Πρόγραμμα Μεταπτυχιακών Σπουδών

στη Φορολογική, Λογιστική και Χρηματοοικονομική Διοίκηση

Στρατηγικών Αποφάσεων

Τμήμα Οργάνωσης και Διοίκησης Επιχειρήσεων

Διπλωματική Εργασία

«Διερεύνηση της επίδρασης των σκορ ESG στις συγχωνεύσεις/εξαγορές με βάση την ισότιμη συμμετοχή των δύο φύλων»

του

Πετρίδη Κωνσταντίνου του Ευστρατίου

Υποβλήθηκε ως απαιτούμενο για την απόκτηση του Μεταπτυχιακού Διπλώματος στη Φορολογική, Λογιστική και Χρηματοοικονομική Διοίκηση Στρατηγικών Αποφάσεων

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«Investigating the effect of ESG scores on M&A's through a gender equality prism»

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Αφιερώσεις

Θα ήθελα να αφιερώσω την συγκεκριμένη εργασία στην σύζυγό μου Ελένη και στο αγέννητο ακόμα παιδάκι μας.

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Ένα όμορφο ταξίδι φτάνει στο τέλος του με την κατάθεση αυτής της εργασίας. Το ΠΜΣ Φορολογική, Λογιστική και Χρηματοοικονομική Διοίκηση Στρατηγικών Αποφάσεων πρόσφερε πολλά εφόδια και μου άνοιξε νέους ορίζοντες στην κατανόηση λειτουργιών τω επιχειρήσεων από οικονομική, φορολογική και χρηματοοικονομική άποψη.

Σε αυτό το ταξίδι είχα συνοδοιπόρους τα οικεία μου πρόσωπα, την οικογένειά μου, τους γονείς μου και τον αδερφό μου τους οποίους και ευχαριστώ καθώς και καθηγητές με τους οποίους ταιριάξαμε ερευνητικά.

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Περίληψη

Η σύγχρονη προσέγγιση των συγχωνεύσεων και εξαγορών (Σ&Ε) δεν βασίζεται αποκλειστικά σε οικονομικές μετρήσεις για την απόδοση, παρά σε μια πιο ολοκληρωτική εταιρική προσέγγιση. Τα τελευταία χρόνια, οι εταιρείες έχουν επικεντρωθεί περισσότερο σε περιβαλλοντικούς, κοινωνικούς και διακυβερνητικούς παράγοντες, κοινοποιώντας τις αντίστοιχες ενέργειες μέσω εκθέσεων Εταιρικής Κοινωνικής Ευθύνης (ΕΚΕ) στο κοινό. Ένα άλλο σημείο ενδιαφέροντος για τους επενδυτές και την επιστημονική κοινότητα είναι εάν η διαφοροποίηση των φύλων στο διοικητικό συμβούλιο επηρεάζει άμεσα ή έμμεσα την αξία των Σ&Ε. Ως εκ τούτου, ένα σημείο ενδιαφέροντος έγκειται στο κατά πόσον προστίθεται αξία στις Σ&Ε των επιχειρήσεων με υψηλές βαθμολογίες κριτηρίων Περιβαλλοντικών, Κοινωνικών και Διακυβέρνησης με αυξημένη διαφοροποίηση των φύλων στο διοικητικό συμβούλιο.

Ένα από τα κύρια προβλήματα στον τραπεζικό και χρηματοπιστωτικό τομέα είναι η μέτρηση της αποτελεσματικότητας των Σ&Ε, λόγω του πλήθους των μέτρων και των μεταβλητών που είναι διαθέσιμα. Σε αυτή την εργασία, η αποτελεσματικότητα 441 συμφωνιών Σ&Ε έχει αξιολογηθεί με βάση συγκεκριμένες εισόδους και εξόδους, μεταξύ των οποίων η αλλαγή των βαθμολογιών κριτηρίων Περιβαλλοντικών, Κοινωνικών και Διακυβέρνησης. Λόγω της παρουσίας αρνητικών δεδομένων, έχουν εφαρμοστεί πολλά μοντέλα Περιβάλλουσας Ανάλυσης Δεδομένων (ΠΑΔ). Εφαρμόζονται δύο τύποι αναλύσεων δεύτερου σταδίου. Το πρώτο είναι ένα μοντέλο παλινδρόμησης που εξετάζει την επίδραση των μεταβλητών ελέγχου στην αποτελεσματικότητα των βαθμολογιών ΠΑΔ, ενώ το δεύτερο είναι ένα μοντέλο Support Vector Machine που έχει προσαρμοστεί για να παρέχει μια χαρτογράφηση της αποτελεσματικότητας βάσει της διαφορετικότητας των φύλων. Τα αποτελέσματα δείχνουν ότι η ποικιλομορφία των φύλων και το σχετικό μέγεθος επηρεάζουν θετικά την απόδοση των συμφωνιών Σ&Ε, ενώ η συμφωνία έχει αρνητική αξία. Η ταξινόμηση του μοντέλου SVM δείχνει ποιες περιοχές του παράγοντα αποτελεσματικότητας και σταθερότητας αντικατοπτρίζονται από την καλή ή κακή εκπροσώπηση των γυναικών στα διοικητικά συμβούλια.

Λέξεις κλειδιά: Περιβάλλουσα Ανάλυση Δεδομένων, Support Vector Machines, Ταξινόμηση, Σ&Ε, ESG, Διαφοροποίηση φύλλων

Abstract

Modern approach to Mergers & Acquisitions (M&As) do not purely rely on financial metrics for performance, rather than, on a more wholistic approach of the firm. Over the recent years, firms have focused more on environmental, social and governance (ESG) factors, communicating the corresponding actions via Corporate Social Response (CSR) reports to the public. Another point of interest for investors and scientific community is whether gender diversification in the board of directors affects directly or indirectly the value of M&A. Therefore, a point of interest lies on whether M&A have increased values within the firms with high ESG scores and increased gender diversification in the board of directors.

One of the main problems in banking and finance is to measure the efficiency of M&A, due to the fact of the plethora of KPIs and variables. In this study, the efficiency of 441 M&A deals have been evaluated based on specific inputs and outputs, among which the change of ESG scores. Due to the presence of negative data, multiple DEA models have been applied. Two types of second stage analyses are applied. The first is a regression model which examines the impact of control variables on the efficiency of DEA scores whereas the second is a Support Vector Machine model which has been adjusted to provide a mapping of the efficiency based on gender diversity. Results indicate that gender diversity, and relative size affect positively the performance of M&A deals whereas the deal value negatively. The classification of SVM model indicate which regions of efficiency and stability factor is reflected by good or bad representation of women in boards.

Keywords: Data Envelopment Analysis, Support Vector Machines, Classification, M&A, ESG, Gender Diversification

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1. Introduction

In the latest years, companies need success in the long run, and in order to achieve this should focus and immediately deal with the moral values and wishes of all the involved parties. Modern economic conditions have set a basic viability prerequisite, not only the foundation and stabilization of a business, but also the ongoing effort on achieving goals, throughout duration of their operation. Some new important factors which have been determined worldwide, such as globalization, wealth distribution, governance, regulatory framework and thoughts about environmental risks as well as the fast-evolving business environment, are aspects that companies need to take into account so as to become competitive.

Companies tended to gain trust of creditors, banks and other involved parties, by presenting a good image on balance sheets, profit and loss statements or any other financial element. In the past years, companies' primary goal was economic wealth without caring for the environmental consequences. This belief was proven wrong and companies were reporting social and environmental facts along with economic/financial results. Company's attitude towards issues concerning organization and operation changed over time. This period is characterized by the transition from the logic of quality control, to quality assurance and to total quality control. Nowadays, an increased interest and sensitivity towards environmental protection is observed, fact that made companies to operate in a more ecological friendly way. Companies' main concern is to care about their brand name and link it to positive impact in the minds of all involved parties, such as consumers, investors, creditors and others.

However, environment is not the only aspect that businesses care about. Dimensions like employee safety, working conditions, employee's benefits and ongoing education and the overall business contribution to their working personnel and society (such as provision of scholarships or sponsorships), are among the main concerns of companies. In fact, these policies were extended to other social aspects, such as the employment of women, ban of childhood labour, and implementation of working labour, were some of the many aspects that companies take into account.

Through Corporate Social Responsibility (CSR), companies present their initiatives and sensitivity, which becomes known through word – of – mouth to all involved

parties. Therefore, a modern company should survive in a fast evolving and globalized environment. The corporate stand towards several social aspects has come to offset consequences that the neoliberal economic model had on society, culture and environment.

Another critical aspect in the operations of business nowadays, is the gender diversification/equality. This issue has drawn significant attention over the last years due to the increasing sensitivity towards gender inequality and minorities in the boards of companies. Also, another point of interest rises on the performance of these companies with high gender diversifications since studies demonstrate higher performance and better results in comparison to the ones with low gender diversification.

Besides the companies' well-being and growth, an important section of business analysis is the potential Mergers and Acquisitions decisions. The global mergers and acquisitions (M&A, henceforth) transactions result in enormous amounts of money flow each year. This global funds' transfer, raises the interest of academics and managers towards the study of the potential synergies and the risks coupled with M&As. The M&As deals can fail due to wide variety of reasons; shareholder opposition, regulatory intervention, financing problems or internal target resistance. In this context, the stakeholders' role and gender diversification in the board of directors, together with firms' CSR and Environmental, Social and Governance Ratings (ESG, henceforth) are emerging issues to be further investigated.

Although CSR is a relatively new term the in-business literature, the evolution of the concept itself has taken place over the last decades. Studies linking CSR to the market value of firms for marginal investor, have found mixed evidence. However, the case of strategic acquirers has scarcely been analysed. At the same time ESG's increased presence in M&A activity the last few years.

In this thesis, the relationship between ESG and Corporate Financial Performance (CFP) in M&As is investigated, in terms of efficiency score.

The **contributions** of this thesis are manifold. Firstly, the effect of ESG scores in M&As' under the gender prism is investigated. Even if the boardroom gender diversification as a factor of firm performance has been widely examined, the impact of gender in the ESG ratings and M&As is a rather unexplored field. Second, the

literature is enriched by proposing a multi- stage methodology. In the first stage, a Linear Programming model reformulated as a Range Directional Model is applied in order to obtain the DEA efficiency scores, which are afterwards classified as control parameters using SVM models. At the second stage, a regression analysis is employed in order to evaluate the factors on the efficiency score and then the analysis utilized the application of a machine learning methodology that highlights the regions by which the control variables affect the efficiency scores. In that sense a multi-layer analysis is possible. The proposed approach has not yet been published or investigated in the relevant literature.

The thesis proceeds as follows. Section 2 presents the relative Literature Reviews. In this section the main concepts and definitions are presented, together with the relative studies on the research field. Section 3 includes the proposed Methodology. In this, the proposed models are presented, together with the available data, the inputs and the outputs of the analysis. Section 4 presents the Results of the analysis and finally Section 5 concludes the thesis, by presenting the main findings and recommendations for future study.

2. Literature review

Over the years the essence of sustainability has become more important. This is attributed to the fact that the objectives for measuring sustainability extended from purely economic to societal and environmental. To this end, the rise of concepts like corporate social responsibility (CSR) have gained ground, measuring its impact on financial performance (FP) (Brooks & Ikonomou, 2018).

2.1. Corporate Social Responsibility (CSR)

Although CSR is not a new concept, as in the late 1770s Adam Smith introduced a similar and in the same time totally different concept, the "invisible hand", in which entities and firms are trying to increase their owns profits, through economic social welfare, the big questions, which has not been answered yet, is a sole definition of CSR (Wan - Jan, 2006). This inability is stressed through Kitchin's (2003) sayings:

…"*one moment (CSR) seems to mean the engagement of nongovernmental organizations (NGOs), the next it is all about charitable donations, and 5 minutes later it seems to mean the ethical treatment of employees. One minute the NGOs are calling the shots, the next the accountants are in on the act selling reputation assurance*".

At first, one can discriminate the definition of CSR as two ways of thoughts according to how CSR is used by firms. Some authors are that it is an excellent means to promote firm's brand name and therefore acquire a bigger market share (e.g Lantos, 2001; Lewis 2003) while others state that CSR is the correct way that every firm should operate (Trevino and Nelson, 2016). In this line is the concept of Frooman (1994), who he reviewed nine empirical studies and reached the conclusion that firms which demonstrate asocially irresponsibly attitude, are punished by stock markets. An example of such phenomenon is products recalling. In the unlike case where firms are obligated to recall their products from the market, their share prices in stock markets

decrease, however, these firms exhibit CSR. On the other hand, if they did not recall their products, share prices would remain the same.

According to relevant literature, Carroll (1979) is the first to provide with a unified definition of CSR, by combining corporation's responsibilities and expectations, which are perceived by firm's objectives (economic and social), perceived by firms as an undivided part of a business context and not as inharmonious concepts.

Nonetheless, a great effort is put by many scholars, so as to conclude with a definition of CSR, which will cover many aspects of economic activity. In that way, in Dahlsrud's study (2008) an identification of 37 different definitions of CSR was made, by using a combination of content analysis and questionnaires. He concludes that CSR definitions and perceptions vary realty among authors.

Not only scholars have put effort so as to define CSR, but also public organizations. Such organization is the EU Commission which is the highest rank legislative body and suggested the following definition of CSR as "*actions by companies over and above their legal obligations towards society and the environment*" (European commission, 2011). Due to the vast literature, CSR perceptions differ among companies, managers and individuals (Lau, Hulpke, To, & Kelly,2007).

Having provided different approaches concerning definitions of CSR, it is important to present the different ways that CSR is measured. At first, measuring CSR is difficult process, for the following reasons: 1) there is no unified definition of what CSR is and 2) there are many and different dimension s of CSR which are going to be measured. However, a considerable amount of efforts have been conducted by many scholars so as to provide with a reliable and valid means of CSR measurement.

