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Essays in Finance: Sustainability in Credit Risk, Carbon Risk and Portfolio Theory

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1 Introduction

In the ongoing and aggravating global climate crisis, the effects of the ecological disruption on firms, investors, and society as a whole have been studied extensively and are still being investigated in the current research. Recently, Stroebel & Wurgler (2021) conducted a survey study for finance scholars, practitioners, and regulators on climate finance, where the survey participants believe climate risk to be by far underestimated by asset markets and identify physical risks, such as increasing average temperatures or rising sea levels, as the top climate-related risk factor for investors over a time horizon of 30 years. Such risk assessment explains the increasing demand for green assets, which are expected to surpass a total volume of 41 trillion Dollars in 2022 (Bloomberg, 2022).

However, a large body of literature is divided on how green assets perform in comparison to non-green assets (see e.g., Bello, 2005; Galema et al., 2008), while most studies adhere to the theory of segmentation, which states that the segmentation between investors who seek ESG objectives and those who do not, leads in equilibrium to higher expected returns for non-green companies and sin stocks (Merton, 1987; Luo & Balvers, 2017). Furthermore, many studies question whether the firm performance is influenced by corporate social performance (CSP) (see e.g., Waddock & Graves, 1997; Donker et al., 2008).

This dissertation ties in with these theoretical considerations in the literature and consists of three diverse and independent essays, which all aim to contribute to a better understanding of sustainable finance and the effect of sustainable practices on firm performance and investor behavior. After this short introduction, the remainder will present detailed summaries of the individual essays and publication details.

The first part of this dissertation covers one chapter that deals with the question of how corporate social responsibility influences the firm's cost of capital, which is directly linked to firm performance. Oikonomou et al. (2012) show that firms with low ESG performance exhibit a higher systemic risk, which is in line with the findings of Albuquerque et al. (2018), where this conclusion is attributed to high ESG firms being faced with a relatively lesser price elastic demand. This relationship between ESG performance, the cost of capital, and firm risk suggests an association with corporate credit ratings. There is mixed evidence regarding the impact of ESG on credit ratings. While Seltzer et al. (2021) show that firms with low environmental scores have poorer credit ratings and higher yield spreads, similar to the findings of Oikonomou et al. (2014), Stellner et al. (2015) find no significant relationship between ESG performance and corporate credit ratings.

Chapter 2 investigates the connection between ESG performance and the probability of corporate credit default. By using a sample of 902 publicly-listed firms in the US from 2002 to 2017 and by converting Standard & Poor's credit ratings into default probabilities from rating transition matrices, we find the probability of corporate credit default to be significantly lower for firms with high ESG performance, indicating that ESG may induce lower credit ratings and thereby lower the firm's cost of capital. This result is robust to controlling for several firm characteristics, industry- and year-fixed effects. One main reason for using default probabilities from credit rating transition matrices instead of credit ratings as the dependent variable in our model specification is that credit rating classes are not equidistant, e.g., a change from rating B to BB significantly differs from AA to AAA. Furthermore, by expanding the time window in our regression analysis, we observe that the influence of ESG and its constituents strongly varies over time. We argue that these dynamics may be due to financial and regulatory shocks. In a sector decomposition, we additionally find that the energy sector is most influenced by ESG regarding the probability of corporate credit default, which is in line with its ongoing restructuring towards greener technologies (REN21, 2020).

The second essay of this dissertation only indirectly aligns with the ESG theme and deals with the volatility spillover effect for prices of European carbon allowance (EUA) futures. To efficiently tackle global warming, the European Union (EU) has implemented the world's most advanced cap-and-trade system for carbon allowances, the European Emissions Trading System (ETS), which sets an annually declining carbon allowance cap for the energy-producing and energy-intensive sectors. More stringent adjustments of the cap since phase three of the ETS in 2015 and an increasing demand for energy have tripled the EUA price to over 97€/t, hence inducing stark volatility in the market (European Central Bank, 2022). While EUA volatility spillovers have been analyzed with regard to energy-producing stocks, see e.g,. Ji et al. (2019), or oil, as in Reboredo (2014), we fill a gap in the literature regarding the spillover of EUA prices on the whole economy.

Chapter 3 analyzes the volatility spillover effect between prices of EUA futures and European stock market sectors. For this purpose, we employ the connectedness network model, which was first introduced by Diebold & Yilmaz (2009, 2012) and relies on vector autoregressions (VAR), to study the static and dynamic network connectedness as well as spillover effects for our sample of EUA futures and FTSE sector index prices from 2015 to 2022. In the static and dynamic setting, we find that carbon is mostly a recipient of volatility from the financial sector and key sectors in the ETS, namely the energy-producing and energy-intensive sectors, e.g., basic materials and utility. As a possible explanation for the transmission of volatility connectedness from stock market sectors to the EUA, we propose the demand for and supply of energy as a key factor, since e.g., an increase in demand for consumption may lead to a higher demand for energy and hence EUAs, driving the EUA price and volatility. Interestingly, while the EUA price is experiencing a steady increase since phase three of the ETS, the increasing production costs for key sectors in the ETS seemingly did not yet lead to a contagion effect on the European economy. Moreover, our sample covers the Covid-19 crisis, where energy-intensive industries were shut down by the governments, which decreased the demand for energy and EUAs, leading carbon to receive volatility from the market. Furthermore, during the recent European energy crisis, carbon further received volatility from various sectors. Our results hold for differing forecast parameters of the VAR and an alternative range-based volatility proxy, proposed by Parkinson (1980).

The third and last essay of this dissertation deals with the preference for sustainable assets of ethically motivated investors and bridges a gap between the segmentation theory for green assets and the classical portfolio theory. Currently, only a few studies present a practical guide for investors on how to incorporate sustainability into their portfolio choice (see e.g., Ballestero et al., 2012; Utz et al., 2014; Pedersen et al., 2021). However, one practical difficulty that remains is the estimation of an investor's preference for sustainable assets in the portfolio. While some approaches have been presented to optimize the sustainable portfolio selection problem (see e.g., Dorfleitner & Nguyen, 2016), the literature is mainly focused on portfolio allocation.

Against this background, **Chapter 4** investigates how an investor's preference for sustainable assets in the portfolio varies for differing levels of risk aversion. Using a sample of 411 publicly-listed firms in the S&P 500, we calculate financial and sustainability returns, on which the investor's utility depends. The sustainability returns are calculated as the logarithmic return of a firm's relative sustainability performance, proxied by ESG ratings. A positive sustainability return would reflect that the respective firm has increased its relative sustainability rating over one period, which is an indicator of a successful implementation of ESG-friendly business conduct and hence favorable for an ethically motivated investor. Analogously, a negative sustainable return either shows that a company suffered from misconduct, e.g., due to managerial controversies or environmental pollution, or that the company does not keep up with the market standards of ESG practices, e.g., when the overall ESG ratings of other companies increase. One main assumption in our model is that sustainability returns are stochastic, since it is ex-ante not possible to predict what good intentions of the management of a firm will be realized (Dorfleitner & Nguyen, 2016). We approximate the investor's preference by the exponential and s-shaped utility function and optimize with regard to the sustainability preference parameter, using an evolutionary algorithm. As we are not interested in finding the optimal portfolio allocation vector, we determine the minimum-variance and maximum Sharpe ratio portfolio, based on financial returns, and detect whether a risk-averse investor shifts from using financial returns to sustainability returns when the risk appetite varies. Our findings suggest that with increasing levels of risk aversion, both minimum-variance and maximum Sharpe ratio type investors seek to shift their preference towards sustainable returns in their portfolio. The results are robust to an alternative, additive utility function and show a similar behavior for both the exponential and s-shaped utility functions.

1.1 Publication Details

Paper I (Chapter 2):

Are Sustainable Companies More Likely to Default? Evidence from the Dynamics between Credit and ESG Ratings

Authors:

Aydin Aslan, Lars Poppe and Peter N. Posch

Abstract:

We investigate the relationship between environmental, social and governance (ESG) performance and the probability of corporate credit default. By using a sample of 902 publicly-listed firms in the US from 2002 to 2017 and by converting Standard & Poor's credit ratings into default probabilities from rating transition matrices, we find the probability of corporate credit default to be significantly lower for firms with high ESG performance. Furthermore, by expanding the time window in our regression analysis, we observe that the influence of ESG and its constituents strongly varies over time. We argue that these dynamics may be due to financial and regulatory shocks. In a sector decomposition, we additionally find that the energy sector is most influenced by ESG regarding the probability of corporate credit default. We expect an increasing availability of ESG data in the future to reduce possible survivorship bias and to enhance the comparison between ESG-rated and non-ESG-rated firms.

Publication Details:

Sustainability (2021), 13(15), 8568.

https://doi.org/10.3390/su13158568

Paper II (Chapter 3):

Does Carbon Price Volatility Affect European Stock Market Sectors? A Connectedness Network Analysis

Authors:

Aydin Aslan and Peter N. Posch

Abstract:

We investigate how the volatility of carbon emission allowance (EUA) prices affects European stock market sectors. We employ a connectedness network analysis on prices of EUA futures and FTSE stock market sector indices and find that the EUA is mostly a net receiver of volatility connectedness and significantly receives volatility across most sectors during the recent European energy crisis.

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Paper III (Chapter 4):

How Do Investors Value Sustainability? A Utility-Based Preference Optimization

Authors:

Aydin Aslan and Peter N. Posch

Abstract:

We investigate how an investor's preference for sustainable assets in the portfolio varies for differing levels of risk aversion. Using a sample of 411 publicly-listed firms in the S&P 500, we calculate financial and sustainability returns, on which the investor's utility depends. We approximate the investor's preference by the exponential and s-shaped utility function and optimize with regard to the sustainability preference. We find that with increasing levels of risk aversion, both minimum-variance and maximum Sharpe ratio type investors seek to incorporate sustainable assets in the portfolio.

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2 Are Sustainable Companies More Likely to Default? Evidence from the Dynamics between Credit and ESG Ratings

The following is based on Aslan et al. (2021).

2.1 Introduction

The relationship between environmental, social and governance (ESG) performance, the cost of capital and firm risk suggests an association with corporate credit default. Credit rating agencies issue credit ratings, which represent an assessment of the overall creditworthiness and the ability of a firm to meet its financial obligations. The credit ratings take into account market-level and firm-level data, as well as risk factors. Therefore, credit ratings reflect the market's perception of a firm's financial soundness. Interestingly, the rating agency Standard & Poor (S&P) recently stated that it has started incorporating ESG risk factors in their credit ratings Standard & Poor's (2021). Nevertheless, the precise methodology of the inclusion of ESG risks and whether ESG had an influence on corporate default in the past remain unclear.

In this study, we analyze the effect of ESG performance on the probability of corporate credit default by using a sample of ESG scores and credit default ratings for 902 firms in the US from 2002 to 2017. We obtain the probabilities of corporate credit defaults from credit rating transition matrices. One main reason for using probabilities instead of rating classes as the dependent variable is that credit rating classes are not equidistant, e.g., a change from rating B to BB is different from AA to AAA. Furthermore, the rating transitions demonstrate relative stability and volatility and thereby enhance the interpretability of our results. We find the probability of corporate credit default to be lower for firms with high ESG performance. We also examine whether the impact of

ESG performance changes over time in an expanding window approach. In addition, we consider different sectors in order to further disaggregate the influence on the probability of default. Our results hold in univariate and multivariate tests, as well as in several robustness checks.

Our paper contributes to the existing literature by directly applying corporate credit default probabilities and showing that high ESG performance is associated with a lower default probability. We additionally relate to the development of ESG on credit default probabilities over time, finding that ESG more heavily affects the probability of corporate credit default during financial distress or regulatory shocks (see e.g., Amiraslani et al., 2017). Furthermore, we investigate this relationship on an industry-level and find that especially the energy, financial and information technology sectors especially exhibit a negative association between ESG and the probability of corporate credit default. Although our research is limited by missing ESG data on firms that defaulted, we believe that our early findings contribute to the evolving literature on this topic. We expect an increasing availability of ESG data in the future to reduce such survivorship bias and to enhance the comparison between ESG-rated and non-ESG-rated firms.

The remainder of this paper is structured as follows. Section 2 elaborates on the theoretical foundation. Section 3 presents the data set and results of our empirical analysis as well as robustness tests. Section 4 concludes the paper.

