Efficiency Analysis of Risk, Return on Assets, and ESG Performance in U.S. and European Corporate Manufacturing Firms

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Abstract

Traditional mean-variance stock performance metrics overlook ESG factors. This research integrates ESG factors into these traditional evaluation models, aligning modern CSR investment preferences with existing investment models. This research focuses on panel data of U.S. and European corporate manufacturing firms between 2016 and 2021. This study has utilized RISK, ROA, and ESG to assess overall and specific inefficiencies with a directional distance function in DEA. Key findings revealed that U.S. firms tend to exhibit higher levels of inefficiency across all three dimensions: RISK, ROA, and ESG. The bootstrap truncated regression associated firm age, firm size, and Tobin's Q negatively with inefficiency in the U.S. In European firms, firm size was negatively related to overall inefficiency for all years. Tobin's Q was negatively associated with inefficiency in 2016 and 2018 and the R&D intensity was negatively associated with inefficiency in 2018 and 2019 in Europe. The underlying theories explaining these associations are the economies of scale theory for size, the business life cycle theory for age, the resource-based view theory for the R&D intensity, and the Q-theory for Tobin's Q. The analysis did not reveal any significant relation between leverage and overall inefficiency in the U.S. and Europe.

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Disclaimer

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1. Introduction

1.1. Background

With climate change as an issue, solutions to this must be sought in all facets of society. One of the approaches described in the IPCC report is an approach via finance (Pörtner, 2022). To improve transparency in sustainable investing the European Commission initiated a plan for financing sustainable growth, commencing with new obligations for corporate sustainability reporting (European Commission, 2018). Under Regulation (EU) No 575/2013 of the European Parliament, large institutions whose securities are open to trading on a regulated market must, from 5 January 2023, disclose information on ESG risks (European Commission, 2018).

These ESG risk ratings consider various factors, including a company's environmental practices of their assets, environmental regulations, management of connections with the community, consumers, employees, and suppliers, as well as the firms' overall business conduct (Sipiczki, 2020). Formerly, traditional methods to evaluate the financial performance of assets mainly focussed on a mean-variance approach that solely combined risk and return (Sengupta, 1989). Nevertheless, due to the increased interest in securities' environmental, social, and governmental implications, ESG ratings hold value for contemplation.

Data Envelopment Analysis (DEA) can be used to assess the effectiveness of risk, return, and ESG ratings. DEA is referred to as a mathematical linear programming approach, which has previously been widely applied to analyse the effectiveness of decision-making units (DMUs) like large institutions (Banker, Charnes, & Cooper, 1984). In finance, implementations of this non-parametric approach are applied to benchmark the performance of mutual funds in terms of their benefit-to-cost ratios (Murthi, Choi, & Desai, 1997). Horta et al. (2016) implemented a DEA analysis in which the impact of internationalization and diversification was investigated on company performance.

A company's commitment to environmental, social, and governance and how actively it handles corporate social responsibility (CSR) is assessed through ESG ratings. Commercial organizations publish ESG ratings as a CSR measurement method to evaluate how corporate claims, performance, and business strategies adhere to sustainability objectives (Gupta, 2021; van Duuren et al., 2016). Therefore, both CSR and ESG construct environmental, social, and governance principles (Sassen et al., 2016; Terjesen & Sealy, 2016; Terjesen et al., 2009).Assessing a company's environmental pillar involves analyzing several factors, including emissions, the proportion of renewable energy utilized in manufacturing, or other related aspects. For instance, if a company integrates eco-friendly technologies into its products, it is regarded as adopting a sustainable practice (Katsikease et al., 2016).

The social pillar of ESG scores includes diversity, inclusion, safety measures, human rights, and the absence of child labour in production. Governance is associated with the inspection bodies to ensure compliance with the sustainability standards (Dathe et al., 2022).

Over the preceding years, the interest in ESG has increased within the finance sector. Within the S&P 500, a market index for the 500 largest companies listed on the New York Stock Exchange, the number of companies reporting on ESG increased heavily from 100 in 2011 to 430 in 2019 and is currently only increasing (Gillan et al., 2021). These numbers indicate an increased interest from managers in sustainability reporting. In addition to corporate firms focusing on ESG, financial investors also show an increased interest in the ESG performance of corporate firms (Rau & Yu, 2023). The paper of Bannier et al. (2019) shows clear evidence that the monetary amounts invested using ESG criteria were 25.7% of all managed assets in the United States and 48.8% in Europe. Their results showed a notable increase in comparison to previous years.

To further increase transparency regarding investment risks that arise from sustainability issues and to counteract greenwashing, governmental interventions have included mandatory ESG reporting requirements (European Commission, 2019; Lokuwaduge & De Silva, 2022). In the European Union, all substantial large firms are required to share information about their risks related to social and environmental issues and the consequences of their internal and external operations on people and the environment (European Commission, 2013). Another example of governmental interference in ESG disclosure is observed in the United Kingdom. Companies with over 500 employees and revenues higher than £500 million are obliged to report on their ESG performance (Government UK, 2022). All in all, over the period spanning from 2002 to 2020, 35 countries have implemented ESG reporting requirements (Krueger et al., 2021). Nevertheless, there are still countries where the ESG reporting requirement is under amendment but not yet into force (U.S. Securities and exchange commission, 2023).

1.2 Problem statement

Classical approaches to evaluating a stock's performance in finance are based on getting the highest return and the lowest stock volatility. In the Capital Asset Pricing Model (CAPM), for instance, the performance of a share is evaluated based on the expected return based on its risk (volatility) relative to its actual return and related volatility (Fama & French, 2004). The Markowitz portfolio theory assumes that investors prefer a portfolio with low volatility levels and high return levels (Markowitz, 1952). In this classical approach, ESG is not included as a determinant of stock performance, making it hard to account for efficiency in terms of risk, return, and additionally ESG. Adding ESG to the classical risk-return approach will result in more alignment between the identified current ESG preferences, and available models to assess investment performance. The model can be employed to construct an optimal portfolio for a single investor regarding his risk, return, and CSR preferences (Gasser, Rammerstorfer, & Weinmayer, 2017).

1.3 Research objective

The general research objective is to estimate the inefficiency in RISK, Return on Assets (ROA), and ESG across stocks of U.S. and European corporate manufacturing firms. Subsequently, this study will assess the impact of different variables on the inefficiency scores. The specific research sub-objectives include:

1. To conduct a literature review to identify studies that examine the relationship between RISK, Return on Assets, ESG, and the associated factors affecting inefficiency.
2. Identify the inefficiency of U.S. and European corporate manufacturing firms concerning RISK, Return on Assets, ESG score, and the overall inefficiency in these terms.
3. Analyse the association between overall inefficiency and the identified explicative variables by implementing a bootstrap truncated regression.

1.4 Research outline

The problem addressed in this study, and its significance is described in section 1, which sets forth the study's goals. Section 2 offers a comprehensive literature review. The theoretical background is described in section 3. Section 4 discusses the methodology, which is broken down into two components: the data and variables, and the empirical model. The results and discussion are reported in section 5, which is followed by the limitations & further research recommendations in section 6. Section 7 of the paper concludes the results and section 8 provides the business implications of the research. This is followed by the reference list and the appendix.

2. Literature review

Section 2.1-2.3 presents the results of the literature review. The results are based on three categories: studies applying efficiency analysis in the field of ESG, studies investigating the relation between ESG and RISK, and studies investigating the relationship between ESG and financial performance. These results hold significance for this research for multiple reasons. Firstly, a literature review on efficiency analysis enhances the understanding of methodological aspects in the context of efficiency literature. Second, the literature review identifies and substantiates relevant explanatory variables that affect inefficiency. Furthermore, the literature review provides context for this research by clarifying relationships between RISK, ROA, and ESG, thereby supporting this research by providing a background within the field of the existing literature. During the literature review, a search strategy was developed for the following databases: Scopus, WUR-library, and Google Scholar.

Firstly, to obtain relevant literature in the field of inefficiency studies related to ESG, the following keywords were applied: Inefficiency AND/OR efficiency AND Corporate social responsibility AND/OR ESG. The articles were scanned for period, region, sector, methodology, inputs, outputs, and determinants of (in)efficiency. The selected time frame, 2018-2023, was made due to the relative recency of ESG. To broaden the research scope, snowballing was employed to expand the number of papers in the analysis.

Second, in order to gain sufficient literature results considering the ESG-risk relationship, the following search keywords were applied: ESG AND/OR Corporate social responsibility AND systematic risk OR systemic risk AND/OR risk AND/OR Beta. The obtained results were scanned for authors, research purpose, research period, the relationship between ESG and risk, country, sample details, and applied methodology. In this part of the literature review, the search period was extended to gain additional relevant results. The results were reported in section 2.2.

Lastly, in section 2.3 of the literature review, the relationship between ESG and financial performance is investigated. Keywords applied for this literature search were: Return on Assets AND/OR financial performance AND/OR profitability AND/OR return AND Corporate Social Responsibility AND/OR ESG AND/OR CSR. The articles were scanned for author, research purpose, research period, the relationship between ESG and financial performance, country, sample details, and applied methodology.

2.1 Efficiency analysis approaches

The results of the review of studies that have conducted efficiency analysis in the field of ESG are presented in Table 2.1. The Table includes information on various aspects, including the region, sector, determinants of (in)efficiency, and inputs and outputs of the efficiency analysis. When reviewing the efficiency analysis implemented in the field of ESG, most studies are conducted within the food and beverage sector in the EU and the U.S. (Aparicio et al., 2020; Engida et al., 2018, 2020; Engida et al., 2022a; Kapelko, Oude Lansink, & Guillamon-Saorin, 2021; Kapelko & Oude Lansink, 2022). Only the research of Puggioni & Stefanou (2019) applied worldwide data from the food and beverage industry. As Table 2.1 states, other implementations of studies were implemented with firms of multiple industries in the U.S., Europe, and China (Aparicio, Kapelko, & Ortiz, 2023; Engida et al., 2022b; Guillamon-Saorin, Kapelko, & Stefanou, 2018; Kapelko, Oude Lansink, & Stefanou, 2021; Pham et al., 2022). In the literature in Table 2.1, all papers utilized publicly listed firms in their samples. The methodologies implemented varied among articles that analysed (in)efficiency. To measure inefficiency, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis were frequently applied (Table 2.1).

In the literature, the results of the efficiency values were, in some instances further employed for regression. In the paper of Guillamon-Saorin et al. (2018), the results of the dynamic inefficiency values were regressed on the three different ESG dimensions to investigate possible associations. In the paper of Engida et al. (2020), a directional distance function was applied to characterize technical inefficiency (Chambers, Chung, & Färe, 1998; Kapelko, Lansink, & Stefanou, 2016). A bootstrap truncated regression followed this up with the explanatory variables: size, leverage, Free Cash Flow, Return on Assets, R&D intensity, as well as either network or market orientation. This was applied to find possible associations between inefficiency and the explanatory variables. A truncated regression analysis was applied since the inefficiency values were truncated to zero (Lee, Worthington, & Wilson, 2019).

In the paper of Engida et al. (2022a), OLS bootstrap regression was implemented on the dynamic Luenberger indicators. These indicators represented the change of input used to produce an output. This indicator for efficiency change allowed comparison to previous firm years, for instance, an indicator of -.035 indicated an increase of user input with similar outputs if input-orientation was used. In this paper, the dynamic Luenberger indicators were compared with the explanatory variables: size, leverage, ROA, FCF, R&D, and company orientation type, either market- or network orientation. Pham et al. (202 analysed efficiency scores with OLS regression to investigate whether E, S, and G scores influenced business performance regarding inputs and outputs.

In the literature, a dynamic approach was applied in multiple research papers (Aparicio et al., 2023; Engida et al., 2022a; Engida et al., 2022b; Guillamon-Saorin et al., 2018; Kapelko, Oude Lansink, & Stefanou, 2021). For instance, in the paper of Guillamon-Saorin et al. (2018), a dynamic framework was implemented to tackle biased measures of a firm's performance. The latter research was compensated for adjustment costs (i.e., costs associated with investments such as search- and learning costs) to improve accuracy. In addition, with the significant increase in sample size, aggregated data over time enhances confidence in the DEA ratings' accuracy. In turn, this aggregation improved the ability to make a distinction between efficient and inefficient firms (Tulkens & Vanden Eeckaut, 1995).

In addition to regression, different methods are often combined with DEA. For instance, in the papers of Aparicio et al. (2020) and Engida et al. (2018), DEA was combined with the composition of multiple indicators for CSR into a reduced number of indicators. Engida et al. (2018) and Puggioni & Stefanou (2019) applied a Principal Component Analysis (PCA) for this. In the paper of Aparicio et al. (2020), a PLA-based composite indicator was applied to compose multiple indicators. In the paper of Engida et al. (2020),Engida et al. (2018) as well as the research of Puggioni & Stefanou (2019), different policies and actions were composed using PCA to one socially responsible output indicator, while controversies or incidents were similarly composed to an undesirable output indicator in terms of CSR.