CSR is used to be measure based on reputation indices, which are constructed by specialized rating agencies. Erhemjamts, et al. (2013) proposed MSC KLD 400 social index while Preston & O'Bannon,(1997) proposed Fortune magazine reputation indices and others (e.g Girerd-Potin, Jimenez-Garcès, & Louvet, 2014) the Vigeo index. These indices verify the fact that CSR is a multidimensional phenomenon and it should be measured based on different number of dimensions such as natural environment, Community and Society, customers, employees and supply chain as

well as governance and ethics. As far as the Fortune Magazine reputation index is concerned, Innovation, use or corporate assets, people management and other similar dimensions are used to construct such index. Similar to Fortune magazine reputation index is the Vigeo index, in which the important aspects of measuring CSR are human resources, environment, corporate governance, community involvement, business behavior and human rights. MSC KLD index is often used so as to measure CSR, because it of its comprehensive nature of the data as well as because of the fact that the data are available public. KLD assess a company's strong and weak points concerning several social aspects such as community relations, issues concerning social discrimination, protection of environment, quality producing safely and human rights. This index, however, takes into account several aspects concerning businesses decisions which may have a negative impact on society, such as financing military violent actions or weapons of mass destruction, alcohol, tobacco or gambling. On disadvantage of KLD index is that it does not provide insight about impact on society for every company's action, and therefore many investors suggest the use of FTSE KLD 400 Social index, so as to make policy. In order a firm to proceed in an investment or business move, it needs to meet certain financial, social and environmental criteria. Due to the fact that KLD index does not provide information about financial criteria, it is usually ignored over FTSE KLD 400 Social index.

The second methodology applied so as to measure CSR is content analysis. This methodology is used to identify the most important aspects of CSR, provide information on these aspects as well as to extract quantitative data from qualitative inputs, and finally process that information in a statistical way so as to reach conclusions. It is primarily conducted by counting phrases of interest and concern aspects of CSR such as environment or working behavior, in relative articles and reports. Afterwards, qualitative information is transformed into quantitative either by assigning binary variables and implementing simple descriptive statistics, or by applying more sophisticated and advanced techniques, among which are generalized linear models. Yang, Lin, and Chang (2010) used such scale so as to evaluate companies for five different CSR aspects. These are: 1) employee relations, 2) environment, 3) shareholder relations, 4) product quality and relations with providers and customers and 5) community.

Questionnaire – based surveys, are another useful and straightforward means to measure CSR, and can be conducted primarily by researchers and not specialized rating agencies. Various questionnaire based studies have been conducted so as to measure CSR aspects. The most important dimensions which have been investigated are appraise social, economic and environmental dimensions of CSR (Gallardo-Vαzquez and Sanchez-Hernandez, 2014), or economic, legal, ethical and discretionary (Carrol, 1979). Questionnaires' analysis is similar to that of content analysis, however it is more flexible tool as it allows researcher to construct his/her own aspects of interest. On the other hand, its main drawback is that researchers should be aware of the CSR aspects in advance, while by using content analysis information is extracted by various sources.

Last means of measuring CSR is one dimensional measure. It focuses on one aspect of CSR, completely ignoring the rest, as Carrol (1979) suggested, CSR is a multidimensional problem. The primary advantage of this measure is that the aspect which is investigated is known and there are available data for it, while the main disadvantage is that it does not take into account several other dimensions, which may directly or indirectly affect the aspect under study.

Corporate Social Responsibility consists of various factors and definitions, therefore, it cannot be measured since there is not a surrogate variable to approximate any behavior (Beurden & Gössling 2008, Espinós-Vañó 2016, Jankalová & Jankal 2017). Due to the fact that CSR is not measurable, researchers have introduced CSP (Corporate Social Performance) as set of "soft" indicators, including but not limited to: Customer Relationship, charity programs, increasing work balance in the workplace, as well as, "hard" indicators like toxic releases, tons of CO2 emissions, etc (Marom 2006, Arribas-Fernández et al. 2018, Chen & Delmas 2011).

2.2. Environmental, Social and Governance Ratings (ESG)

The adoption of the ESG criteria in the selection of investment placements is a rapidly rising trend internationally. These criteria concern Environmental, Social and Governance aspects of every day life. The ESG scores reflect the three key factors in measuring the ethical and environmental impact of an investment in a company or enterprise. More specifically, each dimension of ESG criterion is analyzed as follows:

- Environmental criteria examine how businesses take into consideration in their operations and production process the natural environment. Essentially, this pylon measures how business respect the Environment, Tackling Climate Change, CO2 emissions, air / water pollution, energy efficiency. The aforementioned are just some of the indicators in the wide variety of the indicators used.
- Social criteria put an emphasis on the relationships with employees, suppliers, customers in the inner and outer environment of the business. In other words, social issues such as labor and human rights, animal rights, consumer protection, workers' health and insurance, gender equality, etc. are examined.
- Corporate governance concern indicators dealing with the companies' leadership, business ethics, executive pay, employment relationships, internal audits, transparency, corruption and shareholder rights. This criterion actually reflects the transparency of the business operations.

One of the main key elements of ESG philosophy is the fact that it is adopted by investors who are sensitive towards sustainable development with their investment behavior, as well as by managers who choose investment schemes that contribute to sustainability.

Because of the complexity of CSP measurement, a number of specialized firms, the so-called ESG (environmental, social, and governance) rating agencies, have emerged in the last years. These firms provide ESG information and tools for measuring the contribution of companies to sustainable value creation (Muñoz-Torres et al. 2019). ESG rating agencies assess and rate the environmental, social, and governance-related business practices of firms throughout the world (Guijarro & Poyato 2018, Guijarro

2019). In this vein, these agencies use information collected from each of the companies through questionnaires and analysis of public information (e.g., CSR reports, annual reports, news, etc.), which is examined by interdisciplinary work teams in different geographical areas (Escrig-Olmedo & Fernández-Izquierd 2019). Some of the most important ESG rating scores include the Thomson Reuters ESG Score, the Bloomberg ESG Disclosure Score, the Vigeo-Eiris ESG Score, and the MSCI ESG Score. Based on the literature review and to the best of our insight, only a few studies have analyzed the relationship between ESG rating agencies and CFP (Mattingly 2019, Landi & Sciarelli 2019). Nonetheless, the empirical results of these studies are inconclusive. Considering the above introduced consideration, this paper intends to contribute to the extensive literature in this field by employing the Thomson Reuters ESG Score in order to measure the level of CSP. To our knowledge, this approach is one of the first that uses the Thomson Reuters ESG score in academic research about the impact of the ESG rating on CFP.

2.2. Financial Performance (FP)

Financial progress is generally associated with lower environmental scores, and under certain circumstances, lower social acceptance. The relationship between companies' sustainable behavior and their financial performance has been investigated by Martínez-Ferrero & Frías-Aceituno (2015). Based on a dataset, the results obtained via the generalized method of moments' estimator allow us to support the existence of a positive bidirectional relationship between corporate social responsibility and FP.

FP is usually measured with indices and indicators based on *accounting* (such Returns on Assets – ROA, Returns on Equity – ROE, Returns on Capital Employed – ROCE, Returns on Sales – ROS, Net operating Income, Net income and other similar), *market* (Stock returns, Market value of a company, change in stock returns) or *a mixing of both* (such as Tobin's Q, or Market Value Added – MVA). The main advantage of accounting based measures, is the data availability for the majority of companies while market based criteria tend to have a more immediate effect on CSR, than the accounting ones. Several other researchers (Garcia-Castro, Ariρo, & Canela,

2010; Rodgers, Choy, & Guiral, 2013) used a combination of accounting and market based measures, applying Tobin's Q or MVA indices. Recent studies show, that scholars tend to utilize more than a single measure of FP.

2.3. Relationship between CSP and FP

CSP and FP's association has been over examined by many scholars; however no unique conclusion has been reached due to several problems. Such difficulty stems from the fact that both CSR and FP are not well measured and the means by measuring them are backed by problematic theoretical frames (Griffin & Mahon, 1997). The lack of a single definition is a possible cause of what consumers, investors and other involved parties misperceive CSR as a wide social concept. The majority of the existing definitions which have been proposed from times to times have in common the fact that corporations and firms must contribute to society however none of them implies a straightforward way how to do so.

In fact, Margolis and Walsh (2002) examined 22 published studies using meta – analysis statistical methodology so as to conclude about t the relationship between SCR and FP.From 1975 until now several studies have been published, investigating the relationship between CSP and FP and Adewale & Rahmon (2014) recognized that this relationship is examined under two prisms. Some authors, using survival analysis of discrete time events, evaluate the short – run financial performance as a result of corporate being involved in socially responsible acts.

Therefore, when firms are acting in the correct manner, no noteworthy change in financial performance is expected. The second school of investigating CSP and FP focus on the long – run association between CSP and several FP measures such as ROE, balance sheets and others. The investigation of works conducted by Cochran & Wood, (1984); Aupperle et al., (1985); Waddock& Graves (1997) and McWilliams & Siegel (2001) did not show a clear result concerning the relationship between CSP and FP.

Cochran and Wood (1984) and Posnikoff (1997), among others, found that CSR results in improved FP, however Aupperle et al., (1985) concluded in a non – statistically significant relationship when they examined the impact of societal attributes of CSR, based on Carrol's (1979) aspects of CSR which are economic, legal, ethical and discretionary, and financial performance measures – ROA.

The latter finding is not backed up by Waddock and Graves (1997), who suggests that between CSR and FP there is a positive relationship, and in specific CSR acts as the exogenous variables affecting FP. Based on Freeman's well established theoretical background, their study results in a positive relationship between CSR and FP which comes from enhancing bonds between firms and involved parties (such as clients, investors and others), when firms act socially responsibly. From the above, one could easily conclude that CSR and FP is a well studied issue, which divide scholars between those who believe that they are totally independent and those who believe that CSR enhances FP. Aupperle et al., (1985) suggests that mixed findings extracted from several studies is caused by author's political bias, inappropriate statistical analysis, lack of a valid and reliable measure and most important of all, appropriate and careful selection of proxy variables. Other (e.g. Wright and Ferris, 1997) empirical studies, investigating the relationship between CSR and FP have concluded that there is a negative association between them.

Work of Barnett and Salomon (2012) attempted empirical formulation of CSR and FP. They concluded in the finding that firms with a weak or moderate CSR activity resulted in deteriorated FP measures, while companies with intense CSR acts tended to have improved FP. This interesting finding was supported many years before by Bowman , & Haire (1975), who suggested that relationship between CSR and FP is not linear and follows a U – shaped curve. This finding suggests that the more effort firms put on acting socially responsibly, the more improved their financial indices would be. However, this finding, although interesting, can be added to results from several studies implying a mixed or confusing relationship between CSR and FP.

Possible explanations for such inconclusive findings have been offered by many authors (Surroca, Tribσ, & Waddock, 2010). These include, among others: (1) the poor theoretical foundation of the CSR concept (Rufet al., 2001); (2) the omission of relevant variables in model specifications (McWilliams & Siegel, 2000); (3) the lack

of a clear direction of causality (Waddock & Graves, 1997); and (4) measurement issues (Davidson & Worrell, 1990; Griffin & Mahon, 1997), and sampling limitations (van Beurden & Gφssling, 2008).

The adoption however of CSR may lead to corporate organizational changes. The aforementioned fact is grounded by analyses applied to corporations adopting sustainability policies. Eccles et al. 2014 stress the role of the board of directors of high sustainability companies in comparison to low sustainability ones. The comparison of the two types of corporations indicated that the ones with high sustainability scores are more likely to have established processes for stakeholder engagement.

Since the CSR has been applied and adopted by an increasing number of corporations, the impact of social rating is of high importance. In their paper, Cellier et al. (2016) propose a model for the examination of the effects of Vigeo social ratings announcements on the firm's shareholder value. A link between the cumulative abnormal returns (CAR) and CSR ratings is also presented.

The linkage between the value creation for the company and the expenditure for CSR purposes is presented by Fatemi et al. (2015). Using simulation model with discrete and continuous probability distribution concluded that the costs of CSR engagement may be more than offset by their positive effects over the intermediate- and long-term cash flows.

In the same notion, the effect of CSR on the cost of equity is investigated. El Ghoul et al. (2011), have approached the issue by applying regression analysis. The results indicate that improving certain areas of CSR such as responsible employee relations, policies for better environmental management and sustainable design of products will eventually lead to cost on equity reduction.

The impact of CSR is significant not only for the characteristics of the cost parameters of the company (cost on equity, cost of capital etc) but on the price of the stock of the company. Based on a specific data set of stock markets, Krüger (2015), examined how the markets react positively to positive CSR news and announcements from companies.

Similarly, the evaluation of a firm based on its ESG activities and eventually performance by the prism of capital market investors is proposed by Mervelskemper & Streit (2017). Using empirical analysis concluded that ESG performance is valued strongly indicating a positive direction between firms which publish ESG and increasing ESG performance.

Examining the CSR from a broader perspective, the essence of Environmental Social and Governance (ESG) score is introduced. Since there is diversity in ESG scoring, Lokuwaduge & Heenetigala (2017) proposed an ESG disclosure index for measuring comparing the ESG performance.

Efficiency measurement has been firstly introduced by Charnes Cooper and Rhodes (1978, 1981) with DEA. One of the widely known methodologies for assessing efficiency is DEA. Due to its ease of use, DEA has been applied in a wide range of areas and disciplines. According to the productivity theory, any economic system assumes an underlying production function where inputs are consumed to produce outputs. In this context, inputs are labor and capital which are consumed to produce goods and eventually revenue.

Over the years, numerous applications of DEA have been published in a wide variety of areas and disciplines which span from economics, to healthcare management, environmental management and so on.

Regarding the application of DEA to measuring ESG efficiency, there are not significant number of publications due to the fact that the notion of ESG performance is relatively new.

Performance measurement of ESG scores under the assumption of multiple production stages has been proposed by Galagedera (2019). A two stage model for the performance measurement of mutual fund (MF) in a multi-dimensional framework with ethical level as one of its performance measures. Lin et al. (2017) have proposed a dynamic network DEA model for evaluation of mutual funds.

Wu et al. (2019), have proposed an Assurance Region (AR) model for measuring Corporate Social Performance (CSP). Applications of AR DEA model has been also proposed to measure the relationship of insight debt and CSP (Wu & Lin, 2019, Plaksina et al 2019).