2.2 Theoretical Foundation

In order to understand the impact of corporate social responsibility (CSR) on different aspects of firm performance and why CSR can have a possible influence on firm risk, the relationship between CSR and stakeholder theory can be examined. There remains ambiguity as to whether these concepts are subsets of one another, are complementary, or are two distinct principles. The difference between those two concepts can be explained by the prioritization of certain responsibilities as CSR only evaluates responsibilities towards society. The stakeholder theory also takes different parties into account, such as financiers, customers or suppliers, whose interests the company responds to. However, an overlap between both concepts exists as, e.g., communities can be seen as stakeholders, which are part of the society at large. This results in the consequence that both the stakeholder theory as well as CSR drives the realization of societal interests in business conduct (Freeman & Dmytriyev, 2017; Garriga & Melé, 2004). This contrasts with instrumental theories that see maximizing profits for shareholders within the legal framework as the only accountability (Friedman, 2007). Windsor (2001) addresses the question of whether the interests of society and firms converge on a longer time horizon, arguing that wealth accumulation progressively dominates the firms' concept of responsibility.

Several studies have observed a positive impact of corporate social performance (CSP) on firm performance (see e.g., Waddock & Graves, 1997; Donker et al., 2008). A conceptual framework developed by Luo & Bhattacharya (2006) outlines a relationship between a firm's CSR activities and its market value, suggesting that CSR is a driver of customer satisfaction, which can result in higher future cash flows and increase a firm's growth prospects (Gruca & Rego, 2005). In addition to increasing shareholder wealth, reducing the cost of capital is an important mechanism through which CSR may create firm value, where a firm's cost of capital is directly linked to its risk (see e.g., Starks, 2009; El Ghoul et al., 2011). Albuquerque et al. (2018) link the association between CSR and firm risk to a product differentiation strategy, suggesting that high ESG firms face a relatively lesser price elastic demand, which results in lower systematic risk. They argue that the effect is stronger for firms with high product differentiation. This is in line with other research, which has shown that firms with higher ESG ratings have lower systematic risk, e.g., Oikonomou et al. (2012) show that firms with low ESG performance exhibit higher systematic risk and El Ghoul et al. (2011) hypothesize that firms with high ESG performance have lower firm risk since their investor base is relatively larger compared to those of firms with poor ESG performance. Sun & Cui (2014) further show that CSR can decrease firm default risk by creating intangible assets, which may protect a firm's assets during financial turmoil.

Using bond credit ratings, corporate credit ratings or CDS spread as measures of firm risk, there is mixed evidence on the association regarding the impact of ESG. Seltzer et al. (2021) show that firms with low environmental scores tend to have poorer credit ratings and higher yield spreads. The authors further show that this is effect is particularly significant if firms are located in states with strict environmental regulations. Oikonomou et al. (2014) find that a firm's CSP reduces bond yield spreads, especially for long maturities, and is thus associated with lower risk. These results are consistent with a study by Attig et al. (2013), who also observe a positive impact of good social performance on credit ratings. While Jiraporn et al. (2014) assume that a firm's ESG performance positively affects the corporate bond credit rating, Stellner et al. (2015) find no statistically significant relationship between ESG performance and corporate credit ratings among firms in the eurozone. Ahmed Badayi et al. (2020) examine the impact of CSR activities on the probability of default of firms in developing countries. Here, a decreasing influence of CSR performance on default probabilities was observed, which were estimated with the Altman Z-Score model. CSR rating announcements also have a direct impact on credit default swaps (CDS) according to Drago et al. (2019). Using an event study, they find a significant decline in corporate CDS spreads after the announcement of a CSR rating upgrade.

In this paper, we contribute to the mixed findings on the association between ESG ratings and corporate credit default risk. Similar to Ahmed Badayi et al. (2020) we examine CSR performance on corporate credit default probabilities, which we derive from S&P credit rating transition matrices. We find US firms with high ESG performance to have a significantly lower probability of corporate credit default. We additionally decompose ESG into its constituents, showing that all pillars drive this result, while the social pillar exhibits the largest influence.

Moreover, it must be investigated to what extent the effect of CSR activities on firm performance develops over time once a certain market standard has been established. The contrast between proactive and reactive environmental strategies was investigated in an earlier study by Sharma & Vredenburg (1998). It was shown that the proactive implementation of environmental strategies can result in a competitive advantage over reactive firms. Due to the increase in attention and the presence of CSR related topics, the question arises whether this effect is temporary or persistent enough to possibly affect firm performance. In the report on firm CSR reporting, KPMG outline that in 2017, 93% of the world's 250 largest companies published their CSR activities in reports compared to 45% in 2002. In another sample that includes the 100 largest companies in 52 countries by revenue, the reporting rate is 18% in 2002 compared to 77% in 2017 KPMG (2020). The institutionalization of CSR reporting is addressed and explained by Shabana et al. (2017) in a three-stage model, which explains the motivation of companies to engage in reporting. According to this model, companies adopt defensive reporting early after they fail to meet stakeholders' expectations. A subsequent proactive reporting driven by accumulation and knowledge diffusion about

CSR reporting and its benefits is later followed by imitative diffusion. For this reason, we also pursue the question of whether the impact of ESG performance on the probability of corporate credit default varies over time. By taking into account the recent statement by Standard & Poor's (2021) on incorporating ESG risks in the credit risk evaluation, our empirical findings suggest that ESG performance may has already, in the past, significantly influenced the probability of corporate credit default.

Consistent with Borghesi et al. (2014), we assume that ESG performance varies across industries since it may be difficult for some industries to attain high ESG performance due to differences in the nature of operation. The energy sector takes on a key role in the area of CSR, especially with regard to environmental sustainability (see e.g., Omer, 2008). Pätäri et al. (2014) find that CSR strengths and concerns regarding firms operating in the energy sector have different impacts on the firm's financial performance. In particular, it was shown that changes in CSR strengths have no influence on profitability, but changes in concerns negatively affecting it. In our analysis of the influence of ESG on the probability of credit default over different industries, we find that the energy sector is most significantly affected.

2.3 Methods and Results

2.3.1 Data

Our sample consists of 7776 yearly observations for 902 publicly-listed firms in the US from 2002 to 2017. We obtain long term domestic credit issuer ratings by Standard & Poor's (S&P) from Compustat/Capital IQ. Intermediate ratings are assigned to the respective major rating category in order to match credit issuer ratings with the corporate default probabilities. The most recently available rating during the year was assigned to the respective observation if several ratings were issued during the year. The probabilities of default for each rating class are provided by the average one-year US credit rating transition matrices provided by Standard & Poor's (Vazza et al., 2007, 2008; Standard & Poor's, 2011; Vazza & Kraemer, 2012, 2013, 2014, 2015, 2016, 2017, 2018). The probabilities of default in our sample are derived from the average one-year US corporate transition rates from a given rating to default (D), which include rating transitions from 1981 to the year of the report. For the years 2002 to 2005, 2008 and

2009, no reports were available and, thus, we assigned the ratings to the probability of default from the upcoming available report. The credit ratings in our sample offer intermediate ratings that have been adjusted to their associated level in order to match them with the default probabilities.

Table 2.1: This table presents summary statistics for the variables used in this paper. The sample consists of 902 US firms. The definitions of the involved variables are provided in appendix Table A3.

	Obs.	Min.	Max.	Mean	Median	Std.
PD	7774	0.0000	28.8500	0.6545	0.2400	1.6503
ESG	6994	0.6250	95.0733	42.8084	40.6092	19.6751
E	6994	0.0000	98.5288	29.4241	22.2561	28.8941
S	6994	0.8260	97.7517	44.3801	41.7488	21.3936
G	6994	0.2516	98.5049	51.5762	52.9908	22.2557
Volatility	7776	0.0766	1.6521	0.2521	0.2113	0.1442
Abnorm. Return (AR)	7776	-2.4462	2.5907	-0.0108	0.0089	0.2783
WC/TA	5935	-0.3193	0.7681	0.1241	0.1001	0.1433
RE/TA	7769	-8.8191	2.3369	0.1980	0.1785	0.4214
EBIT/TA	7774	-2.7568	1.2852	0.0871	0.0767	0.0863
ME/TL	7042	0.0063	37.5695	2.0685	1.4178	2.3964
S/TA	7774	-0.0524	5.7449	0.7746	0.6135	0.6916
NI/TA	7774	-2.2832	1.0235	0.0464	0.0418	0.0754
TL/TA	7773	0.0317	2.3667	0.6598	0.6427	0.2023
CA/CL	5939	0.1749	17.3875	1.7144	1.4840	0.9993
Size	7774	4.8543	14.7606	9.4016	9.1773	1.4063

We use Thompson Reuters Refinitiv Eikon to obtain annual ESG scores for the companies in our sample over the respective period. For our analysis, we use the ESG scores, which comprises corporate environmental (E), social (S) and governance (G) performance. The environmental performance includes but is not limited to emissions and resource, while social performance covers human rights and workforce and the governance performance measures management, stakeholder and CSR strategy. Similar to Capelle-Blancard et al. (2019), we lag the ESG rating scores in all our specifications by one period. This is due to our interest in the association between ESG and the credit default probability, where ESG influences the PD. In addition, we hereby reduce problems arising from endogeneity and simultaneity bias. Another practical reason is that we assume that credit rating agencies do not obtain the contemporary ESG score prior to their credit evaluation. Table 2.1 provides descriptive statistics for the dataset used.

2.3.2 ESG Performance and Probability of Default

We perform ordinary least squares (OLS) regressions of the following specification to assess the effect of ESG rating scores on the probability of default (PD):

$$PD_{it} = \beta_0 + \beta_1 \times Score_{it-1} + \beta' \times X_{it} + \alpha_k + \alpha_j + \varepsilon_{it} \tag{2.3.1}$$

where i denotes the firm, t denotes the year, α_k and α_j representing industry-fixed and year-fixed effects respectively, and ε stands for the error term. The additional k independent or control variables are denoted by the $1 \times k$ regressor vector X with the $k \times 1$ coefficient matrix β'. By using the PD (in %) instead of ordinally scaled credit ratings, we account for the non-equidistant scaling of credit ratings. We are specifically interested in the lagged independent variable ESG and the respective pillar scores E, S and G. We then extend our analysis by controlling for the market-driven variables abnormal return, denoted as AR, and $Volatility$, which is the firm's annual idiosyncratic volatility defined as the standard deviation of daily abnormal returns. The daily abnormal returns are defined as the difference between observed daily log returns and expected returns, which in turn are estimated by using a simple market model. We use daily log returns of the S&P 500 index in the market model and retrieve annual abnormal returns from daily by summation.

Additionally, we implement various firm controls proposed by Shumway (2001) who developed a hazard model to forecast bankruptcy, as well as industry and time-fixed effects in our regression. For the sector classification, we use the Global Industry Classification Standard's (GICS), which defines 11 sectors in total. We report cluster-adjusted standard errors at firm-level.