In the literature, different bootstrap methods were identified. In the research of Engida et al. (2018), bootstrapping was implemented after the construction of composite indicators. DEA inefficiency estimates were bootstrapped, with underlying reasons: the correction of the DEA results from sampling bias and the construction of confidence intervals to investigate the accuracy of the inefficiency scores (Simar & Wilson, 1998). In the paper of Engida et al. (2020), a truncated bootstrap regression was demonstrated to assess which variables explained variation in input and output-specific inefficiencies. An Advantage of bootstrap regression is an increased model stability and a more accurate estimation of uncertainty (Field, 2005). In the paper of Engida et al. (2022a), ordinary least squares (OLS) bootstrapping was employed to examine the association between firm-specific parameters and the dynamic input, output, and investment-specific variables. These variables represented a measure of technical inefficiency change.

Table 2.1, Overview efficiency studies in the field of ESG.

Authors	Panel	Region	Sector	Method	Efficiency Determinants	Inputs	Outputs
(Benlemlih & Bitar, 2018)	1998-2012	U.S.	-Multiple industries	-Regression analysis	-Size -Age -Tobin's Q -ROA	-	-
(Guillamon-Saorin et al., 2018)	2004-2015	U.S.	-Multiple industries	-DEA (input-oriented) -Regression analysis	-Size -Leverage -R&D -Marketing -Cash flow -Market-to-book ratio (MTB)	-Fixed assets -Employees -Costs of goods sold -Investment	-Revenue
(Engida et al., 2018)	-	EU	-Food -Beverage	-DEA Bootstrap (Output oriented) -PCA (output-oriented)	-	-CSR PCA scores	-Composite CSR indicator
(Puggioni & Stefanou, 2019)	2014	Global	-Food -Beverage All manufacturing	-DEA (output-oriented)	-	-Undesirable CSR input, -Social responsibility -Cost of goods sold -Labour -Fixed assets -Employees	-Desirable outputs (sales), -Undesirable outputs (incidents) -Socially responsible output.
(Aparicio et al., 2020)	2017	EU	-Food -Beverage -Tobacco All manufacturing	-DEA, (output-oriented)	-	-5 CSR dimensions	-Composed CSR indicator
(Engida et al., 2020)	2013-2017	EU	-Food -Beverage All manufacturing	-Directional distance function (DDF) (Input and output-oriented) -Truncated bootstrap regression	-Size -Leverage -Free Cash Flow (FCF) -ROA -R&D intensity -Orientation market/network	-Investment -Material cost - Quasi-fixed inputs	-Undesirable CSR output -CSR output (policy and programs)
(Kapelko, Oude Lansink, & Stefanou, 2021)	2010-2017	EU	-Capital, -Consumption -Other	-DEA (output- & input oriented oriented)	-	-Material -Labour -Quasi fixed	-Marketable outputs (sales) -CSR-output -Undesirable output (incidents/ controversies)
(Kapelko, Oude Lansink, & Guillamon-Saorin, 2021)	2004-2015	U.S.	-Food -Beverage	-DEA (input-oriented) -Linear regression	-Size -MTB -Leverage	-Costs of goods sold -Materials -Employees, -Investment	-Revenue

Authors	Panel	Region	Sector	Method	Efficiency Determinants	Inputs	Outputs
(Kapelko & Oude Lansink, 2022)	2004-2018	U.S.	-Food -Beverage	-DEA (input and output oriented), -Latent class analysis	-Size -Leverage -MTB -R&D -Marketing	-Labour -Material -Investment	-CSR output -Marketable output (revenue)
(Engida et al., 2022a)	2013-2016	EU	-Food -Beverage All manufacturing	-DEA (input-oriented) -OLS bootstrap regression	-Size -ROA -R&D intensity -FCF -Leverage -Orientation market/network	-Materials (costs), -Labour (costs), quasi-fixed	-Sales -Undesirable outputs (ESG indicators)
(Engida et, et al., 2022b)	2009-2016	EU	-Multiple sectors	-Stochastic frontier analysis	-Size -Free cash flow divided by capital (CF/K) -Tobin's Q	-	-
(Pham et al., 2022)	2019	U.S. China	-Multiple sectors	-DEA(input and output oriented) -OLS regression	-Size -Age -Leverage	-Operating expenses, -Property plant and equipment, -#employees	-Revenue -Market value
(Aparicio et al., 2023)	2014-2016	EU	-Capital -Consumption -Other	-FDEA (input and output oriented)	-	-Labour -Materials -Investments	-CSR-scores, revenues
(Iazzolino, Bruni, Veltri, & Baldissarro, 2023)	2021	EU	-Energy -Materials -Consumer -Finance, -Healthcare -Technology -Utility	-DEA	-Sector	-Total assets -Total equity	-EBITDA -Revenues ESG-scores

Pham et al.'s (2022) research indicated that the Environmental and Social pillars positively affected business performance while the governance pillar negatively affected business performance (Revenue and the firm's market value). Furthermore, the research of Puggioni and Stefanou (2019) identified that the average shadow price of producing ESG outputs is positive. This outcome indicates that the costs associated with the implementation of CSR are compensated by the advantages ESG provides.

The combination of studies from Engida et al. (2022a) and Engida et al. (2022b) suggests that a high R&D intensity not only stimulates input efficiencies but also stimulates a firm's financial performance. The research of Engida et al. (2020) found that CSR is positively associated with R&D intensity and size. Similar papers indicate a positive relation between CSR and R&D intensity (Engida et al., 2022a; Guillamon-Saorin et al., 2018). The research of Kapelko et al. (2022) also revealed that firm size, measured as the natural logarithm of total assets, is positively related to CSR performance, while leverage was negatively associated with CSR. The underlying reason was that more indebted firms spend less on CSR activities. Engida et al. (2022a) found similar results with underpinning argumentation that high-leverage companies are subjected to financial constraints, resulting in a lower focus on CSR. Another outcome suggests that network-oriented systems in Germanic and Latin countries have a higher association with CSR than market-oriented systems in Anglo-Saxon countries. This result indicates that the country level can explain variation in CSR performance (Engida et al., 2020).

Other results also propose that sectors can explain variations in CSR performance. In the research of Lazzolino et al. (2023), the effect of ESG on financial efficiency in different sectors was described. The results pointed out that the energy, material, consumer, and technology sectors were sensitive to ESG performance, indicating that a change in ESG performance can seriously affect their financial efficiency. This financial efficiency was measured in terms of the conversion of assets and equity into revenues. The underlying reason behind this is that the aforementioned sectors are under increased vigilance from stakeholders.

Other findings from the paper of Kapelko, Oude Lansink, & Guillamon-Saorin (2021) indicate that a firm's CSR performance is positively related to dynamic efficiency improvement associated with direct inputs. Nevertheless, a firm's CSR performance is adversely associated with investment-specific dynamic change in productivity and change in dynamic technology. Moreover, this research shows a high dynamic efficiency of material and other direct inputs which is associated with higher social and governance pillar scores. Nevertheless, higher dynamic productivity of investments is related to lower social and governance pillar scores. Similar research by Guillamon-Saorin et al. (2018) provides similar results where a high CSR is associated to low dynamic inefficiencies in terms of inputs like fixed assets, number of employees and costs of goods sold. The paper of Engida et al. (2022b) and Benlemlih & Bitar (2018) suggested that high CSR is negatively related to investment inefficiency through a reduction in information asymmetry and increased stakeholder solidarity.

2.2 ESG and RISK relation

The results of the relation between ESG and risk consisted of 25 papers, most of which applied regression analysis with panel data sets that varied between 1992 and 2020. Additionally, one research conducted a literature review, and another performed a meta-analysis (Chang, Fu, Jin, & Liem, 2022; Brad Cornell, 2020). Table 2.2 contains the detailed results. For each paper, the author, research purpose, research period, the relationship between CSR and risk, country, sample details, and applied methodology were noted.

Most papers discussed the relationship between ESG and systematic risk, which can be defined as the risk inherent in all assets in the entire market (Albuquerque et al., 2019; Braune et al., 2019; Chang et al., 2022; Chollet & Sandwidi, 2018; Farah et al., 2021; Hoepner et al., 2022; Hsiao et al., 2021; Jo & Na, 2012; Korinth & Lueg, 2022; Oikonomou et al., 2012; Sharfman & Fernando, 2008). The latter risk type affects all company's returns in the market and can be measured by the firm's Beta. This Beta represents the relative volatility of a stock relative to the entire stock market (Bodie, Kane, & Marcus, 2014). The paper of Aevoae et al. (2022) identified a negative relationship between ESG and systemic risk within banks. Systemic risk includes the whole financial system and thus differs from systematic risk, which focuses on the market (Bodie et al., 2014). Another risk type identified in the literature is the idiosyncratic risk (Becchetti, Ciciretti, & Hasan, 2015; Farah et al., 2021; Korinth & Lueg, 2022; López Prol & Kim, 2022). This refers to a firm's specific volatility of returns driven by non-market volatility (Bodie et al., 2014).

Table 2.2, Literature review results of the ESG-risk relationship.

Authors	**Purpose**	**Panel**	**CSR-risk relation**	**Region**	**Sample details**	**Method**
(Aevoae et al., 2022)	Investigates the effect of an increase of ESG on systemic risk.	2007-2020	Negative	56 countries	Banking sector	Regression
Chollet & Sandwini, 2018	Investigates the effect of CSR engagement on financial risk.	2003-2012	Negative	European and U.S. firms	40 sectors	Regression
(Farah et al., 2021)	Investigates the effect of CSR on firms' systematic risk.	2005-2017	Negative	43 countries	Excluding financial and utility companies	Regression
(Korinth & Lueg, 2022)	Investigate the effect of ESG on systematic risk.	2012-2019	Non-linear	Germany	100 Largest stock listed companies	Regression
(López Prol & Kim, 2022)	Investigate the effect of high optimized ESG portfolios on risk and return.	2018-2019	Negative	United States	NYSE listed companies	Regression
(Dorfleitner & Grebler, 2022)	Investigate the impact of corporate social responsibility on systematic risk.	2002-2018	-	Japan, Pacific, Europe, North America	Publicly listed companies	Regression
(Hsiao et al., 2021)	Investigate the relationship between Corporate social responsibility and risk.	2018-2019	No relation	China	Shanghai and Shenzhen stock exchange	Regression
(Braune et al., 2019)	Investigate the effect of Corporate social responsibility on financial performance and risk in economic instable periods.	2005-2014	Negative	United States	S&P 500 firms	Regression
(Jo & Na, 2012)	Examine the relation between CSR and firm risk.	1999-2010	Negative	United States	Alcohol, tobacco, gambling	Regression
(Albuquerque et al., 2019)	Investigate how CSR affects systematic risk and firm value.	2003-2015	Negative	United States	Publicly listed companies	Regression
(Oikonomou et al., 2012)	Investigate the impact of CSR performance on financial risk.	1992-2009	Negative weak	United States	Publicly listed firms	Regression

Authors	Purpose	Panel	CSR-risk relation	Region	Sample details	Method
(Sharfman & Fernando, 2008)	Investigate whether environmental risk management is associated with reduced cost of capital.	1999-2002	Negative	United states	S&P 500 firms	Regression
(Luo & Bhattacharya, 2015)	Investigate the effect of CSR on firm idiosyncratic risk.	2002-2003	Negative	United states	Top 1000 US companies in size	Regression
(Becchetti et al., 2015)	Investigate the effect of CSR on risk.	1992-2010	Negative	United States	Publicly listed firms	Regression
(Humphrey, Lee, & Shen, 2012)	Investigate whether corporate social performance impacts cost of capital and risk.	2002-2010	No relation	UK	Publicly listed firms	Regression
(Dumitrescu & Zakriya, 2021)	Investigate the impact of ESG activities on stock market crash risk.	1991-2015	Negative	United States	Publicly listed firms	Regression
(Hoepner et al., 2022)	Investigate the effect of engagement in CSR on downside risk.	2005-2018	Negative	worldwide	Publicly listed firms	Difference in difference model, Regression
(Brad Cornell, 2020)	This paper explores the relation between ESG and risk.	-	No relation	-	ESG in portfolio composition	Literature review
(Chang et al., 2022)	Review of literature on CSR/ESG literature and value implications on public listed companies	-	Mostly Positive	Worldwide	-	Meta-analysis
(Aevoae et al., 2022)	Investigates the effect of an increase of ESG on systemic risk.	2007-2020	Negative	56 countries	Banking sector	Regression
Chollet & Sandwini, 2018	Investigates the effect of CSR engagement on financial risk.	2003-2012	Negative	European and U.S. firms	40 sectors	Regression
(Farah et al., 2021)	Investigates the effect of CSR on firms' systematic risk.	2005-2017	Negative	43 countries	Excluding financial and utility companies	Regression
(Korinth & Lueg, 2022)	Investigate the effect of ESG on systematic risk.	2012-2019	Non-linear	Germany	100 Largest stock-listed companies	Regression
(López Prol & Kim, 2022)	Investigate the effect of high optimized ESG portfolios on risk and return.	2018-2019	Negative	United States	NYSE listed companies	Regression
(Dorfleitner & Grebler, 2022)	Investigate the impact of corporate social responsibility on systematic risk.	2002-2018	-	Japan, Pacific, Europe, North America	Publicly listed companies	Regression

According to the study of Aevoae et al. (2022), an increase in ESG has a negative effect on systemic risk in banks through the stakeholder theory. The stakeholder theory suggests that general firm performance depends on the ability to create value for all stakeholders. This can be achieved through the implementation of CSR (Freeman & Dmytriyev, 2020). Becchetti et al. (2015) identified that CSR engagement reduces the risk of conflicting with stakeholders but can also reduce firms' ability to cut

CSR expenses. This inability to cut CSR expenses causes an increase in idiosyncratic risk. Chollet and Sandwidi (2018) found that high social- and governance pillar performance reduces financial risk (i.e., the risk resulting from the method of financing the firm) by enforcing commitment to strong governance and responsible environmental practices (Hardaker, Huirne, Anderson, & Lien, 2004). The research of Hsiao et al. (2021) suggested that, for low-risk companies, improvements in CSR performance may lead to an increase in systematic risk in an environment where equivalent companies do not disclose CSR information. The latter observation aligns with the paper of Korinth and Lueg (2022), in which was stated that the effect of ESG on volatility depends on the level of existing CSR in the capital market.

