00018	0.00500	0.00230	0.00001	0.00009	0.00004
Rio Tinto (U10)	0	0.00065	0.00566	0.01165	0.00025	0.00024	0.01446	0.00001	0.00013	0.00005
Barrick (U11)	0	0.00047	0.00035	0.00025	0.01018	0.00017	0.00109	0.00001	0.00009	0.00004
BHP B. (U12)	0	0.00144	0.00038	0.00026	0.00019	0.01031	0.00077	0.00001	0.00010	0.00004
Glencore (U13)	0.2428	0.00076	0.00058	0.01696	0.00029	0.00028	0.00636	0.00020	0.00015	0.00006
Yamana (U14)	0	0.00139	0.00091	0.00029	0.00016	0.00863	0.00062	0.00001	0.00008	0.00003
JX Nippon (U15)	0	0.00057	0.00043	0.00030	0.00943	0.00021	0.00197	0.00001	0.00011	0.00060
Gold Fields (U16)	0.3338	0.00240	0.00043	0.00030	0.00021	0.01138	0.00088	0.00001	0.00011	0.00004
Mitsubishi Materials (U17)	0.6937	0.00135	0.00102	0.00071	0.01324	0.00049	0.00603	0.00006	0.00026	0.00313
Gold Corp(U18)	0	0.00042	0.00032	0.01287	0.00016	0.00016	0.00124	0.00001	0.00008	0.00003
Teck (U19)	0	0.00063	0.00048	0.00777	0.00722	0.00023	0.00600	0.00001	0.00012	0.00005
ARM(U20)	0.3359	0.00122	0.00093	0.00064	0.01190	0.00127	0.00585	0.00003	0.00024	0.00276
Codelco (U21)	0	0.00044	0.00034	0.00235	0.00017	0.00681	0.00321	0.00001	0.00017	0.00011
Sumitomo (U22)	0.5117	0.00176	0.00134	0.00093	0.00066	0.00670	0.00252	0.00045	0.00034	0.00512
De Beers (U23)	0	0.00062	0.00398	0.00383	0.00670	0.00106	0.00780	0.00001	0.00015	0.00005
Anglo American Pt(U24)	0.0885	0.00041	0.00031	0.00057	0.00016	0.00864	0.00059	0.00001	0.00008	0.00003
$\bar{\beta}_k^*$	0.1168	0.00159	0.00246	0.00373	0.00297	0.00343	0.00432	0.00004	0.00023	0.00054
$SD_{\beta_k^*}$	0.1988	0.00286	0.00379	0.00529	0.00455	0.00418	0.00514	0.00009	0.00048	0.00127

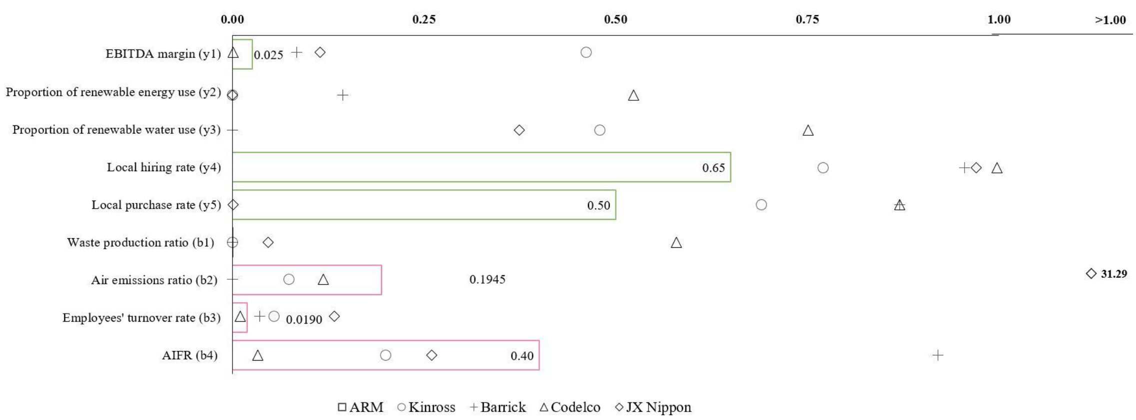

Figure 5.3: Illustration of benchmarking amongst mining firms.