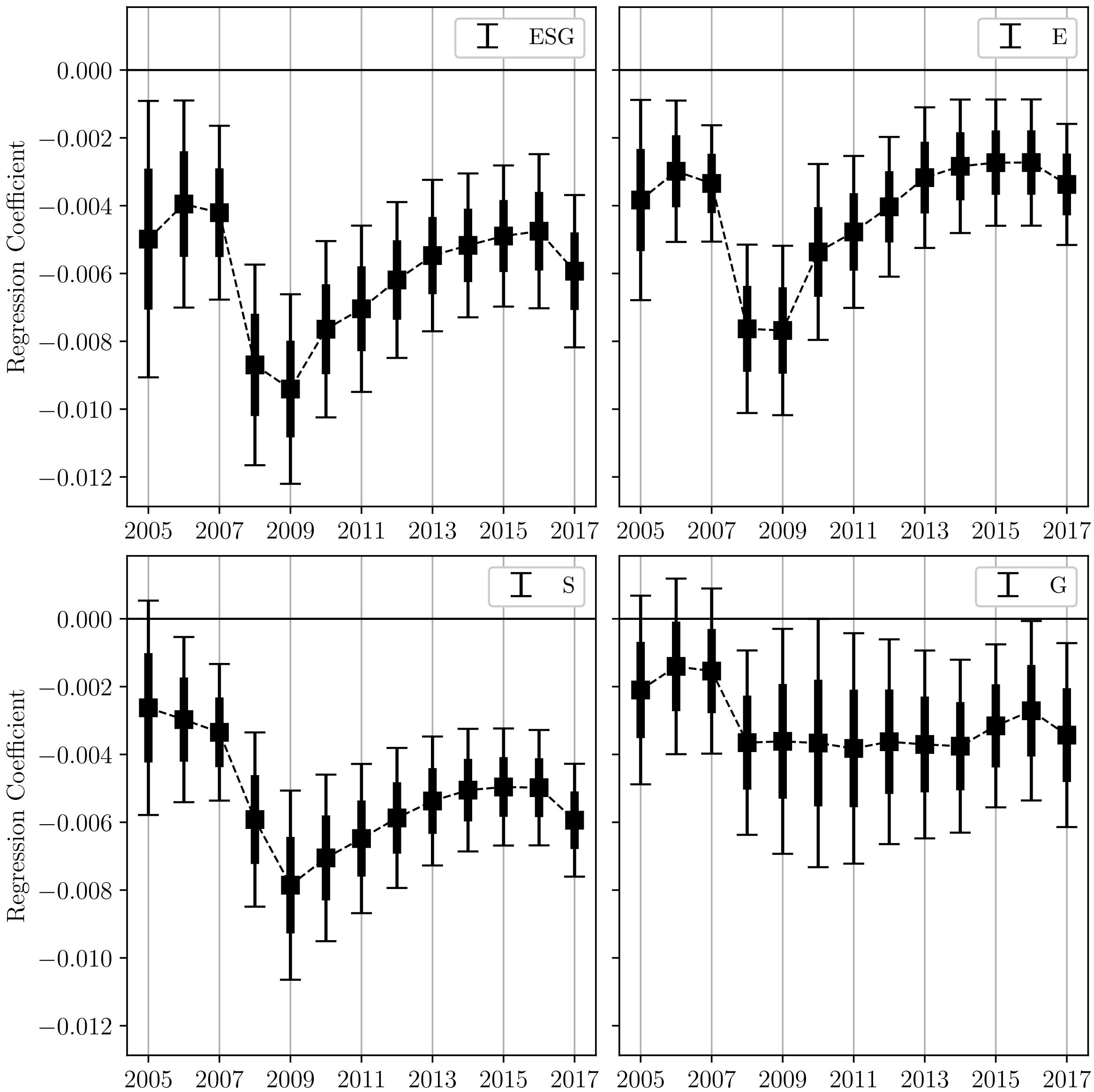
Table 2.2: In this table results from the univariate regression analysis (models (1)-(4)) for ESG Score and the associated pillar score are shown. Additionally, the models are extended into a multivariate analysis by adding idiosyncratic volatility and abnormal returns in models (5)-(8) which are estimated using a simple market model. To account for heterogeneities between different industries and years, the models have been estimated with years and industry fixed effects (FE) based on the Global Industry Classification Standard's (GICS) sector classification. We report robust cluster-adjusted standard errors on firm-level in parentheses, where ***,**,* denotes the coefficient's statistical significance at the 1%, 5%, and 10% level.

Dependent Variable: PD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG	-0.0134***				-0.0062***			
	(0.0015)				(0.0012)			
E		-0.0088***				-0.0038***		
		(0.0011)				(0.0010)		
S			-0.0118***				-0.0060***	
			(0.0014)				(0.0009)	
G				-0.0069***				-0.0035***
				(0.0015)				(0.0013)
Volatility					6.3159***	6.3512***	6.3310***	6.4681***
					(0.9597)	(0.9631)	(0.9404)	(0.9489)
Abnormal Return					0.2774**	0.2789**	0.2811**	0.2919**
					(0.1162)	(0.1161)	(0.1160)	(0.1165)
Observations	6992	6992	6992	6992	6992	6992	6992	6992
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R-Squared	0.0228	0.0197	0.0213	0.0082	0.1705	0.1693	0.1710	0.1679

In Table 2.2 we present the results of our baseline regressions. Our dependent variable is PD and we employ the one-year lagged ESG score and its lagged single constituents as independent variables in univariate regressions (models (1) to (4)). We then add the contemporary market-driven controls $Volatility$ and AR for each specification (models (5) to (8)). We find that in the univariate models, all independent variables are highly significant and all coefficients are negative. As we include market controls, the coefficients for ESG and its respective pillar scores remain highly significant, even when maintaining controls for industry- and time-fixed effects and clustering of standard errors on the firm-level. The coefficients for ESG and the constituents are negative and have nearly half the magnitude compared to the univariate models. As for $Volatility$ and abnormal returns AR, the coefficients are positive and are also highly significant across all specifications. For the aggregate ESG score in the multivariate case, we conclude that an increase in ESG by one unit decreases the probability of default by 0.0062%, on average and while holding everything else constant. This first set of results indicates that environmental, social and governance performance as well as the aggregate ESG score significantly affects the probability of corporate credit default.

To further understand the effect of ESG on PD over time, we plot the estimated coefficients for ESG and its constituents in the specification from Table 2.2 (models (5) to (8)) over 2005 to 2017 in Figure 2.1. By using an expanding time window starting in 2002 for the estimation, we observe that the ESG score and each respective pillar score negatively affect the probability of corporate credit default in every subsample that is created by adding observations from the subsequent year.

Figure 2.1: This figure shows the results of OLS models estimated with annual extending window samples starting with the first year covered by the study, 2002. The dependent variable is probability of default (PD). The independent variable is ESG or one of the associated pillar scores. In addition, abnormal returns (AR) and idiosyncratic volatility are added as market-driven control variables. Because of the small number of observations, the first two time windows are neglected. The coefficient for the year 2017 corresponds to the coefficients from models (5)-(8) in Table 2.2. The thicker inner bar describes the estimated standard error (68% confidence interval), while the thinner error bar depicts the 95% confidence interval. All models are controlled for industry-fixed effects based on the Global Industry Classification Standard's (GICS). We report robust cluster-adjusted standard errors on firm-level. The corresponding Table A1 can be found in the appendix.



We observe a sharp decline of the coefficients' magnitude from 2007 to 2008, which indicates an increased effect of ESG on PD. By taking into account the subprime mortgage crisis during the respective period, a stronger impact of ESG performance on the probability of default during this financial shock can be observed. The relevance of ESG criteria is perceived by credit rating agencies, for example, the rating agency Fitch's addresses the importance and integration of the so-called ESG relevance scores, which are embedded in the credit rating process (Fitch Ratings, 2020). From this, it may be deduced that the rating agency readjusted its credit risk model with regard to ESG performance.

The magnitude of the ESG coefficient increases post-crisis to a slightly lower value than pre-crisis, indicating that the rating agencies may have decreased the importance of ESG in their evaluation of credit default risk. We observe that the coefficients for ESG are decreasing since 2016, which might indicate that ESG performance is regaining importance for the risk evaluation of credit rating agencies. The increased emphasis on ESG from 2016 onward is consistent with the literature, which links this trend to the Paris Climate Change Agreement and the UN Principles for Responsible Investment (PRI) initiative of 2016 on ESG in Credit Ratings (see e.g., Ilhan et al., 2021; Beeching et al., 2017). Companies that operate in high-emission industries or generally have poor environmental performance tend to a higher average bond yield spread post Paris Climate Change Agreement (Seltzer et al., 2021).

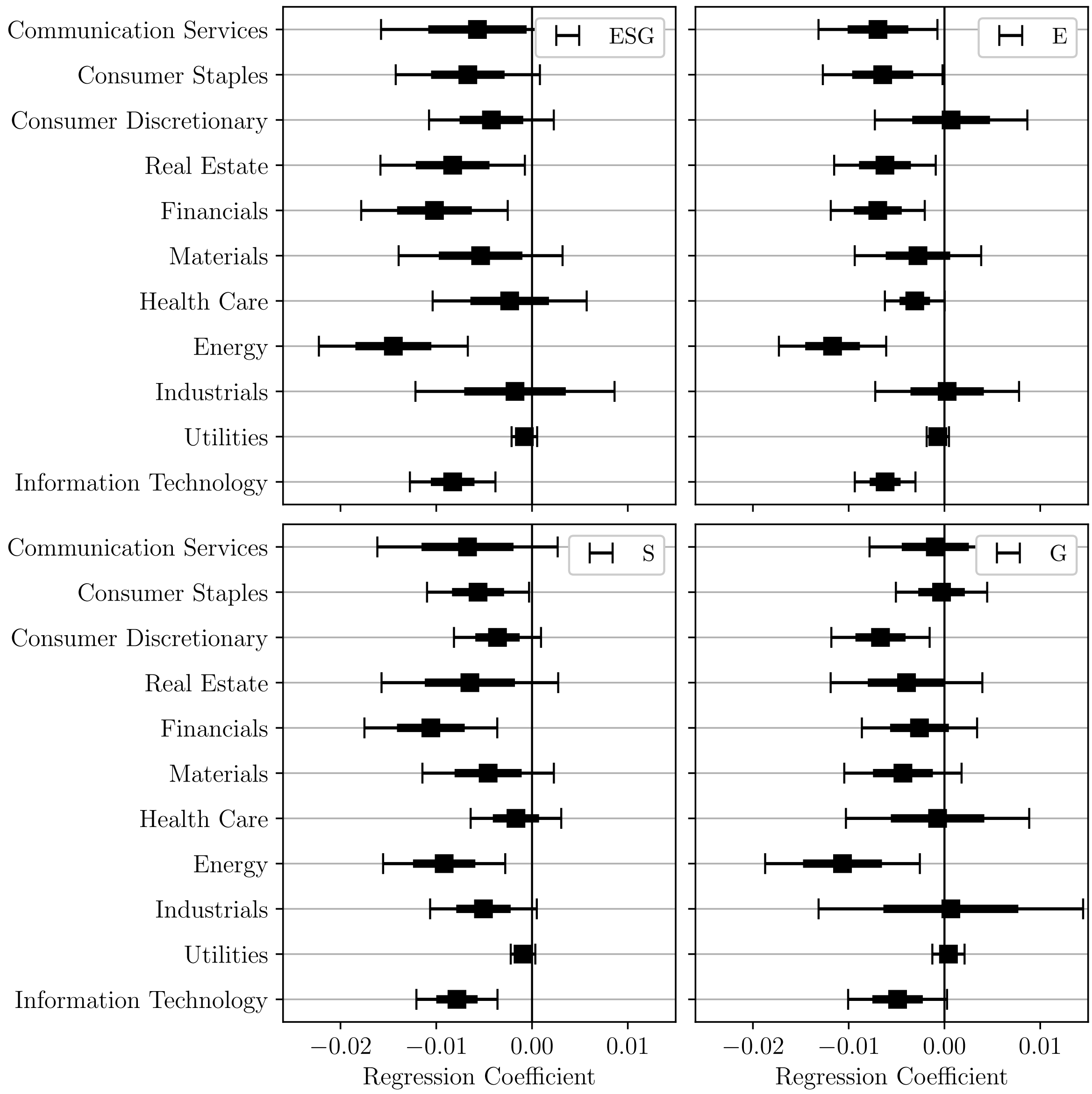
Compared with the other pillars, the time evolution of the governance pillar score is very different; in particular, no minimum can be observed around the year 2009 and overall the influence is much smaller and shows little variation. A similar observation was made by Bebchuk et al. (2013), who could not document any correlation between governance indices and abnormal returns during the period of 2000-2008. In the original work on the governance index (or G-Index), which uses various guidelines to define a proxy for the level of shareholder rights, a strong correlation between shareholder rights and firm value was observed in the 1990s (Gompers et al., 2003). The authors explain the subsequent disappearance of the effect with a learning effect on the part of the market participants, which allows them to distinguish between companies that score well and those that score poorly on the governance indices. Moreover, the structural break between the governance-return correlation corresponds to a simultaneous increase in media attention to corporate governance.

In Figure 2.2, we partition our panel to observe the magnitude of the estimated coefficient from Table 2.2 and specification (5) to (7) for different GICS sectors. Considering the aggregated ESG, all industries show a negative influence of ESG on PD. The industries *Energy*, *Financials* and *Real Estate* are most heavily influenced by ESG in their PD. By further breaking down ESG into its constituents, we can state that the environmental performance has the highest influence on PD in the *Energy*, *Financials* and *Communication Services* sectors. This is in line with the ongoing debate on the need for an ecological disruption, which affects the *Energy* sector in particular (REN21, 2020). In contrast, we observe that *Industrials* and *Consumer Discretionary* have a positive coefficient for the effect of the environmental pillar score on PD, indicating that an increment in E increases the probability of credit default.

We interpret the positive coefficient that investment in environmental performance may be costly in these sectors and, therefore, negatively affects the PD. For the social pillar score S, we observe the highest impact of ESG on PD for *Financials*, *Energy* and *Information Technology.* The effect of governance performance on reducing PD is most influential in *Energy*, *Consumer Discretionary* and *Information Technology.* The *Industrials* and *Utilities* sectors show a positive coefficient, which indicates that increasing governance performance in these sectors is costly and increases the PD.

Overall, the results from our tests indicate that environmental, social and governance performance significantly affects the probability of credit default. Although the average magnitude of the effect is not very large, we observe that the size of the coefficients varies strongly over time. This finding indicates, that rating agencies may adjust the weighting of ESG performance in their credit risk modeling. We thereby conclude that ESG may contribute to reducing the cost of capital through the credit risk channel.