On the other hand, Oikonomou et al. (2012) found that participation in the social pillar of ESG is associated with a reduction in systematic risk, and that social irresponsibility is positively associated with financial risk. Moreover, a meta-analysis conducted by Chang (2022) found evidence that improving ESG practises was mostly associated with a reduction in systematic risk for publicly listed firms. Farah et al. (2021) reported that CSR engagement reduces a firm's systematic risk via intangible assets such as reputation and employee loyalty. The latter research also observed a U-shaped relationship between systematic risk and CSR, indicating that CSR activities for small companies might be a waste of money when aiming to reduce systematic risk.

Similarly, Korinth and Lueg (2022) also proposed a U-shaped relationship between systematic risk and CSR. This results indicated that overinvestment in social and environmental pillars can increase systematic risk. Jo and Na (2012) provided evidence for a negative relation between CSR and systematic risk. Arguments for this negative correlation were improved risk management through CSR, CSR provides market appeal to customers, CSR improves information transparency, and CSR makes financial markets more accessible. According to Albuquerque et al. (2019), CSR reduces systematic risk via higher product differentiation and improved financial performance.

In the paper of Braune et al. (2019) CSR was found to be reducing systematic risk in times of economic instability. Similarly, Dumitrescu and Zakriya (2021) reported that the social pillar of CSR helps to reduce firms' stock price crash risk and increase firm value. Stock price crash risk can be defined as the likelihood of a sudden decline in stock prices, measured by analysing the volatility of share prices and assessing the probabilities related to large market declines (Habib et al., 2018). Hoepner et al. (2022) found that engagement in CSR, particularly in the environmental pillar, helps in reducing downside risk. Downside risk can be defined as the risk that a security declines if market conditions become adverse (Hardaker et al., 2004). Finally, Sharfman and Fernando (2008) indicated that environmental risk management reduces systematic risk through a reduction in information asymmetry.

Other results of the literature review provided information on the effect of ESG on idiosyncratic risk and risk of ESG integrated into investment portfolios consisting of shares. For instance, Farah et al. (2021) found that CSR improves the relationship with suppliers, and in this way, reduces supply chain disruption risk. The latter risk encompasses the probability of unforeseen events restricting a supply chain and the risks negatively affecting supply-demand coordination events (Shekarian & Parast, 2021). The research of Dorfleitner & Grebler (2022) found differences in the effect of CSR on systematic risk for various regions, a more robust relationship was observed in North America and Europe and a weaker relationship in Japan and the Asian Pacific.

2.3 ESG and financial performance

The results from the relationship between ESG and financial performance are reported in Table 2.3 and consist of 29 papers. Many studies combine U.S. data with regression analysis, while other studies often research global data and combine this in a meta-analysis or a literature review.

Table 2.3, Literature review results of the ESG-financial performance relationship.

Authors	**Purpose**	**Panel**	**CSR financial performance relation**	**Country**	**Sample details**	**Method**
(Whelan, Atz, & Clark, 2020)	Investigating the relation between ESG and financial performance	2015-2020 studies	Positive relation	Multiple	-	Literature review Meta-analysis
(López-Arceiz et al., 2019)	Investigating the association between social and economic performance	-	Positive relation	Multiple	-	Literature review Meta-analysis
(Busch & Friede, 2018)	Investigate the relation between social and financial performance	2014-2018 literature	Positive relation	Multiple	-	Meta-analysis
(Gallardo-Vázquez, Barroso-Méndez, Pajuelo-Moreno, & Sánchez-Meca, 2019)	Investigate the relation between CSR disclosure and financial performance	1982-2018 literature	No relation	Multiple	-	Literature review Meta-analysis
(Hang, Geyer-Klingeberg, & Rathgeber, 2019)	Investigate the causal effect of corporate environmental and corporate financial performance.	2012-2019 literature	Bidirectional relation	Multiple	-	Literature review Meta-analysis
(Vishwanathan et al., 2020)	Investigates the relation between CSR and financial performance.	1978-2016 literature	Positive relation	Multiple	-	Literature review Meta-analysis

Authors	Purpose	Panel	CSR financial performance relation	Country	Sample details	Method
(Bradford Cornell & Damodaran, 2020)	The paper investigates the relation between ESG criteria and value	-	Positive relation	-	-	Literature study
(Brad Cornell, 2020)	This paper explores the relationship between ESG, risk and return	-	No relation		-ESG in portfolio composition	Literature study
(Pham et al., 2022)	The effect of ESG combined score on the business performance of enterprises	2019	Positive relation	China, U.S.	Transportation industry	DEA, Regression
(Chang et al., 2022)	Identify value drivers that enhance firm value (and financial performance)	-	Positive relation	Multiple	Multiple sectors	Meta-analysis
(Benlemlih & Bitar, 2018)	Investigate the relation between CSR and investment efficiency	1998-2012	Non-linear relation	U.S.	All sectors except financial firms	Regression
(Cheng, Hong, & Shue, 2020)	Investigate incentives to spend on CSR	1991-2012	Negative relation	U.S.	All sectors, S&P 1500	Regression
(Di & Kostovetsky, 2014)	Investigate whether democratic-leaning firms are associated with more social responsibility than Republican-leaning firms	2003-2009	Negative relation	U.S.	All sectors, S&P 500	Regression
(Masulis, 2015)	Investigate the effect of corporate expenditures (this paper highlights that corporate giving is part of CSR) on financial performance (revenues/shareholder wealth)	1996-2006	No relation	U.S.	All sectors, Fortune 500 firms	Regression
(Lins, Servaes, & Tamayo, 2017)	Investigate the effect of CSR on firm performance in the financial crisis of 2009-2013	2008-2009	Positive relation	U.S.	- S&P 500 (excluding financial firms)	Regression
(Albuquerque et al., 2019)	Investigate how CSR affects systematic risk, and firm value, and does the effect differs among firms.	2003-2015	Positive relation	U.S.	-Publicly listed companies	Regression
(Flammer, 2015)	Examine the effect of shareholder proposals related to CSR on financial performance	1997-2011	Positive relation	U.S.	S&P 500 companies	Regression
(Benlemlih, 2019)	Investigate the relation between CSR and firm value	1991-2012	Positive relation	U.S.	Publicly listed companies	Regression

Authors	Purpose	Panel	CSR financial performance relation	Country	Sample details	Method
(Chava, 2014)	Effect of an environmental profile of a company on the cost of equity and debt capital	1992-2007	Negative relation	U.S.	S&P 500 firms, Russel 2000 firms	Regression
(Kim, 2022)	Investigate whether high ESG portfolios perform better	2018-2019	Negative relation	U.S.	NYSE firms	Regression
(Hong & Kacperczyk, 2009)	The effect of social norms on markets	1962-2006	Negative relation	U.S.	Alcohol, tobacco and gaming	Regression
(Eccles, Ioannou, & Serafeim, 2014)	Investigate the effect of CSR on organizational processes and performance.	1993-2010	Positive relation	U.S.	-multiple sectors	Multivariate-analysis
(Fama & French, 2007)	This paper investigates how disagreement among investors affects asset prices.	-	Negative relation	U.S.	Publicly listed firms	Analysis of CAPM
(Pástor, Stambaugh, & Taylor, 2021)	Model the expected returns that consider ESG criteria	-	Negative relation	Multiple	Publicly listed firms	Literature review
(Dimson, Karakaş, & Li, 2015)	Investigate the effect of ESG and CSR on firm value	1999-2009	Positive relation	U.S.	Publicly listed firms	Literature review
(Wilson, Heron, & Perry, 2020)	Investigate the relation between CSR and financial performance	2003-2013	No relation	U.S.	Publicly listed firms	Univariate comparison
(Schmidt, 2020)	What are optimal ESG portfolio's and what are the returns and risks	2015-2019	Negative relation	U.S.	Dow jones index firms	Linear programming
(Pedersen, Fitzgibbons, & Pomorski, 2021)	Investigating the highest attainable Sharpe ratio for each ESG ratio.	1963-2019	Negative relation	U.S.	S&P 500 firms	Regression

López-Arceiz et al. (2018) identified a positive relationship between financial and social pillar performance. This relationship depended on the financial performance indicator. For instance, accounting-based performance measures like Return on Equity and Return on Assets were found to be more highly correlated with social performance than market-based measures like investor returns, P/E ratio, dividend yield, or total shareholder return (Busch & Friede, 2018; López-Arceiz et al., 2018; Gallardo-Vázquez et al., 2019). The stakeholder theory was identified as the main driver for this positive relationship (López-Arceiz et al., 2018).

Regarding the relationship between corporate environmental performance and financial performance, Dumitrescu & Zakriya (2021) found that corporate environmental performance positively affects financial performance in terms of market-based measures value and accounting-based measures through the stimulation of innovation. Vishwanathan et al. (2020) identified the following underpinning arguments for an association between CSR and market- or accounting-based performance measures: CSR enhances corporate reputation, CSR promotes shareholder reciprocity, CSR reduces corporate risk, and CSR strengthens a firm’s innovation capabilities. Similarly, Lins et al. (2017), Albuquerque et al. (2019), and Eccles et al. (2014) found that CSR promotes Return on Assets and Return on Equity via trust building between stakeholders and investors, which in turn, reduces systematic risk. Hang et al. (2019) found that corporate financial performance (CFP) influences corporate environmental performance positively in the short term through an increased investment potential but negatively in the long term through an increased managerial focus on gaining shareholder value. On the other hand, the paper of Hang et al. (2019) found that corporate environmental performance only improves corporate financial performance in the long term.

Overall, most studies with worldwide data that implemented a literature study or meta-analysis indicated a positive relationship between CSR and different types of financial performance measures. It is noticeable that studies focussing specifically on the United States, on average, provide more ambiguity on the latter statement. For instance, Di & Kostovetsky (2014), identified a negative relationship between CSR and financial performance indicators Return on Assets and Return on Equity, suggesting that benefits to stakeholders via CSR come at the firm's expense. Furthermore, Wilson et al. (2020) found no significant relationship between financial performance and CSR.

During the literature review on the relationship between CSR and financial performance, different results were identified concerning sectorial or industrial dissimilarities moderating the relationship between CSR and financial performance. In the research of Vishwanathan et al. (2020), a stronger relationship between CSR and financial performance was identified in the financial service industry. Eccles et al. (2014) found evidence that high CSR Business-to-consumer (B2C) firms were more likely to outperform high CSR business-to-business firms in terms of accounting performance (Return on Assets and Return on Equity) and a stock market performance measure, the market-to-book ratio. Furthermore, this research also found that high environmental pillar scores are more beneficial in sectors that are characterized by intensive natural resource extraction, like gas, oil, chemicals, industrial metals, and mining industries. In the meta-analysis of López-Arceiz et al. (2018), evidence was found that the relationship between financial and social performance was significantly stronger in the service sector. In addition, the meta-analysis of Busch & Friede (2018) indicated that industry type moderated the relation between corporate social performance and corporate financial performance. On the other hand, the research of Gallardo-Vázquez et al. (2019), who focussed on the relationship between CSR-disclosure and organizational performance, found no moderation effect of industry type.

In the literature review, some studies investigated the effect of ESG on portfolio returns. The results indicate that Investors who prefer to invest in ESG companies may face lower expected returns relative to risk due to diversification constrains, limiting their exposure to high-performing assets (Pástor et al., 2021; Hong & Kacperczyk, 2009; Cornell & Angeles, 2022). Furthermore, adding ESG considerations to portfolio models may result in reduced Sharpe ratios and more concentrated portfolios, according to the research of Schmidt (2020) and López Prol & Kim (2022).