Figure 5.3 depicts graphically the comparison between ARM achievements in each indicator and the performance attained by the efficient firms (peers). The x-axis in the graph represents the values of all burdens and benefits. The indicators representing percentages are reported in their original scale, and the indicator b_4 was rescaled by diving by 10^2. Learning opportunities in the economic dimension of the TBL, reflected by the EBITDA margin (y_1), could be provided by JX Nippon, Kinross and Barrick. Codelco shows best practices in the environmental indicators proportion of renewable energy use (y_2) and proportion of renewable water use (y_3). Note that ARM reported null values for these environmental benefits, so the benchmarking exercise shows considerable potential for improvement for these indicators. Concerning the environmental burdens, there is no evidence of potential for improvement in the waste production ratio (b_1), as this value is already very small for ARM and for two of its peers. Barrick can be an example of good practices implementation in what concerns reducing air emissions ratio (b_2). This is the firm with the best performance in this feature.

In the social dimension, the local hiring rate (y_4) could be improved by observing the practices of all peers, and the local purchase rate (y_5) could adopt as reference the practices of Kinross, Barrick and Codelco. On the side of social burdens, the employees' turnover rate (b_3) can be improved by learning from Codelco, and the best performance in terms of AIFR (b_4) is available at Codelco, followed by Kinross and JX Nippon.

5.4.2.2 Industry-level Analysis

The industry-level analysis began with the estimation of a common sectoral set of weights using model (5.4), also with the addition of weight restrictions (5.3) with a LB equal to 1.5%. These lower bounds were specified to ensure that the same modeling assumptions are to keep in both firm-level and industry-level analysis. Table 5.9 reports the results obtained with this procedure. The average deviation goal, corresponding to the objective function of the Goal Programming model, was $\overline{d_j}$=0.5824.

Table 5.9: Common weights for CSR with LB = 1.5%

Indicator (weight)	CSW
EBITDA margin (u_1^{CW})	0.0003976
Proportion of renewable energy use (u_2^{CW})	0.0003022
Proportion of renewable water use (u_3^{CW})	0.0003680
Waste production ratio (p_1^{CW})	0.0027183
Air emissions ratio (p_2^{CW})	0.0003538
Local hiring rate (u_4^{CW})	0.0001497
Local purchase rate (u_5^{CW})	0.0001458
Employees' turnover rate (p_3^{CW})	0.0000774
All injury frequency rate (p_4^{CW})	0.0003735

Normalizing the CSW by diving the values of the weights by the same denominator (representing the weight of one of the indicators considered in the assessment), we can obtain the industry trade-offs between the performance indicators. These trade-offs are reported in Table 5.10 using the weight of the indicator air emission ratio (p_2^{CW}) as the denominator for the normalization.

These trade-offs can express the coefficients defining the facet of the mining industry frontier, against which all the firms are evaluated.

Table 5.10: Example of trade-offs obtained with the CSW

Indicator (weight)	Trade-offs
EBITDA margin (u_1^{CW})	1.1238
Proportion of renewable energy use (u_2^{CW})	0.8542
Proportion of renewable water use (u_3^{CW})	1.0401
Waste production ratio (p_1^{CW})	7.6832
Air emissions ratio (p_2^{CW})	1
Local hiring rate (u_4^{CW})	0.4231
Local purchase rate (u_5^{CW})	0.4121
Employees' turnover rate (p_3^{CW})	0.2188
All injury frequency rate (p_4^{CW})	1.0557

These relative values allow analyzing the scope for adjustment among indicators that allows maintaining the same level of CSR. For instance, if a decision maker desires to explore the compensatory relationship between the indicators air emission ratio (b_2), corresponding to an environmental burden, and the percentage of renewable water use (y_3), corresponding to an environmental benefit, keeping all other indicators fixed at their current levels. Table 5.10 shows that an increase of air emission ratio by one unit would require an enhancement of renewable water use by 1.0401 to keep the current level of CSR.

Next, the industry trade-offs were used to define normalized DMU-specific weights, so that the firms can be ranked based on their levels of CSR. The linear system of equations specified in (5.6a), (5.6b), and (5.6c) was used for this purpose, resulting in the sets of individual normalized weights reported in Table 5.11.

