ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
Bachelor Thesis Economics & Business
Specialization: Financial Economics

The Influence of ESG Scores on Stock Returns: Corporate Credit Ratings as a Mediator in the Covid-19 Context

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Finish date:	**08/08/2024**

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second reader, Erasmus School of Economics or Erasmus University Rotterdam.

ABSTRACT

Previous literature has found conflicting results regarding the effect of ESG scores on stock returns and how this relationship may have changed during the COVID-19 pandemic. Consequently, to further understand the mechanism behind this effect, many previous papers have attempted to find specific mediators through which ESG affects stock returns. This paper finds Corporate Credit Ratings to be a channel through which ESG indirectly affects stock returns during the COVID-19 pandemic, even when considering abnormal returns using the Carhart four-factor model. When looking at a time-period beyond the COVID-19 period, the Corporate Credit Ratings channel is not significantly higher during the pandemic period compared to outside of the pandemic period. These findings highlight the importance of Corporate Credit Ratings during the COVID-19 pandemic regarding the effect of ESG on stock returns.

Keywords: ESG, Credit Ratings, Stock Returns, Mediation

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CHAPTER 1 Introduction

Amidst an unprecedented period like the COVID-19 pandemic, the role of ESG factors and Corporate Credit Ratings, which perpetually adjust over time, becomes ever so pertinent. The emergence of the COVID-19 recession in the USA was characterised by underlying anticipations of "increased financial distress in the form of corporate defaults" analogous to what was seen during the Great Recession in 2008/09. Nevertheless, the average US corporate default rate in the year of 2020 of 3.79% is trumped by the 6.01% rate observed in 2009 (Kingsley, 2022). Additionally, the response of the stock market during this period was very ambiguous and perplexing. The American stock markets went through phases of all-time highs, and swift collapses (market crashes) entailed by rapid recoveries, all in a brief amount of time. It is thus no surprise that "studies on ESG and ethical portfolio performance during the market-wide financial crisis caused by the COVID-19 pandemic have reported contradictory findings" (Pavlova & de Boyrie, 2022). Subsequently, the prospect of Corporate Credit Ratings (CCR) as a mediator for the effect of ESG ratings on Stock returns entices high curiosity, especially during the COVID-19 crisis.

With regards to stock returns, it would be logical to follow the intuition of the Modern Portfolio Theory (Markowitz, 1952) that investors face a trade-off between risk and return, i.e. firms with higher ESG risk as well as credit risk require higher returns for investors. However, this does not apply when looking at the influence of ESG ratings on abnormal stock returns, as the risk-return trade-off is incorporated into it. Rather, according to the model of Pederson et al. (2022), ESG instigates two opposing effects that can lead to a return premium or discount. The positive effect is mechanised via better ESG metrics sending promising signals about a firms' prospects thereby increasing expected returns. The negative impact is caused by more institutional investors being attracted to high-ESG firms, leading them to be overvalued and subsequently yield sub-par returns.

This explains the variance in empirical findings. Papers like that of Albuquerque et al. (2020), which examined the returns of US stocks based on ESG ratings during the COVID-19 recession, indeed find that higher ESG scores lead to better stock performance. On the other hand, other papers like that of Demers et al. (2020), who controlled for intangibles, find the opposite. Accordingly, a lot of papers found no significant effect: Nirino et al. (2022) aimed to find the impact of sustainable practices (as well as the Environmental and Social scores) on stock returns in Europe and found a negative but non-significant negative relationship. Looking at a higher aggregation, Pavlova & de Boyrie (2022), observed that ETFs with higher sustainability ratings don't protect from losses during the economic turndown, but they also do not outperform the market. They employed 5 factor models to investigate the risk adjusted returns of 62 sustainability ETFs based on their Morningstar ESG ratings and found that the ETFs with lower sustainability ratings have slightly higher alphas, yet they are all insignificant.