3. Theoretical background

3.1 Production Theory

The production theory focuses on the utilization of certain inputs (e.g., labour, capital, or raw materials) to produce a particular output. The focus of the production theory is the optimal allocation to reach the most outputs for a given set of inputs (output-oriented efficiency) or alternatively, the least inputs to produce output (input-oriented efficiency) (Färe, 1991). The production function is defined as (see Coelli et al., 2005):

$$q = f(x) \quad (3.1)$$

in which q represents the output of the function f with a vector of inputs $x = (x1, x2, \dots, xN)$ consisting of multiple inputs that are under the control of the producer. Several properties are associated with the classical production function (Robert G. Chambers, 1988): i) non-negativity, assuming that $f(x)$ is a non-negative finite number; ii) weak essentiality indicates that production is not possible without the usage of input; iii) monotonicity that refers to the property of a function that always increases when input increases; iv) concavity in the production function that implies that the production function exhibits decreasing marginal productivity. In other words, as variables such as more labour are added to the production cycle while holding other inputs constant, the additional output per additional input gradually decreases. The Cobb Douglas function is one of the most widely applied production function (Chowdhury et al., 1975). The Cobb-Douglas mathematical specification assumes that the output level is a function of the amount of labour input and capital inputs used in the production process (Cobb & Douglass, 1928).

3.2 Efficiency analysis

In economics, efficiency is referred to as the situation in which an economy is optimally utilizing its resources. This results in the lowest attainable costs of production and the highest attainable outputs of services or goods. Economic efficiency means resources are being utilized to their full potential (Coelli et al., 2005). Farrell (1957) proposes that the technical efficiency of a firm can consist of two components: i) technical efficiency, reflecting a firm's ability to obtain maximum outputs from a given set of inputs, and ii) allocative efficiency, which reflects a firm's ability to use inputs in the optimal proportion given their production technology and prices.

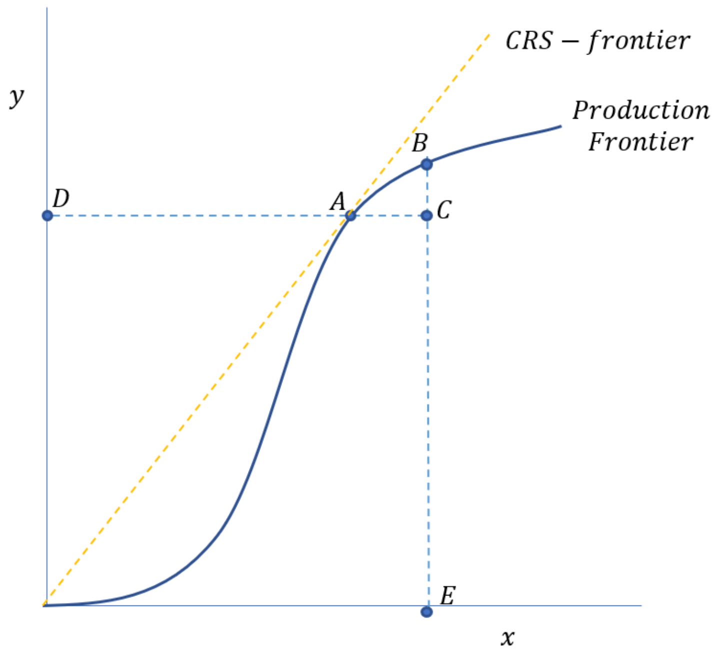

Figure 3.1. The production frontier including efficient DMU "A" and "B", and inefficient DMU "C".

According to the literature of Cooper et al. (2012), a DMU reaches complete technical efficiency if the performance of other DMUs shows that the inputs used cannot be improved without either reducing other outputs or increasing other inputs. This can be graphically represented in Figure 3.1. in which the production frontier represents the relationship between maximum attainable output (y) for each level of input (x) (Coelli et al., 2005). Efficient firms produce on the frontier. In this example, DMU A and DMU B are technically efficient. DMU C is considered technically inefficient as it could increase output to the level of B by using the same amount of input, the output oriented technical efficiency can be calculated with:

$$Technical\ efficiency\ (output - oriented) = \frac{EC}{EB} \qquad (3.2)$$

In which EC represents the distance between E and C, and EB represents the distance between E and B. When viewing the graph in terms of input-oriented technical efficiency, the input of DMU C can be reduced towards the level of DMU A while producing the same amount of output. In this way, technical efficiency can be reached (Kumbhakar & Tsionas, 2006). Based on the latter example, the input-oriented efficiency can be calculated with:

$$Technical\ efficiency\ (input - oriented) = \frac{DA}{DC} \qquad (3.3)$$

In this case, a firm can produce both allocative- and technical-efficient and cost efficiency can be reached. Cost efficiency can be reached in case a firm can produce the maximum output using the minimum amount of resources for the lowest possible cost (Tutulmaz, 2014). Within the field of efficiency, cost efficiency is relevant as it allows organizations to achieve maximum profitability by minimizing the cost of production. Cost efficiency can be calculated by multiplying the technical efficiency with the allocative efficiency (Coelli et al., 2005).

Apart from cost efficiency, scale efficiency if an often-applied measure of efficiency in terms of whether a firm is operating at optimal size or scale. For instance, if the production levels of a firm increase, this results in lower cost per unit and an increased scale efficiency (Silberston, 1972). In Figure 3.1, DMUs A and B are technically efficient. Although these two DMUs are all technically efficient, we can see that they are not all equally productive because the productivity of each of these businesses is equal to the ratio of $\frac{y}{x}$ (Coelli et al., 2005). This can also be seen at the Constant returns to scale (CRS) frontier (representing the maximum production level attainable with the same input), which cuts the production frontier at point A (Charnes et al., 1978). The difference in productivity is caused due to differences in economies of scale. The scale efficiency can be calculated with the horizontal distance between the CRS frontier and the production frontier in Figure 3.1 (Balk, 2001).

3.3 Markowitz portfolio theory

Markowitz introduced the concept of the efficient frontier, which is a set of portfolios that offer the highest expected return for a given level of risk. The Markowitz Portfolio Theory assumes that investors are risk-averse and strive to achieve the highest possible returns for a given level of risk by favourably applying the dispersion and correlation of the investment assets. By constructing a portfolio out of various shares that fall on the efficient frontier, investors seek to achieve the optimal balance between risk and return (Markowitz, 1952). In this process, the weights invested in each asset are constantly changed. Furthermore, the covariances between different stocks are constantly considered to reach the efficient frontier. The covariance, in this case, measures the extent to which the returns of e.g. two investments move together and, via this way, affect the riskiness of a portfolio. In the case of a portfolio of two risky assets, the expected rate of return can be calculated as follows:

$$E(r_p) = W_1 * E(r_1) + W_2 * E(r_2) \qquad (3.4)$$

In which $E(r_p)$ is the expected return of the portfolio, W_1 the proportion invested in assets 1, W_2 the proportion invested in asset 2, $E(r_1)$ the expected return of assets 1 and $E(r_2)$ the expected return of asset 2 (Bodie et al., 2014). The total variance of this portfolio of two assets can be calculated with:

$$\sigma_p^2 = w_1^2 * \sigma_1^2 + w_{2*}^2 \sigma_2^2 + 2 * w_1 * w_{2*}\, Cov(r_1, r_2) \qquad (3.5)$$

In which σ_p^2 is the variance of the portfolio, σ_1^2 is the variance of asset 1, σ_2^2 is the variance of asset 2, and $Cov(r_1, r_2)$ is the covariance between asset 1 and asset 2 expressed as ($Cov(r_1, r_2)$). The covariance of 2 assets can be calculated with the following formula:

$$Cov(r_1, r_2) = \mathrm{r}_{1,2} * s_1 * s_2 \tag{3.6}$$

In which $\mathrm{r}_{1,2}$ is the correlation coefficient between asset 1 and asset 2, s_1 is the variance of asset 1 and s_2 is the variance of asset 2 (Bodie et al., 2014). This model can be extended by combining multiple assets into a combined expected return and a total portfolio variance. By allocating investments among low-covariance assets, investors can reduce the overall risk of their portfolio and obtain more optimal risk-return combinations than any individual security can reach (Duchin & Levy, 2009). In Figure 3.2, the dots represent individual assets or companies. The line represents the mean-variance efficient frontier, representing the maximum attainable returns for a given level of volatility (Bodie et al., 2014). The minimum-variance portfolio represents the portfolio of combined assets with the lowest attainable variance. The tangency portfolio represents the portfolio of individual assets that maximizes the Sharpe-ratio, i.e. the risk-adjusted performance of an investment or investment portfolio, calculated by the assets' excess return in relation to its volatility (Sharpe, 1994).

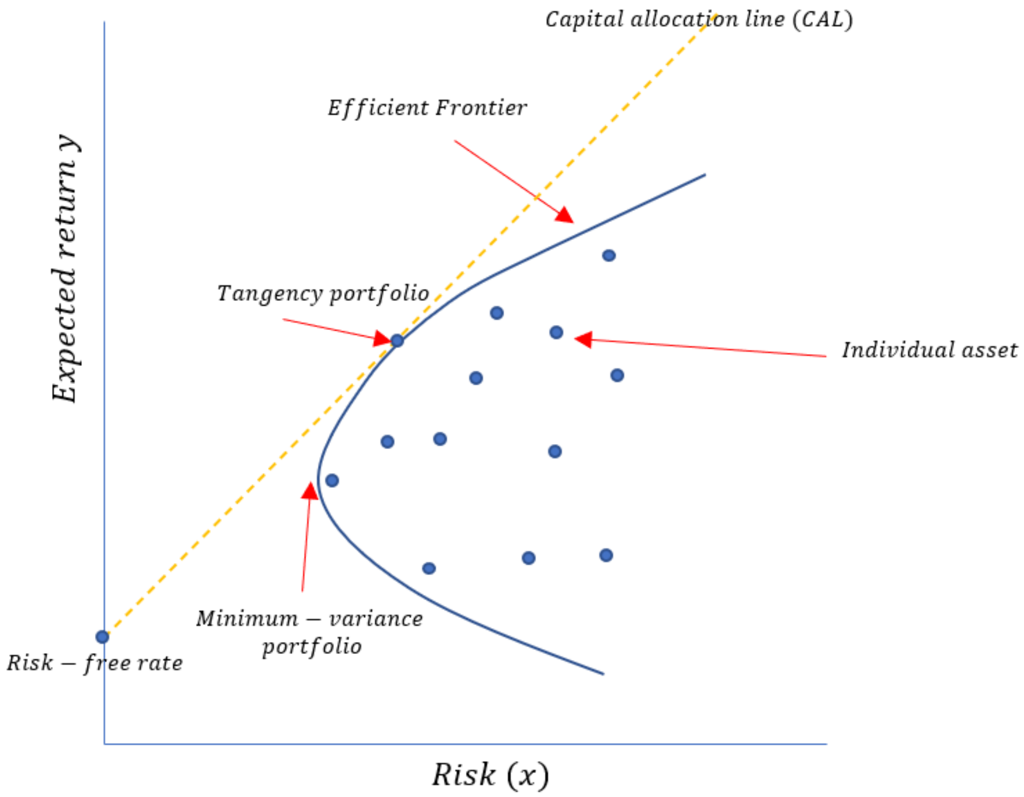

Figure 3.2. Markowitz Portfolio theory graphically.

In this research, the Markowitz portfolio theory is applied by creating an efficient frontier from individual assets without dividing the weights into different assets. Each asset is seen as a portfolio. In this way, an efficient frontier will be made from the most efficient companies in terms of return and volatility. As explained in the problem statement, the classical mean-variance approach applied in the Markowitz model involves making a trade-off between the risk (volatility), and (expected) return (Markowitz, 1952). In this thesis, similar to the research of Gasser et al. (2016), a trade-off between ESG and return will be documented. This trade-off is graphically visible in Figure 3.3b, in which an efficient frontier is constructed that shows the highest attainable ESG value for each level of return. Similarly, an efficient frontier can be made that aims to minimize the risk, while maximizing the ESG score, finding an efficient frontier on the top-left of the curve (Figure 3.3a).