Table 5.11: Final Scores and normalized weights

DMU	β_j^{rank}	u_1^{rank}	u_2^{rank}	u_3^{rank}	u_4^{rank}	u_5^{rank}	p_1^{rank}	p_2^{rank}	p_3^{rank}	p_4^{rank}
Vale (U01)	0.5852	0.00126	0.00096	0.00117	0.00048	0.00046	0.00864	0.00113	0.00025	0.00119
Alcoa (U02)	0.8250	0.00100	0.00076	0.00093	0.00038	0.00037	0.00685	0.00089	0.00020	0.00094
A. American Ni(U03)	0.0823	0.00331	0.00252	0.00306	0.00125	0.00121	0.02263	0.00295	0.00064	0.00311
Rio Norte (U04)	0.9302	0.00025	0.00019	0.00023	0.00009	0.00009	0.00172	0.00022	0.00005	0.00024
Sama (U05)	0.9777	0.00025	0.00019	0.00023	0.00010	0.00009	0.00173	0.00022	0.00005	0.00024
Samarco (U06)	0.7404	0.00091	0.00069	0.00084	0.00034	0.00033	0.00622	0.00081	0.00018	0.00086
Votorantim (U07)	0.8794	0.00045	0.00034	0.00041	0.00017	0.00016	0.00305	0.00040	0.00009	0.00042
N. Hydro (U08)	0.9701	0.00024	0.00018	0.00022	0.00009	0.00009	0.00165	0.00021	0.00005	0.00023
Kinross (U09)	0.6465	0.00122	0.00093	0.00113	0.00046	0.00045	0.00835	0.00109	0.00024	0.00115
Rio Tinto (U10)	0.1312	0.00268	0.00204	0.00248	0.00101	0.00098	0.01831	0.00238	0.00052	0.00252
Barrick(U11)	0.0000	0.00573	0.00436	0.00530	0.00216	0.00210	0.03919	0.00510	0.00112	0.00538
BHP Billiton (U12)	0.8846	0.00054	0.00041	0.00050	0.00020	0.00020	0.00371	0.00048	0.00011	0.00051
Glencore (U13)	0.8838	0.00103	0.00079	0.00096	0.00039	0.00038	0.00706	0.00092	0.00020	0.00097
Yamana (U14)	0.9036	0.00023	0.00017	0.00021	0.00009	0.00008	0.00154	0.00020	0.00004	0.00021
JX Nippon (U15)	0.9434	0.00034	0.00026	0.00032	0.00013	0.00013	0.00234	0.00030	0.00007	0.00032
Gold Fields (U16)	0.9553	0.00022	0.00017	0.00021	0.00008	0.00008	0.00154	0.00020	0.00004	0.00021
Mitsubishi MTL. (U17)	0.9782	0.00056	0.00043	0.00052	0.00021	0.00021	0.00383	0.00050	0.00011	0.00053
Gold Corp (U18)	0.7573	0.00074	0.00056	0.00069	0.00028	0.00027	0.00506	0.00066	0.00014	0.00070
Teck (U19)	0.0000	0.00396	0.00301	0.00367	0.00149	0.00145	0.02710	0.00353	0.00077	0.00372
ARM (U20)	0.9500	0.00055	0.00042	0.00051	0.00021	0.00020	0.00377	0.00049	0.00011	0.00052
Codelco (U21)	0.7809	0.00061	0.00047	0.00057	0.00023	0.00022	0.00419	0.00055	0.00012	0.00058
Sumitomo (U22)	0.9518	0.00074	0.00056	0.00068	0.00028	0.00027	0.00506	0.00066	0.00014	0.00069
De Beers (U23)	0.8056	0.00071	0.00054	0.00065	0.00027	0.00026	0.00484	0.00063	0.00014	0.00066
A.American Pt (U24)	0.9588	0.00023	0.00017	0.00021	0.00008	0.00008	0.00154	0.00020	0.00004	0.00021

Once the normalized weights were retrieved, the composite indicator scores representing the CSR of mining firms were obtained using expression (5.7). These results allow the construction of a robust ranking, based on common grounds. Figure 5.4 depicts the robust CSR ranking of mining firms.