This divergence is almost analogous when looking at how stock returns can be influenced by credit risk, which can be represented by ratings or Credit Default Swaps (CDS). As per the CFA institute, “A credit default swap (CDS) is a contract between two parties in which one party purchases protection from another party against losses from the default of a borrower for a defined period of time”. Via CDS, a party is effectively enabled to transfer credit risk associated with credit to the seller of the swap, which is more highly demanded if more risk is involved. Thus, it is proportional to credit risk and inversely correlated with CCR values. This paper focuses more on implied CCR, which are credit ratings based off CDS premia, as the way this reflects credit risk is more analogous to how ESG ratings reflect ESG activity, seeing as they both depend on ratings. Considering the existing body of research, the variance in findings regarding the relation between CCR and stock returns underscores the need for further investigation into the nuanced relationship between credit risk ratings and stock returns. In the context of banks, Ahmed et al. (2022) for instance find that higher credit risk and more non-performing loans lead to worse financial performance. Additionally, they find that the COVID-19 recession is a mediator of this effect. Avramov et al. (2009) found that stock returns do not differ across Credit Risk groups, although observations like those of Li and Lin (2021) rather follow the risk premium intuition, pointing at a positive correlation between credit risk and stock returns.

Evidently, ESG and CCRs exhibit similar traits in terms of asset pricing predictability. Past literature reveals that ESG measures are a factor that greatly determine changes in credit ratings of non-financial companies (Chodnicka-Jaworska, 2021). This may suggest that the effect of ESG scores on stock returns are caused by the correlated credit risk ratings. Furthermore, a recent study by Zhao and Lu (2024) found that credit default swap (CDS) trading causes significant improvements in a firms ESG performance. It is well established that the existence of credit default swaps act as a proxy for corporate credit ratings (Callen et al., 2007; Karagozoglu and Jacobs, 2008). Regardless, there is a glaring research gap with regards to how credit ratings of Corporations act as mediators for the causal effect of ESG scores on stock returns, and how this effect differs during the COVID-19 crisis. By shedding light on the complex intertwined relationship between ESG, credit risk, and stock returns in different time periods, this paper makes a substantial contribution to the financial literature. Thereby, it can yield valuable findings for practitioners searching for favourable investment strategies during specific time-periods, as well as for future researchers who will want to research related topics.

To find the mediation role of CCR on the effect of ESG scores on Stock returns, three relationships are pivotal:

1) The effect of ESG scores on CCR scores
2) The effect of CCR scores on stock returns
3) The effect of ESG scores on stock returns

If relationship 3 is insignificant before controlling for CCR scores (as Pavlova & de Boyrie (2022) and Nirino et al. (2022) find), the potential existence of competitive mediation or indirect-only mediation is investigated, as opposed to complementary mediation. Subsequently, this paper consists of a mediation analysis via a Baron and Kenny (1986) method, and attempts to answer the following research questions:

1) Do CSR scores mediate for the effect of ESG scores on stock returns during the COVID-19 crisis?
2) How does this effect differ inside vs outside of the COVID-19 crisis?

The remaining part of this research consists of six additional chapters. Chapter 2 provides a theoretical framework by giving an overview of the developments in ESG, and stock returns, covers existing literature regarding relationships between the three main studied variables, and formulates the hypotheses. Subsequently, Chapter 3 describes how the data is derived and transformed. Chapter 4 revolves around the methodologies used to answer the hypotheses. The respective results of these are described in chapter 5. Finally, chapter 6 discusses these results, along with its implications and relevance for future research, followed up by a general conclusion.

CHAPTER 2 Theoretical Framework

2.1 The rise of ESG

Towards the end of the 20th century, the contentions highlighting the importance and moral obligations of companies to incorporate philanthropic and ethical decisions disassociated with profit maximisation started gaining traction and accelerated ever since. With this traction came the rise of pivotal terms like CSR (Corporate Social Responsibility) and ESG (Environmental Social Governance), with interpretations that constantly evolve (Sheehy, 2015). Indeed, CSR is underscored by a diverse set of major models such as Carroll's Pyramid (Caroll, 1991), which emphasizes the importance of philanthropic and ethical responsibilities alongside the already undisputed legal and economic responsibilities. Another significant model is the "Triple Bottom Line," coined by John Elkington (1998), which incorporates the trichotomy of the social, environmental, and economic aspects. Through an investigation of 37 definitions for CSR, Dahlsrud (2008) discovers that although the definitions slightly differ, they are generally congruent and revolve around environmental, social, economic, stakeholder, and voluntariness dimensions.