Network DEA models are generally applied for measuring ESG or CSR performance due to the fact that multiple stages with external inputs can be applied. Belu (2009) proposed a network DEA model linking CSR and economic and stock market performance.

The performance of ESG is also examined using Data Envelopment Analysis (DEA). In their analysis, Xie et al. (2019) applied DEA analysis to Efficiency measurement is based cost, labour and assets and the output is based ESG scores. In the second stage analysis, the results of the ESG efficiency scores are regressed against ESG scores and corporate characteristics.

One of the advantages of assessing DEA performance is the utilization of data (inputs and outputs) to measure performance. Nevertheless, not all variables can be used in the DEA analysis. To this end, second stage analyses are proposed using control variables to investigate their effect on the efficiency scores of each unit. In most of the cases, regression analyses are employed (McDonald, 2009) (Hoff, 2007), or Structural Equation Modeling (Zhu et al. 2019) (Kalapouti et al. 2017).

Data Envelopment Analysis models have been applied for measuring performance in many scientific areas and disciplines from environmental science (Petridis &Dey, 2017, Seyoshi&Goto, 2011), to education (Thanassoulis et al., 2017) and supply chain management (Grigoroudis el al., 2014, Petridis et al., 2017).

Nevertheless, handling negative data is a special case of DEA. There have been proposed a wide selection of models for handling negative data since classical DEA models cannot adjust to the correct direction.

A directional DEA approach has been proposed by Portela et al. (2014) with application to bank branches (Portela et al., 2010). Negativity in data is a common phenomenon when trying to model change or growth.

To tackle the problem of the data receiving both positive and negative values, Emrouznejad et al. (2010) proposed a semi – oriented radial measure. The proposed approach has been compared with other DEA models which handle negative data. Sharp et al. (2007), have proposed a modified slack-based measure (MSBM) in which both negative outputs and negative inputs could be handled. In the same context,

Sheel (2010) proposed a DEA model for handling undesirable outputs in the sense of negative data.

In this paper, the performance of the change of ESG scores is measured assuming economic data for inputs. Since aim of the analysis is to investigate which deals are more efficient and to investigate the effect of deal characteristics and gender diversity on the efficiency, two types of second stage analyses are applied. The first analysis one is a regression analysis to evaluate all the aforementioned factors on the efficiency score. The second type of analysis is a machine learning methodology applied to this context to highlight the regions by which two control variables affect the efficiency scores. In that sense an analysis on multiple layers is possible. The proposed approach has not yet been published or investigated in the relevant literature.

3. Methodology

The field of Production Economics has rapidly changed over the last decades. This rapid change is partly ought to Data Envelopment Analysis (DEA) technique which measures the performance of several units based on inputs and outputs, measuring the efficiency of the transformation procedure. The inputs are consumed in order to produce outputs; thus the fraction of outputs produced to inputs consumed is the efficiency of the transformation.

Performance measurement is a valuable tool for businesses and firms with multiple branches (like banks) as the position, of each business/firm or any other economic organization, can be found compared to an ideal benchmark. For instance, if an organization consumes more inputs producing the same amounts of outputs, compared to another unit (firm, business, organization etc), then probably the transformation mechanism needs to change in order for the unit to perform better or to be closer to the ideal situation, the benchmark. The benchmark consists of units that perform better in comparison to other units.

This analysis helps the units that are involved in the analysis to improve their operations, making short of long term policy decisions; performance measurement provides also a policy tool for this dynamically changing economic environment that businesses have to survive and be viable. Improving a unit's operations like reduction in inventory, minimizing lead and transportation time, lead to improved service levels and less production cost.

The importance of the use of DEA technique is that it can be applied to any organization, unit etc taking more than one inputs and outputs into account in order to extract unit's efficiency. This allows providing a more realistic image of the actual operations conducted modeling the transformation procedure with greater detail and therefore providing a realistic performance score.

The unit (process, procedure, business or any other economic or other organization) will be called Decision Making Unit (DMU) for ease of use; aim of DEA technique is to identify fully efficient DMUs by comparing each DMUs inputs and outputs against similar DMUs. Upon the formulation of the problem, the Decision Maker (DM) may

need to examine an input or an output oriented model. In the first case, the inputs are minimized while the outputs are considered constant while in the output-oriented model the outputs are maximized while inputs are kept constant. The frontiers in these two cases are demonstrated in Figure 1.

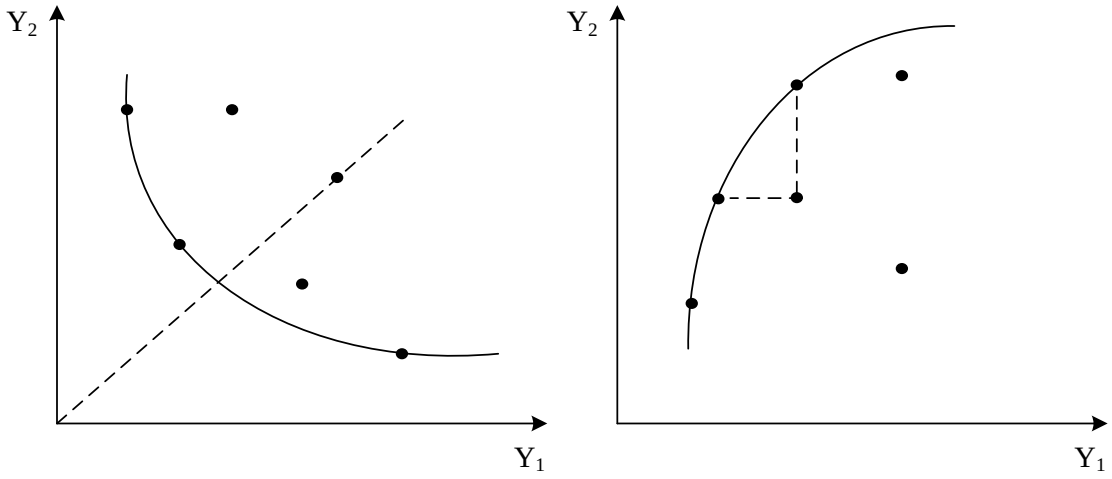

Figure 1: Efficient frontiers based on input oriented (left) and output oriented (right) DEA models.

Besides the type of orientation, there is a variety of DEA models for extracting the efficiency of DMUs based on pre-determined inputs and outputs. These DEA models are the multiplier and envelopment forms which will be extensively analyzed in the next sections.

To evaluate the efficiency of each unit under investigation or Decision-Making Unit (DMU), data regarding the inputs and outputs of each DMU are introduced in DEA which is a non-parametric technique. The initial model has been proposed by Charnes Cooper and Rhodes (1978, 1981) and is modeled with Linear Programming model (Table 1).

3.1 Envelopment models

The envelopment models are presented in Table 1. Model presented in Table 1 (*a*) is input oriented model while the one presented in (*b*) is the output oriented model. The objective function in the first case is to minimize free variable θ which measures the efficiency of each DMU; the evaluation of each DMU's efficiency is conducted upon a pre-determined set of i inputs ($x_{i,j}$) and r inputs ($y_{r,j}$) for each DMU j.

Variables λ_j are the peers of each DMU j; peers are used in order to provide information regarding the proximity of the DMU under investigation with other DMU. Both mathematical formulations (*a*) and (*b*) represent Linear Programming (LP) models which are solved for each DMU under examination, o. If for example, DMU5 has in its reference set DMUs 2 and 6, then $\lambda_2, \lambda_6 \neq 0$. Nonnegative variables s_i^- and s_r^+, are slack variables corresponding to the inputs and outputs. A fully efficient DMU is the one with $\theta^* = 1$ and $s_i^- = s_r^+ = 0$ for model (*a*), while for model (*b*), $\varphi^* = 1$ and $s_i^- = s_r^+ = 0$, whereas θ^* and φ^* are the optimal values after solving LP models (*a*) and (*b*) for each DMU under examination. The range of values for input efficiency is $0 \leq \theta \leq 1$ while for output oriented efficiency $\varphi \geq 1$; for output oriented models, in order to capture the degree of inefficiency of a DMU, then the reciprocal is calculated, such that $0 \leq 1/\varphi^* \leq 1$.

Table 1: Input (*a*) and output (*b*) oriented DEA models.

$min\ \ \theta - \varepsilon \cdot \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$	$max\ \ \varphi + \varepsilon \cdot \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$
s.t.	*s.t.*
$\sum_{j=1}^{n} x_{i,j} \cdot \lambda_j + s_i^- = x_{i,o} \cdot \theta,\ i = 1,..,m$	$\sum_{j=1}^{n} x_{i,j} \cdot \lambda_j + s_i^- = x_{i,o},\ i = 1,..,m$
$\sum_{j=1}^{n} y_{r,j} \cdot \lambda_j - s_r^+ = y_{r,o},\ r = 1,..,s$	$\sum_{j=1}^{n} y_{r,j} \cdot \lambda_j - s_r^+ = y_{r,o} \cdot \varphi,\ r = 1,..,s$
$\lambda_j, s_i^-, s_r^+ \geq 0,\ \forall j,i,r$	$\lambda_j, s_i^-, s_r^+ \geq 0,\ \forall j,i,r$
θ *free*	φ *free*
(*a*)	(*b*)

Following the discussion about the orientation of input and output DEA models, the optimal values of efficiency variables are of great interest as the projections of inputs and outputs to the efficient frontier are calculated. In order to do that, the following equations are the following:

$$\hat{x}_{i,j} = x_{i,j} \cdot \theta^{*} - s_i^{*,-} \qquad \hat{x}_{i,j} = x_{i,j} - s_i^{-,*}$$

$$\hat{y}_{r,j} = y_{r,j} + s_r^{+,*} \qquad \hat{y}_{r,j} = y_{r,j} \cdot \varphi^{*} + s_r^{+,*}$$

(*a*) (*b*)

To introduce VRS technology $\sum_{j=1}^{n} \lambda_j = 1$ constraint is added. By solving each of the models (irrespective of their orientation), a reference set is formulated for each DMU, namely, if a unit is not - efficient then which DMU should be resemble as to their quantity of inputs and outputs in order to become efficient. Reference set of each DMU is constructed with optimal values of variables λ_j^{*}.

3.2 DEA with negative data

One special case of DEA is the one with negative inputs and/or outputs. Since the construction of the conventional DEA models as presented in the previous section, assume only non-negative data, the negativity of the inputs or the outputs can be physically expressed via a wide variation of causes. In some cases, negative data represent undesirable either inputs or outputs whereas in some other cases, negative data are formulated from the difference of two parameters.

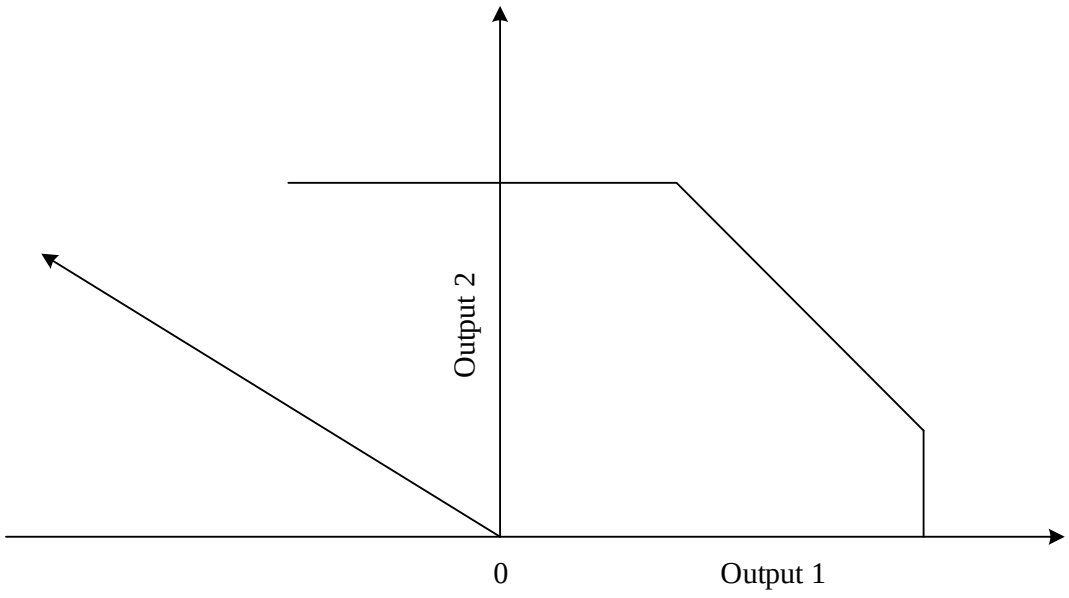

Figure 2: A simple case with two outputs (one negative) (Portela et al. 2014)

As it can be seen in Figure 1, the negativity of the outputs creates problem in the orientation. More specifically, assuming that there is a DMU on the arrow on the negative side of the x-axis, then since this DMU is inefficient, by expansion of the output then the DMU becomes efficient which does not reflect the situation. To overcome this issue, a wide selection of DEA variant models has been proposed one of which is the following:

$$
\begin{aligned}
&max\ \beta \\
&s.t. \\
&\sum_{j=1}^{n} x_{ij} \cdot \lambda_j \le x_{io} - \beta \cdot g_x \ \ i = 1,...,n \\
&\sum_{j=1}^{n} y_{rj} \cdot \lambda_j \ge y_{ro} + \beta \cdot g_y, \ r = 1,...,s \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&g_y, g_x, \beta \ge 0 \\
&\lambda_j \ge 0
\end{aligned}
\qquad (1)
$$

In oriented models, g_x and g_y are set to 0 however, when the data are strictly positive, the values of g_x and g_y receive the values of the inputs and outputs respectively. Model (1) is modified to incorporate the range of possible improvement of inputs and outputs with the introduction of the following parameters:

$$R_{io} = x_{io} - \min_j \{x_{ij}\} \text{ and } R_{ro} = \max_j \{y_{rj}\} - y_{ro}$$

Linear Programming model (1) is then reformulated as the following Range Directional Model (RDM) (Model 2).

$$
\begin{aligned}
&max\ \beta \\
&s.t. \\
&\sum_{j=1}^{n} x_{ij} \cdot \lambda_j \le x_{io} - \beta \cdot R_{io}\ \ i = 1,...,n \\
&\sum_{j=1}^{n} y_{rj} \cdot \lambda_j \ge y_{ro} + \beta \cdot R_{ro},\ r = 1,...,s \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\beta \ge 0 \\
&\lambda_j \ge 0
\end{aligned}
\qquad (2)
$$

In model (2), variable β in the binding case equals $\frac{x_{io} - x_i^*}{R_{io}}$ and $\frac{y_r^* - y_{ro}}{R_{ro}}$ therefore it can be interpreted as a measure of inefficiency. Subsequently, $1-\beta$ is the efficiency measure of RDM.