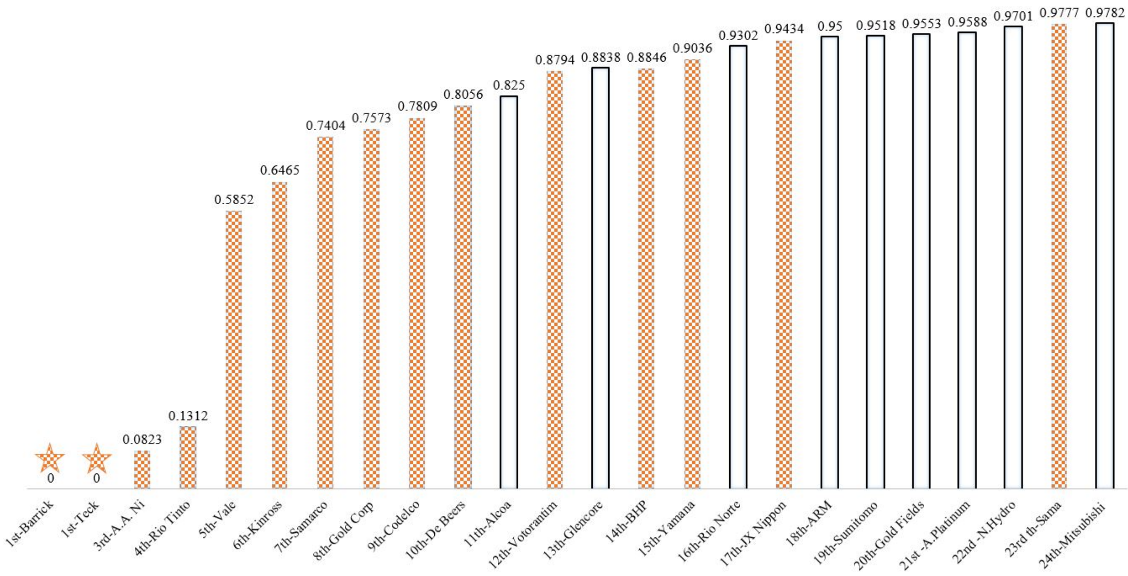

Figure 5.4: CSR ranking of mining firms.

Barrick Gold Corporation (U11) and Teck Resources (U19) lead the sector in terms of CSR practices (for the year 2012), and both appear at the top of the ranking (1^{st} position). They are marked with stars for being the only firms operating on the industry frontier ($\beta_j^{rank} = 0$).

This ranking method also shows that when all firms are compared against the same facet of the industry frontier, some of the firm-level benchmarks (with a beta score equal to zero in the firm-level analysis) are no longer considered equally good when adopting the industry perspective.

The DMUs shaded in Figure 5.4 are the efficient firms in the firm-level stage of the analysis. For example, the case of Yamana Gold Inc. (U14) will be explored in greater detail. This firm has a diversified portfolio of assets, exploiting and processing gold in 12 locations in North and South Americas. Despite being considered efficient in the firm level analysis, and used as a benchmark for Gold Fields (U16) and Rio Norte (U04), it is located in the middle positions of the industry ranking (15^{th} place). Yamana (U14) is particularly good in the generation of benefits in all three dimensions of the TBL, reporting values above the sample average. However, this firm also has the highest levels of burdens observed in the sample, in particular for the indicators of waste production ratio, air emissions ratio and AIFR. Consequently, the system of weights estimated at the firm-level for this firm disregards to some extent the burdens it imposes on society whilst crediting the benefits. This specific weighting system is misaligned with the industry-level analysis, which attributes higher weights to the indicators of social burdens (b_1 , b_2 and b_4), and lower weights to all benefits (see the weights comparison in Table 5.12).

Table 5.12: Comparison of the weights choice

	Weight of Benefits					Weight of Burdens			
Yamana (U14)	u_1	u_2	u_3	u_4	u_5	p_1	p_2	p_3	p_4
Firm-level	0.00139	0.00091	0.00029	0.00016	0.00863	0.00062	0.00001	0.00008	0.00003
Industry-level	0.00023	0.00017	0.00021	0.00009	0.00008	0.00154	0.00020	0.00004	0.00021

In summary, these results show that companies with outstanding performance in some indicators, which can highlight these aspects in the firm-level analysis through a judicious choice of weights, may lose their "benchmark" status in the industry level analysis. In this case, the weights must reflect a more balanced assessment, encompassing all performance dimensions.