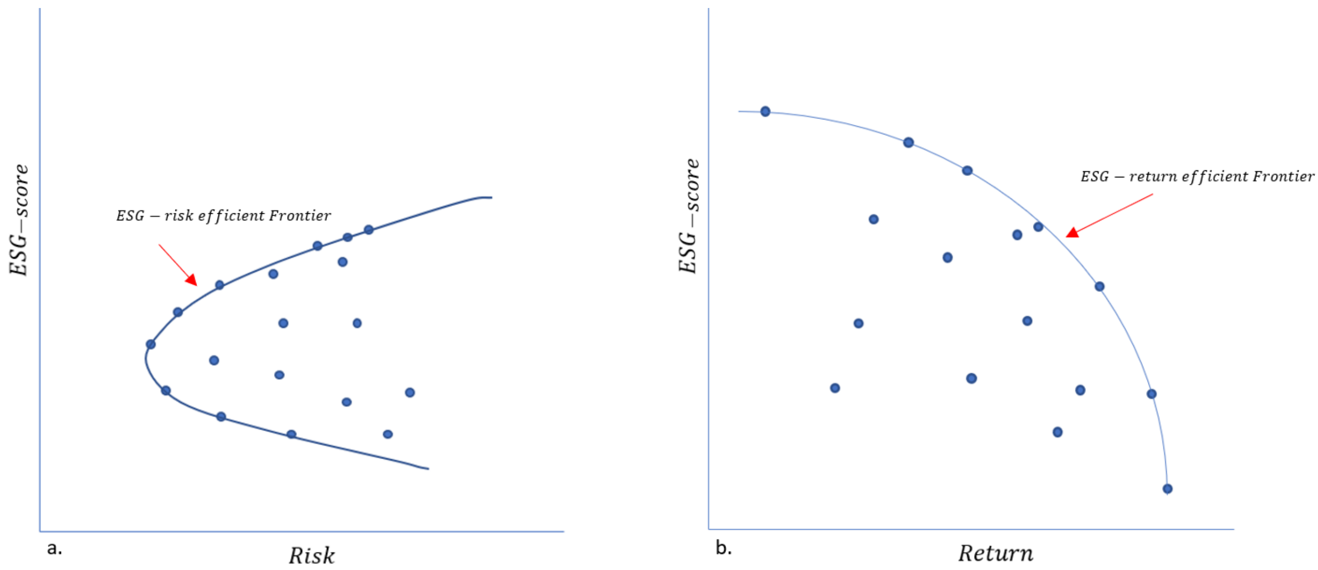

Figure 3.3. Graphical representation of the expected ESG-risk frontier (a) and ESG-return frontier (b).

3.4 Capital Asset Pricing Model

Another theory applied in this research is the Capital Asset Pricing Model (CAPM). The CAPM model explains the relationship between expected return and systematic risk of investing in security linearly. This is done by considering the risk of an asset relative to the whole market. By utilizing the CAPM model, the expected return of a portfolio can be estimated based on different components (Perold, 2004). The components of the CAPM model consist of an asset's Beta, the risk-free rate, and the market risk premium.

When assessing the CAPM model, an increase in the Beta is associated with a higher expected return to compensate for the excess risk (Fama & French, 2004). To calculate the Beta of an asset, two components are relevant: the covariance between an asset's return Ri_i and the market return Rm. The covariance expressed as $Covariance\ (Ri, Rm)$, indicates how a change in the stock market relates to changes in the overall market return. The second relevant component for calculating a company's

Beta is the $Variance\ (Rm)$. The variance indicates the variance of the return on the market, or the extent to which the market return is dispersed from the average value of the market return (Lakonishok & Shapiro, 1984). This leads to an expression of the Beta:

$$Beta(i) = \frac{Covariance\ (Ri,Rm)}{Variance\ (Rm)} \qquad (3.7)$$

The results give a Beta indicator that measures the correlation of an individual security to the market. A Beta of 1 indicates that a stock moves with the market, and the associated return is similar to the market return $E(R_m)$ when disregarding idiosyncratic risk. A Beta greater than 1 indicates that a stock is more volatile than the market, while a Beta lower than 1 indicates the stock is less volatile than the market (Bodie et al., 2014). In this thesis, the Beta will be used as a measurement of an asset's risk. In this way, an ESG-Beta frontier can be composed to assess an asset's inefficiencies in terms of ESG.

Overall, the CAPM model is a useful tool for investors to estimate the expected return on an investment based on the Beta and expected market return (Jagannathan & McGrattan, 1995). In addition, the CAPM model also helps in determining the excess return that is associated with a particular risky asset. To conclude, CAPM helps in constructing a well-diversified portfolio by combining different assets with different Beta's to achieve a specific desired risk and return levels (Giorgi & Post, 2005).

3.5 Hypotheses

A set of hypotheses is formulated to explore the association between overall inefficiency and several explanatory variables. The identified variables have been formulated according to the literature discussed in section 2. This has resulted in the formulation of the hypotheses in this section.

As primary consideration, various literature on efficiency identified firm *age* and firm *size* as explanatory variables for efficiency (Benlemlih & Bitar, 2018; Engida et al., 2022b; Horta et al., 2016; Kapelko & Oude Lansink, 2022; Kapelko, Oude Lansink, & Guillamon-Saorin, 2021). According to Benlemlih & Bitar (2018), the longer a firm has been listed, the more likely it is that it is in the mature stage of the business cycle, indicating that the firm is more experienced, resulting in increased efficiency. This finding is based on the business life cycle theory, which suggests that as a company matures, it shows stable revenue streams, an established market share, and increased operational- and investment efficiency (Ahmed et al., 2021). Regarding *size*, Schiersch (2013) suggests that larger firms, in terms of assets, are more efficient than smaller firms due to their ability to exploit economies of scale. Furthermore, Kapelko & Oude Lansink (2014) asserted that firm *size* enhances firms' bargaining power and draws in more qualified personnel, consequently improving efficiency.

$\boldsymbol{H_1}$***: More mature corporate manufacturing firms have a lower overall inefficiency.***

$\boldsymbol{H_2}$***: Larger corporate manufacturing firms have lower overall inefficiency.***

According to the paper of Engida et al. (2022a), *leverage* is positively associated with technical inefficiency, primarily as more indebted firms are unable to mitigate efficient outcomes. Similarly, Engida et al. (2020) and Kapelko & Oude Lansink (2014) found evidence that leverage positively relates to inefficiency. They argue that creditors closely watch companies with greater debt loads to ensure timely debt payments and, therefore, prioritise debtholders' interests above shareholders' interests. Other literature identified a negative relationship between *leverage* and financial performance. These papers suggested that agency issues may lead to inappropriately high debt levels, implying an expected positive relation between leverage and inefficiency (Gleason & Mathur, 2000; Shapiro, 2005). The agency theory elucidates the underlying issue of the effect of *leverage* on efficiency. Given this context from the literature, the hypothesis that high-leverage manufacturing firms will have a higher inefficiency if formed.

$\boldsymbol{H_3}$***: High-leverage corporate manufacturing firms will exhibit a higher overall inefficiency.***

Previous literature provided that R&D intensity is positively associated with lower levels of technical inefficiency in terms of CSR (Guillamon-Saorin et al., 2018). Engida et al. (2020) describe *R&D* intensity as an investment that improves the number of processes that reduce the amount of input used and, consequently, improves efficiency in terms of cost reduction or negative CSR outputs. The paper of Padgett et al. (2019) describes the relationship between R&D intensity and performance through the resource-based view theory. This theory suggests that strong intangible resources contribute to a sustained competitive advantage in firms. Furthermore, a higher R&D intensity leads to more efficiency due to innovations, thereby improving efficiency (Mcwilliams & Siegel, 2016). Based on this evidence, and evidence from the literature review, the hypothesis is drawn that *R&D* is negatively associated with inefficiency.

$\boldsymbol{H_4}$***: The R&D intensity is negatively associated to overall inefficiency in corporate manufacturing firms.***

Another variable, the Tobin's Q, is seen as an explanatory variable for efficiency in earlier efficiency research (Benlemlih & Bitar, 2018; Engida et al., 2022b). According to the Q-theory of investments, the market value of capital stock to its replacement cost ratio can be used to describe investment opportunities. A high Tobin's q suggests that there are attractive opportunities for a firm to invest in new initiatives as the company's market value is assumed to be much more than the cost of replacing existing assets. Based on this, the firm is likely to undertake projects that create value exceeding their costs, reflecting the efficient allocation of resources and, consequently, increased investment efficiency (Engida et al., 2022b). Based on the Q-theory of investments and its implications for investment efficiency, the following hypothesis is formed:

$\boldsymbol{H_5}$: *A higher Tobin's Q is associated with lower overall inefficiency in corporate manufacturing firms.*

Building upon these findings, Table 3.1 summarizes the hypotheses, explanatory variables, expected relation of the explanatory variable with the overall inefficiency, and relevant theories.

Table 3.1. Potential determinants of overall inefficiency, related theories, and hypothesis.

Explanatory variable	**Hypothesis**	**Expected relation with overall inefficiency**	**Related Theory**
Age	1	Negative	Business life cycle theory
Size	2	Negative	Economies of scale theory
			Stakeholder theory
Leverage	3	Positive	Agency theory
R&D	4	Negative	Resource-based view theory
Tobin's Q	5	Negative	Q-theory

4. Methodology

4.1 Data and variables

The data in this research was retrieved from Refinitiv Eikon and Orbis. The final data set consisted of 193 U.S. manufacturing firms and 179 European manufacturing firms. The dataset from Refinitiv Eikon included annual data on relevant financial variables of firms in the period between 2016-2021, these variables consisted of: *Return on Assets, total assets, indebtedness, Beta, R&D,* and *age* (Orbis, 2021; Refinitiv, 2021). Refinitiv Eikon also provided data on CSR measures, including the ESG score measured and the scores for each of the environmental, social, and governance pillars in all years during the period 2016-2021. To enhance model accuracy and improve its robustness, we dropped registers for missing information or outliers in their financial performance indicators. Additionally, firms within the U.S. and European subsets were excluded in case of missing R&D and leverage values to maintain data completeness. In the end, the U.S. subset, the explanatory variable *R&D,* was removed entirely as it was missing a total of 38 values. Consequently, this resulted in a panel dataset of 141 US firms and a dataset of 123 European firms covering the period of 2016-2021.

We compute the efficiency scores and construct a frontier in the dimensions ROA and ESG as outputs and the company Beta as input jointly. The financial performance of the companies was proxied by ROA ratio, calculated as the net income to total assets (Kapelko & Oude Lansink, 2022; Guillamon-Saorin et al., 2018; Kapelko & Oude Lansink, 2022; Pham et al., 2022; Guillamon-Saorin et al., 2018; Kapelko & Oude Lansink, 2022; Pham et al., 2022). CSR involvement was proxied by the annual Environmental-Social-Governance (ESG) index measure as the score on the environmental, social and governance pillars-. Figure 4.1 gives an overview of the establishment of the used ESG index (Refinitv Eikon, 2020). Finally, the input of firm systematic risk was measured using the annual company Beta value calculated from 3 years of weekly data, this input was denoted as RISK in this research (Dorfleitner & Grebler, 2022; Gallardo-Vázquez et al., 2019; Hoepner et al., 2022; Jo & Na, 2012).

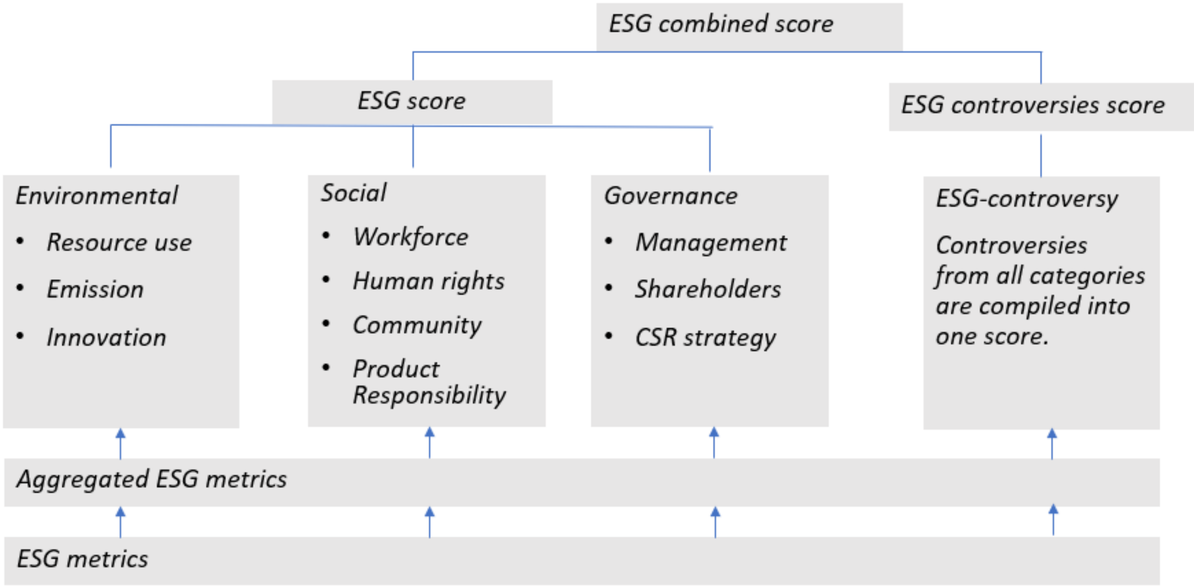

Figure 4.1. Establishment of ESG scores, as delineated in this study (Refinitiv Eikon, 2020).

In this research, the explanatory variables were examined and, if necessary, transformed to the appropriate application as explanatory variables in a bootstrap truncated regression. With regards to firm *Leverage*, the most common measurement in literature was total liabilities divided by total assets (Benlemlih & Bitar, 2018; Engida et al., 2020; Kapelko, Oude Lansink, & Guillamon-Saorin, 2021). *Size* is measured as the natural logarithm of the total assets of the firm and is widely applied in regression literature (Engida et al., 2022b; Engida et al., 2020; Kapelko et al., 2021). *R&D* was noted as R&D expenses to total sales ratio (Benlemlih & Bitar, 2018; Engida et al., 2020; Kapelko & Oude Lansink, 2022). *The age* of the firm is measured by the natural logarithm value of the number of years between the founding year and the fiscal year (Benlemlih & Bitar, 2018; Chincarini et al., 2020; Maside-sanfiz et al., 2020). *Tobin's Q* has been used as outlined in the research of Engida et al. (2022b) and thus remained unchanged.