3.3 Slacks based models

A slacks-based model (SBM) which is non-directional, has been introduced by Tone (2001), where the efficiency measure is the optimal value of ρ; the fractional DEA model is presented in Model (3).

$$min\ p = \frac{1 - \frac{1}{m} \cdot \sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 - \frac{1}{s} \cdot \sum_{r=1}^{s} \frac{s_r^+}{y_{ro}}}$$

s.t.

$$\begin{aligned}
&\sum_{j=1}^{n} x_{ij} \cdot \lambda_j + s_i^- = x_{io}\ \ i = 1,...,n \\
&\sum_{j=1}^{n} y_{rj} \cdot \lambda_j - s_r^+ = y_{ro},\ r = 1,...,s \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&s_i^-, s_r^+ \geq 0 \\
&\lambda_j \geq 0
\end{aligned} \tag{3}$$

A modified slack-based model (MSBM) has been proposed by Sharp et al. (2006). The proposed model can inherently manage better naturally negative inputs, and the optimal value of the objective function (τ) equals the one from Model (2). The MSBM is presented below:

$$min\ \tau = t - \sum_{i=1}^{m} \frac{w_i \cdot s_i^-}{R_{io}}$$

s.t.

$$\begin{aligned}
&\sum_{j=1}^{n} x_{ij} \cdot \lambda_j + s_i^- = t \cdot x_{io}\ \ i = 1,...,n \\
&\sum_{j=1}^{n} y_{rj} \cdot \lambda_j - s_r^+ = t \cdot y_{ro},\ r = 1,...,s \\
&\sum_{r=1}^{s} \frac{v_r \cdot s_r^+}{R_{ro}} + t = 1 \\
&\sum_{j=1}^{n} \lambda_j = t \\
&\sum_{r=1}^{s} v_r = 1,\ \sum_{i=1}^{n} w_i = 1 \\
&s_i^-, s_r^+, t \geq 0 \\
&\lambda_j \geq 0
\end{aligned} \tag{4}$$

3.4 SVM for classification

Once the DEA efficiency scores are obtained using LP models (2) or (4), the scores are classified as per control parameters. To obtain the classification, SVM models are employed.

Generally, SVM analyses are applied in machine learning to segregate data into categories. Aim of the technique is to create a hyperplane to divide data into two or more categories.

The SVM classifier is represented based on the following mathematical programming model (5).

$$
\begin{aligned}
&min \ \frac{1}{n}\cdot\sum_{i=1}^{n}\zeta_i + \lambda\|w\|^2 \\
&s.t. \\
&y_i\cdot\left(w\cdot x_i - b\right) \geq \zeta_i - 1,\ i = 1,..,n \\
&\zeta_i \geq 0,\ i = 1,..,n
\end{aligned}
\qquad (5)
$$

In model (5), ζ_i is a small non negative number satisfying the condition such that $\zeta_i = max\left(0, 1 - y_i\cdot\left(w\cdot x_i - b\right)\right)$. In quadratic programming model (5), λ is used for determining soft/hard margin classifiers.

Based on the dataset, several SVM models can be potentially applied.

The simpler case of SVM kernels is the Linear. The Linear kernel is defined as $K\left(x, x'\right) = x^T\cdot x'$

Among the most popular kernels are the following:

- RBF kernel (radial): $K\left(x, x'\right) = e^{\frac{-\|x - x'\|^2}{2\sigma^2}}$
- Polynomial kernel: $K\left(x, x'\right) = \left(\gamma\cdot x\cdot x' + a\right)^p$ where p is the polynomial degree and γ is the scale factor.
- Sigmoid kernel: $K\left(x, x'\right) = tanh\left(a\cdot x\cdot x' - b\right)$

3.5 2nd Stage Analysis – Beta Regression

It is quite common to apply a linear regression equation, in order to assess the impact of independent variables on the dependent variable. However, when dependent variable falls into the interval (0,1), the ordinary linear regression equation, is not the appropriate tool, due to the fact that fitted values may exceed 1 or be lower than 0.

Some scholars use transformations, so as to deal with this problem, which assume that dependent variable's values are real and linear based on a set of independent variables. However, the previous approach may fix the potential problems there are some practical disadvantages; 1) concerning regressions' coefficients, they may not be interpreted easily and 2) confidence intervals and hypothesis testing for regressions' coefficient may not be reliable due to the fact that normality assumption could be violated.

In our case, the dependent variable is deal - efficiency score ($y = 1 - \beta^*$) and is measured on the standard unite interval, namely $1 - \beta^* \in (0,1)$.

Hence, in order to assess the impact of independent variables on the deal - efficiency score, we assume that the response follows beta distribution (Ferrari, & Cribari-Neto, 2004). Beta distribution, which is a two parameters function, is flexible for modeling proportions and ratios and this is ought to its density function:

$$\pi(y; p,q) = \frac{\Gamma(p+q)}{\Gamma(p)\cdot\Gamma(q)} \cdot y^{p-1} \cdot (1-y)^{q-1}, 0 < y < 1 \qquad (6)$$

Where $p,q > 0$ and $\Gamma(*)$ is the gamma function. In terms of regression equation, mean and variance of response variable can be written as:

$$E(y)=\mu$$
$$Var(y)=\frac{V(\mu)}{1+\varphi} \quad (7)$$

Where $V(\mu)=\mu\cdot(1-\mu)$, μ is the population mean of response and is the precision parameter equal to $\varphi=p+q$. Let $y_1,...,y_n$ be random variables which are beta distributed, with mean μ_t and unknown precision parameter φ equal to the aforementioned ones, then the linear model in its general form can be written as:

$$g(\mu_t)=\sum_{i=1}^{k} x_{it}\beta_i=\eta_t \quad (8)$$

Where $\beta_i=(\beta_1,\beta_2,...,\beta_k)^T$ denotes the vector of unknown parameters to be estimated, while $x_{it}=x_{1t}\oplus x_{2t}\oplus...\oplus x_{kt}$ are observation of *k* independent variables. The link function $g(\cdot)$ is strictly monotonic and twice differentiable and there is a variety of specifications which can be used.

Logit specicification is one of them, in which the link function of mean is modeled as:

$$g(\mu)=log\left(\frac{\mu}{1-\mu}\right) \quad (9)$$

The advantage from applying a Logit specification, is that the regression coefficients are directly interpretable. Other possible specifications are the Probit specification in which dependent's mean is supposed to be a function of cumulative distribution function of a standard normal random variable, namely $g(\mu)=\Phi^{-1}(\mu)$ and the complementary log – log link, namely $g(\mu)=\log\left[-\log(1-\mu)\right]$.

The log – likelihood function, on which estimation process is conducted on *n* independent observations, is the following:

$$l(\beta,\varphi)=\sum_{t=1}^{n} l_t(\beta,\varphi) \quad (10)$$

Where:

$$l_t(\beta,\varphi) = log\,\Gamma(\varphi) - log\,\Gamma(\mu_t\varphi) - log\,\Gamma\left[(1-\mu_t)\varphi\right] + (\mu_t\varphi - 1)log(y_t) + \left[(1-\mu_t)\varphi - 1\right]log(1-y_t)$$

Let $y^* = \log\left(\frac{y_t}{1-y_t}\right)$ and $\mu_t = \psi(\mu_t\phi) - \psi((1-\mu_t)\phi)$, where $\psi(\cdot)$ the digamma function, then the estimation of unknown parameters is β, is given as:

$$\frac{\partial l_t(\beta,\varphi)}{\partial \beta_i} = \sum_{t=1}^{n} \frac{\partial l_t(\mu_t,\varphi)}{\partial \mu_t} \frac{d\mu_t}{d\eta_t} \frac{\partial \eta_t}{\partial \beta_i} \qquad (11)$$

3.6. Data and variable description

In this section, the presentation of the inputs and outputs are presented. Since the presented methodology aims to investigate the efficiency of the deal, the production process assumes the consumption of financial and mergers' characteristics, in terms of financial equivalent parameters. Data concern 441 M&A cases and retrieved from Data stream database (https://www.thomsonone.com/).

3.6.1 Inputs

The first input refers to the size of the deal which is defined as the natural logarithm of acquirers' market capitalization twenty-one days preceding the announcement date

$$SIZE = ln(d) \qquad (12)$$

The AGE input refers to the days between the deal announcement and first date on which Datastream has data for the particular firm and is defined as follows:

$$AGE = ln(\Delta d) \tag{13}$$

The Return On Equity (ROE) input is a measure of financial performance which is defined as the ratio of net income to average stakeholder's equity.

$$ROE = \frac{Net\ Income}{Average\ Stakeholders\ Equity} \tag{14}$$

The RISK input is the acquirers' provision for loan losses to total loans ratio at year-end preceding the deal announcement.

The ASSET is the acquirers' ratio of total loans to total assets at year-end preceding the deal announcement.

$$ASSET = \frac{Total\ Loans}{Total\ Assets} \tag{15}$$

The DEBT_EQ stands for the debt-to-equity ratio which is calculated by dividing a company's total liabilities by its shareholder equity.

The LIQ_CASH represents the Liquidity ease with which an asset, or security, can be converted into ready cash without affecting its market price.

The LIQ_LOANS represents the Funding liquidity which is the availability of credit to finance the purchase of financial assets.

3.6.2 Outputs

The outputs refer to the possible combinations of the relative change of ESG scores from one year before the deal (ESG_{-1}) to one year after the deal (ESG_{+1}); the year of the deal is denoted as ESG_0. The following outputs are formulated based on the aforementioned:

The $\%\Delta ESG_{-1,1}$ is the percentage change of the ESG score one year before and one year after the deal.

$$\%\Delta ESG_{-1,1} = \frac{ESG_{-1} - ESG_{+1}}{ESG_{-1}} \quad (16)$$

The $\Delta ESG_{0,1}$ is the percentage change of the ESG score one year after and at the year of the deal.

$$\%\Delta ESG_{0,1} = \frac{ESG_{0} - ESG_{+1}}{ESG_{0}} \quad (17)$$

The $\%\Delta ESG_{-1,0}$ is the percentage change of the ESG score one year before and at the year of the deal.

$$\%\Delta ESG_{-1,0} = \frac{ESG_{-1} - ESG_{0}}{ESG_{-1}} \quad (18)$$

3.6.3 Surrogate measures

To examine the impact of external factors on the efficiency, surrogate measures are examined.

One of the variables that are used as proxy in the analysis is the Cross-border deal (*CBD*) which is a dummy variable taking the value of 1 if the acquisition is cross-border and 0 otherwise.

To control for the listing status of targets, a dummy variable (Target Public Status) is used that is assigned the value of 1 if the target is listed and 0 if the target is a private firm.

The investigation of potential effects of product diversification is conducted through a Horizontal dummy variable. A value of 1 is assigned for bank-to-bank deals (i.e.,

bidder and target share the same 2-digit Standard Industrial Classification (SIC) code) and 0 for bank-to-non-bank deals.

The variable Winsorized % women in Board represents the percentage reduced by extreme values or outliers which may possible affect the results.

Another measure which is used as dummy variable is the Deal value *(DVALUE)* which is defined as the natural logarithm of the deal value (in $ m).

Also, the Relative deal size *(RSIZE)* is the ratio of deal value to acquirers' market capitalization twenty-one days preceding the announcement date.

A graphical representation of the proposed analysis is presented in Figures 2 and 3. Initially, the Deal Efficiency is measured based on inputs and outputs as derived from the relevant literature; a second stage analysis is performed to evaluate the characteristics that may impact the deal efficiency as magnitude (value of coefficient) and corresponding direction (sign of the coefficient) (Figure 2). A Support Vector Machine is applied to extend the 2nd stage analysis by specific dummy variables in order to extract qualitative conclusions.

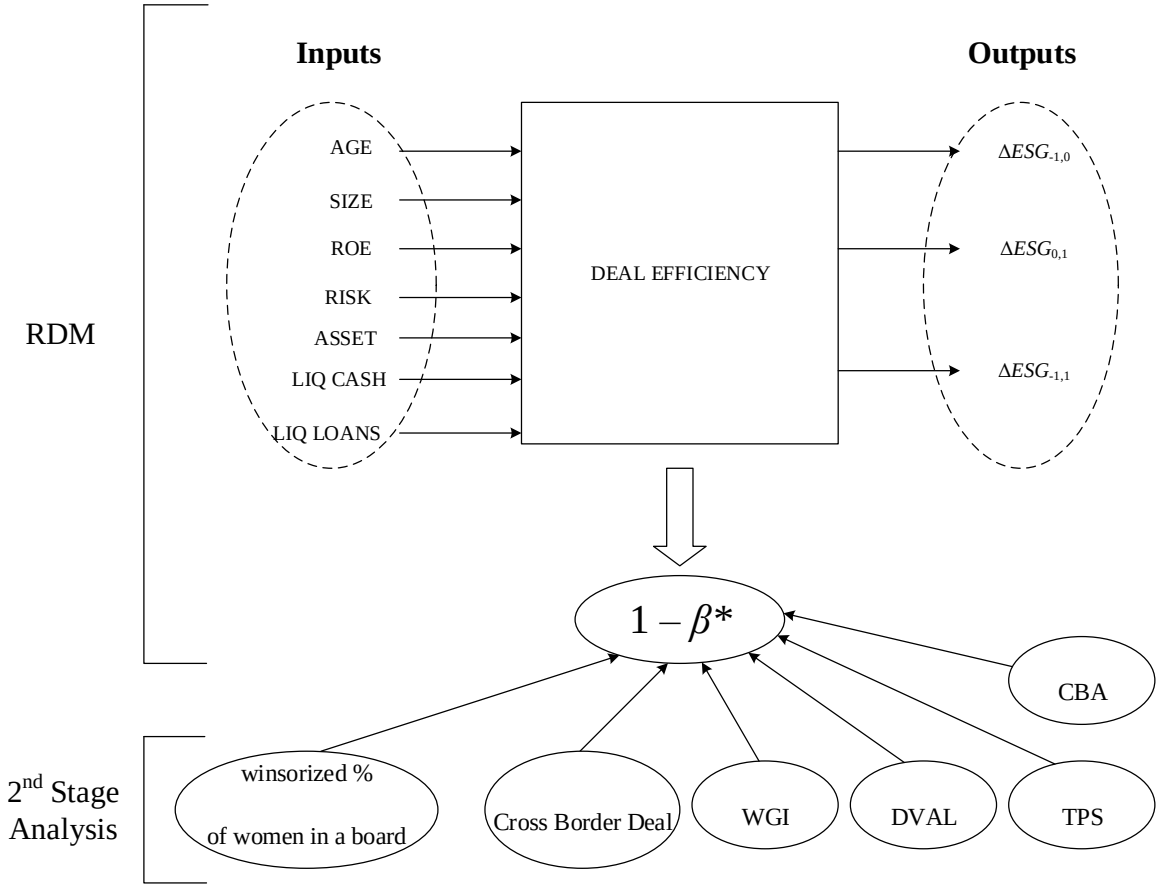

Figure 3: Graphical representation of the proposed methodology.