Figure 2.2: This figure shows the results of separately examining the effect of ESG on PD for each industry based on the Global Industry Classification Standard's (GICS) using OLS regression models. The independent variable is ESG or the associated pillar scores (E, S or G). In addition, abnormal returns (AR) and idiosyncratic volatility are added as market-driven control variables. All models are controlled for year-fixed effects. The thicker inner bar describes the estimated standard error (68% confidence interval), while the thinner error bar depicts the 95% confidence interval. The associated results can be seen in Table A1. A description of the variables can be found in Table A3. We report robust cluster-adjusted standard errors on firm-level.



2.3.3 Robustness

We perform several robustness checks to ensure the validity of our results. First, we examine the linear dependence in our regression specification by using a scatterplot of standardized residuals against the independent variables, yielding an indication of linear dependence. We further observe a serial correlation in our dependent variable by testing, as proposed by Wooldridge (2002) (see e.g., Table A4), but clustering the standard errors on a firm-level ensures robustness regarding inference (Petersen, 2009). We confirm stationarity for our dependent variable by performing the Dickey-Fuller test in our panel as proposed by Choi (2001) (see e.g., Table A5). Furthermore, a quantile-quantile plot of regression residuals on the inverse normal distribution shows that we have deviations from the normal distribution in the tails. In addition to the linear model estimated in this paper, we estimate a logistic regression with the probability of default as the dependent variable, which is similar to Orlando & Pelosi (2020). Additionally, we estimate an ordered logit with the respective credit rating as the dependent variable in order to better account for possible nonlinearities and the boundedness of our dependent variable. In both models, we estimate univariate models with the ESG Score as our main independent variable. Moreover, we estimate multivariate models by adding idiosyncratic volatility and abnormal returns as market driven control variables. We observe significant parameters and qualitatively equal signs, which are consistent with the results of the linear model. For reasons of brevity, we do not report the respective tables here.

After introducing market control variables in Table 2.2, we follow Shumway (2001) and add a set of firm controls which consist of Altman's variables proposed in his Z-Score model (Altman, 1968). These include ratios of working capital to total assets (WC/TA), retained earnings to total assets (RE/TA), earnings before interest and taxes to total assets ($EBIT/TA$) market equity to total assets (ME/TA) and sales to total assets (S/TA). According to the Z-score model, these five selected ratios are particularly well suited for describing or predicting corporate default. From the model estimates, the ratio of retained earnings to total assets (RE/TA) as a measure of cumulative profitability over the company life is shown to be particularly meaningful for describing the probability of default. Furthermore, the ratio describes the degree of leverage of the firm, since firms that finance their assets by retaining profits may require less debt capital. The ratio of EBIT to TA has a significant influence as a measure of the companies' profitability (Altman & Hotchkiss, 2005). Due to the substantially higher leverage compared to other sectors as well as increased sensitivity to financial risks, we neglect financial service firms in the following models (Foerster & Sapp, 2005). The models were additionally calculated by including the companies from the financial sector and consistent results with significant effects were obtained. In addition, we add ratios of net income to total assets (NI/TA) (return on assets), total liabilities to total assets (TL/TA) to account for firm's financial leverage and current assets to current liabilities (CA/CL) to control for liquidity as proposed by (Zmijewski, 1984).

Since we leave out interpreting the respective coefficients for the additional control variables, their use in Table 2.3 and Table 2.4 is labeled *Additional Controls* for purposes of clarity.

Table 2.3: In this table the results from the OLS models that take further firm controls into account are shown which consist of various accounting variable ratios. The dependent variable is probability of default. We report robust cluster-adjusted standard errors on firm-level in parentheses, where ***,**,* denotes the coefficient's statistical significance at the 1%, 5%, and 10% level.

Dependent Variable: PD	(1)	(2)	(3)	(4)
ESG	-0.0033**			
	(0.0016)			
E		-0.0021*		
		(0.0013)		
S			-0.0032***	
			(0.0011)	
G				-0.0018
				(0.0018)
Volatility	4.7083***	4.7170***	4.7202***	4.7830***
	(0.5755)	(0.5851)	(0.5582)	(0.5587)
Abnormal Return	0.1342	0.1344	0.1362	0.1423
	(0.1119)	(0.1120)	(0.1123)	(0.1123)
Observations	5197	5197	5197	5197
Industry Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
Additional Controls	yes	yes	yes	yes
Adjusted R-Squared	0.2758	0.2755	0.2760	0.2750

The results presented in Table 2.3 are similar to those from our baseline and market model, which indicates the aggregate ESG score as well as environmental and social pillar score to be significantly associated with the lower probability of credit default. There exists a strong correlation between ESG scores (ESG) and firm size ($Size$), which can be explained by better organizational legitimacy and resources available to a firm (Drempetic et al., 2020; Hahn & Kühnen, 2013). These dissimilarities are also discussed in the context of stakeholder theory and social capital by Russo & Perrini (2010), who argue that a distinction must be made between SMEs and large companies, since different idiosyncrasies between large companies and SMEs must be taken into account. Therefore, we further determine whether firm size affects our model and, therefore, estimate models with an interaction term between ESG score and the respective pillar scores with the natural logarithm of total assets as a proxy for firm size. Since the added firm controls are already calculated as ratios divided by either total assets or current liabilities, we do not adjust it further.

Table 2.4: This table shows the extended models where interactions between ESG variables and firm size are considered. The independent variable is the probability of default while firm size is defined as the natural logarithm of total assets. We report robust cluster-adjusted standard errors on firm-level in parentheses, where ***,**,* denotes the coefficient's statistical significance at the 1%, 5%, and 10% level.

Dependent Variable: PD	(1)	(2)	(3)	(4)
ESG × Size	-0.0003**			
	(0.0002)			
E × Size		-0.0002*		
		(0.0001)		
S × Size			-0.0003***	
			(0.0001)	
G × Size				-0.0002
				(0.0002)
Volatility	4.6742***	4.7043***	4.6861***	4.7346***
	(0.5837)	(0.5888)	(0.5669)	(0.5706)
Abnormal Return	0.1333	0.1342	0.1355	0.1398
	(0.1116)	(0.1117)	(0.1120)	(0.1119)
Observations	5197	5197	5197	5197
Industry Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
Additional Controls	yes	yes	yes	yes
Adjusted R-Squared	0.2761	0.2755	0.2762	0.2755

Table 2.4 displays our results for the regression with PD as the dependent variable and interacted one-year lagged ESG scores. Despite the coefficients for $ESG \times Size$, $E \times Size$ and $S \times Size$ are significant and they are smaller in magnitude compared to the results from Table 2.3. Although not reported for reasons of brevity, we additionally subdivide our data based upon the investment-grade boundary. Companies with a credit rating better than BB are defined as investment grade. Observations with a credit rating of BB or worse correspond to high yield or speculative grade. We calculate the extended regression specifications from Table 2.4 with size interaction terms and find more significant results for firms that are marked as investment-grade ($N = 3626$). For the subsample corresponding to the speculative grade, no significant influence ($p > 0.1$) of $ESG \times Size$ on PD can be observed ($N = 1571$). In addition, we use ESG scores with greater lags and obtain similar results, although the magnitude decreases proportionally with increasing lag (see Table A2). Overall, our various robustness checks provide further support for the negative relationship between ESG and the probability of corporate credit default PD.

2.4 Conclusion

In this study, we analyzed whether ESG performance affects the probability of corporate credit default in the US. Investigating a sample of 902 firms, we find that the aggregated ESG scores and its corresponding pillar scores to negatively affect the probability of credit default, which indicates that ESG may induce lower credit ratings and thereby lower the cost of capital of the firms. These results emerge from univariate and multivariate regression analysis by using market-driven control variables. In further robustness checks, the results for the aggregated ESG score and social pillar score can be reproduced, while the significance of the influence of the environmental pillar score is reduced and the effect of the governance score cannot be substantiated. We contribute to the literature on ESG performance and its effect on firm risk and the cost of capital. Translating credit ratings into corporate default probabilities circumvents the problem of ordinal scaling of credit ratings in linear models. In particular, the crossing of the investment-grade boundary induces a strong increase in the probability of default. By utilizing control variables from classical credit default prediction models, a robust relationship between ESG performance and the probability of default is shown.

In an expanding time window approach, a strong variation in the coefficients for the aggregated ESG as well as the environmental and social pillar score was observed. This trend could not be observed for the governance pillar, which may be attributed to a learning effect of market participants (Bebchuk et al., 2013). For the aforementioned scores, the largest effect was observed around 2008 and 2009, concurrent with the subprime mortgage crisis. A time-dependent sensitivity or susceptibility to external shocks of the influence of ESG performance can be deduced from this. By conducting a sectoral analysis, it was possible to show that the influence of ESG performance plays a particularly important role in the energy sector, since the greatest influence was observed here.

The link between ESG factors and difficult-to-measure risk management practices by firms may explain the effect of ESG on credit risk and, thereby, on the probability of corporate credit default. The identification and management of low-probability risks using ESG factors inside firms are hypothesized to be correlated with fewer negative shocks on the firm side, e.g., fewer accidents and lawsuits, as well as fewer negative shocks on sales, revenue and profitability (Henisz & McGlinch, 2019). Such material credit events substantially influence the credit risk and are linked to the respective firm ESG performance.

This paper might be limited in the sense of a survivorship bias. During the sample selection process, we did not observe ESG scores of companies that defaulted, which yields a sample of financially stable firms that might bias our results. On the other side and in the short time window of our panel, it is unlikely to observe large numbers of corporate defaults. Moreover, we expect that the increasing availability of ESG rating data will further reduce the survivorship bias and allow for a more precise comparison between ESG-rated and non-ESG-rated firms regarding the effect of ESG ratings on credit ratings and the probability of default.

The exact determination and definition of ESG criteria continues to be the subject of ongoing debate. Furthermore, there exist methodological differences between different rating agencies, which motivates further investigations of ESG ratings of different rating providers (see e.g., Dorfleitner et al., 2015). Developments at the policy level, such as the discussion on the introduction of an EU taxonomy as a classification system for describing environmentally sustainable economic activities, could have an impact on the assessment of companies' ESG activities (Technical Expert Group, 2020). The use of these redefined measures could reveal new insights between the creditworthiness of firms and their CSR performance.

The results of the study have implications from both a management and investor perspective. Implementing, reporting and pursuing CSR or ESG activities can reduce the probability of corporate credit default. However, this effect depends on the sector in which the company operates. Investors should take the ESG performance of companies into account when assessing default risk.

3 Does Carbon Price Volatility Affect European Stock Market Sectors? A Connectedness Network Analysis

The following is based on Aslan & Posch (2022a).

4 How Do Investors Value Sustainability? A Utility-Based Preference Optimization

The following is based on Aslan & Posch (2022b).

4.1 Introduction

A recently conducted survey study by Stroebel & Wurgler (2021) asked 861 finance academics, practitioners, public sector regulators, and policy economists about climate finance and identified physical risks, such as rising sea levels and increasing average temperatures, as the main risk type on the horizon of over 30 years. Furthermore, the survey participants believe that asset prices underestimate climate risk. This is why in the field of socially responsible investments (SRI), ecological and ethical risk factors are increasingly considered in the portfolio risk assessment. There is growing demand from private and institutional investors for information on such risk factors, partly due to regulatory efforts, e.g., in Europe (EU, 2020), independent rating agencies began publishing scores for companies based on publicly available information, covering environmental, social, and governance (ESG) aspects, to measure corporate social performance (CSP).

While some studies, e.g., Pedersen et al. (2021), have proposed methods to optimally implement these ESG scores to obtain the best-possible portfolio allocation, only a few studies focus on an investor's preference for sustainable investment. Pástor et al. (2021) modeled sustainable investing for agents with differing preferences for sustainability, where besides financial wealth, an agent's utility is affected by holding green assets, the firm's social impact, and the impact on climate risk. Their analysis reflects the investors' preferences using an exponential utility function; however, the authors' empirical analysis does not simultaneously cover risk-seeking behavior of investors.