The industry level analysis can also support the study of scenarios in which further improvements in some indicators could place a firm in a better rank position. For example, if the firm Yamana (U14) reduced the air emission ratio to 50% of its current value ($b_2 = 0.5 \times 3545.0682 = 1772.5341$), assuming all other indicators are fixed at their current level, the composite indicator score $\beta_{j=14}^{rank}$ would change from the original value of 0.9036 to 0.5443. Note that $\beta_{j=14}^{rank} = -\sum_{r=1}^{s} y_{rj}^{rank} u_{rj}^{rank} + \sum_{i=1}^{m} b_{ij}^{rank} p_{ij}^{rank} = -\ (0.00023 \times 54.8339 + 0.00017 \times 31 + 0.00021 \times 80.4744 + 0.00008 \times 75 + 0.00008 \times 88)\ +\ (0.00154 \times 79.9804 + 0.0002 \times 1772.5341 + 0.00004 \times 6 + 0.00021 \times 544) = 0.5443$. This new score would place Yamada in the 5^{th} position in the ranking. In another scenario, by promoting simultaneous reductions of all Yamana burdens to 45% of their current levels, keeping the benefits fixed at their current levels, the firm would reach the 3^{rd} position of the ranking, with a score of 0.4728.

5.5 Conclusions

This study proposed a method for evaluating and ranking firms according to their performance on Corporate Social Responsibility. The literature suggests that the evaluation of CSR requires consensus, and this challenge is addressed in this chapter by focusing on the assessment of CSR using composite indicators. The first contribution of the paper relies on the development of a framework for the multidimensional evaluation of CSR, reflecting both the main recommendations of international standards and state of the art in the CSR field. The inseparability of the economic, environmental and social practices leading to responsible behavior at the firm level is emphasized. In addition, the framework proposed in this study was designed to meet the sectoral requirements of CSR for mining.

The second contribution is the construction of a composite indicator for quantifying CSR. The performance assessment is conducted with two different perspectives. The first perspective is focused on the firm-level and resorts to a DDF model. This evaluation shows each firm in the best possible light and can be used to support benchmarking efforts. The second perspective is focused on the industry-level and derives a robust ranking based on common grounds. In addition, the industry-level analysis can assert if the practices observed in efficient firms are aligned with the industry trends on CSR. This innovative feature of our composite indicator can provide insights that enable firms classified as benchmarks in the firm-level assessment to pursue an extra mile towards excellence. The integration between DDF and Goal Programming models for this purpose is an innovative feature of our approach. The proposed methodology is versatile and can be applied to other industrial sectors.

A major limitation of this study regards the collection of reliable and updated information on indicators related to firms' CSR. Whilst financial data is usually available in international or national databases, the social and environmental indicators are seldom available at these levels. Particularly in the mining sector, this type of information can only be collected from company sustainability reports. An additional limitation concerns the unavailability of information on the impact of mining on local communities.

Future research at the local level should deepen the analysis of the social and environmental implications observed during the reclamation of deactivated mines. Other research opportunities could involve conducting CSR evaluations over time for exploring firms' pathways towards excellence.

CHAPTER 6
Conclusions

This chapter discusses the main conclusions derived from this dissertation. Section 6.1 discusses the fulfillment of the research objectives as well as the main contributions delivered by this doctoral research. Section 6.2 acknowledges the limitations of this research. Section 6.3 presents the main insights derived from the illustrative applications. By the end of this chapter, section 6.4 indicates directions for future research.

6.1 Fulfillment of the Research Objectives

This thesis had as main objective the development of innovative models, based on optimization techniques, for quantifying Corporate Social Responsibility in the mining sector. CSR is a multidimensional concept that comprises that criteria associated with economic, environmental and social aspects. Therefore, the achievement of this objective involved a close examination of the dimensions of the Triple Bottom Line (TBL) and the criteria that can be used for their representation. The evaluation of CSR was intended to support assessments at both firm-level and industry-level.