In this paper, ESG and CSR are regarded as complementary; as explained by Polley (2022), CSR provides a general sustainability framework, whilst ESG provides a measurable sustainability and ethical performance assessment, using Environmental, Social, and Governance aspects as the basis. Since the 2008 financial crisis, the importance of ESG amongst investors have soared, causing rating agencies to go through a concentration process (Olmedo et al., 2019). Olmedo et al. raise the concern of a potential bias within major rating agencies caused by their connection with industry-related companies and document that some ESG rating agencies fail to fully integrate sustainability practices. Currently, there is no mandate for ESG reporting in the United States; however, research like that of Guan et al. (2020) and Guiso et al. (2006) find that informal institutions like societal norms and culture can work as a mechanism to replace legal enforcement for companies when it is weak. In the context of ESG, this mechanises many companies to voluntary disclose their ESG information and entices ESG rating agencies to be more objective which somewhat improves the biasness problem. Additionally, Olmedo et al. mention how "ESG raters" like MSCI, Refinitiv, Moody's, S&P and Fitch constantly integrate new criteria into their assessment models to measure corporate performance more accurately and robustly in order to respond to new global challenges.

2.2 Stock Returns

Stock returns can be defined as the percentage change in the nominal value of a stock holding over time. Financial literature regarding predicting stock returns based on specific factors dates back to the

CAPM model developed by Sharpe (1964), which formalises that a stock with higher market sensitivity and thus systematic risk must compensate with higher returns. Fama and French (1992) extended the CAPM model by adding a size (SMB) and value (HML) factor, constructed from the empirical findings that small-cap companies on average outperform large-cap companies, and high-value companies on average outperform low-value companies.

Since then, many other anomalies helping predict stock returns have been found. Jagadeesh and Titman (1993) first touched upon the momentum factor, observing a persistence in the direction of asset price movements. Based on research finding return premiums in companies with high profitability as well as companies with low levels of capital investments, Fama and French (2015) extended their model by adding profitability (RMW) and investment (CMA) factors. However, many papers like that of Avramov and Chordia (2005) put equity premium predictability into question and found that predictability-based investments are more effective in predicting stock returns. On the other hand, studies constructing functioning predictor variables for stock returns have been vastly growing, ranging from principal components to investor sentiment (Stock and Watson, 2012; Huang et al., 2015). Due to its multifaceted relationship with firm fundamentals and investor preferences (Petersen et al., 2021), it comes as no surprise that a broad variety of research regarding ESG in asset pricing models exist.

2.3 Effect of ESG ratings on Stock returns

2.3.1 ESG effect on financial metrics

The ESG assets market value is just over 18.4 trillion, with the USA accounting for 11%, which signifies its significance in the financial realm (Jovene, 2023). This saturation gives lots of room for research regarding the impact that ESG and its' ratings have in financial markets. For instance, Dhaliwal et al. (2011) revealed that firms with better CSR/ESG scores have a lower cost of equity for US firms, which was also confirmed in a study by El Ghoul et al. (2011). By the same token, Reverte (2011) finds a negative relationship between CSR disclosure ratings and the cost of equity capital within Spanish firms. Clearly, ESG scores are causal with beneficial financial attributes. To further support this, there is an immense amount of evidence indicating that CSR activity is positively correlated financial performance, establishing grounds for companies to remedy social ills (Margolis et al., 2009; Gilian et al., 2021).
It remains conceivable that companies employing high CSR practices outperform those employing low CSR practices even outside of financial downturn periods (Edmans, 2021). In fact, Pedersen et al. (2021) pin this down to Profitability, which is deemed to channel this positive effect during stable economic periods. This is contingent on the rationale that ESG is a driver of long-term value creation

(Starks et al., 2017). On the other hand, Pedersen notes an "investor demand channel", entailing investors that derive a positive utility from holding ESG stocks, causing stocks to be overpriced and subsequent stock returns to be lower. As a culmination, Darolles et al. (2023) conducted a causal mediation analysis to address the "investor demand channel" effect, and indeed confirms that it explains a significant part of the effect of ESG on stock returns. Regarding CSR, Bardos et al. (2020) analysed the mediation role of product market perception on the effect of CSR on stock returns.