This is where our study contributes to the existing literature. First, we analyze how the preference for sustainable assets in the portfolio shifts for increasing levels of an investor's risk aversion. Instead of relying on numerical examples, we employ a sample of 411 firms in the Standard and Poor's S&P 500 index from 2015 to 2019 and first determine the minimum-variance and maximum Sharpe ratio portfolio, solely based on financial returns. We then calculate sustainability returns as the log performance difference of a firm's ESG ratings and, thereafter, impose an exponential and an s-shaped utility function, based on financial and sustainability returns, to depict the investor's utility, similar to Dorfleitner & Utz (2012) and Dorfleitner & Nguyen (2016). Especially, the use of the s-shaped utility function is novel in this approach and offers a great advantage in the analysis of sustainability preference by extending the risk spectrum for the analysis, since the function simultaneously depicts risk-averse and risk-seeking behavior. Furthermore, contrary to the existing literature, rather than focusing on portfolio weights, we optimize with regard to the sustainability preference parameter, by which we seek to identify shifts between financial and sustainable returns. We find that with increasing levels of risk aversion, both types of investors seek to incorporate sustainable assets. The conclusion is mainly driven by the characteristics of the sustainable returns, which exhibit a lower return and variance than the financial returns. This return to variance pattern is in line with the current literature on the effects of holding ESG assets on asset prices (Pástor et al., 2021; Pedersen et al., 2021; Baker et al., 2018). Our results hold in several robustness tests, where we alternatively use an additive utility function and different measures of sustainability returns, underlining the validity of our findings.

The remainder of the paper is structured as follows. After a literature review in Section 2, we explain our data and methodology in Section 3. We present the results of the paper in Section 4, before the robustness tests in Section 5, while Section 6 concludes.

4.2 Theoretical Foundation

Generally, the healthy functioning of equity and banking markets is important to achieve sustainable economic growth (Saleem et al., 2021). The empirical literature is divided over whether sustainable assets under- or overperform in comparison to non-green stocks. Hamilton et al. (1993) and Bello (2005) conducted such performance analyses and found that sustainable funds do not significantly over- or underperform, similar to the findings of Auer & Schuhmacher (2016), while Galema et al. (2008) discovered a significant impact of SRI on stock returns. One reason for such over- or underperformance is given by Fama & French (2007), who modeled the taste for assets as consumption goods either depending on asset returns or not depending on asset returns under the CAPM and found that an investor's preference, e.g., for holding green assets, affects asset prices. However, their model is mainly focused on asset pricing effects and does not take into account changes in risk appetite. Furthermore, the authors do not explicitly employ different utility functions to depict investor preferences, whereas we specifically model such investor preferences and investigate the effect of risk appetite on the respective preferences. Theoretical studies based on Merton (1987) suggest that investors who seek ESG objectives refuse to hold assets that do not match their ecological and ethical preferences. This is the foundation of segmentation theory, which states that in equilibrium, such market segmentation of investors due to ecological and ethical motives leads to higher expected returns for non-green companies and sin stocks, as shown in Heinkel et al. (2001) and Luo & Balvers (2017). Hong & Kacperczyk (2009) supported the segmentation theory by finding that sin stocks generate positive abnormal returns, a so-called sin premium. Similarly, stocks with good governance or high employee satisfaction have been found to generate positive abnormal returns as well (Sloan, 1996; Gompers et al., 2003; Edmans, 2011). In further support of the segmentation theory, Baker et al. (2018) showed that green municipal bonds are issued at a higher price than similar non-green bonds. The authors modeled two investors with mean-variance preferences, of which one investor had a preference for green assets, using a fixed risk aversion parameter for returns and variances for both investors. However, the authors did not empirically model changes in risk aversion and the respective affect on investors' preferences. Benson & Humphrey (2008) found that the SRI fund flow is less sensitive to returns than the conventional counterpart. In a more recent strain of research, Pástor et al. (2021) argued that shifts in investors' preferences might lead to green assets outperforming brown assets. While the authors reflect the investors' preferences using an exponential utility function, their empirical analysis does not cover risk seeking behavior of investors, e.g., as depicted by the s-shaped utility. A related study by Avramov et al. (2022) analyzed the implications of uncertainty about corporate ESG profiles. In their model, investors believe that ESG scores and the underlying distribution is uncertain, which is proxied by the dispersion, or disagreement, between different ESG rating agencies. The authors found that in equilibrium, the market premium for equities increases and stock demand declines under ESG uncertainty.

Furthermore, despite several studies analyzing the performance of sustainable assets, only a few present a guide on how to incorporate sustainability aspects into the portfolio choice. Typically, SRI investment follows two steps, in which the assets under consideration are first screened regarding their ESG criteria, and afterwards the portfolio weights are optimized to obtain an efficient financial solution (Dupré et al., 2004). Ballestero et al. (2012) presented a bi-criteria model for financial and ethical aspects, which is suited for SRI portfolio selection. An extending method was proposed by Steuer et al. (2013) and Hirschberger et al. (2013) to enhance Markowitz's bi-criterion portfolio selection to a tri-criterion model, which enables incorporating a third dimension, e.g., sustainability, as shown in Utz et al. (2014). Schmidt (2020) employed a mean-variance framework and expanded it to incorporate investors' preferences for ESG in the portfolio by adding a linear function of the weighted sum of the portfolio constituents' ESG scores to the optimization problem. Similar to Pástor et al. (2021), Pedersen et al. (2021) attempted to establish a bridge between studies showing that ESG investing negatively impacts performance and those that show the opposite effect. Therefore, Pedersen et al. (2021) extended Markowitz's theory to demonstrate an ESG-efficient frontier, which displays the highest possible Sharpe ratio for each ESG score. Their frontier defines the optimal possibilities for an investor's portfolio allocation, suggesting that ESG is a positive predictor of future firm profits and, hence, not fully priced in the market. Following this reasoning, the authors predict that ethically motivated investors should be willing to accept lower returns for more sustainable stocks.

One practical difficulty that remains present in the current literature is the modeling of an investor's preference for sustainable assets in the portfolio and sustainability itself. While Dorfleitner & Utz (2012) modeled stochastic sustainable returns, derived from ESG scores, and implemented these in a similar bi-criterion Markowitz portfolio selection framework, Dorfleitner & Nguyen (2016) complemented the mean-variance model with the expected utility theory to show the change in optimal portfolio weights depending on an investor's preference for sustainability. Nonetheless, their analysis is still mainly focused on portfolio allocation and only covers basic utility functions.

Similarly, Escobar-Anel (2022) studied a multivariate utility to attach risk aversion levels to different sources of wealth under consideration of ESG investments. For a numerical example, not based on empirical data, the authors found solutions to optimal allocations in an expected utility setting and showed an increase in green investments by 33% when accounting for differential risk aversion levels.

Our study fills several gaps in the literature. First, different from the existing literature, we do not investigate the sustainable portfolio weighting but, rather, the change of an ethically motivated investor's preference for sustainable assets under a varying risk appetite. Therefore, using the Markowitz portfolio theory, we determine two financially optimized portfolios for stocks in the S&P 500 from 2015 to 2019, namely, the minimum-variance portfolio and the maximum Sharpe ratio portfolio. Second, similar to Dorfleitner & Nguyen (2016), we employ the expected utility theory and optimize an exponential and s-shaped utility function under differing risk appetites concerning the sustainability preference. To our knowledge, this is the first study that investigates the effect of risk aversion on sustainability preference under such complex utility functions. We solve the optimization problem using an evolutionary algorithm and find that with increasing levels of risk aversion, an ethical investor's preference for SRI increases both for a minimum-variance and maximum Sharpe ratio investor. Our study relates to the theory of taste-based discrimination from Becker (1957), as we suggest that ethical investors may be more keen in investments based on sustainability returns than in financial returns, which consequently favors green and discriminates non-green or brown investments. Similarly, following Phelps (1972), we state that sustainability of firms cannot be observed perfectly; hence, we use annual ESG ratings as an approximation hereof. An ethically motivated investor who is maximizing only with regard to financial returns may discriminate against sustainability if the cost for gaining information on a firm's sustainability performance is very high. However, as the availability of ESG ratings has been increasing significantly in the past decade, the cost of obtaining such data has decreased.

4.3 Data and Methodology

4.3.1 Data

We employed daily stock closing prices from Compustat for 411 publicly listed firms in the US included in the Standard and Poor S&P 500 index from 2015 to 2019 and estimated annualized returns and variances. Furthermore, we obtained annual ESG scores for the respective firms in our sample from Refinitiv. The ESG scores are a composition of corporate environmental (E), social (S), and governance performance (G). Environmental performance includes, but is not limited to, emissions and resources; social performance measures human rights and the workforce; and governance performance covers management, stakeholder, and CSR strategy. Due to missing ESG scores for several firms of the S&P 500 index, especially for 2019, we mitigated the risk of survivorship bias by using the Global Industry Classification System (GICS) to assign the minimum ESG score per industry and year to the respective firm. Hence, our sample consists of 1644 annual observations for 411 firms.

4.3.2 Investor Utility and Sustainability Preference

Our main goal is to model an investor's preference for sustainable assets in the portfolio for a varying risk appetite, given different specifications of the underlying utility function. In the first step, we calculate logarithmic stock returns as

$$r_{n,t} = log\left(\frac{p_{n,t}}{p_{n,t-1}}\right) \tag{4.3.1}$$

with $p_{n,t}$ being the closing price of stock n at time t. In a second step, to determine the sustainability equivalent, we take an approach similar to Dorfleitner & Utz (2012) and calculate a log performance ratio using ESG data as a proxy for a firm's sustainability and denote it sustainability return. We assume randomness for the sustainability returns since it is ex ante not possible to predict what good intentions the management of a company has will be realized (Dorfleitner & Utz, 2012). To calculate sustainability returns, we employ the ESG ratings obtained from Refinitiv, which are scaled between 0 and 100 (worst to best). While such scaling of ESG returns allows for an assessment of how sustainably a company operates, our intuition is to measure how the ESG rating of a firm is performing in comparison to the ESG ratings of other firms. This practice allows to identify whether a firm is over- or underperforming with regard to industry standards. Therefore, we divide a company's individual ESG rating $ESG_{n,t}$ at time t by the average ESG rating of all companies in the current rating universe across industries $\overline{ESG_{N,t}}$ to obtain the relative sustainability performance measure as

$$sp_{n,t} = \frac{ESG_{n,t}}{\overline{ESG_{N,t}}} \tag{4.3.2}$$

for company n at time t. This allows us to define the sustainability return as the logarithmic return of the sustainability performance

$$sr_{n,t} = log\left(\frac{sp_{n,t}}{sp_{n,t-1}}\right) \tag{4.3.3}$$

for company n at time t. While an investor's interpretation of financial returns is apparent, a positive sustainability return would reflect that the respective company has increased its relative sustainability rating over one period, which is an indicator for a successful implementation of ESG-friendly business conduct and, hence, favorable for an ethically motivated investor. Analogously, a negative sustainable return either shows that a company suffers from misconduct, e.g., due to managerial controversies or environmental pollution, or that the company does not keep up with the market standards of ESG practices, e.g., when the overall ESG ratings of other companies increase. Therefore, similar to financial returns, an ethical investor would prefer positive sustainable returns over negative sustainable returns. We report the descriptive statistics for the financial and sustainable returns in Table 4.1.

Table 4.1: This table reports the descriptive statistics of the financial and sustainable returns. The data come from Compustat and Refinitiv and include annual data for 411 firms from 2015 to 2019. In the process of computing sustainable returns, our sample of financial and sustainable returns shortens by one year and reaches from 2016 to 2019, consisting of 411 return series. We report the minimum, mean, and maximum for each central moment.

	Financial returns			Sustainable returns		
Statistic	Min.	Mean	Max.	Min.	Mean	Max.
Mean	-1.4119	0.0582	0.4948	-0.3714	-0.0002	0.2588
Volatility	0.0194	0.2179	2.0781	0.0097	0.1140	0.9067
Skewness	-1.1541	0.2100	1.1306	-1.1545	0.0187	1.1461
Kurtosis	-1.9992	-1.1758	-0.6671	-1.9977	-1.1245	-0.6668

The aim of this study does not lie in detecting the optimal portfolio weights, given the sustainability returns, but rather in identifying how the preference for sustainable assets changes as the risk appetite varies with differing utility function specifications. To answer this, we first compute two optimized portfolios, solely based on the financial returns, namely, the minimum-variance ($Min.Var$) and maximum Sharpe ratio ($Max.Sharpe$) portfolio. The global minimum-variance portfolio is defined as the portfolio with the lowest possible variance

$$Min.Var = \min_{\theta} \sigma_p^2 = \theta' \Sigma \theta \quad \text{s.t.} \quad \theta' 1 = 1 \quad \text{and} \quad \theta_i \geq 0 \quad \text{for} \quad i = 1, \ldots, N \tag{4.3.4}$$

where θ denotes the portfolio allocation vector with dimensions $N \times 1$, σ_p^2 is the portfolio variance, and Σ is the matrix of covariances. The portfolio allocation vector contains the weighting of each asset in the portfolio. We apply a full investment constraint by setting the sum of the portfolio weights in the portfolio allocation vector θ to be equal to one and a no-short-selling constraint by setting the portfolio weights greater than or equal to 0. The Sharpe ratio measures the risk premium on the portfolio per unit of risk, which is defined by the portfolio volatility σ_p. Hence, the maximum Sharpe ratio portfolio is given by

$$Max.Sharpe = \max_{\theta} \frac{\theta'\mu}{\sqrt{\theta'\Sigma\theta}} = \frac{\mu_p - r_f}{\sigma_p} \quad \text{s.t.} \quad \theta'1 = 1 \quad \text{and} \quad \theta_i \geq 0 \quad \text{for} \quad i = 1, \ldots, N \tag{4.3.5}$$

with μ_p being the expected portfolio return and r_f denoting the risk-free return. Given the low-interest environment during our sample period, caused by quantitative easing programs of central banks, we hereafter assume the risk-free rate to be equal to zero. Here, we once again apply the full investment and no-short-selling constraint on the portfolio weights.