The three papers composing this thesis include methodological developments and illustrative applications using real data of large mining firms. The studies conducted are aligned with the specific objectives proposed for this thesis. The attainment of these objectives through the research reported in chapters 3, 4, and 5 is discussed next.

Chapter 3 explored the relationship between the environmental dimension and the economic dimension of the TBL. This study included three main theoretical contributions to the field of eco-efficiency analysis. The first contribution concerns providing an expanded view of firms' eco-efficiency (specific objective 1 of the thesis). This objective was attained with the proposition of an expanded framework of indicators that reflect environmental burdens e benefits. This framework comprises criteria recommended by international standards, sectoral guidelines and empirical studies. The criteria proposed encompass conservation issue, which enable exploring the potential for strengthening good environmental practices.

The second contribution of chapter 3 regards the development of an enhanced optimization model based on DDFs to assess eco-efficiency from different perspectives (specific objective 2). The model proposed can accommodate multiple directional vectors that allow incorporating alternative managerial preferences in the model and exploring distinct assessment scenarios.

The last contribution of chapter 3 concerns optimizing the proportion of renewable resource consumed by firms (specific objective 3). This feature allows crediting the efforts made in the substitution of non-renewable resources by more sustainable alternatives.

The empirical support of the theoretical contributions delivered in this chapter is ensured by an illustrative application composed by 25 large mining companies in year 2011. The results showed that firms in this sector could reduce simultaneously their burdens (e.g., air emissions, waste) and balance the consumption of water and energy with renewable alternatives.

Chapter 4 addressed the evolution of social performance over time. A framework, composed of burden and benefit indicators, was developed to enable a detailed analysis of the social dimension of the Triple Bottom Line (specific objective 4).

A composite indicator model was developed in chapter 4, which enables benchmarking analysis of firms (specific objective 5). Furthermore, the model developed has the feature of preventing the occurrence of infeasibility in the estimation of mixed-period Directional Distance Functions. The values of the composite indicator were used to calculate a Malmquist index of productivity change over time. The calculation of the MI required the use of exact equivalences between radial efficiency scores and CI scores obtained with three particular directional vectors (specific objective 6).

The illustrative application of chapter 4 analyzed the evolution of social performance over time using a sample of 24 large mining firms in years 2011 and 2012. It also included a benchmarking analysis for the year 2012 and the identification of innovative firms.

Chapter 5 proposed an methodology to summarize the three dimensions of the Triple Bottom Line in a composite indicator representing Corporate Social Responsibility.

The first contribution of 5 was the development of a framework to select appropriate indicators that meet the sectoral requirements of mining activity (specific objective 7). The performance criteria selected to compose the framework reflect the main international sectorial recommendations regarding the economic, environmental and social dimensions of the TBL. The indicators accounted for firms' burdens and benefits conveyed to society, with special attention to local development practices and the use of renewable resources.

The second contribution of chapter 5 regards the evaluation of mining companies at the firm-level and at the industry-level (specific objectives 8). The evaluation at the firm-level shows firms in the best possible light and allows supporting benchmarking efforts. The industry-level analysis provided a ranking of firms, based on a consensual system of weights, estimated using a Goal Programming model. Regarding learning opportunities, the advanced optimization models, developed to quantify CSR, permitted learning opportunities to all firms evaluated including the efficient ones at the industry-level.

Regarding lessons to be learned at the firm level analysis, the model used enables inefficient firms to mirror the CSR practices of their peers in a benchmarking exercise. In this context, evaluating the use of renewable resources and local development efforts are some of the innovative features addressed in this dissertation.

At the industry level, the estimation of an industry frontier based on common grounds, represents another innovative feature of the methodology proposed. The frontier of the industry can be used as a reference for efficient firms to assert if their practices are aligned with the industry trends on CSR. This innovative feature of our composite indicator enable all firms in the sample to pursue an extra mile towards excellence.

The methodology proposed in chapter 5 was illustrated using real data from 24 large mining companies in the year 2012. The results obtained can be used to promote the awareness of this topic among decision-makers and the society in general, supporting the sustainable development of industrial activities.