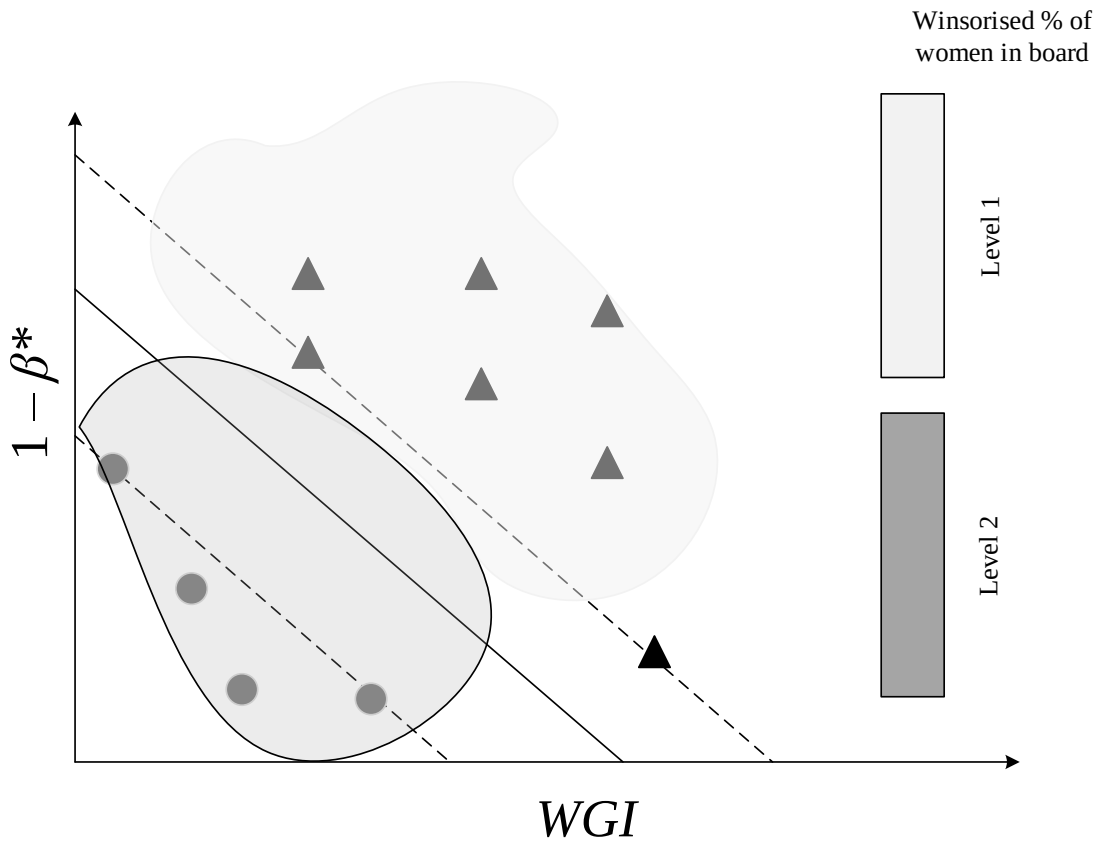

Figure 4: Extension of second stage analysis with Support Vector Machines model.

4. Results

4.2 Inputs and outputs descriptive statistics

In this section the results of the descriptive statistics of the inputs and outputs are presented. In Table 2, the descriptive statistics for input and output variables are presented.

Table 2: Descriptive statistics for inputs and outputs.

	Mean	Median	Std. Deviation	Variance	Min	Max	P_{25}	P_{75}
Inputs								
AGE	8.71	8.80	0.68	0.47	6.12	9.71	8.46	9.15
SIZE	9.88	10.09	1.28	1.64	6.25	11.99	9.11	10.92
ROE	10.06	12.25	15.48	239.56	-119.35	29.30	5.31	17.55
RISK	0.72	0.56	0.72	0.52	-0.06	4.92	0.29	0.92
ASSET	56.33	63.31	21.98	482.96	0.00	90.02	39.91	72.25
DEBT_EQ	728.63	658.11	414.83	172080.90	-517.38	2424.08	456.53	899.72
LIQ_CASH	103.61	69.74	87.48	7652.51	0.00	430.48	45.55	147.81
LIQ_LOANS	143.45	141.95	63.37	4015.51	0.00	454.51	104.72	168.96
Outputs								
$\%\Delta ESG_{0,1}$	0.05	0.02	0.16	0.03	-0.74	0.90	-0.02	0.09
$\%\Delta ESG_{-1,0}$	0.01	0.01	0.27	0.07	-1.00	1.08	-0.03	0.08
$\%\Delta ESG_{-1,1}$	0.06	0.04	0.33	0.11	-1.00	1.56	-0.04	0.15

Mean and median of Age are approximately equal (8.71 and 8.80 correspondingly), which signs that its distribution is approximately normal. The minimum value of Age which was observed is 6.12 years while the maximum value 9.71. Also values of Age can be considered homogeneous as standard deviation's value is quite small and coefficient of variation does not exceed 10%.

Variable of size performs a mean of 9.88 and a median of 10.09. Due to the fact that these values are very close one to another, Size's distribution can be considered as normally distributed variable. Standard deviation's value is 1.28 and the sample can be considered marginally homogeneous, as coefficient of variation marginally

exceeds 10%. In addition, there is no sign that extreme values exist, due to the fact that third quarter and maximum values are very close.

Return on Equity (ROE)'s distribution seems to be slight skewed, due to the fact that median value is larger than its mean value. There is a large dispersion of values as the minimum value is equal to -119.35, while the maximum value is 29.30. There is a slight possibility of extreme values, as the first quarter is way larger than the minimum value.

Risk's mean and median value differ not significantly and this implies that it distribution seem to be left skewed. Values of risk are highly not – homogeneous because standard deviation is equal to mean and coefficient of variation is 100%. Existence of extreme values is highly likely due to the fact that first quarter exceeds minimum value.

4.3 Analysis of inputs

In Figure 3, the inputs are plotted against the dummy variable CBD.

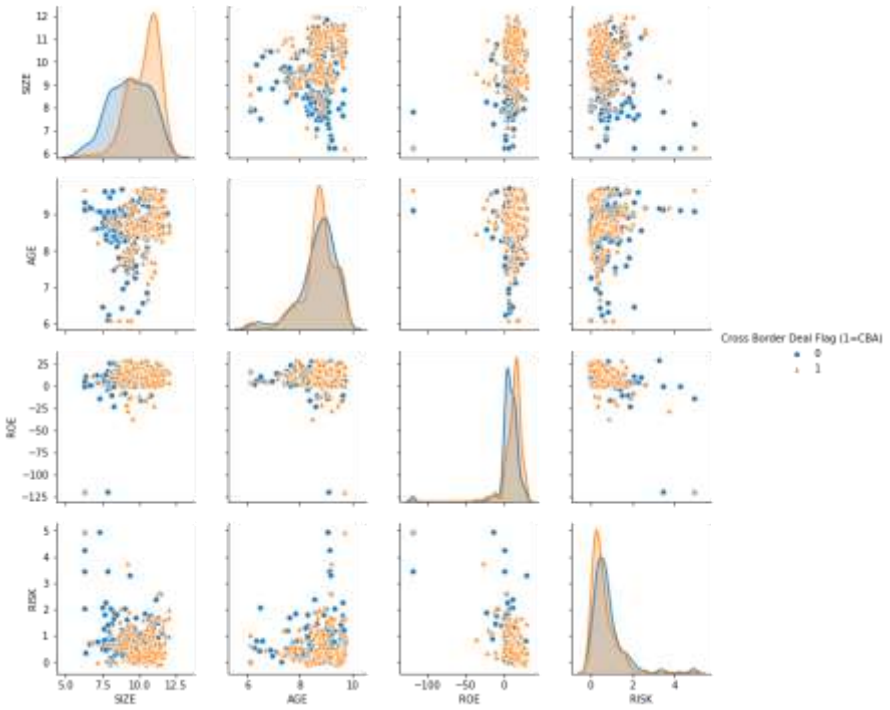

Figure 5: Pairplot analysis of SIZE, AGE, ROE and RISK inputs by CBD variable.

It can be seen that deals with no Cross Border Deals, tend to have lower values in the corresponding inputs in comparison to the ones with Cross Border Deals.

In Figure 3, the ASSET, DEBT_EQ, LIQ_CASH, and LIQ_LOANS inputs are examined. Based on the pairplot, it can be seen that inputs with no Cross Border Deals tend to have lower values compared to the ones with Cross Border Deals.

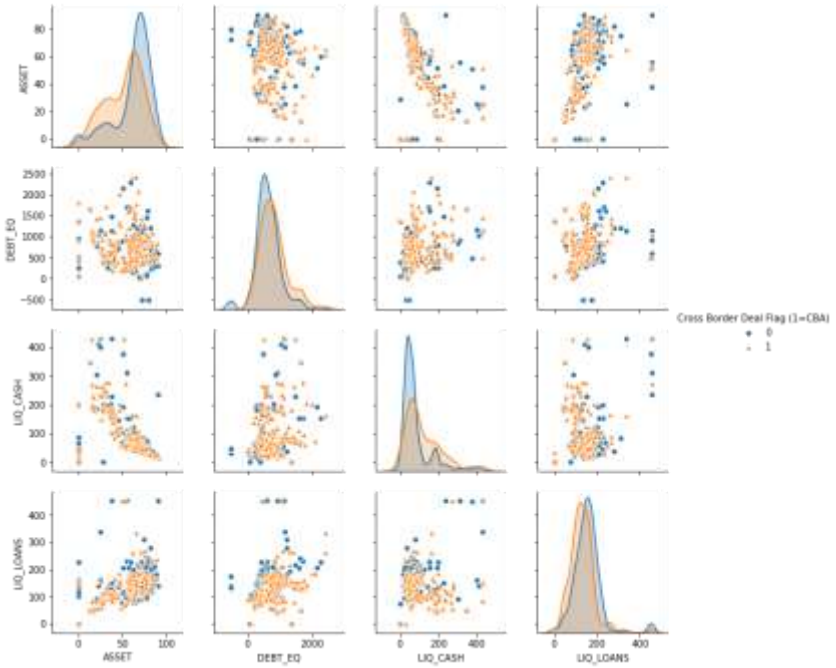

Figure 6: Pairplot analysis of ASSET, DEBT_EQ, LIQ_CASH, and LIQ_LOANS inputs by CBD variable.

On the contrary when the analysis is extended as per the TPS variable, the values on the inputs examined, tend to be the same compared to the different levels of TPS variable.

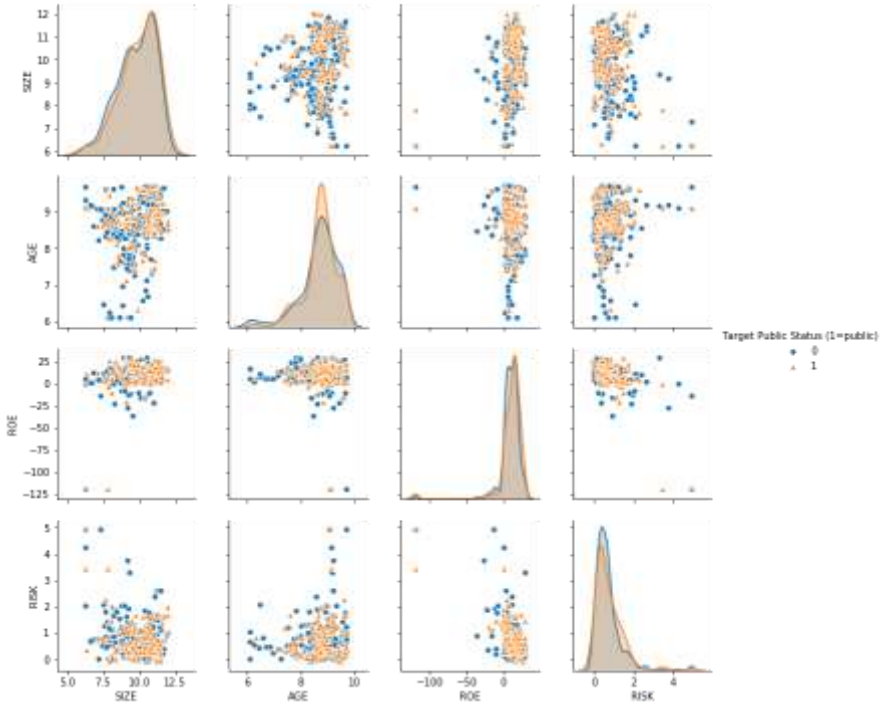

Figure 7: Pairplot analysis of SIZE, AGE, ROE and RISK inputs by TPS variable.