Multiplying the portfolio allocation vector of the minimum-variance or maximum Sharpe ratio optimization with the vector of firms' financial returns r yields the financial portfolio returns $\theta' r = R$; we analogously obtain the sustainability portfolio returns as $\theta' sr = SR$, where R and SR are matrices of the dimensions $(N \times T)$ over the time period $t = 1, ..., T$ for N financial assets.

To explain why an investor would allocate investments to sustainable assets, we resort to the theory of expected utility. Similar to Dorfleitner & Nguyen (2016), we model the general utility of an investor depending on financial and sustainability returns as

$$U(R, SR) = U((1-\gamma)R + \gamma SR), \tag{4.3.6}$$

where $\gamma \in [0, 1]$ is the sustainability preference parameter and describes the weighting of sustainable assets relative to their financial counterpart. Under this utility model, an investor can gain utility from capital gain and ethically based non-financial sustainability returns. One shortcoming of this model is that financial losses in terms of negative financial returns may be offset by positive sustainability returns, regardless of the amount of money that is lost (Dorfleitner & Nguyen, 2016). Even though investors who seek socially responsible investments are willing to trade financial returns with sustainability returns, as found by Lewis & Mackenzie (2000); Nilsson (2009) and Dorfleitner & Utz (2014), it is unlikely that such an investor would fully waive financial returns; however, for the sake of simplicity, we use the above specification for the further analysis and cover an additive utility function model in the robustness section.

Since we are interested in the maximization of the expected investor utility with regard to the sustainability preference parameter γ, we define the optimization as

$$\gamma^* = arg \max_{\gamma} \left[T^{-1} \sum_{t=1}^{T} U\left(R, SR\right) \right], \quad \gamma \in \Omega, \tag{4.3.7}$$

where U is the utility function from Equation (4.3.6) and Ω defines the constraint of the sustainability preference parameter

$$\Omega = \left\{ 0 \leq \gamma_i \leq 1 \quad \text{for} \quad i = 1, \ldots, N \right\}. \tag{4.3.8}$$

Having introduced the general optimization problem, we now specify which utility functions approximate an investor's behavior in this study. We implement two families of utility functions that describe the risk-averse behavior of investors, namely, the exponential and s-shaped utility functions. As stated above, we assume that the utility is dependent on the financial and sustainable return, which implies a normalization of initial wealth to one. The motivation behind this assumption is that investors focus more on the return of an investment than on the level of wealth (Kahnemann & Tversky, 1979). Closed-form utility functions such as the exponential utility are commonly used in the literature (Dorfleitner & Nguyen, 2016). The exponential utility is defined as

$$-exp(-A(1 + r_p)), \tag{4.3.9}$$

where A denotes the degree of constant absolute risk aversion (CARA) and r_p is the (financial or sustainability) portfolio return. The implication for the CARA in the exponential utility is that, e.g., for an increase in wealth, the amount of money invested in risky assets remains unchanged, which stands in contrast to the constant relative risk aversion (CRRA), derived from the Arrow–Pratt risk measure, where the level of risk aversion changes with the amount of wealth.

The s-shaped utility function depicts an investor's preference for a certain gain to an uncertain gain with a higher expected value and, analogously, a preference for an uncertain loss to a certain loss with a higher expected value, including an inflection point between these two preferences. The function is defined as

$$\begin{aligned} -A(z - r_p)^{\lambda_1} \quad &\text{for} \quad r_p \leq z \\ B(r_p - z)^{\lambda_2} \quad &\text{for} \quad r_p > z \end{aligned} \tag{4.3.10}$$

with the curvature parameters $A, B, \lambda_1, \lambda_2$ and the inflection point z, where the parameters λ_1 and A influence the downside of the function and λ_2 and B, respectively, affect the upside of the function. The s-shaped utility is especially well suited to depict investor preferences, taking into account higher moments of returns, such as the skewness and kurtosis.

In further analysis, we vary the risk aversion parameter A of the exponential utility between 1 and 10. For the s-shaped utility, we perform one set of tests where we vary λ, holding everything else constant and equal, and another set of tests varying A and B, where we set λ equal. The behavior of both utility functions for varying parameters is depicted in Figures 4.1 and 4.2.

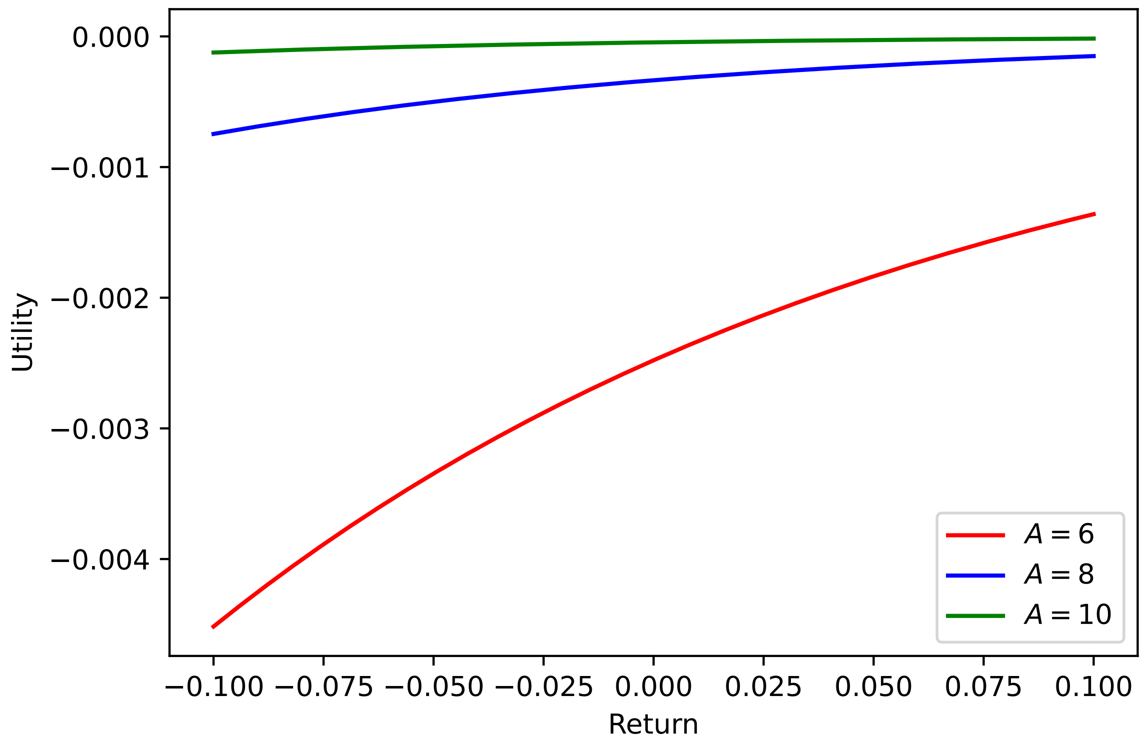


Figure 4.1: This figure shows the behavior of the exponential utility function for some of the different specifications used in this study.

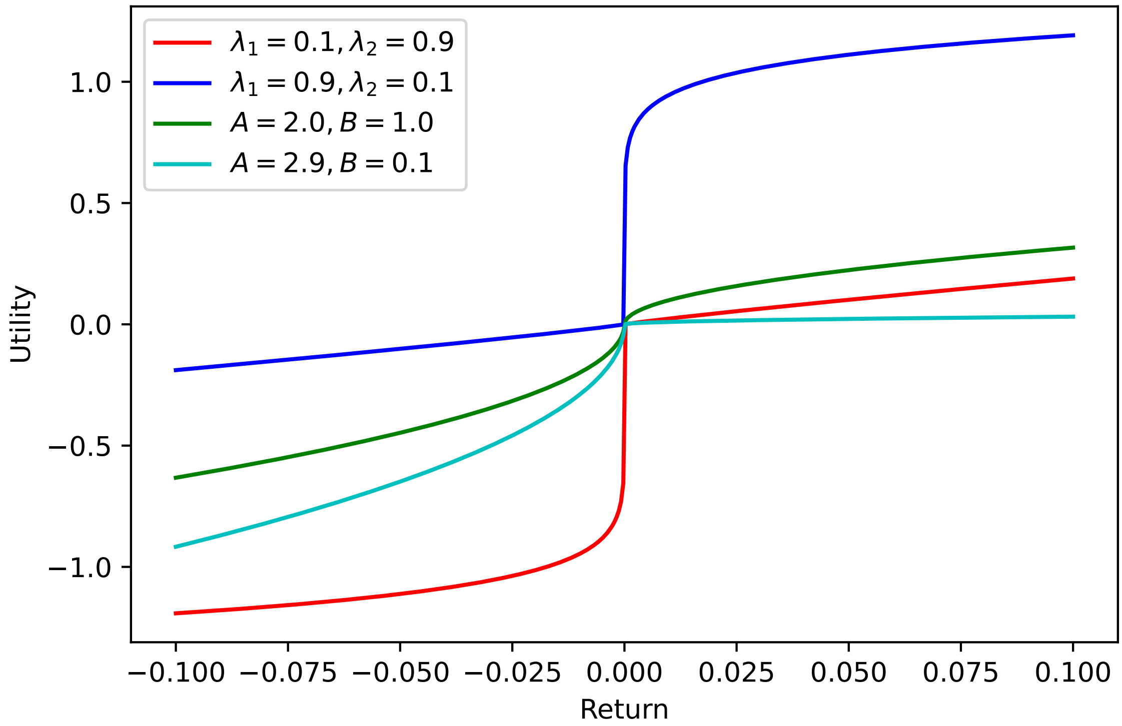


Figure 4.2: This figure shows the behavior of the s-shaped utility function for some of the different specifications used in this study.

Generally, the optimizations regarding the minimum-variance and maximum Sharpe ratio portfolio vector can be solved by quadratic programming; however, our objective function in Equation (4.3.7) requires a global optimizer. Hence, in the next subsection, we present the differential evolution algorithm, which is adequate to solve such a non-linear objective function.

4.3.3 Differential Evolution

Differential evolution is a global optimization technique that applies self-learning algorithms to find optima in vast solution surfaces (Hagströmer & Binner, 2009). Furthermore, it is a user friendly framework as it only requires few parameters to be defined. The optimizer is population-based and chooses its starting point by sampling the objective function at multiple, randomly chosen initial points (Storn & Price, 1997). The algorithm operates in five essential steps. Firstly, the upper and lower bounds for each parameter (in our case γ) to be optimized must be specified before initializing the population. Then, a set of P starting value vectors $\gamma_{i,1,g}$ of length N, subject to a constraint matrix Ω is randomly generated, where $i = 1, ..., P$ and P is the population size. The subscript g signifies that a new random value vector is generated for each parameter (Storn & Price, 1997).

In a second step, the algorithm mutates and recombines the population in order to create a population of NP trial vectors. This is conducted by a differential mutation technique, which adds a scaled, randomly sampled vector difference to a third vector (Storn & Price, 1997). The mutant vector is obtained as

$$\gamma_{i,2,g} = \gamma_{j_1,1,g} + F\left(\gamma_{j_2,1,g} - \gamma_{j_3,1,g}\right), \tag{4.3.11}$$

where j_1, j_2, and j_3 are randomly drawn discrete numbers from the set $1, \ldots, P$. The scale factor $F \in (0, 1+)$ controls the rate at which the population evolves.