The descriptive statistics for the period 2016-2021 have been presented in Table 4.1. This Table includes descriptive statistics, such as the mean, standard deviation, minimum, and maximum values, for both the explanatory variables as well as the input-output variables of both U.S. and European corporate manufacturing firms. The European dataset comprises a total of 738 observations, whereas the U.S. dataset encompasses 846 observations. Notably, the U.S. shows a substantially higher variation in RISK, ROA, and ESG values. Further, it is visible that European firms, on average, have a lower ROA, a higher ESG performance and a lower RISK in comparison to the U.S. Moreover, the data indicates that U.S. firms, on average, carry a higher level of debt in contrast to their European counterparts. Nevertheless, U.S. manufacturing firms have a lower level of variation in debt. The descriptive statistics indicate that European manufacturing firms, on average, appear to be larger and more mature than U.S. manufacturing firms. This observation is accompanied by higher standard deviation, signifying greater variability in both *size* and *age* among European manufacturing firms. The U.S. manufacturing firms have a higher mean *Tobin's Q* and a larger variation in this ratio.

Table 4.1. Descriptive statistics for RISK, ROA, ESG, and the explanatory variables for U.S. and European manufacturing firms.

Region	*Variable*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
U.S.	*ROA*	0.0834	0.0400	-0.0067	0.3028
(n=141)	*ESG*	58.453	17.682	8.5880	94.5730
	RISK	1.1562	0.4462	0.01636	2.8668
	Explanatory variables				
	Leverage	0.3288	0.1331	0	1.1791
	Age	1.5544	0.3369	0.6021	2.1399
	Size	9.991	0.5337	8.5590	11.5020
	Tobin's Q	1.5930	1.1721	0.1170	9.5130
Europe	*ROA*	0.0720	0.0352	0.0066	0.2360
(n=123)	*ESG*	72.5000	13.8856	24.8900	95.5900
	RISK	1.0151	0.3607	0.1021	2.5900
	Explanatory variables				
	Leverage	0.2417	0.1071	0.0002	0.5505
	R&D	4.2520	5.0065	0	28.7310
	Age	1.7563	0.3857	0.8451	2.5211
	Size	10.049	0.5846	8.8850	11.481
	Tobin's Q	1.4154	1.0044	0.1270	8.9400

4.2 Empirical model

This chapter discusses the methodological approach applied in this research following Simar and Wilson's two-step efficiency analysis in which first, the input-output oriented directional efficiency scores are calculated according to the methodology of Färe & Primont (2006), which are followed by a single bootstrap truncated regression from the theory of Simar & Wilson (2007).

4.2.1 Efficiency analysis with classical Data Envelopment Analysis

In this research, the non-parametric method of Data Envelopment Analysis was applied to measure the efficiency of multiple inputs and outputs (Farrell, 1957). The core theory behind DEA is to assess the efficiency of DMUs by quantifying how well inputs are converted into outputs (Bogetoft & Otto, 2011). DMUs that are positioned on the efficient frontier are labelled as efficient DMUs, while DMUs below the frontier are considered inefficient, the efficient DMUs form the peers for the inefficient DMUs (Coelli et al., 2005). In DEA, efficiency is usually measured by the distance to the frontier with values between 0, not technically efficient, and 1, technically efficient (Charnes et al., 1978). Within

DEA, multiple orientations exist. These orientations examine how the efficiency of DMUs changes as inputs and outputs are used on a larger or smaller scale. In DEA, the main scale options are constant returns to scale (CRS), which indicates an unchanged efficiency regardless of the operations scale and variable returns to scale (VRS), varying efficiency depending on the scale of operations (Thrall & Banker, 1992). This research applies VRS as it considers the differentiation of scale efficiency.

4.2.2 The Directional Distance Function in DEA

The classical CRS model of Charnes et al. (1978) and the VRS model of Banker et al. (1984) were developed under the assumption that the data of inputs and outputs should be non-negative. Furthermore, the CRS DEA models' underlying assumption that any component of an efficient unit is also efficient only holds for positive data (Portela et al., 2004). Similarly in the VRS model, when applying negative data, a positive movement to the frontier can in the case of negative data expand the negative output in a negative direction, which is not desired.

In this research, negative data was observed for the variables ROA and RISK. The directional distance function of Chambers et al. (1998) was implemented to obtain input-output inefficiency scores that were used for benchmarking DMUs despite the presence of negative values. The implementation of a directional vector caused the slacks to go in a desired positive direction towards the efficient frontier. Inefficiency is, therefore, expressed as the improvement that can be made for each DMU in terms of RISK, ROA, and ESG. In this research, this inefficiency is defined as the overall inefficiency, θ_i for all DMUs, $i = \{1, \ldots, n\}$. In DEA with a directional distance function (DDF), inefficiency is depended on the directional vector (Bogetoft & Otto, 2010). In this analysis, the direction was based on the average annual values of RISK (g_x), ROA (g_{y1}) and ESG (g_{y2}), forming an annual directional vector $V = (g_x, g_{y1}, g_{y2})$ (Bogetoft & Otto, 2010; Engida et al., 2020; Minvielle et al., 2008; Simar, Vanhems, & Wilson, 2012).

An input-output orientation of the DDF with VRS was applied in the empirical application since both inputs and outputs could be improved. For this, the package 'Benchmarking' of Bogetoft & Otto (2022) in the software program R studio was installed and applied. This package allowed for a simultaneous reduction of input risk and expansion of outputs ROA and ESG-score with the same value of θ_i times the direction of the directional vector (Bogetoft & Otto, 2011). The model of the VRS range directional distance function can be formulated as in model 4.1:

$$\vec{D}(y_1, y_2, x; g_{y1}, g_{y2}, g_x) = \tag{4.1}$$

$$\sup\{\theta_i : (\mathrm{x} - \theta_i g_x, y_1 + \theta_i g_{y1}, y_2 + \ g_{y2}) \in V(y_1, y_2)$$

Where, $V(y_1, y_2)$ is a production function where x produces y_1, y_2, in which x is a vector of inputs, y_1 and y_2 are vectors of outputs (Färe & Primont, 2006). $\theta_i$represents the overall inefficiency. This model is applied for each firm-year for both the U.S. and European manufacturing firms**.**

For interpretation of the DDF, the translation property ensures that inputs are scaled down, or outputs are scaled up without changing their proportions. The inefficiency score remains constant along the same direction of the vector (Portela et al., 2004). The overall inefficiencies are proportional measures of improvement. The latter makes the inefficiency measures suitable for benchmarking. The input-output oriented DDF can be illustrated according to the theory of Färe & Primont (2006). In Figure 4.2, a one-input, one-output case is illustrated where the θ_i represents the measure of how far x_1 and y_2 must be projected along (g_x, g_{y2}) to reach the efficient VRS frontier.

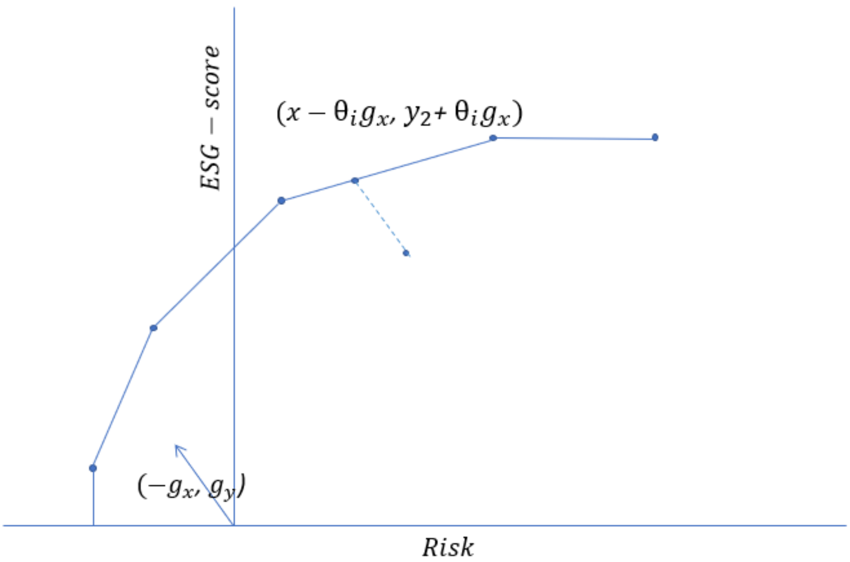

Figure 4.2. Graphical representation of the directional vector in the case of RISK- and ESG inefficiency.

In order to generate specific inefficiency estimates for RISK, ROA, and ESG, the overall inefficiency (θ_i) was calculated for each firm as mentioned above. This overall inefficiency was then multiplied by the corresponding mean directional vector for RISK, ROA, and ESG. Resulting in a new vector representing each firm's potential improvement in the direction of the efficient frontier in terms of RISK, ROA, and ESG metrics. To obtain relative efficiency estimates, these potential improvements were normalized by dividing them by the actual, realized values of RISK, ROA, and ESG for each firm. This resulted in annual RISK, ROA and ESG-specific inefficiencies suitable for analysis (Färe & Primont, 2006). The following equations were applied to calculate specific inefficiencies related to RISK, ROA, and ESG for each firm i. For RISK specific inefficiency equation 4.2 holds:

$$RISK\ specific\ inefficiency\ (i)\ = \frac{\theta_i * g_x}{x} \quad (4.2)$$

In which θ_i is the value of the overall inefficiency for firm i, as calculated in model 4.1, g_x indicates the average annual value of RISK of all DMUs $i = \{1, \dots, n\}$, and x is the realized value of RISK for firm i.

$$ROA\ specific\ inefficiency\ (i)\ = \frac{\theta_i * g_{y1}}{y1} \quad (4.3)$$

In equation 4.3, the ROA-specific inefficiency is given, g_{y1} indicates the average annual value of ROA of all DMUs $i = \{1, \dots, n\}$, and y_1 denotes the realized value of Return on Assets for firm i . The ESG-specific inefficiency is given in equation 4.4, in which, g_{y2} is the average annual value of ESG of all DMUs $i = \{1, \dots, n\}$, whereas y_1 denotes the realized value of ESG for firm i.

$$ESG\ specific\ inefficiency\ (i)\ = \frac{\theta_i * g_{y2}}{y2} \quad (4.4)$$

The above-mentioned equations to calculate specific inefficiencies were separately applied for all firm years 2016-2021 for each U.S. and European manufacturing firm.

4.2.3 Single bootstrap procedure

Following up the gathering of overall inefficiency measures for 2016-2021 for each of the U.S. and Europe, the single bootstrap procedure of Simar & Wilson (2007) (Algorithm 1) was applied as theoretically formulated in equation 4.5. In this analysis, the dependent variable of overall inefficiency (expressed in 4.5 as θ_i) was regressed against a vector of z_{it} explanatory variables in order to identify a vector of coefficients for each predictor. In this model, the α is the constant and the error term ε_i was assumed to be normally distributed with parameters $\mu = 0$ and σ and left-truncated at zero (Zhu & Lansink, 2022). With the truncated bootstrap regression analysis, the hypotheses in section 3.5 of this research were tested for the U.S. (Equation 4.6) and the European (Equation 4.7) sample.

$$\theta_i = \alpha + \beta\, z_{it} + \varepsilon_i \quad (4.5)$$

$$\theta_{iUS} = \beta_0 + age\beta_1 + size\beta_2 + leverage\beta_3 + Tobin\beta_4 + \varepsilon_i \quad (4.6)$$

$$\theta_{iEU} = \beta_0 + age\beta_1 + size\beta_2 + leverage\beta_3 + R\&D\beta_4 + Tobin\beta_4 + \varepsilon_i \quad (4.7)$$

The R-studio 'truncreg' package was installed to run the bootstrap truncated regression of the first algorithm of Simar and Wilson (2007). The steps of the algorithm are described below:

1. Compute θ_i for all DMUs, $i = \{1, \dots, n\}$ using DEA.
2. Use those m (with $m < n$) DMUs for which θ_i > 0 holds in a truncated regression (left truncation at 0) of θ_i on z_i to obtain coefficient estimates $\hat{\beta}$ and an estimate for variance parameter $\hat{\sigma}$ by maximum likelihood.

3. Loop over the following steps 3.1–3.3 B times to obtain a set of B bootstrap estimates $(\widehat{\beta^b}, \widehat{\sigma}^b)$, with $b = 1, \dots, B$.
   3.1. For each DMU $i = 1, \dots, m$, draw an artificial error $\tilde{e}_i$ from the truncated $N(0, \hat{s})$ distribution with left truncation at $1 - z_i\widehat{\beta}$.
   3.2. Calculate artificial efficiency scores as $\tilde{\theta}_i$ as $\boldsymbol{z_i}\widehat{\beta} + \tilde{e}_i$ for each DMU $i = 1, \dots, m$
   3.3. Run a truncated regression (left-truncation at 1) of $\tilde{\theta}_i$ on z_i to obtain maximum-likelihood bootstrap estimates $\widehat{\beta^b}$, and $\widehat{\sigma}^b$.
4. Calculate confidence intervals and standard errors for $\widehat{\beta}$ and $\widehat{\sigma}$ from the bootstrap distributions of $\widehat{\beta^b}$ and $\widehat{\sigma}^b$.