Hong and Kacperczyk (2009), who find that sin stocks have higher expected returns than otherwise comparable stocks (As "sin stocks" are generally associated with low ESG firms, an inverse correlation between ESG scores and stock returns within the lower buckets is implied), provide an alternative channel, arguing that this is due to disregard from norm-constrained investing institutions or investors. Thus, in line with the variance in explanations and findings, Berg et al. (2022) emphasize the convolution involved in determining the relationship. They find that, when correcting for attenuation bias, there is a general positive relationship between the two, and that there is generally a downward bias in the standard regressions. When it comes to ESG rating changes, they generally influence stock returns as one would expect them to: analysing 748 US firms over 2016 – 2021, Shanaev et al. (2022) find that ESG rating upgrades lead to positive abnormal returns of 0.5% as opposed to a more pronounced underperformance of 1.2% caused by ESG rating downgrades.

2.3.2 ESG effect on stock returns

Whilst the effect of ESG ratings on stock returns is contested due to factors mentioned in the previous sections, there is a firm footing to infer that the positive channels outweigh the negative channels during financial downturns. In fact, Ahmed et al. (2022) empirically establish that a negative effect of credit risk on financial performance is mediated by the COVID-19 recession. This is highly significant as inverse proportionality between credit risk and ESG ratings aswell as proportionality between financial performance and stock returns are well grounded assumptions of this paper (although the former is tested in the methodology). Intuitively, a turning point like the COVID-19 recession could cause investors to get disproportionate preferences for stocks that pertain to altruistic values and lower ESG related risks, safeguarding those stocks from major losses. Godfrey et al. (2008) reinforce this by showing that CSR activity creates an "insurance" that to an extent protects firms from negative reactions from the market when the firm suffers negative events. Albuquerque et al (2020) explain two mechanisms of resiliency for firms with high ESG: customer loyalty, which enhances profitability and lowers risk through strong brand reputation, and investor segmentation, which reduces systematic risk as high ESG firms are typically held by investors with a long-term perspective.

Generally Financial crises create a challenging environment for investors and are typically characterised by heightened levels of uncertainty and panic. Indeed, risk aversion amongst investors is more pronounced during market downturns (Guiso et al., 2018). As per MSCI, companies with robust ESG practices pertain to higher values and tend to display lower volatility. This amongst many other factors indicating a positive relationship is underpinned by many credible papers that indeed confirm this positive relationship during the 2008 financial crisis (Cornett et al., 2016; Lins et al., 2017; Berkman and Henk, 2021).

The COVID-19 crisis was unique compared to other financial crises. Whilst significant, the impact on stock returns, insolvencies, and GDP was less adverse than in the 2008 recession. However, general uncertainty and global economic uncertainty was higher during the COVID-19 crisis (Rzepczynski, 2020). Consequently, it is the most appealing to conduct this research during the COVID-19 crisis and compare the results to other periods, as the complex interactions between ESG factors and stock performance are likely different during this period. According to Ding et al. (2020), corporations that assumed more responsibility were more resilient to the market downturn. During this period, a positive effect of ESG scores on stock returns is found by the likes of Albuquerque (2020) and Diaz et al. (2021). Nevertheless, many researchers like Dermer et al. (2021), Pavlova & de Boyrie (2022), and Nirino et al. (2022) observe no such effect.