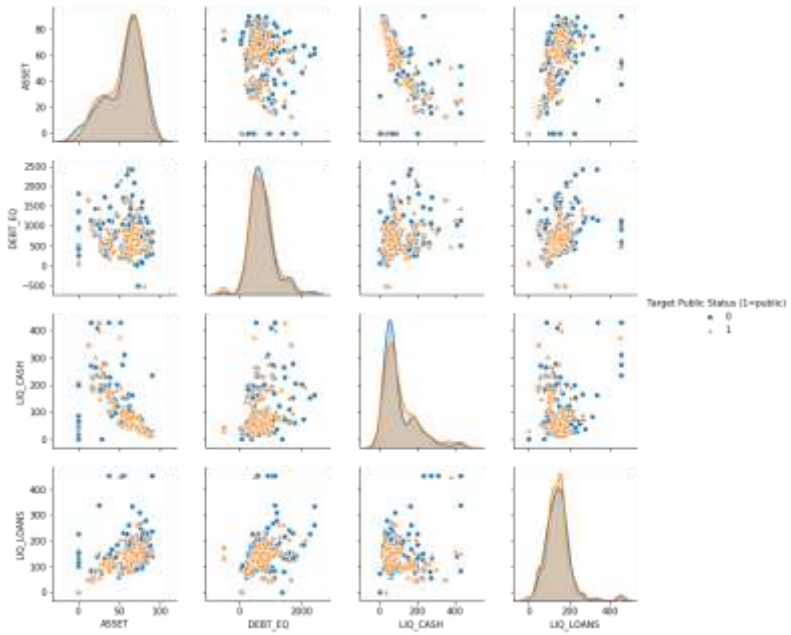

Figure 8: ASSET, DEBT_EQ, LIQ_CASH, and LIQ_LOANS inputs by TPS variable.

4.4 Analysis of outputs

Similar to the inputs, the outputs are analyzed with respect to CBD and TPS dummy variables. As seen in Figure 6, it can be seen that the Target Public Status seems to affect only $\%\Delta ESG_{0,1}$. More specifically the $\%\Delta ESG_{0,1}$ values tend to increase when the Target Public Status is not adopted.

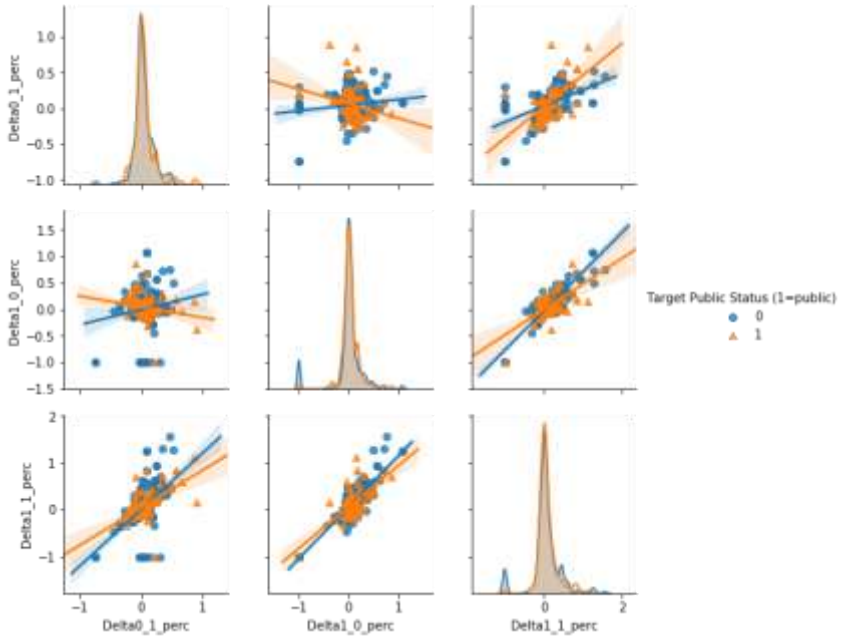

Figure 9: $\%\Delta ESG_{-1,1}$, $\%\Delta ESG_{-1,0}$ and $\%\Delta ESG_{0,1}$ outputs byTPS variable.

On the contrary, the analysis for Cross Border Deal does not seem to affect the outputs as it can been seen in Figure 7.

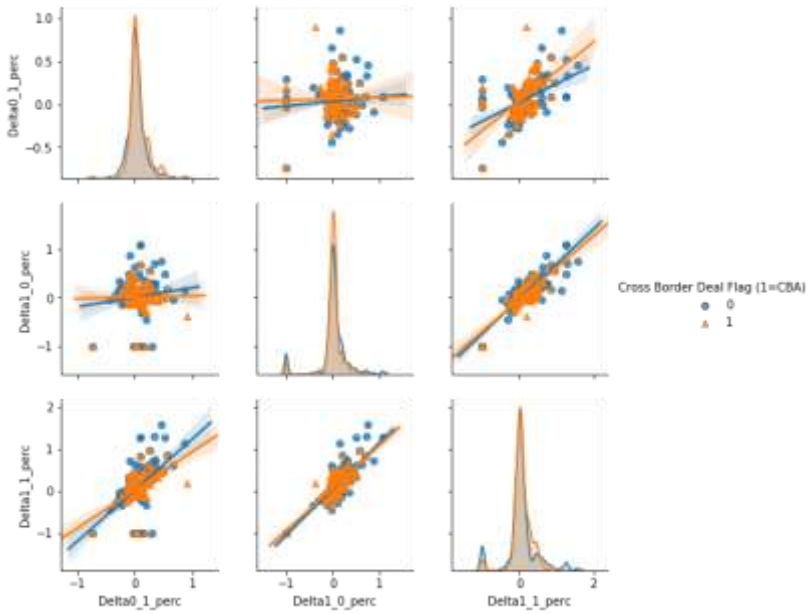

Figure 10: $\%\Delta ESG_{-1,1}$, $\%\Delta ESG_{-1,0}$ and $\%\Delta ESG_{0,1}$ outputs by CBD variable.

4.5 Correlation analysis of inputs/outputs

In Table 3 the correlation matrix of independent variables which are used in the 2nd stage analysis, is presented. At first, correlations between all pairs of independent variables are low. Pearson correlation coefficient was computed for pair of variables which are continuous, while Spearman coefficient when variables were a pair of nominal and continuous or both nominal. TPS is associated positively with DVALUE (r = 0.24), however this correlation is weak and not - statistically significant. CBD and WGI present the most intense relationship among all other pairs, scoring a Spearman correlation coefficient of r = 0.36. This value may be positive, although it is not strong or statistically significant. The highest correlation coefficient value is reported for the pair DVALUE and Relative Size (r = 0.43). Though this value is statistically significant at 5% level of significance, it is medium strong.

The above results, concerning low correlation values between continuous and nominal variables, are a sign that mulitcollinearity is missing. This allows the simultaneous inclusion of all independent variable in a regression model, so as to investigate the effect of those variables on efficiency scores.

Table 3: Correlation matrix for variables in 2nd stage analysis

	TPS	CBD	Horizontal	WGI	DVALUE	Relative Size	% Winsorized Women on Board
TPS	1	-	-	-	-	-	-
CBD	0.11	1	-	-	-	-	-
Horizontal	0.08	0.08	1	-	-	-	-
WGI	0.02	0.36	-0.14	1	-	-	-
DVALUE	0.24	0.08	0.25	0.09	1	-	-
Relative Size	0.16	-0.15	0.23	-0.07	0.43**	1	-
% Winsorized Women on Board	-0.01	0.11	-0.11	0.39	-0.09	-0.08	1

4.6 Efficiency analysis

The analysis of LP models (2) and (3) is shown in Figure 8. It can be seen that model (2) demonstrate better discrimination power over model (3) since the majority of efficiency scores are scattered from 0.2 to 1. On the contrary, there is a large concentration of efficiency scores in the range or 0.6 – 1 based on model (3). Data Envelopment Analysis models (2) and (3), were modeled and solved with GAMS software using CPLEX solver for solving LP models.

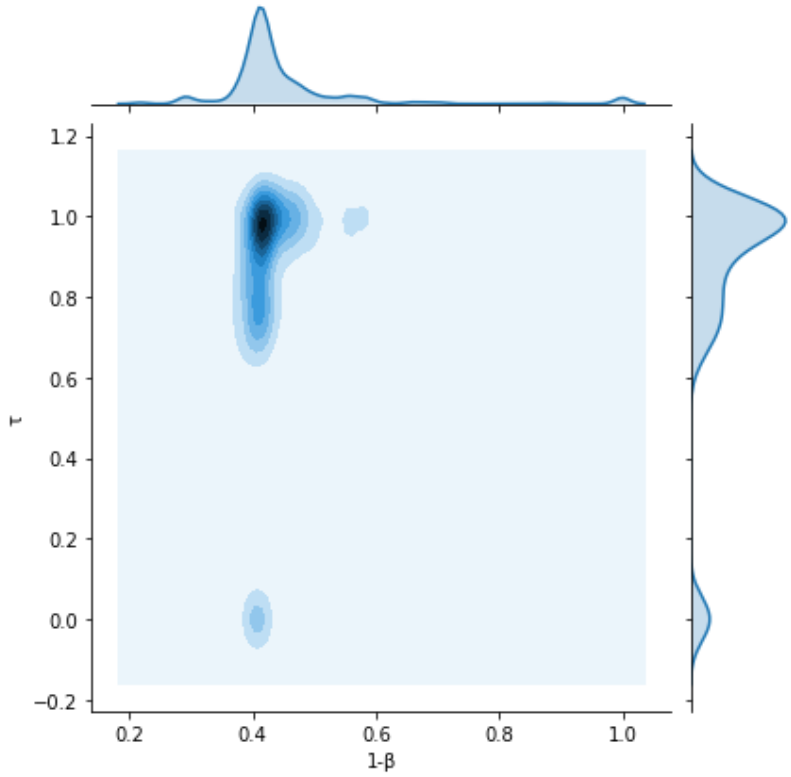

Figure 11: Joint distribution plot of $1-\beta$, τ.

4.7 2nd stage analysis - Linear regression vs Beta regression results

Based on the results of efficiency analysis, it seems that model (3) provides more discrimination power, therefore is selected for 2nd stage analysis. To investigate the impact of various external variables on the analysis, the following regression model is constructed:

$$1-\beta^{*} = \alpha_1 \cdot TPS + \alpha_2 \cdot CBA + \alpha_3 \cdot Horizontal + \alpha_4 \cdot WGI + \alpha_5 \cdot DVAL + \alpha_5 \cdot Relative\ Size + \alpha_6 \cdot Winsorized\%\ Women\ (Board) \quad (10)$$

The results of the beta regression model, as formulated in (10) and assuming different link functions, are presented in Table 3:

Table 4: Results of beta regression analysis.

Variables	*Logit*	*Probit*	*Complementary Log – Log*	*Log*	*Log – Log*
TPS	0.369***	0.214***	0.213***	0.103***	0.258***
(1=Public)	(0.099)	(0.061)	(0.066)	(0.039)	(0.073)
CBA	-0.426***	-0.277***	-0.335***	-0.224***	-0.272***
(1=CBA)	(0.098)	(0.061)	(0.067)	(0.038)	(0.071)
Horizontal	0.271***	0.158***	0.188***	0.195***	0.188***
(1=Horizontal)	(0.094)	(0.059)	(0.067)	(0.04)	(0.068)
WGI	0.500***	0.299***	0.351***	0.282***	0.353***
	(0.128)	(0.079)	(0.084)	(0.042)	(0.094)
DVALUE	-0.156***	-0.091***	-0.101***	-0.075***	-0.110***
	(0.028)	(0.018)	(0.019)	(0.011)	(0.021)
Relative Size	0.051***	0.025***	0.019***	0.007***	0.042***
	(0.004)	(0.002)	(0.002)	(0.001)	(0.004)
% Winsorised women in board	-0.015***	-0.009***	-0.010***	-0.008***	-0.010***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)
Constant	0.289*	0.198*	-0.124	-0.544***	0.551***
	(0.175)	(0.109)	(0.118)	(0.071)	(0.129)
Obs	441	441	441	441	441
AIC	-144.17	-132.85	-121.35	-110.62	-144.66
BIC	-107.37	-96.05	-84.55	-73.81	-107.87
LogLikelihood	81.085	75.426	69.677	64.308	81.334

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors in parentheses

In Table 4, beta regressions which assume Logit and Log – Log link functions to be appropriate for the specific dataset, compared to other link specifications. This is implied by the values of AIC and BIC. However, when a coefficient is statistically significant, coefficient's value does not vary dramatically across different link specification regression.

Assuming beta regression with Logit link specification, TPS is statistically significant at 1% level of significance. Public TPS are exp(0.369) = 1.45 more efficient compared to private TPS. On the other hand, Cross Border Deals which are CBA (value 1), tend to be 0.653 less efficient than Cross Border Deals which are not CBA. The effect of CBA on $1 - \beta$, is statistically significant at 1% level of significance.

Units that are Horizontal, tend to be more efficient, than units which are not Horizontal. In specific, Horizontal units are 1.311 times more probable to be efficient compared to non – horizontal units. The effect of Horizontal on efficiency is 1% statistically significant.

WGI tends to increase efficiency of units. In specific, a one unit increase of WGI, will have a 1.649 increase in efficiency score and this result is statistically significant at 1% level of significance.

On the contrary, and increase in DVAL is associated with reduced efficiency score. One unit increase in DVAL would result in 0.855 times increase in efficiency score and this effect is statistically significant at 1%.

Relative Size of units has a positive effect on the efficiency score. An one unit increase in Relative Size, would suffer a 1.05 times larger efficiency and this result is statistically significant.

Lastly, the percent of Winsorised women in board is associated with decreased efficiency. In specific, a 1% increase in the amount of winsorised women in board, would lead in a 0.98 times less efficiency and this negative relationship is statistically significant at 1% level of significance.

Log – log link specification, tend to have similar, yet less deflated coefficient values for all the aforementioned variables, which is a sign of increased robust estimation process.