In these steps, Step 2 continued with identifying inefficient units and removing all efficient DMUs, as this bootstrap truncated regression solely focused on inefficiency. DMUs that are deemed inefficient and have a value of $\theta_i > 0$, truncated since inefficiencies cannot be less than 0.

The objective of this step is to retain the estimates of the parameter's $\widehat{\beta}$ (estimated regression coefficients) and $\widehat{\sigma}$, which indicated the difference between observed inefficiency and the inefficiency predicted by the model's explanatory variables. These estimates were thereafter used for the execution of the bootstrap procedure in step 3 of Simar and Wilsons's algorithm (2007).

The uncertainties associated with the maximum likelihood estimation were derived in this bootstrap procedure. Step 3.1 generated a random sample from the random sample distribution. In Step 3.2, new inefficiency scores were generated, which were later utilized in Step 3.3 to estimate the model's $\widehat{\beta^b}$, and $\widehat{\sigma}^b$. Steps 3.1 to 3.3 was iterated 2000 times, as recommended by the literature of Simar and Wilson (2007). Upon completion of the bootstrap procedure, the model calculated the means of the bootstrapped parameters. These means represented the final bootstrap coefficient estimates. Furthermore, the bootstrap confidence intervals were computed, which provided a range of plausible values of the explanatory variables that eventually determined the confidence intervals for all coefficients.

5. Results and discussion

In this section, we first present and compare the overall inefficiency values, RISK-specific inefficiencies, ROA-specific inefficiencies, and ESG-specific inefficiencies for both the U.S. and European manufacturing firms' samples. Thereafter, the bootstrap-truncated regression analysis results are provided to explain sources of variation in overall inefficiencies.

5.1 Inefficiency estimates

The specific inefficiency values related to RISK, ROA and ESG have been obtained for each year in the period 2016-2021. These results were generated under the assumption of variable returns to scale (VRS). Furthermore, Table 5.1 also provides the overall inefficiency (Färe & Primont, 2006).

The results of Table 5.1 show that U.S. manufacturing firms, on average, could improve their overall RISK, ROA and ESG performance with 38.72%, while European manufacturing firms, on average, could improve their overall performance with 21.33%. The results also reveal that in the U.S., the overall inefficiency gradually reduces over time. This is not the case for the sample with European manufacturing firms.

Table 5.1. Overall inefficiency and RISK, ROA, and ESG-specific inefficiencies in the U.S. and Europe for the period 2016-2021.

	U.S.				*Europe*			
Year	*Overall inefficiency*	*RISK*	*ROA*	*ESG*	*Overall inefficiency*	*RISK*	*ROA*	*ESG*
2016	0.4785	0.4629	0.6361	0.6662	0.2418	0.2497	0.3187	0.2924
2017	0.4203	0.4058	0.5428	0.5664	0.2418	0.2260	0.2749	0.2552
2018	0.3589	0.3477	0.4704	0.4968	0.2203	0.1966	0.2470	0.2228
2019	0.3841	0.3767	0.5091	0.5397	0.2057	0.2084	0.2606	0.2360
2020	0.3633	0.3472	0.5895	0.4865	0.2168	0.2297	0.3254	0.2502
2021	0.3181	0.3116	0.4781	0.4055	0.2022	0.2119	0.2619	0.2314
2016-2021	0.3872	0.3753	0.5377	0.5268	0.2133	0.2204	0.2814	0.2480

In addition to a general measure of inefficiency, the RISK-, ROA-, and ESG-specific inefficiencies were calculated. In this way, the inefficiency for RISK, ROA and ESG were expressed as relative improvement in terms of input reduction and output expansion (Portela et al., 2004). This facilitated the utilization of inefficiency values to benchmark these DMUs. Results show that U.S. and European manufacturing firms perform best in terms of RISK and perform the worst in terms of ROA followed by ESG.

Regarding the RISK variable, U.S. manufacturing firms could, on average, reduce their RISK by 37.53% while European manufacturing firms could reduce their RISK by 22.04% of the average annual value of RISK. In terms of ROA, from 2016 to 2021. U.S. manufacturing firms could, on average, improve their

ROA value by 53.77% while European firms could improve, on average, this ROA value with 28.14%. Notable is the ROA difference in fiscal year 2020 compared to the previous and subsequent years for both European and U.S. manufacturing companies. One possible rationale can be attributed to the global economic disruptions stemming from the COVID-19 pandemic, as explored by Demirhan & Sakin (2021).

For ESG-specific inefficiency, U.S. manufacturing firms, on average, could improve their ESG scores with 52.68% of the average annual value of ESG. In contrast, European firms show a comparatively lower potential for improvement with a value of 24.80%. As a comparison, Kapelko & Oude Lansink (2022), measured a CSR-specific inefficiency of 37.7% for the U.S. food and beverage manufacturing firms sample whereas, Kapelko et al. (2021) found an inefficiency of the socially responsible output of 19.5% of the value of the directional vector in a European sample of the capital, consumption, and other industries. Divergence in terms of ESG-specific inefficiencies may be attributed to differences between sectors, furthermore, dissimilarities in ESG policy requirements like the Corporate Sustainability Reporting Directive (CSRD) also play a significant role in this divergence (Baumüller & Grbenic, 2021; European Commission, 2018). In the research of Cicchiello et al. (2023), a difference-in-difference analysis between U.S. and European firms in the period of 2015-2020, pointed out that the implementation of regulations that focussed on the increase of transparency of the ESG performance has resulted in an improvement in ESG commitment and effectiveness.

The findings of the specific inefficiencies related to RISK, ROA, and ESG and the overall inefficiency reveal that U.S. manufacturing firms exhibit a significantly higher average level of inefficiency across all dimensions. This seems to be in line with the research of Engida et al. (2020), which identified that network-oriented systems (Germanic and Latin) tend to be more socially responsible than market-oriented systems (Anglo-Saxon). This phenomenon was attributed due to more robust stakeholder networks in network-oriented systems, which eventually resulted in more stakeholder involvement in managerial decision-making. Nevertheless, it is important to keep in mind that roughly 16% of the manufacturing firms in the European sample in this thesis consisted of United Kingdom manufacturing firms which belong to the network-oriented system type. Therefore, this research cannot confirm earlier research on the divergence in the inefficiency-CSR association, which differed between network- and market-oriented systems.

It must be noted that the possible presence of unnoticed outliers may also have led to the increased variability by affecting inefficiency results positively. If the U.S. dataset had more outliers in comparison to the European dataset, possibly leading to greater variability, this could have potentially contributed to an increased mean inefficiency, and via this way, negatively influenced the robustness of the research findings.

5.2 Bootstrap truncated regression

This chapter displays the findings of the regression model to test the association between inefficiency and the explanatory variables *age*, *size*, *leverage*, *R&D* and *Tobin's Q*, for U.S. and European manufacturing firms. Drawing upon relevant literature aims to provide insights in the relationships and assess them in the context of the hypothesis formulated in section 3.5.

Appendix Table 1 contains a correlation matrix of environmental variables to control for multicollinearity among the covariates. The correlation coefficients between the independent covariates for each year ranged between -0.3650 and 0.2666, indicating no correlation between the predictors and, thus, there is no sign of collinearity (Field, 2005). Table 5.2 displays the bootstrap truncated regression coefficient and their associated significance levels for the U.S. and European manufacturing firms over the period 2016-2021.

Table 5.2. Bootstrap Truncated Regression Coefficients and the robustness of the coefficients.

	2016	*2017*	*2018*	*2019*	*2020*	*2021*
U.S.						
Constant	*3.4415***	*2.8439***	*3.2635***	*3.5498***	*3.5715***	*3.3958***
Age	-0.1629**	-0.0978	-0.1166*	-0.1874**	-0.1403*	-0.1495**
Size	-0.2510**	-0.2009**	-0.2626**	-0.2775**	-0.2896**	-0.2771**
Leverage	-0.0209	-0.2686	0.0019	0.0126	-0.0004	-0.0331
Tobin 's Q	-0.1601**	-0.1356**	-0.0970**	-0.0738**	-0.0761**	-0.0339**
Europe						
Constant	2.2541**	1.5577**	1.5414**	1.9165**	1.8064**	1.3394**
Age	-0.0207	-0.0164	0.0394	-0.0064	-0.0046	-0.0086
Size	-0.1939**	-0.1269**	-0.1366**	-0.1622**	-0.1556**	-0.1096**
Leverage	0.0784	0.0119	0.0343	-0.0666	-0.0586	0.0466
R&D	-0.0007	-0.0021	-0.0075*	-0.0061*	-0.0009	-0.0032
Tobin 's Q	-0.0613*	-0.0353	-0.0461*	-0.0305	-0.0147	-0.0098

* and ** indicate statistical significance at the 5%, and 1% levels, respectively.

A consistently significant coefficient for *age* exists in the U.S. across all years except for 2017. Taking only the significant results into account, it can be concluded that an increase of firm ag*e* with 1% is associated with a decrease in overall inefficiency between 0.1166 and 0.1874 units, *ceteris paribus*. Based on this, $\boldsymbol{H_1}$, which suggests that more mature corporate manufacturing firms have a lower overall inefficiency, is confirmed for all U.S. firm years with exception of 2017. This finding aligns with the expectations of Benlemlih & Bitar (2018), who suggested that more mature firms are more experienced, causing increased efficiency. The research of Ahmed et al. (2021) investigated the effect of different firms in business cycle stages on investment efficiency. Their results indicated similarly that firms in a mature business stage are positively associated with investment efficiency. In the European sample, no statistically significant association was identified between *Age* and overall inefficiency, leading to the rejection of $\boldsymbol{H_1}$ in the European manufacturing firm sample. Possible clarifications may be the smaller sample size of the European sample or a difference between the effect of age on inefficiency between the U.S. and Europe.

Concerning the impact of firm *size* on inefficiency, the significance of all firm years in both the U.S. and Europe is evident at a significance level of 1%. The results reveal a consistent pattern: on average, for every 1% increase in *size*, we can expect inefficiency to decrease by approximately 0.2009-0.2896 units in the U.S. and 0.1096-0.1939 units in Europe, *ceteris paribus*. This result lends substantial support to the hypothesis $\boldsymbol{H_2}$, which suggests that larger corporate manufacturing firms are associated with a lower overall inefficiency. This observation validates the economies of scale theory of Schiersch (2013), indicating that larger firms exhibit lower inefficiency. This result is in line with Kapelko & Oude Lansink (2014), who suggest that larger firms can more efficiently transform inputs into outputs. Furthermore, through a stakeholder theory framework, Artiach et al. (2010) indicated that an increase in firm size resulted in more public pressure to operate sustainably; this was substantiated in the research of Engida et al. (2020. This research found a negative coefficient for the association of ESG with inefficiency. It must be noted that the latter approach was applied in cases where solely ESG-specific inefficiency was considered. Still, this theory can partly influence this research's' results through the ESG aspect in the overall inefficiency. In the research of Kapelko & Oude Lansink (2022), a more broader perspective on inefficiency was taken. The results of their latent class analysis revealed that *size* was associated with the high-performance class which was characterized by not only high CSR, but also investment efficiency and the most beneficial scores for input- output efficiencies.

In Table 5.2, the *leverage* coefficients did not show a significant value, indicating no significant association between *leverage* and overall inefficiency. Furthermore, the *leverage* coefficients fluctuated between negative and positive, suggesting that no apparent positive or negative association between *leverage* and overall inefficiency was present for both the U.S. and the European manufacturing sample. This has led to the rejection of hypothesis $\boldsymbol{H_3}$. This means that the agency theory cannot be linked to the association of *leverage* with the overall inefficiency in this research. The results are opposed to Engida, et al. (2022) papers, which stated that an increased *leverage* resulted in less mitigation of undesirable CSR outputs (e.g., greenhouse gas emission). Furthermore, Kapelko & Oude Lansink (2014) and Engida et al. (2020) found a significant negative coefficient of the association between *leverage* and technical inefficiency. This finding opposes the current results. Also, Kapelko & Oude Lansink (2022) found a negative association between *leverage* and high CSR, investment efficiency, and the most beneficial scores for inputs and outputs.