2.4 Corporate Credit Ratings

Corporate Credit Ratings (from now on CCR) refer to independent assessments of a firm's creditworthiness and are thus inversely correlated with credit risk. The cost of debt is known to go up if credit risk goes down, they can thus be used reciprocally interchangeably in this paper. Although the notion of credit risk has been around much longer than CSR/ESG, its measurement has also dramatically evolved and refined itself over time, driven by the worldwide trends of a structural increase in bankruptcies, disintermediation of borrowing, and increases of off-balance sheet instruments with inherent default risk exposure (Altman and Saunders, 1997).

Sharpe's CAPM model notion that higher systemic risk firms require higher returns shows that financial theory projects a general positive relationship between credit risk and stock returns (Sharpe, 1964). Nevertheless, empirical research are inconclusive, moreover, Dichev (1998) and Campbell et al. (2008) have somewhat puzzlingly observed the opposite in US-markets since the 1980s. There is still debate with regards to whether this credit risk effect is a market inefficiency or simply due negative market perceptions (Merton, 1973), or latent components such as human capital (Fama and French, 1996). Periods of financial downturns pose alternative drivers behind this credit risk effect;

Avramov et al. (2009) show that poor performance of low rated stocks during periods of financial distress manifest a negative effect of credit risk on stock returns.

Besides this, Avramov et al. ‘s (2009) findings underpin an additional mechanism. Engagement on ESG issues and higher ESG proactivity reduces downside risk of firms (Hoepner et al., 2024). Accordingly, higher ESG scores within firms thus protects from this credit risk effect, and through this channel subsequently also alleviate the negative effect of credit risk on stock returns. This firstly underscores the role of credit risk (and indirectly thereby CCRs) as a mediator for the effect of ESG on stock returns, and secondly highlights the footprint that financial distress periods have on this mediation phenomenon. Papers like that of Bhuiyan et al. (2019) find that the cost of capital is in fact negatively affected by CSR, thus CSR disclosures reduce financing costs, implicating a negative effect of ESG on credit risk. A lower cost of capital implies that a stock needs less returns to be attractive to investors, meaning that this is another channel in which CSR/ESG scores can affect stock returns and credit ratings simultaneously.

Based on everything mentioned so far, there are many channels based on or related to credit risk through which ESG affects stock returns, moreover, it is quite evident that CSR and ESG display similar financial characteristics. The correlation between the two is reflected in modern academia; credit ratings are empirically shown to be positively related with ESG scores/CSR measures around the world (Li et al., 2022; Chodnicka-Jaworska, 2021). Additionally, a paper of Weber et al. (2008) shows that banks that incorporated components of ESG to assess a credit rating were more accurate (Weber et al., 2008). Subsequently, the prospect of SCR as a mediator for the effect of ESG on stock return becomes a viable one.

2.5 Hypotheses

Mediation analyses aim to disentangle the direct effect of an independent variable on the dependent variable from the indirect effect caused by pathways through other variables. Petersen et al. (2021) as well as Darolles et al. (2023) successfully manage to find mediator variables for the effect of CSR on stock returns. As priorly mentioned, there are several mechanisms where ESG metrics affect stock returns via credit risk. Therefore, the following hypothesis is made:

H1: Credit Risk is a significant mediator for the effect of ESG on stock returns.

When controlling for the Carhart 4 factor model, which is commonly used when observing the effect of ESG/CSR on abormal stock returns (Lins et al., 2017; Pavlova and de Boyrie, (2021)), the mediation effect of Credit Risk is isolated from asset pricing factors. Nevertheless, Chodnicka-

Jaworska (2021) and Zhao and Lu (2024) still establish causal relationships between ESG and CCR when controlling for factor models. Thus, hypothesis 2 is the following:

H2: Credit Risk is a significant mediator for the effect of ESG on abnormal stock returns.

As touched upon in this chapter, previous papers have identified channels/mediators through which ESG scores affect stock returns. However, this paper brings the novelty of attempting to find a mediator that is unique or more pronounced during the COVID-19 period. Ahmed et al. (2022) as well as the research of Avramov et al. (2009) and Hoepner (2024) indicate that the effect of credit risk ratings on stock returns is stronger during crises including the COVID-19 financial crisis. Past literature strongly indicates the possibility of the credit risk channel through which ESG affects returns to be stronger during the COVID period.