Beta regression models of all different link specification are statistically significant simultaneously.

In Figure 10, the relationship between $1 - \beta$ and percent of Winsorised women in board is presented. The negative association is obvious, when the fitted values from applying a logit (blue dashed line) and log (red solid line) beta regression

specification, are drawn. In general, Logit and Log link specifications perform similar results, however, the downward slope of Logit specification is steeper than Log's slope, leading to the result that Logit specification tend to present a more negative effect of percent of Winsorised women in board on the efficiency score, than Log link does.

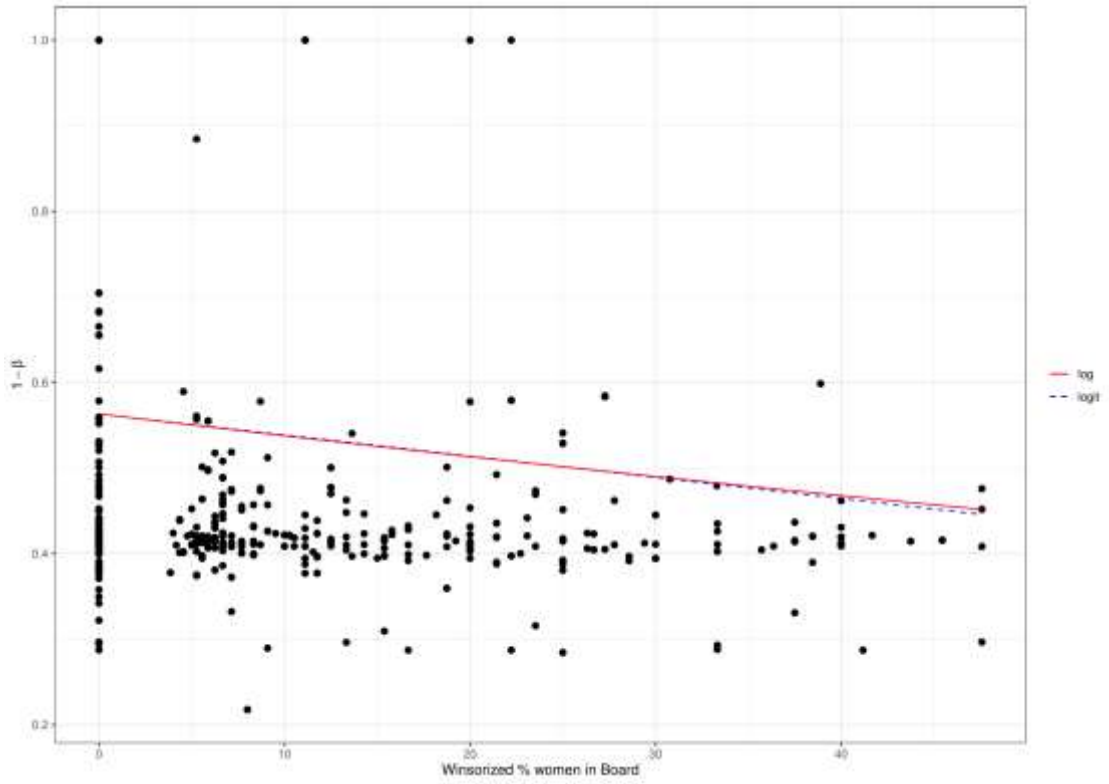

Figure 12: Scatter plot of $1-\beta$, against Winsorised % women in board

The inflated values of Logit link beta regression specification, is presented in Figure 11, in which the scatter diagram of $1 - \beta$ against Relative Size is depicted. Fitted values of Logit link beta regression specification (green dashed line) are increasing when Relative Size of units also increases, and this increment is larger than fitted values obtained by complementary log – log link (blue solid line) and log link specification (red dashed line) (Figure 12). This means, that complementary log – log and log link specifications tend to underestimate the positive effect of Relative Size on the efficiency score.

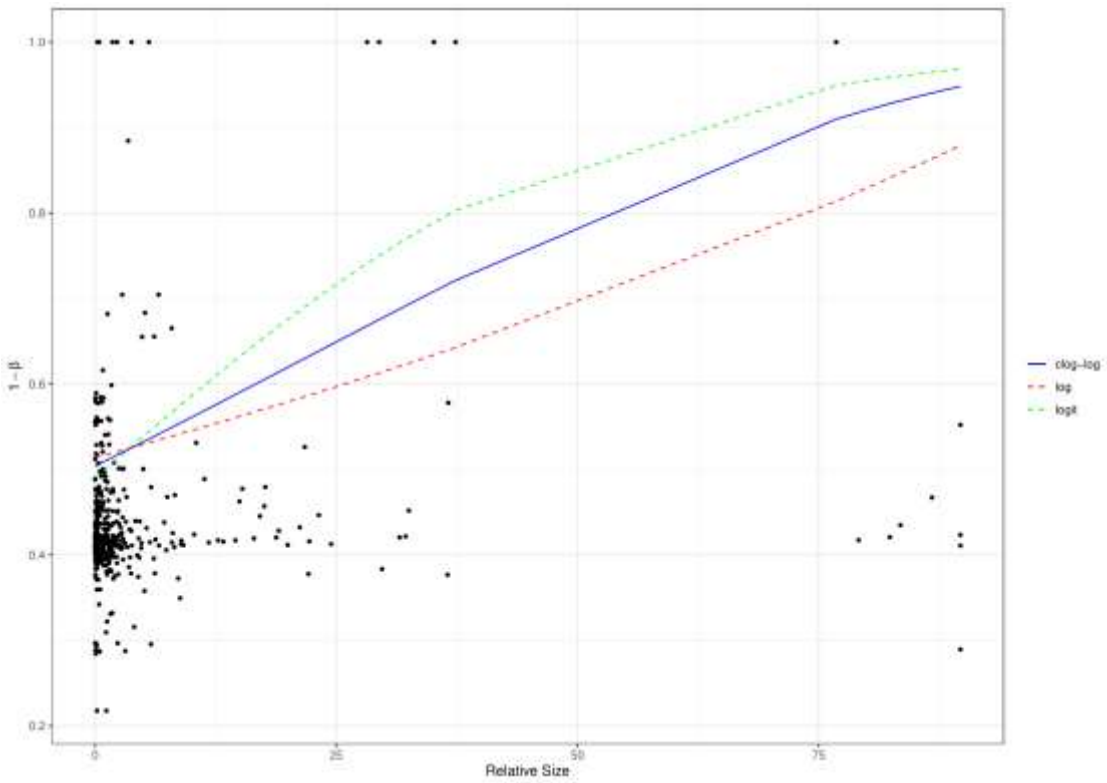

Figure 13: Scatter plot of $1-\beta$, against Relative Size

In Figure 13 the relationship between efficiency and WGI is depicted, assuming that this relationship is best described by logit specification beta regression model. It is obvious that WGI's effect on efficiency is positive, as the fitted line (dashed blue line), upwards slightly. In the results from estimating all beta regression specifications, the coefficient of WGI is less than unities, implying that a unit increase in WGI would result in efficiency score less than 1%.

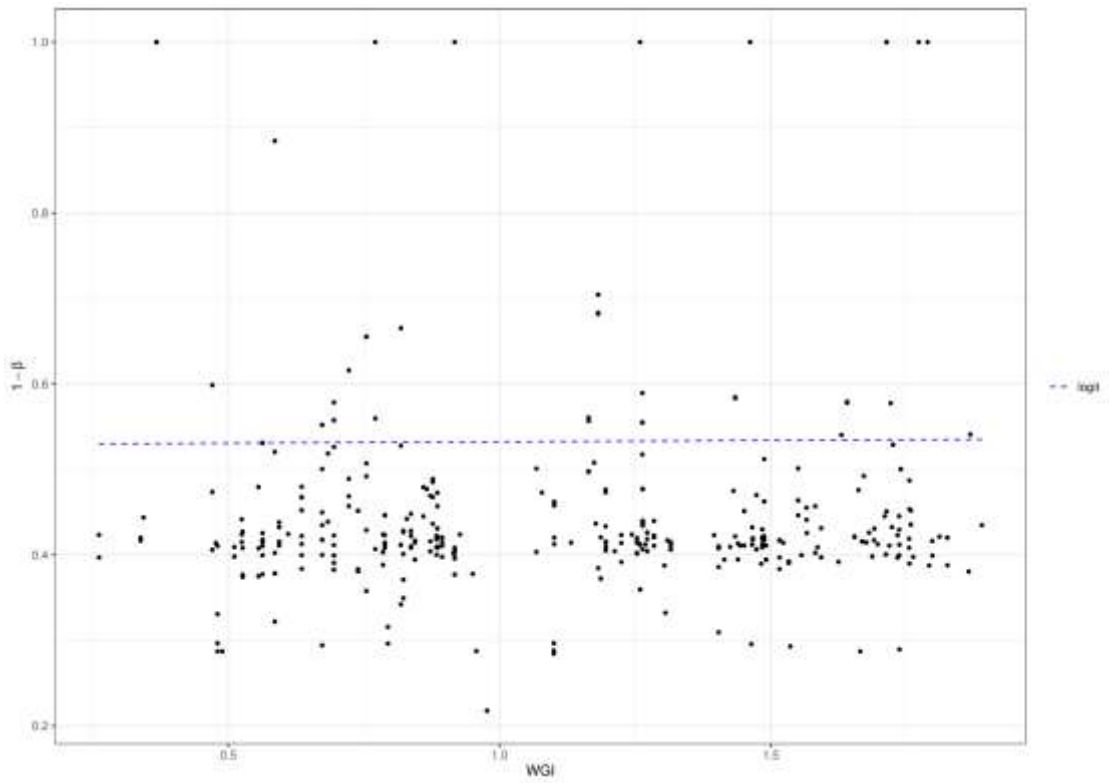

Figure 14: Scatter plot of $1-\beta$, against WGI

The same magnitude, yet different direction is the effect of DVALUE on the efficiency scores. DVALUE coefficients in all beta regressions specifications are negative; however the values are very close to zero. This result is depicted in Figure 14, where the fitted values from applying a logit beta regression model assuming logit link specification, are slightly down warding. This finding indicates the marginal effect that DVALUE has on efficiency score, and that efficiency is going to be decreased as DVALUE increases largely.

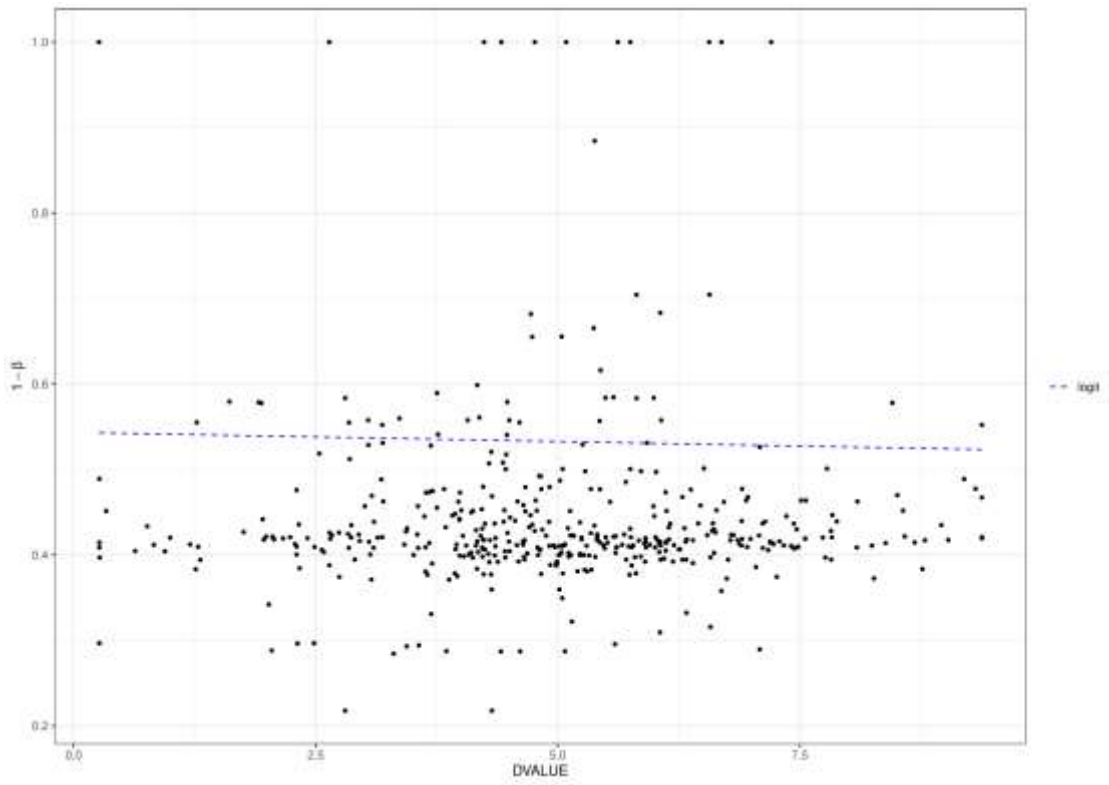

Figure 15: Scatter plot of $1-\beta$, against DVALUE

As depicted in Table 3, Logit specification performs the best fit to data. In order to investigate the mediate effect of the interactions between binary variables (TPS, CBA and Horizontal) and continuous ones, on efficiency scores, estimation of Logit beta regression model with interaction effects is conducted.

The first model assumes that efficiency score depends on independent variables included in Table 3, adding interactions of TPS with WGI, DVALUE, Relative Size and % of Winsorized Women in board. TPS retains positive sign, although the effect on efficiency score is larger than that in Table 3. CBA's coefficient value is negative and the magnitude is the same as in Table 3. All other main effects' coefficients values are similar to the model fitted assuming Logit specification beta regression.

Concerning the interaction term of TPS by WGI, its coefficient is negative and statistically significant at 1% level of significance. This implies that a one unit increase in WGI will decrease the efficiency score for units of TPS of value 1 (Public) by exp(-1.053) = 0.35 times less than for units which are not public. Although TPS' coefficient was positive and statistically significant in main effects, the combined effect of TPS by WGI, suffers a decrease in efficiency score.