6.2 Limitations of the Research

Although the research described in this thesis reached all the objectives proposed, there are a few limitations in the empirical part of the papers composing this thesis. The limitations concerning data formats and coverage are noteworthy.

The limitation of data formats regards the absence a structured sets of data (or databases) open to public domain. There are restricted databases that report indicators constructed from expert opinion (e.g., ratings for emission reduction policies), but objective information the firms' outcomes (e.g., CO_2 emissions of tons) is not available. Particularly in the mining sector, information on the results of firms could only be collected from companies' sustainability reports and financial reports, which are available in digital libraries (e.g., GRI repository).

The GRI reports and firms' financial reports are the primal data source of this thesis. The GRI digital library provides sustainability reports with external validation emitted by certified offices in compliance with international standards (e.g., ISAE 3000 and AA1000AS). This external assurance of information enhanced the reliability of data and motivated our option to restrict the analysis only to large mining firms affiliated with the Global Reporting Initiative (GRI). Similary, the firms financial reports used were externally audited by third parties.

Despite the reliability of information assured by the digital library and the reports chosen, the limitation of coverage was not fully surpassed. The absence of quantitative information within the reports accessed, mostly on social indicators, dictated the reduced sample size underlying the empirical illustrations. For that reason, indicators reflecting land use, disputes with indigenous communities and achievements regarding local communities could not be considered in this research.

As consequence of these two limitations, the firms' samples were collected individually from the reports selected from the repositories available to public domain. The non-automated construction of the data collection had the following implications:

- The eco-efficiency assessment reported in chapter 3 used a sample of 25 large mining companies in year 2011.

- The longitudinal evaluation of social performance reported in chapter 4 used a sample of 24 mining firms in years 2011 and 2012. Note that the dataset used in this chapter excluded one of the firms used in chapter 3 (Usiminas) due to the lack of social indicators in the firm's sustainability reports of 2011 and due to the unavailability of the sustainability report of Usiminas for 2012.

- The assessment of CSR reported in chapter 5 used a sample of 24 firms in the year 2012, which includes the same companies evaluated in the previous chapter.

Due to the small sample size, the empirical results obtained must be interpreted carefully and should not be generalized.

6.3 Insights from the Illustrative Applications

The methodological enhancements presented in this dissertation allowed obtaining some insights on the performance of the large mining firms in recent years. The main insights extracted from the illustrative applications of this research are presented in the following paragraphs.

Insight 1: Eco-efficiency does not mean social awareness.

The analysis of eco-efficiency and social performance showed that some firms with low performance in terms of eco-efficiency can have high-performance in the social domain and vice versa. For example, the social performance of the firm Samarco in 2011 makes a good case for firms that are on the frontier of social practices but hit the bottom in terms of eco-efficiency. Similarly, eco-efficient companies may not necessarily operate on the frontier of social performance. For instance, the firm Glencore in year 2011 is a top performer in terms of eco-efficiency, but has one of the lowest social performance score in that year.

The results obtained in independent evaluations of eco-efficiency and social performance reinforce the premise that none of these measures should be interpreted as an overall quantification of Corporate Social Responsibility. Therefore, the estimation of an overall indicator of CSR requires taking into account simultaneously social, environmental and economic domains.

Insight 2: Tracking performance over time is a must in the mining sector.

The longitudinal analysis of performance reported in this dissertation focused the social component of Corporate Social Responsibility. Despite the controversial nature of the mining exploitation, efforts to create safer workplaces and social development at the local level are observable in the illustrative application of chapter 4. However, the analysis of the shift in each indicator between 2011 and 2012 indicates that even innovative firms have difficulties to deliver solid improvements in all social practices simultaneously. Overall, none of the innovative firms in the mining sector showed improvement, or at least stability, in all the indicators simultaneously. For example, Anglo American Ni reduced the "employees' turn over rate" burden indicator by 25%, but experienced reductions by more than 30% in the "% female workforce" and "% local hiring” benefit indicators. This phenomenon may be an indication that the practices adopted in this sector require additional efforts to stabilize and ensure higher levels of social performance in the long term.