H3: The studied mediation effect is significantly stronger during the COVID-19 crisis compared to non-crisis periods.

CHAPTER 3 Data

3.1 Sample Data and Collection Method

The empirical research consists of a cross-sectional part to observe the data during the COVID-19 period as well as a panel data section to compare the mediation significance during the COVID-19 period vs other periods. For the cross-sectional section, the cumulative stock returns from the Friday of 21/02/2020 until the Friday of 29/05/2020 are analysed (from here the COVID-19 refers to this); this is defined as the COVID-19 crisis period for the rest of this paper, following Pavlova and de Boyrie (2022). The panel data stock returns are collected on a monthly basis spanning from 2019 up to and including 2022. All of the data is collected from US firms that are either listed in the NYSE of NASDAQ.

Stock returns are derived by extracting the respected stock prices from Eikon, which is financial data engine owned by LSEG providing data on over 30,000 firms across 180+ countries. With regards to abnormal stock returns, the Fama-French three-factor plus momentum factor is implemented as in Carhart (1997). This factor model is commonly used with regards ESG and Credit Ratings on abnormal stock returns the likes of Lins et al. (2017), Pavlova and de Boyrie (2022), and Demers et al. (2020). These factor loadings are obtained from the Kenneth R. French data library (2024). Additional financial data is extracted from Orbis and includes total assets, net profit, Price-to-Book ratio, and total debt.

ESG data is also derived from the Eikon database, specifically the ESG Combined Score Grade which provides an ESG score ranging from 0 (being the lowest) until 100 (being the highest. Eikon computes ESG scores based on 3 steps. Firstly, ESG data is collected by analysts from publicly disclosed sources, and then filter this based on 186 ESG subcategories. These are subsequently aggregated into ten ESG based categories and then further aggregated to their respective ESG pillars. Finally, an ESG controversies overlay is added to compute the ESG Combined Score. This data is provided on a yearly basis, ESG score is adjusted in accordance with the year of the monthly stock data. Nevertheless, the 2019 ESG scores are used for the cross-sectional analysis within the COVID -19 period to negate ESG rating changes caused by the COVID-19 crisis or pre-emptive ESG related changes in anticipation of the COVID-19 crisis.

The implied **Corporate Credit Rating**, which attributes a credit risk score based on credit default swap (CDS) premia, are used to represent Corporate Credit Ratings, and evaluate the credit risk of firms. This is extracted from Orbis, a financial database owned by Moody’s that contains financial information of over 400 million entities. Orbis computes the implied credit rating from CDS by using a daily pricing grid from CDS quotes to infer market-implied rating gaps, which are then averaged with Moody's senior ratings. CDS are arguably more accurate in representing credit risk than traditional credit ratings, as these are more liquid and responsive (Ederington et al., 2015). Table 1 displays rankings (from top to bottom) of these ratings, and the assigned numeric equivalent that are used in the regressions, with the highest being the best. Firms with a rating of "D" are not used in this paper.

Table 1: Assigned numerical equivalents for the implied corporate credit ratings used in the empirical analysis.

Description	Implied Credit Rating	Ranking
	AAA	9
Low risk of default	AA	8
	A	7
	BBB	6
Moderate risk of default	BB	5
	B	4
	CCC	3
High risk of default	CC	2
	C	1
Defaulted	D	-

3.2 Data handing

The data handling is done using Excel, Excel VBA, and R. The data extracted from Eikon is matched with the data extracted from Orbis using the ISIP code of each firm. Companies that are missing ESG data, Implied Credit Rating data, or relevant financial data are omitted from the dataset. Next, all financial firms are omitted from the dataset as these are given a disproportionate amount of financial support from the government during financial crises (Lins et al., 2017). Furthermore, only companies with a market capitalization of over 250 million dollars are considered, because low cap stocks tend to have low liquidity, high bid-ask spreads, and are subject to more price pressure effects of trading (Lins et al., 2017). The ESG score variable does not contain outliers, whilst the stock returns do; they are thus winsorized at a 1% and a 99% level for the whole extent of this paper, following prior papers looking at the effect of ESG on stock returns (Berg et al., 2022, Lins et al., 2017). For the cross-sectional analysis, companies that lack data during the COVID-19 time period are removed, subsequently, companies that lack data regarding any of the variables tracing back to 2019 are further removed for the longitudinal analysis.