The third step involves a crossover, in which trial vectors are build out of parameter values that have been copied from two different vectors. The algorithm crosses each vector with a mutant vector, where the crossover probability π is a user-defined value to control the fraction of parameter values that are replicated from the mutant (Storn & Price, 1997). This means that a third set of P vectors $\gamma^*_{i,3,g}$ with length N is created using the crossover probability π equaling $\gamma_{i,1,g}$ and a probability $(1 - \pi)$ equaling $\gamma_{i,2,g}$ (Hagströmer & Binner, 2009). These vectors are adjusted by a function f_c such that they satisfy the problem constraints in Ω

$$f_c(\gamma^*_{i,3,g}) = \gamma_{i,3,g} \in \Omega. \tag{4.3.12}$$

To ensure that the sustainability preference parameter is scaled between 0 and 1, the function f_c first sets all negative values of $\gamma_{i,g}$ equal to 0 and, in a second step, divides all elements by the sum of the solution vector. Then, a fourth set of P vectors of length N is generated, which contains the best solution vectors in set 1 and set 3, by using

$$\gamma_{i,4,g} = arg\max\{\gamma_{i,1,g}, \gamma_{i,3,g}\}(U(R, SR)). \tag{4.3.13}$$

As differential evolution compares each trial vector with the target vector from which it inherits parameters, it is said to more tightly integrate recombination and selection than other evolutionary algorithms (Storn & Price, 1997). Through iteration, new vector generations are created by setting

$$\gamma_{i,1,g+1} = \gamma_{i,4,g} \tag{4.3.14}$$

and repeating the steps of mutation, recombination, and selection until a halting criterion $g = G$ is met (Storn & Price, 1997).

The optimum is obtained as

$$\gamma^* = arg \max\{\gamma_{i,4,G}\}(U(R, SR)). \tag{4.3.15}$$

To verify that the optimum is not influenced by the random starting values leading to a local maximum, we repeat the whole procedure five times. In this study, we set the bounds of the sustainability preference parameter γ to be between 0 and 1. We choose the mutation scale parameter F to be between 0.5 and 1. This range enables us to apply dithering, which randomly changes the mutation constant with the generations and, hence, increases the speed for convergence. The crossover probability π equals 0.7, which is within recommended limits (Hagströmer & Binner, 2009). We set the population size ($P = 10$) ten times as high as the number of parameters that are to be optimized and do not implement a halting criterion, but set the number of maximum iterations to 2500. If a relative convergence of up to 0.01 is reached, the algorithm stops mutating.

4.4 Results

In this section, we present the results of the utility preference optimization. Table 4.2 reports the sustainability preference γ^* for differing constant absolute risk aversion parameters using the exponential utility in a minimum-variance and maximum Sharpe ratio portfolio setting.

In the minimum-variance scenario, we find that with increasing risk aversion, a minimum-variance investor's preference shifts towards sustainability returns. The shift begins at a risk aversion of $A = 3$, where an investor would optimize the personal utility when the portfolio consists of 12.2% sustainable returns and 87.8% financial

Table 4.2: This table reports the sustainability preference parameters γ^* for the minimum-variance portfolio and maximum Sharpe ratio portfolio under differing parameters for absolute risk aversion A, using the exponential utility function as an approximation of investor utility.

Risk aversion parameter	Sustainability preference (%)	
A	$\gamma^*_{Min.Var}$	$\gamma^*_{Max.Sharpe}$
1	0.0	0.0
2	0.0	0.0
3	12.2	0.0
4	36.8	0.0
5	51.5	0.0
6	61.3	0.0
7	68.5	5.0
8	73.3	20.8
9	77.4	31.0
10	80.7	40.3

returns. This ratio increases towards sustainable returns as the risk aversion parameter increases, which indicates that with an increasing preference for low portfolio risk, the minimum-variance investor would achieve the optimal utility by incorporating more sustainable returns. This can be explained by a lower variance of sustainability returns compared to financial returns. The highest preference for sustainability of 80.7% is obtained at a CARA equal to 10.

For a maximum Sharpe ratio investor, who seeks the optimal trade-off between return and risk, we find that there is also a shift towards sustainable returns but beginning at a significantly higher level of risk aversion $A = 7$. Hence, such an investor holds on to the risk-adjusted optimal portfolio until the preference for risk aversion increases significantly, where incorporating sustainable returns yields a better ratio of return per additional unit of risk. Here, the highest preference for sustainability is at 40.3% using a CARA equal to 10, which is half of the sustainability preference for a respective minimum-variance investor in the same scenario.

We report the results of the optimization of the sustainability preference parameters for the s-shaped utility in a minimum-variance and maximum Sharpe ratio setting in Table 4.3. The utility function in the results features an inflection point at $z = 0\%$, which means that the risk preference of an investor is risk seeking until the portfolio return equals 0% and then changes to risk-averse once a higher portfolio return than z is reached. We interpret z as a target return, which satisfies the investor in such a manner that beyond this target return, further risk per unit return receives marginally less importance in the utility sense.

Table 4.3: This table reports the sustainability preference parameters γ^* for the minimum-variance portfolio and maximum Sharpe ratio portfolio under differing parameters for the curvature parameters (A, B, λ_1, λ_2, z) of the s-shaped utility function with the inflection point at 0% as an approximation of investor utility.

Curvature parameters					Sustainability preference (%)	
A	B	λ_1	λ_2	z (%)	$\gamma^*_{Min.Var}$	$\gamma^*_{Max.Sharpe}$
1.5	1.5	0.1	0.9	0	0.0	0.0
1.5	1.5	0.2	0.8	0	0.0	0.0
1.5	1.5	0.3	0.7	0	0.0	0.0
1.5	1.5	0.4	0.6	0	0.0	0.0
1.5	1.5	0.5	0.5	0	0.0	0.0
1.5	1.5	0.6	0.4	0	0.0	0.0
1.5	1.5	0.7	0.3	0	0.0	0.0
1.5	1.5	0.8	0.2	0	0.0	0.0
1.5	1.5	0.9	0.1	0	0.0	0.0
2.0	1.0	0.5	0.5	0	0.0	0.0
2.1	0.9	0.5	0.5	0	0.0	0.0
2.2	0.8	0.5	0.5	0	0.0	0.0
2.3	0.7	0.5	0.5	0	52.8	0.0
2.4	0.6	0.5	0.5	0	75.2	0.0
2.5	0.5	0.5	0.5	0	83.2	0.0
2.6	0.4	0.5	0.5	0	86.6	0.0
2.7	0.3	0.5	0.5	0	88.2	44.6
2.8	0.2	0.5	0.5	0	88.8	85.3
2.9	0.1	0.5	0.5	0	89.1	93.5

Beginning with the minimum-variance portfolio, we find that the preference for sustainable returns does not increase when the curvature parameters λ_1 and λ_2 are varied, holding other parameters constant, meaning that an investor would not incorporate sustainability returns to optimize the individual preference. As the parameters λ_1 and λ_2 are held constant and the parameters A and B are varied, we observe that the investor holding a minimum-variance portfolio begins to prefer incorporating sustainable returns. Starting at a loss aversion parameter of $A = 2.3$, the sustainability preference parameter increases from 0% to 52.8%, indicating that such an investor would want 52.8% of sustainable returns in the portfolio to optimize the individual risk preference. With the increase in parameter A, the sustainability preference increases up to 89.1%, but after $A = 2.6$, the preference for sustainable returns only marginally increases. Under high values of the curvature parameter A, the additional utility per unit return after the inflection point z decreases significantly; hence, such an investor tries to incorporate sustainable returns with low variance. In the maximum Sharpe ratio portfolio, changing λ_1 and λ_2 does not induce a preference for sustainable returns. Similar to the setting in the exponential utility, varying A and B increases the sustainability preference, but only for high values of $A \geq 2.7$, where the parameter γ^*_{Sharpe} equals up to 93.5%. Hence, under such concave utility functions, where the marginal utility of higher returns is very low, incorporating sustainable returns yields a far better risk premium per unit risk than using financial returns.

To further analyze the s-shaped utility setting, we now vary the inflection parameter z and use curvature parameters similar to Table 4.3. In this scenario, an investor shifts the risk appetite from risk-seeking to risk-averse at a 5% return level. Intuitively, the preference for sustainable returns will change for higher levels of curvature parameters A and B, holding λ_1 and λ_2 constant and equal to 2 because of the higher target return, which is difficult to achieve solely from sustainable returns due to their characteristics of having lower return and variance. The results for an inflection return at $z = 5\%$ are presented in Table 4.4.

Table 4.4: This table reports the sustainability preference parameters γ^* for the minimum-variance portfolio and maximum Sharpe ratio portfolio under differing parameters for the curvature parameters (A, B, λ_1, λ_2, z) of the s-shaped utility function with the inflection point at 5% as an approximation of investor utility.

Curvature parameters					Sustainability preference (%)	
A	B	λ_1	λ_2	z (%)	$\gamma^*_{Min.Var}$	$\gamma^*_{Max.Sharpe}$
1.5	1.5	0.1	0.9	5	0.0	0.0
1.5	1.5	0.2	0.8	5	0.0	0.0
1.5	1.5	0.3	0.7	5	0.0	0.0
1.5	1.5	0.4	0.6	5	0.0	0.0
1.5	1.5	0.5	0.5	5	0.0	0.0
1.5	1.5	0.6	0.4	5	0.0	0.0
1.5	1.5	0.7	0.3	5	0.0	0.0
1.5	1.5	0.8	0.2	5	0.0	0.0
1.5	1.5	0.9	0.1	5	0.0	0.0
2.0	1.0	0.5	0.5	5	0.0	0.0
2.1	0.9	0.5	0.5	5	0.0	0.0
2.2	0.8	0.5	0.5	5	0.0	0.0
2.3	0.7	0.5	0.5	5	0.0	0.0
2.4	0.6	0.5	0.5	5	0.0	0.0
2.5	0.5	0.5	0.5	5	0.0	0.0
2.6	0.4	0.5	0.5	5	38.1	0.0
2.7	0.3	0.5	0.5	5	54.0	0.0
2.8	0.2	0.5	0.5	5	59.0	45.6
2.9	0.1	0.5	0.5	5	60.6	75.2

Similar to the results using an inflection point at 0%, we find that for the minimum-variance portfolio case the preference for sustainable returns is present for a high curvature parameter $A \geq 2.6$, holding everything else constant, where γ_{MV} varies between 38.1% and 60.6% for $A = 2.9$. This is a large difference in magnitude compared with our results in Table 4.3, where $A = 2.3$ already induces a preference for sustainable returns. Furthermore, the amount of sustainable returns has reduced considerably by approximately 30% compared with the previous results, which represents the need for financial returns to meet higher target returns. Regarding the maximum Sharpe ratio portfolio, we find a similar connection as with the minimum-variance portfolio setting. The higher target return of 5% requires a high curvature parameter $A \geq 2.8$ to incorporate sustainable returns, as the risk per unit return gains more importance for the investor. In this case, for extreme values of A, an investor takes advantage of the low volatility of sustainable returns and preferably incorporates these into the portfolio.

Complementary to the above analysis, we consider an additional scenario with the inflection return at $z = -5\%$, which we report in Table 4.5. In this setting, an investor would switch the risk appetite to being risk-averse as soon as the portfolio return is greater than or equal to -5%. Since such a low target return can be reached more easily with sustainable returns, we expect the preference for sustainable returns to be more prevalent than for the previous target returns in Tables 4.3 and 4.4.

Table 4.5: This table reports the sustainability preference parameters γ^* for the minimum-variance portfolio and maximum Sharpe ratio portfolio under differing parameters for the curvature parameters (A, B, λ_1, λ_2, z) of the s-shaped utility function with the inflection point at -5% as an approximation of investor utility.

Curvature parameters					Sustainability preference (%)	
A	B	λ_1	λ_2	z (%)	$\gamma^*_{Min.Var}$	$\gamma^*_{Max.Sharpe}$
1.5	1.5	0.1	0.9	-5	94.3	94.9
1.5	1.5	0.2	0.8	-5	94.5	0.0
1.5	1.5	0.3	0.7	-5	95.3	0.0
1.5	1.5	0.4	0.6	-5	0.0	0.0
1.5	1.5	0.5	0.5	-5	0.0	0.0
1.5	1.5	0.6	0.4	-5	0.0	0.0
1.5	1.5	0.7	0.3	-5	0.0	0.0
1.5	1.5	0.8	0.2	-5	100.0	0.0
1.5	1.5	0.9	0.1	-5	100.0	100.0
2.0	1.0	0.5	0.5	-5	98.1	0.0
2.1	0.9	0.5	0.5	-5	98.1	0.0
2.2	0.8	0.5	0.5	-5	98.1	0.0
2.3	0.7	0.5	0.5	-5	98.1	0.0
2.4	0.6	0.5	0.5	-5	98.1	95.7
2.5	0.5	0.5	0.5	-5	98.1	95.7
2.6	0.4	0.5	0.5	-5	98.1	95.7
2.7	0.3	0.5	0.5	-5	98.1	95.7
2.8	0.2	0.5	0.5	-5	98.1	95.7
2.9	0.1	0.5	0.5	-5	98.1	95.7

For both the minimum-variance portfolio and maximum Sharpe ratio portfolio, we see an advantage for using sustainable returns due to their low variance, since the marginal utility of one unit return, adjusted by volatility, is preferable here. Starting with the minimum-variance portfolio, we find for the first time that the boundary values of γ_1 and γ_2 induce a stark preference for sustainability between 95% and 100%, holding everything else constant. This result is intuitive for highly risk-averse investors and such low target returns, given the characteristics of the first and second moment of the sustainable returns compared to the financial returns. For varying parameters of A

and B, holding everything else constant, we find an optimal sustainability preference of 98.1%. As this optimum remains stable for all variations of A, this shows that the low target return can be reached very well with sustainable returns while adhering to a lower portfolio variance, compared to financial returns. In the maximum Sharpe ratio case, we can draw a similar conclusion. When we vary γ_1 and γ_2, we find a significant preference for sustainable returns of around 95% for the boundary specifications, indicating that under high risk aversion and a low target return, sustainable returns offer a better ratio of return per risk than solely incorporating financial returns. Furthermore, the appetite for sustainable returns is significantly higher compared with our results in Table 4.3, since $A \geq 2.4$ already induces a high demand for sustainable returns of 95.7%.