The coefficient of interaction effect between TPS and DVALUE is negative, yet not statistically significant. Likewise, a potential increase in DVALUE, for those units which Public (TPS = 1), will result in a decreased efficiency score, compared to units which are not Public (TPS = 0).

While relative size of a unit seems to have a positive effect in efficiency score, the interaction effect of relative size by TPS has a negative effect on efficiency. A one unit increase in Relative Size, will result in an decreased efficiency score by exp(-0.074) = 0.93 for TPS = 1(Public), compared to not – public. It is noteworthy, that Relative Size main effect coefficient value's magnitude is the same in interaction, with opposite sign.

The last included interaction term is that of TPS by % of Winsorized Women. In main effects, the coefficient of % of Winsorized Women is negative statistically significant, but too close to 0. The interaction term's coefficient is not statistically significant however the sign is positive.

The second model is estimated including interaction terms of CBA with all continuous variables. Coefficient of CBA is not statistically significant, yet retains the same sign as in link logit beta regression specification depicted in Table 3.

Concerning the interaction term of CBA by WGI, its value is negative and marginally statistically significant at 10% level of significance. A one unit increase in WGI would suffer a decrease, for those which fall under the category CBA = 1, in efficiency scores by exp(-0462) = 0.62 less than those which fall under the category CBA = 0.

On the contrary, coefficient for interaction term of CBA by DVALUE is positive and statistically significant at 5% level of significance. In the estimated model including only the main effects, DVALUE's coefficient was negative and statistically significant, implying that increased DVALUE results in decreased efficiency scores. However, positive coefficient of interaction term implies that subjects that fall in category CBA = 1, tend to perform greater efficiency compared to subjects of the category CBA = 0.

The interaction term of CBA by Relative Size seems to have a negative and statistically significant effect on efficiency scores. In specific, subjects which fall into

the category CBA = 1, tend to perform 0.97 times lower efficiency scores compared to those of category CBA = 0, when Relative Size increases. Interaction term of TPS by Relative Size had also negative effect on efficiency scores.

Last, interaction term of CBA by % of Winsorized women in board, does not have a statistically significant effect on efficiency scores. The same non – statistically significant effect was observed in the logit link specification beta regression model, including CBD interactions.

The third model which was estimated is the logit link specification beta regression model including interaction terms of binary variable Horizontal, with WGI, DVALUE, Relative Size and % of Winsorized women on board.

Coefficients of main effects retain the same sign as logit link specification beta regression model estimated using only main effects (Table 3), with the exception of WGI, DVALUE and %Winsorized women on board. Coefficient's value and sign is the same as in models analyzed before, however, it is not statistically significant.

Efficiency scores tend to increase when WGI increases as well, for those subjects which fall into the category Horizontal = 1, by 1.05 times more than for those subjects which fall into the category Horizontal = 0. This effect is statistically significant at 1% level of significance, and differs from the other interaction terms.

On the contrary, the interaction term of Horizontal by DVALUE is negative and statistically significant at 1% level of significance. This implies that subjects that fall into the category Horizontal = 1tend to perform less efficiency compared to subjects that fall into category Horizontal = 0, by exp(-0.314) = 0.73 times, when DVALUE increases by one unit. interaction term coefficient's sign is the same as in main effects, however, in main effect DVALUE did not seem to affect statistically significantly efficiency scores.

A one unit increase in Relative Size would result in a decreased efficiency score for subjects that fall into category Horizontal = 1, compared to subjects that fall into the category Horizontal = 0. This effect is statistically significant at 1% level of significance. This result is contradictory to the main effect coefficient of Relative Size, which was positive and statistically significant.

Lastly, a one unit increase in % of Winsorized women on board would result in a decreased efficiency score for subjects that fall into category Horizontal = 1, compared to subjects that fall into the category Horizontal = 0. This effect is statistically significant at 1% level of significance. This result is in line to the main effect coefficient of % of Winsorized women on board, which was negative but not statistically significant.

Table 5: Results of beta regression analysis using interactions

	Logit with TPS interactions	*Logit with CBA interactions*	*Logit with Horizontal interactions*
		Main Effects	
TPS (1=Public)	1.883***	0.352***	0.508***
	(0.39)	(0.098)	(0.092)
CBA (1=CBA)	-0.445***	-0.52	-0.254***
	(0.095)	(0.366)	(0.091)
Horizontal (1=Horizontal)	0.355***	0.280***	1.369***
	(0.09)	(0.093)	(0.324)
WGI	0.757***	0.723***	0.046
	(0.144)	(0.17)	(0.161)
DVALUE	-0.133***	-0.241***	-0.036
	(0.034)	(0.042)	(0.035)
Relative Size	0.074***	0.069***	0.111***
	(0.006)	(0.005)	(0.014)
% Winsorised women in board	-0.015***	-0.017***	-0.001
	(0.005)	(0.006)	(0.005)

	Logit with TPS interactions	*Logit with CBA interactions*	*Logit with Horizontal interactions*
		Interactions	
TPS*WGI	-1.053***	-	-
	(0.265)		
TPS*DVALUE	-0.016	-	-
	(0.056)		
TPS*Relative Size	-0.073***	-	-
	(0.008)		
TPS* % Winsorised women in board	0.004	-	-
	(0.009)		
CBD*WGI	-	-0.462*	-
		(0.252)	
CBD*DVALUE	-	0.136**	-
		(0.055)	
CBD*Relative Size	-	-0.032***	-
		(0.009)	
CBD* % Winsorised women in board	-	0.007	-
		(0.008)	
Horizontal*WGI	-	-	0.837***
			(0.222)
Horizontal*	-	-	-0.314***

	Logit with TPS interactions	*Logit with CBA interactions*	*Logit with Horizontal interactions*
DVALUE			(0.054)
Horizontal*Relative Size	-	-	-0.084***
			(0.015)
Horizontal*% Winsorised women in board	-	-	-0.018**
	-		(0.008)
Constant	-0.212	0.398*	-0.204
	(0.197)	(0.225)	(0.218)
Obs	441	441	441
R^2	0.119	0.053	0.203
Log Likelihood	115.3	87.604	151.784

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors in parentheses

4.8 SVM results

Based on the results of the second stage analysis, it can be seen that the statistically significant parameters on efficiency ($1-\beta^*$) are Horizontal, WGI, DVAL, Relative Size and Winsorized % women in in Board. The SVM analysis was conducted in R CRAN software using e1071 package (Dimitriadou et al, 2006).

To extend the analysis by employing kernel segregation of the data, SVM models are employed for the combination of efficiency score with the World Global Index ($1-\beta^*$, WGI)

The Winsorized % women in in Board variable has been categorized in the following levels of representation:

$$women = \begin{cases} Bad\,,\ 0\% < Winsorized\ \%\ women \le 20\% \\ Good\,,\ Winsorized\ \%\ women > 20\% \end{cases}$$

After training the data set with 75% of the observations, the optimal parameters for cost (c), scale factor (γ), coefficients and degree (p) are derived.

The optimal kernel is the radial, with cost parameter = 0.92, scale factor = 1 and the optimal number of support vectors are 92. From the analysis it can be seen that the shape of the data is non-linear leading to non-linear representation of hyperplanes.

The accuracy of the model is reported to be 73.28%. From the analysis it can be seen that the representation of women in the board is good in the red types of regions, whereas is bad for the yellow region.

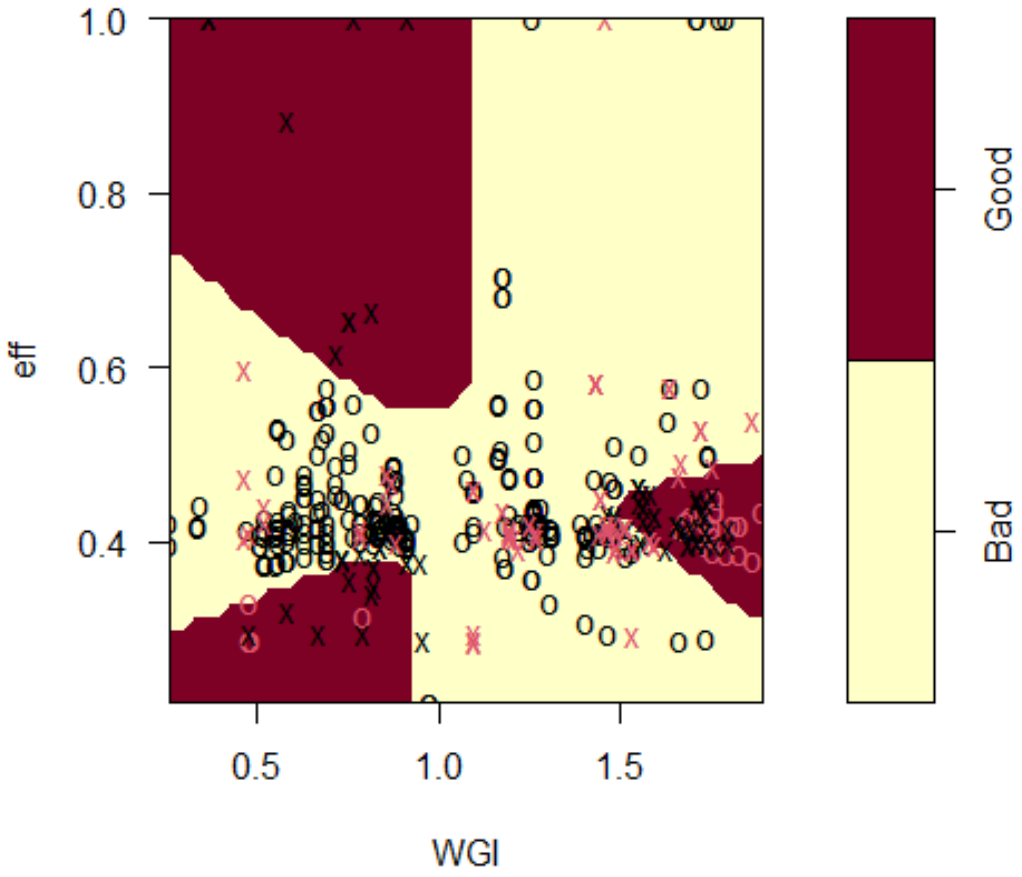

Figure 16: SVM classification plot for 1-β (y- axis) and WGI (x-axis) as per women representation variable

5. Conclusions

Over the years, the indicators for assessing the performance of companies have shifted from purely financial to indicators incorporating environmental, social and governance dimensions. This shift was inevitable in order to reflect the performance of businesses, based on the current situation. The dimensions that each business is or should take into account, concern the Environmental, Social and Governance criteria. The pylon of Environment, concerns the firms with increasing consciousness towards natural resources, preservation of the environmental aspects of day-to-day operations and production processes.

The Social pylon, define the indicators which measure the operations of the company towards the inner and outer environment. In the inner environment, there are the employees which the company should develop, treat with respect and award for their achievements with bonus schemes or other incentives. In the outer environment, there are the suppliers, distributors and customers. Suppliers and distributors are vital for the smooth flow of final products and services to customers, nonetheless, each company should choose carefully the suppliers and distributors; the selection in most of the cases, is based not only on financial criteria (price of raw material, contract for minimum order) rather than whether the tiers of the supply chain of the company embrace the social or environmental aspects. Finally, in the social pylon, the company demonstrates and presents the social achievements to its customers raising sensitivity.

Finally, the Governance pylon defines he operations of the company and demonstrate the transparency to the public.

Each of the indicators of the ESG score are communicated via the Corporate Social Responsibility (CSR) reports to the public. CSR reports are a channel of firms to inform the public regarding the activities towards each ESG pylon. Via this procedure, firms with high ESG scores attract the interest of investors with main emphasis on sustainability rather on pure financial returns. There is evidence from relevant literature indicating that there is a positive correlation between CSR and increased value in M&A.

In most of the studies presented in relevant literature, the analyses examine the effect of several measures stemming from the performance of the M&As or other characteristics of the M&A (such as the Age, Potential Risk and so on) on a dependent variable (e.g. ESG scores). Nevertheless, a different perspective could be adopted assuming that the performance criteria and other characteristics of the M&As are the inputs of an underlying production process while the ESG scores are assumed to be outputs in this production process.

The methodology which is applied to measure the efficiency of homogeneous units which consume one or more inputs and produce one or more outputs is Data Envelopment Analysis which is a non-parametric technique. This technique is based on Linear Programming and by solving iteratively an LP model for each of the units under assessment (Decision Making Units or DMUs), a score is extracted. Based on this score the DMUs are ranked. Throughout the years, there have been numerous applications of DEA technique in all scientific areas and principles. Also, the initial DEA models have been extended to better reflect real life applications.

The performance of M&A has been extensively researched in the world literature. A wide selection of models has been proposed, however, DEA models adjust better to the nature of the problem. In this paper, the efficiency of 441 M&A deals is measured based on financial data as inputs and change in ESG scores as outputs. Due to the presence of negative data, special types of DEA models are applied. A comparison of the directional distance approach proposed by Portela et al. (2004) and the MSBM model, proposed by Sharp et al. (2007) are demonstrated in the paper.

Due to the fact that the directional distance approach provides better results because of higher discrimination power of the efficiency of DMUs comparing to the MSBM model, the efficiency scores are then selected for 2nd stage analyses.

In that sense, a linear regression model is constructed with dependent variable the efficiency score and independent variables external factors, the effect of which is investigated on the performance of M&A deals.

Results indicate that the world global index (WGI), the relative size of the deal and the representation of women in boards (as a percentage) affect positively the efficiency scores of M&A. On the contrary, the deal value, affect negatively the

efficiency scores of M&A. Comparison of the linear regression model with beta regression model indicate that the factors of the second stage analysis are confirming in general terms the findings of the linear regression model.

To further extend the analysis, the application of SVM model is adjusted to the data in order to provide insights as to the areas by which the women representation is good or bad. In that context, the areas by which good or bad female representation in boards in conjunction with the efficiency score and WGI score is examined. Based on one of the hyper planes created, there is good female representation in the boards for low WGI values a high efficiency scores or very low efficiency scores.

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