Finally, this leaves 238 observations for the cross-sectional portion of the analysis and 10272 monthly observations for the longitudinal analysis, i.e. 214 firms over 48 months.

3.3: Control Variables, and Descriptive Statistics

The log of total assets, debt/assets, profit/assets, and BM ratio are employed as control variables in both sections of the methodology, these are extracted from Orbis. Total assets are logged because it would otherwise be skewed to the right with a skewness of 8.21. Another control is a dummy variable that assumes the value of 1 when the BM ratio is negative. Negative B/M firms have higher liabilities than assets and are thus likely to be distressed or financially instable, thus, they may behave more like high B/M firms than low B/M firms (Fama and French, 1992). The usage of this dummy variable has also previously been used in related studies by the likes of Lins et al. (2017), Avramov et al. (2009), and Darolles et al. (2023).

It must be noted that, with regards to the panel dataset, the ESG scores and the financial metrics that are used as control variables are adjusted on a yearly basis for every firm from 2019 to 2022, as these were available on a yearly basis. Additionally, Credit Ratings are adjusted on a quarterly basis and monthly returns are utilized for returns. Tables 2 and 3 display summary statistics for Returns, Implied Credit Ratings, and ESG scores for the cross-sectional dataset and the panel dataset respectively. Finally, table 4 displays ESG and stock return averages by credit rating.

Table 2: summary statistics during the COVID-19 period, with the ESG and ICR ratings being from 2019 as explained in the methodology section. Standard deviation is abbreviated with SD.

Variable	Count	Mean	Median	Lower Quartile	Upper Quartile	SD	Kurtosis	Skewness
Returns	238	0.808	0.833	0.700	0.926	0.180	-0.175	-0.466
ESG	238	57.7	59.8	45.8	69.4	16.7	-0.705	-0.198
ICR	238	5.57	6.00	5.00	6.00	1.13	-0.233	0.0967

Table 3: Summary statistics from the period 2019 until 2022, returns are on a monthly basis, credit risk ratings on a quarterly basis, and ESG scores on a yearly basis. Standard deviation is abbreviated with SD.

Variable	Count	Mean	Median	Lower Quartile	Upper Quartile	SD	Kurtosis	Skewness
Returns	10272	1.01	1.01	0.952	1.07	0.120	7.38	0.528
ESG	10272	58.5	60.3	45.7	58.4	16.26	-0.650	-0.297
ICR	10272	5.795	6.00	5.00	7.00	1.31	-0.500	-0.180

Table 4: Average returns and ESG scores during the COVID-19 period based on credit rating bucket.

Credit Rating	Count	Cumulative returns	ESG Score
AA	13	0.892558469	61.01058227
A	30	0.865878827	59.59323778
BBB	83	0.843055597	63.6233739
BB	72	0.767851289	55.38014402
B	34	0.750034569	47.33824488
CCC	6	0.742121808	46.8744038

CHAPTER 4 Methodology

4.1 Crisis Period Returns

4.1.1 Mediation Analysis

To address the both the first and the second hypothesis, a mediation analysis to test the significance of path a multiplied by path b as illustrated in figure 1 is conducted. For this, the 4-step Baron and Kenny method is implemented (Baron and Kenny, 1986). In this method, the first step establishes the total effect of the independent variable (ESG) on the dependent variable (Returns), the second step establishes the effect of the independent variable on the mediator (path a), whilst the third and fourth step establish the effect of the mediator and direct effect of the independent variable on the dependent variable (path b and path a).