In contrast, the Modigliani and Miller theory suggests an optimal level of leverage, implying a non-linear inverted U-shaped relationship between total leverage and efficiency (Modigliani & Miller, 2013). In the research of Guo et al. (2021), the results indicated that firms with an optimal capital structure achieve high efficiency. To address this, quantile regression analysis may have been more appropriate to assess this effect, as Margaritis & Psillaki (2007) stated. Quantile regression helps to understand how different parts of a dataset (quantiles) respond to changes in predictor variables. This approach goes beyond the average linear relationship applied in this research and may reveal significant results when applied on the dataset (Li & Hwang, 2011). Regarding *R&D,* only the European manufacturing firms' sample was investigated. The results of this sample indicated a negative association between R&D intensity and the overall inefficiency for only two specific firm years, namely, 2018 with a coefficient of -0.0075 and 2019 with a coefficient of -0.0061, both statistically significant at a confidence level of 5%. This result means that an increase in R&D intensity with 1 unit is associated with a reduction of the overall inefficiency between 0.0075 units in 2018 and 0.0061 units in 2019, *ceteris paribus*. This partially confirms $\boldsymbol{H_4}$ for the firm years 2018 and 2019, thereby providing evidence that R&D intensity is negatively associated with overall inefficiency in corporate manufacturing firms. Engida et al. (2020) found, similarly, that an increased R&D intensity reduced the inefficiency more related explicitly to undesirable CSR outputs. A possible explanation for the limited significance in this research may results from the inclusion of systematic risk in the overall inefficiency. The analysis of Ho et al. (2004) identified R&D as a factor increasing systematic risk. This may have resulted in a limited association between R&D intensity and overall inefficiency in this research. Another clarifier for the yet limited relationship in the insignificant years may be based on the fact that R&D does not always lead to an immediate performance stimulation in the same firm year due to R&D projects that may take multiple years. Furthermore, in some cases, R&D investment may lead to an increased risk and lower returns in the short term (Chang, Li, & Gao, 2016).

As far as concerning *Tobin's Q*, all years 2016-2021 indicate that an increase in Tobin's Q with 1 unit is significantly (α=0.01) associated with an average decrease of inefficiency between 0.0339-0.1601 units in the U.S., *ceteris paribus*. This gives rise to accept $\boldsymbol{H_5}$ for all firm years in the U.S. In Europe, this rate only found significance (α=0.05) in 2016 and 2018, with varying coefficients ranging between 0.0461-0.0613. Therefore, the hypothesis $\boldsymbol{H_5}$ is only accepted in Europe for the firm years 2016 and 2018. In the paper of Parmeter et al. (2022), a positive association between Tobin's Q and investment efficiency was identified. The research of Ahmed et al. (2021) that performed an OLS regression also identified a positive regression coefficient when investigating the association between Tobin's Q and investment efficiency. The current research confirms the Q-theory for all years in the U.S. and only two firm years in Europe, suggesting that a high Tobin's Q is associated with effective capital allocation that can boost a firm's efficiency (Benlemlih & Bitar, 2018). A notable observation is the gradual reduction of the regression coefficient for Tobin's Q over time in the U.S. sample. This phenomenon can be potentially attributed to the decrease of the overall inefficiency over time. Yet it is essential to consider the presence of a time lag that may elapse between a change in Tobin's Q and the effect on inefficiency, which is denoted in the research of Parmeter et al. (2022), in which investment inefficiency is measured.

6. Limitations & Further research recommendations

Firstly, in this paper, the measurement method for ESG was based on Refinitiv Eikon data. Dorfleitner et al. (2015) indicated in their article that various measurement methods of CSR exist. They further highlight the caution that is necessary to critically evaluate each of the ESG scoring models and the comparability of these models. Second, technical inefficiency typically serves as a relative metric between DMUs. Table 2.1 has highlighted several different efficiency analysis approaches applied in the context of ESG, including DEA, SFA, and a directional distance function in DEA (Engida et al., 2022; Engida et al., 2020; Guillamon-Saorin et al., 2018). The variety of methodological approaches in literature may lead to divergent outcomes of (in)efficiency scores. This variety limits the comparability of inefficiency scores of efficiency papers identified in the literature review and thus limits the ability to benchmark the results of this analysis.

Another constraint of this research is the robustness of the inefficiency scores. This research applied Algorithm 1 of Simar and Wilson (1998). This entailed no bias correction on the non-parametric computation of the overall inefficiency estimates. The lack of bias correction has made the current results sensitive to outliers and sample variation (Simar & Wilson, 1998). In the research of Kapelko & Oude Lansink (2014) the bias-corrected efficiencies showed lower efficiencies. The bias-corrected inefficiency scores may have provided a more accurate representation of the actual inefficiencies among U.S. and European manufacturing firms (Badunenko & Tauchmann, 2019). In subsequent research, bias issues due to statistical noise can be addressed by applying a double bootstrap truncated regression to correct inefficiency values. This should help to provide a more accurate view on realized inefficiency values.

Another limitation in this research relates to the specific RISK, ROA and ESG inefficiency measures which were derived from the overall inefficiency. The overall inefficiency represents a scalar unit indicating the degree of improvement each DMU could achieve regarding RISK, ROA, and ESG. This limitation has led the bootstrap truncated regression only to analyse the association between overall inefficiency and the identified explicative variables, instead of a more specific analysis focusing on the association between each specific inefficiency and the identified explicative variables. In further research, each RISK-, ROA-, and ESG-specific inefficiency can be regressed against the explanatory variables, including R&D for the U.S. sample. This should provide more accurate effects of the covariates on each of these input and output parameters and gain more precise associations.

In this research the value of the overall inefficiency is strongly dependent upon the direction in which the efficiency improvement (vector) is aimed. The direction of the directional vector is based on mean values of RISK, ROA, and ESG; therefore, efficiency values are dependent on these mean values

(Vardanyan & Noh, 2006). Skewness and outliers may have influenced the vector's direction and thus may have affected the inefficiency estimates.
Another constraint of this research pertains to the lack of causality between inefficiency and the explanatory variables. In this research no direct causality was established. A possible extension of this research can be the application of methods that better establish causality between inefficiency and the explanatory variables. In further research, extending the research with a fixed effects panel model should help to establish significant causality between the explanatory variables and the inefficiency scores.

To conclude, in Chapter 2.3, sectorial dissimilarities have been found to be influencing the relationship between ESG, financial performance and efficiency. The research sample in this study was constrained in size, thereby precluding an assessment of sectorial dissimilarities due to inadequate sample sizes per industry type. The specific industries within the manufacturing firms' sample can be considered as explanatory variables to investigate whether these may influence inefficiency. In further research an extended sample of U.S. and European manufacturing firms can take these sectorial differences into account and may give firms in different industries more specific knowledge.

7. Conclusion

This paper extends the classical mean-variance approach of stock performance, which focuses solely on risk and return by integrating ESG as a performance measure. This performance is measured by integrating RISK, ROA, and ESG into an overall measure of inefficiency and specific measures of inefficiency in these three terms. The literature revealed a mixed relationship between ESG factors and different types of risk. Various studies revealed that ESG factors can enhance accounting and market-based performance. In the literature review, firm *Age*, firm *Size*, *Leverage*, *R&D intensity*, and *Tobin's Q* were identified as explanatory variables for inefficiency. The empirical analysis focussed on a sample of U.S. corporate manufacturing firms and a European sample of corporate manufacturing firms, both over the period of 2016-2021. Based on the directional distance function approach in DEA, the results revealed that U.S. manufacturing firms are more inefficient in all terms (RISK, ROA, and ESG-specific and overall inefficiency). European manufacturing firms show a lower level of inefficiency and perform best in terms of overall and RISK-specific inefficiency.

To analyse the association between overall inefficiency and the explicative variables, for the U.S. sample, *Age*, *Size*, and *Tobin's Q* were significantly found to be negatively associated with overall inefficiency. *Leverage* showed no sign of significance. For the European manufacturing firm sample, *Size* was negatively associated with inefficiency for all years, whereas Tobin's Q was negatively associated with inefficiency in 2016 and 2018. *R&D intensity* was negatively associated with inefficiency in the European sample in 2018 and 2019. *Leverage* and *Age* showed no sign of a statistically significant relationship in Europe.

8. Business implications

Investors and business managers could utilize the results of this study. For example, managers can compare their firms' inefficiency with the findings of this research and, consequently, benchmark their current performance to seek areas of improvement of ESG. Due to the relatively high inefficiency in U.S. manufacturing firms, managers of U.S. firms must consider whether improvements can be made in terms of RISK, ROA, and ESG. Based on these results, managers may want to focus on exploiting economies of scale (especially smaller manufacturing firms) and stimulate further development in the business cycle. Furthermore, improving a firm's R&D intensity may help to enhance the firm's overall efficiency via a CSR way. As a higher Tobin's Q is associated with a reduction in inefficiency, managers should improve this ratio when making business decisions that aim to reduce inefficiency, especially U.S. firms.

For investors with an additional focus on ESG can utilize the results to decide how to compose their investment portfolio. CSR investors can focus on the firms with low ESG-specific or overall inefficiency in case they take a broader approach than solely CSR. In addition, it may be beneficial for CSR investors to consider the factors associated with overall inefficiency and focus more on including European manufacturing firms in their portfolios.

9. References

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10. Appendix

Appendix table 1, Correlation matrix of the explanatory variables 2016-2021 for the U.S. and for Europe.

2016 Europe	*Age*	*Tobin*	*R&D*	*Leverage*	*Size*		*2016 US*	*Age*	*Tobin*	*Leverage*	*Size*
Age	1	-0.1432	-0.3650	0.1543	-0.1936		*Age*	1	0.1111	-0.1409	0.2286
Tobin	-0.1432	1	0.1542	-0.1445	-0.1706		*Tobin*	0.1111	1	-0.1617	-0.0832
R&D	-0.3650	0.1542	1	0.117	0.1693		*Leverage*	-0.1409	-0.1617	1	0.061
Leverage	0.1543	-0.1445	0.117	1	-0.1122		*Size*	0.2286	-0.0832	0.061	1
Size	-0.1936	-0.1706	0.1693	-0.1122	1						
2017 Europe	Age	Tobin	R&D	Leverage	Size		*2017 US*	Age	Tobin	Leverage	Size
Age	1	-0.1375	-0.1437	-0.1169	0.1461		*Age*	1	0.0568	-0.0448	0.2666
Tobin	-0.1375	1	0.1667	-0.1492	-0.3459		*Tobin*	0.0568	1	-0.1122	-0.0691
R&D	-0.1437	0.1667	1	-0.0976	0.1059		*Leverage*	-0.0448	-0.1122	1	0.1241
Leverage	-0.1169	-0.1492	-0.0976	1	0.1438		*Size*	0.2666	-0.0691	0.1241	1
Size	0.1461	-0.3459	0.1059	0.1438	1						
2018 Europe	Age	Tobin	R&D	Leverage	Size		*2018 US*	Age	Tobin	Leverage	Size
Age	1	-0.0983	-0.2985	0.2105	-0.119		*Age*	1	0.1021	-0.072	0.2494
Tobin	-0.0983	1	0.1395	-0.1123	-0.1374		*Tobin*	0.1021	1	-0.1602	0.0079
R&D	-0.2985	0.1395	1	0.1265	0.1165		*Leverage*	-0.072	-0.1602	1	0.1019
Leverage	0.2105	-0.1123	0.1265	1	-0.0634		*Size*	0.2494	0.0079	0.1019	1
Size	-0.119	-0.1374	0.1165	-0.0634	1						
2019 Europe	Age	Tobin	R&D	Leverage	Size		*2019 US*	Age	Tobin	Leverage	Size
Age	1	-0.1166	-0.2366	0.209	-0.1172		*Age*	1	0.0893	-0.025	0.2469
Tobin	-0.1166	1	0.1259	-0.1485	-0.1845		*Tobin*	0.0893	1	-0.1011	-0.0099
R&D	-0.2366	0.1259	1	0.1282	0.0928		*Leverage*	-0.025	-0.1011	1	0.1489
Leverage	0.209	-0.1485	0.1282	1	-0.063		*Size*	0.2469	-0.0099	0.1489	1
Size	-0.1172	-0.1845	0.0928	-0.063	1						
2020 Europe	Age	Tobin	R&D	Leverage	Size		*2020 US*	Age	Tobin	Leverage	Size
Age	1	-0.1271	-0.2192	0.0913	-0.1037		*Age*	1	0.0549	-0.0461	0.2526
Tobin	-0.1271	1	0.1241	-0.1114	-0.1235		*Tobin*	0.0549	1	-0.1092	0.0431
R&D	-0.2192	0.1241	1	0.1316	0.1633		*Leverage*	-0.0461	-0.1092	1	0.1552
Leverage	0.0913	-0.1114	0.1316	1	-0.0195		*Size*	0.2526	0.0431	0.1552	1
Size	-0.1037	-0.1235	0.1633	-0.0195	1						
2021 Europe	Age	Tobin	R&D	Leverage	Size		*2021 US*	Age	Tobin	Leverage	Size
Age	1	-0.1004	-0.1678	0.1257	-0.0953		*Age*	1	0.0371	-0.0032	0.2586
Tobin	-0.1004	1	0.1152	-0.1176	-0.1613		*Tobin*	0.0371	1	-0.1073	0.0141
R&D	-0.1678	0.1152	1	0.1519	0.1457		*Leverage*	-0.0032	-0.1073	1	0.1395
Leverage	0.1257	-0.1176	0.1519	1	0.0181		*Size*	0.2586	0.0141	0.1395	1
Size	-0.0953	-0.1613	0.1457	0.0181	1						