Longitudinal assessments considering the other dimensions of the TBL should also be sought. They are a critical issue not only for firms in this sector but also for regulators and the society at large. In this context, the longitudinal analysis of eco-efficiency of mining firms could support a more in-depth understanding of how companies manage the environmental risks they impose on society. For example, exploring scenarios that focus on reducing “Dispersions” and improving “Conservation” could identify opportunities for solving problems related to waste management, spills, and air emissions. The expanded eco-efficiency model can be particularly interesting for monitoring the operations of firms with large environmental liabilities, such as Yamana and Samarco.

Monitoring the evolution of CSR efforts of companies may be particularly interesting for regulators, especially in what concerns firms recently involved in major environmental accidents (e.g., Samarco, Norksh Hydro, Rio Tinto). In the long run, companies responsible for environmental accidents need to prove to the society the effectiveness of their environmental recovery actions and the adequacy of the compensatory policies implemented to relieve the social burdens imposed on local communities after the disasters.

For instance, the Mariana dam disaster caused by Samarco in the year 2015 drew international attention due to the extent of the social and environmental damages caused. The collapsed dam unleashed toxic sludge over 293 municipalities near Mariana. The impacts of this accident are observable for 600 km in the space between the dam and the plume of the Doce River in the Atlantic. In this context, the following socioeconomic impacts and human health risks are worth noting: the destruction of riparian, freshwater and marine ecosystems, disruption of fisheries, contamination of agricultural farms, the compromise of water provisioning, threats to the Atlantic Forest, and the destruction of the heritage of the municipality of Bento Rodrigues (Fernandes et al., 2016). In this context, the longitudinal monitoring of CSR practices for companies involved in serious accidents is critical and requires increased attention.

6.4 Directions to Further Research

The performance assessment models developed in this thesis were illustrated in the context of mining firms. However, the approaches proposed to assess Corporate Social Responsibility are versatile and can be generalized to other contexts (e.g., from mining to other industrial sectors or from firm-level to local exploration sites).

The illustrative applications of this thesis reported evaluations of multinational companies, based on aggregate data from all operations. Future research in the mining industry should involve methodological refinements to evaluate CSR at local exploitation sites, enabling a bechmarking comparison of individual mines.

The expanded eco-efficiency assessment model enables the search for improvements both in terms of the magnitude and in the composition of the resources consumed. This model is suitable for assessments involving the balance of environmental burdens and benefits in a variety of sectors where energy or water are critical resources (e.g., farming, textile industry, technology industry). The assessment of expanded eco-efficiency on other sectors would require refinements in the indicators analyzed, so that the sectoral requirements can be represented appropriately.

This thesis also focused on the evaluation of CSR from the firm perspective. Future research could change the perspective for evaluating the sustainable development of countries or regions impacted by mineral exploitation. In this context, monitoring the benefits of sharing corporate infrastructure with society (e.g., companies' roads, railways, power plants and recycling stations) could bring insights to the planning of public policies. Another opportunity foreseen is the proposal of methodologies to evaluate the resolution of conflicts, between companies and exploited countries, involving land and water use.

In what concerns access to larger samples containing information about firms, future research could focus on the development of a collaborative database, with longitudinal data, open to public domain. This database could extend existing digital libraries, reporting structured, reliable and multisectoral data representing the three dimensions of the Triple Bottom Line. This initiative would enable tracking the evolution of responsible practices adopted by firms in a variety of industries and the impact of firms' actions on the welfare of future generations.

The incorporation of values judgments in both the expanded eco-efficiency model and the social performance model (e.g., using weight restrictions) would enable expressing of the relative importance of the indicators or criteria according to experts' opinion. The exploratory analysis of the impact of weight restrictions could also guide the design of policies aligned with the decision makers preferences.

It would also be interesting to integrate the methodologies proposed in this thesis with other ranking methods (e.g., MCDM/A). The integration of DEA with other methodologies could be a resourceful approach to analyze the robustness of the ranking constructed. In addition, the integration of techniques could be beneficial to facilitate prioritizing criteria according to decision makers' preferences, especially when the assessments involve conflicting criteria.

Another methodological aspect worth exploring is complementing the DEA results with statistical analysis of data, which can enhance the robustness of the results obtained. In addition, the use of approaches to address extreme values and outliers in DEA assessments, especially in evaluations involving data on environmental accidents, deserves attention in future studies.

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