Overall, our results show that risk-averse investors seek the use of sustainable results to optimize individual utility. From the perspective of a minimum-variance and maximum Sharpe ratio investor, we find that the first is keener on implementing sustainable returns, due to the lower variance of sustainable returns, while the latter only incorporates sustainable returns for high levels of risk aversion. Our results are similar under the exponential and s-shaped utilities.

4.5 Robustness

The main drawback of our utility setting in Equation 4.3.6 is that negative financial returns can be offset by sustainability returns, implying an investor's indifference regarding the amount of financial loss. Therefore, we follow the additive utility criterion proposed by Bollen (2007) and Jessen (2012), and implemented in Dorfleitner & Nguyen (2016), which is defined as

$$U(R, SR) = (1 - \gamma)U(R) + \gamma U(SR), \tag{4.5.1}$$

where γ is the sustainability preference parameter and describes the weighting of sustainable assets in the portfolio. Equation (4.5.1) describes that an investor can gain utility from financial gain and simultaneously from ethically based non-financial sustainability returns. This avoids the problem that high sustainability returns may offset negative financial returns. By substituting Equation (4.3.6) with Equation (4.5.1) and following the same methodology for the optimization, we find that our results are qualitatively similar to those mentioned under Tables 4.2 and 4.3. To further ensure the validity of our results regarding the computation of sustainability returns, we consider three additional measures. First, we calculate the sustainability performance as the firm's ESG rating divided by the median ESG rating of all companies across all industries for the respective year. The descriptive statistics of such sustainability returns only show marginal variation compared with the statistics reported in Table 4.1. The results for the exponential and s-shaped utility are also qualitatively similar to our reported findings. As a second measure, we define the sustainability performance as the firm's ESG rating divided by the average ESG ratings of firms in the same industry for the respective year. In this setting, we again only observe a marginal difference to our reported statistics and results for the exponential and s-shaped utility. Third, we consider sustainability performance as the firm's ESG rating divided by the average ESG rating of firms with ESG scores below the median of the respective industry ESG scores per year. We find qualitatively similar results for the statistics and results of our optimization. We additionally conduct the analysis for two equidistant sub-periods of our sample. The results qualitatively match our results when employing the whole sample period but are significantly lower in magnitude. We expect such sub-sample analysis to offer further insights with increasing ESG data availability in the future. For reasons of brevity, we do not report the respective tables, but they are available on demand.

4.6 Conclusion

While the interest in sustainable investment has received a considerable increase over the past decade, little research has been conducted on the influence of incorporating sustainable returns on investor utility. In this study, we analyze how the preference for sustainable return varies for different risk appetites of investors holding a minimum-variance or maximum Sharpe ratio portfolio under exponential and s-shaped utility functions. We define sustainable returns as the logarithmic change of the ratio of a company's ESG rating relative to the overall market. Our findings suggest that with increasing levels of risk aversion, an ethical investor's preference for sustainable returns increases for both the minimum-variance and maximum Sharpe ratio portfolio setting, where our results are driven by the characteristics of sustainable returns, which exhibit low returns and variances. The findings hold in an additional utility criterion, underlining the robustness of our results. While our analysis is limited by employing a rather short time window, we expect more extensive analyses on the incorporation of sustainable returns for investor utility with increasing ESG data availability in the future. Our findings have implications for periods of economic turmoil, as we expect that during economic turmoil, ethically motivated investors may become more risk averse and, therefore, prefer to hold sustainable assets. Such switching behavior could be observed in the post-COVID-19 period, e.g., where ESG stock indices displayed a lower volatility than non-ESG indices (Mousa et al., 2021).

A Appendix for Chapter 2

Table A1: This table shows the results of looking at each sector separately based on the Global Industry Classification Standard's (GICS). The dependent variable is probability of default (PD). The independent variable is ESG or one of the associated pillar scores. In addition, abnormal returns (AR) and idiosyncratic volatility are added as market-driven control variables. All models are controlled for year-fixed effects. We report robust cluster-adjusted standard errors on firm-level in parentheses, where ***,**,* denotes the coefficient's statistical significance at the 1%, 5%, and 10% level.

Dependent Variable: PD	All (1)	Utilities (2)	Industrials (3)	Inf. Technology (4)
ESG	-0.0062***	-0.0008	-0.0018	-0.0083***
	(0.0012)	(0.0007)	(0.0053)	(0.0023)
Volatility	6.3159***	3.4782***	10.2472***	7.4106***
	(0.9597)	(0.8253)	(3.8605)	(1.0021)
Abnormal Return	0.2774**	0.1476	0.1597	-0.0717
	(0.1162)	(0.1123)	(0.3105)	(0.1446)
Observations	6992	633	462	1056
Year Fixed Effects	yes	yes	yes	yes
Adjusted R-Squared	0.1705	0.4386	0.3375	0.1736

Table is continued on the next page.

Table A1 continued.

Dependent Variable: PD	Materials (5)	Health Care (6)	C. Staples (7)	C. Discret. (8)
ESG	-0.0054	-0.0023	-0.0067*	-0.0042
	(0.0044)	(0.0041)	(0.0038)	(0.0033)
Volatility	5.2968***	6.4142***	5.4909***	6.8514***
	(1.7721)	(1.6136)	(1.9346)	(1.6320)
Abnormal Return	0.5980	0.0635	0.1975	0.3710**
	(0.5109)	(0.2171)	(0.1924)	(0.1840)
Observations	410	588	562	1053
Year Fixed Effects	yes	yes	yes	yes
Adjusted R-Squared	0.1401	0.3926	0.2039	0.1612

Dependent Variable: PD	Energy (9)	Financials (10)	Real Estate (11)	Communication (12)
ESG	-0.0145***	-0.0102***	-0.0083**	-0.0057
	(0.0040)	(0.0039)	(0.0038)	(0.0051)
Volatility	4.3164**	7.8471*	7.9379	4.5445***
	(1.6824)	(4.2104)	(4.9089)	(1.6212)
Abnormal Return	0.6064	0.4889	1.7132*	0.2125
	(0.4111)	(0.5312)	(1.0086)	(0.2363)
Observations	543	984	444	257
Year Fixed Effects	yes	yes	yes	yes
Adjusted R-Squared	0.1596	0.1738	0.3397	0.1830

Table A2: This table shows the influence of increasing lagged ESG scores on corporate default probabilities, where ESG(lag = 1) corresponds to the ESG score used as independent variable in Table 2.2, Table 2.3 and Table 2.4. In addition to the dependent variable *ESG*, abnormal returns and idiosyncratic volatility are used as market-driven control variables. All models are controlled for industry-fixed and year-fixed effects. We report robust cluster-adjusted standard errors on firm-level in parentheses, where ***,**,* denotes the coefficient's statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
ESG(lag = 1)	-0.0062***			
	(0.0012)			
ESG(lag = 2)		-0.0049***		
		(0.0013)		
ESG(lag = 3)			-0.0041***	
			(0.0014)	
ESG(lag = 4)				-0.0033**
				(0.0014)
Volatility	6.3159***	6.4684***	6.5107***	6.7274***
	(0.9597)	(1.1018)	(1.1925)	(1.2669)
Abnormal Return	0.2774**	0.2608*	0.3409**	0.3573**
	(0.1162)	(0.1337)	(0.1389)	(0.1547)
Observations	6992	6204	5500	4978
Industry Fixed Effects	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes
Adjusted R-Squared	0.1705	0.1671	0.1645	0.1662

Table A3: This table gives an overview of the variables used and their definition respectively. Accounting data was obtained from Compustat/Capital IQ, ESG and pillar scores and stock prices from Thomson Reuters Eikon. The scores used are defined as continuous variables between 0 and 100, corresponding to a percentile score (Refinitiv, 2021).

Variable	Definition
Dependent variables:	
PD	Probability of default taken from averaged one-year corporate transition probabilities for U.S. based firms provided by Standard and Poor's.
Independent variables:	
ESG Score	ESG Score.
E Score	Environmental Pillar Score.
S Score	Social Pillar Score.
G Score	Govnernance Pillar Score.
Control variables:	*All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles.*
Abnormal Return	Abnormal Return given as the difference between observed returns and expected returns from a market model based on daily log returns. The annual returns are determined by summation. The market returns are being proxied by the S&P 500 Index returns which are used to estimate the market beta.
Volatility	Idiosyncratic Volatility derived from market model residuals, i.e. the standard deviation of the estimated abnormal returns.
WC/TA	Working Capital to Total Assets.
RE/TA	Retained Earnings to Total Assets.
EBIT/TA	Earnings before Interests and Taxes to Total Assets.
ME/TL	Market Equity to Total Liabilities.
S/TA	Sales to Total Assets.
NI/TA	Net Income to Total Assets (Return on Assets).
TL/TA	Total Liabilities to Total Assets.
CA/CL	Current Assets to Current Liabilities.
Size	Natural logarithm of Total Assets.

Table A4: This table shows the results of the Wooldridge test for serial correlation in panel data. The null hypothesis states that there is no first-order autocorrelation present in the panel data. The test is run with for the panel of our multivariate specification containing the dependent variable PD as well as the independent variables ESG, $Volatility$ and *Abnormal Return*. We report p-values, where ***,**,* denotes statistical significance at the 1%, 5%, and 10% level.

	Statistic	p-value
F-statistic	8.196	0.00***

Table A5: This table shows the results of the Fisher-type Augmented Dickey-Fuller unit root test on our dependent variable PD. The null hypothesis states that all panels contain unit roots while the alternative states that at least one panel is stationary. The test is run with an ADF regression lag of one and a finite number of panels. We report p-values, where ***,**,* denotes statistical significance at the 1%, 5%, and 10% level.

	Statistic	p-value
Inverse χ^2	2801.64	0.00***

Table A6: This table presents the correlation coefficients for the variables used in this paper. The definitions of the variables are provided in Table A3.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) PD	1.00															
(2) ESG	-0.14	1.00														
(3) E	-0.12	0.85	1.00													
(4) S	-0.13	0.88	0.71	1.00												
(5) G	-0.10	0.69	0.43	0.39	1.00											
(6) Volatility	0.38	-0.18	-0.17	-0.15	-0.12	1.00										
(7) AR	-0.05	-0.00	0.00	-0.00	0.01	-0.22	1.00									
(8) WC/TA	0.03	-0.05	-0.04	-0.02	-0.07	0.12	-0.02	1.00								
(9) RE/TA	-0.28	0.12	0.14	0.09	0.09	-0.20	0.04	0.08	1.00							
(10) EBIT/TA	-0.16	0.09	0.11	0.10	0.03	-0.20	0.15	0.14	0.35	1.00						
(11) ME/TL	-0.11	0.02	0.05	0.04	-0.03	-0.10	0.13	0.38	0.28	0.40	1.00					
(12) S/TA	0.01	0.05	0.08	0.03	0.05	0.06	0.05	0.19	0.20	0.35	0.12	1.00				
(13) NI/TA	-0.20	0.09	0.10	0.10	0.03	-0.29	0.19	0.13	0.35	0.78	0.38	0.22	1.00			
(14) TL/TA	0.21	0.04	-0.03	0.04	0.01	0.09	-0.04	-0.35	-0.34	-0.09	-0.51	-0.05	-0.18	1.00		
(15) CA/CL	0.05	-0.07	-0.06	-0.05	-0.09	0.12	-0.04	0.82	0.05	0.04	0.36	-0.03	0.06	-0.39	1.00	
(16) Size	-0.21	0.42	0.35	0.39	0.22	-0.19	-0.03	-0.32	0.00	-0.19	-0.18	-0.28	-0.09	0.21	-0.30	1.00

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