Three main types of mediation are possible in this analysis. The first is that of complementary mediation, where both the direct effect and the indirect effect significantly affect the dependent variable in the same direction. Competitive mediation exists when the direct effect and indirect effect significantly influence dependent variable in opposite directions, leaving the total effect to be ambiguous and sometimes insignificant. Finally, the indirect-only effect occurs when the direct effect is insignificant, and the indirect effect is significant. Although the significance of path c and the total effect of ESG ratings on stock returns would have been a requirement in the traditional Barron and Kenny method, the last type of mediation does not require either, which is why it is not treated as a prerequisite in this analysis.

Accordingly, to test whether implied credit ratings mediate for the effect of ESG on stock returns during the COVID-19 crisis period, the following three OLS regressions are employed:

$$Return_i = \varphi_1 + \gamma ESG_i + \gamma_1^x X_i + \varepsilon_{1i} \quad (1)$$

$$ICR_i = \varphi_2 + \alpha ESG_i + \gamma_2^x X_i + \varepsilon_{2i} \quad \mathbf{(2)}$$

$$Return_i = \varphi_3 + \gamma_3 ESG_i + \beta \boldsymbol{ICR_i} + \gamma_3^x X_i + \varepsilon_{3i} \quad (3)$$

Where $Return_i$ represents the cumulative returns of firm i during the COVID-19 crisis period, φ_x the intercept of regression x, ESG_i is the ESG score of firm i given in 2019, ICR_i the implied credit rating of firm i in Q4 in 2019, X_i is a vector of control variables, ϵ_{xi} is the error term of firm i in regression x with $\epsilon \sim N(0,\sigma 2)$. X_i includes total assets, debt/assets, profit/assets, and BM ratio from the year 2019. Each of the three OLS regressions undergo a Breusch-Pagan test in order to identify the regressions that should be run with standard errors robust to heteroskedasticity. The BP test follows a Chi^2 distribution and tests whether the variance of errors is significantly dependent on the independent variables. Additionally, following the intuition of Lins et al. (2017), the ESG scores and implied credit ratings from 2019 are used to eliminate any concern that firms adjusted their CSR or financial risk policies in anticipation of the crisis.

On condition that the α of formula (2) and β of formula (3) are significant, i.e. ESG has a significant effect on ICR and ICR has a significant effect of returns, the Sobel test is implemented (Sobel, 1982). Two requirements of this test are the normality of the distribution of indirect effects and a big enough sample size, which is arguably met with a sample size of 238. The Sobel test follows a z distribution and determines the significance of the indirect effect the following way:

$$z = \frac{\hat{\alpha} * \hat{\beta}}{Standard\ Error} \quad (4)$$

Where:

$$Standard\ Error = sqrt(\hat{\alpha}^2 \times s_{\hat{\beta}^2}^2 + \hat{\beta}^2 \times s_{\hat{\alpha}^2}^2) \quad (5)$$

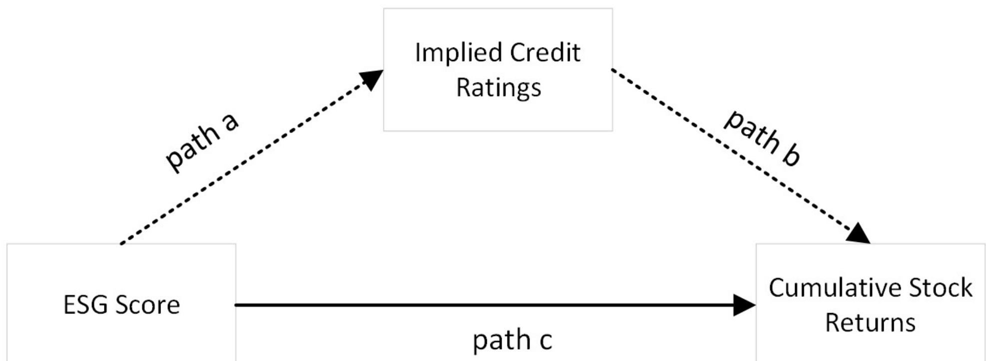

Figure 1

4.1.2 Abnormal Returns

With regards to both the effect of ESG scores and credit ratings on abnormal stock returns, the Carhart 4 factor model (1997) is widely adopted (Lins et al., 2017; Pavlova and de Boyrie, 2022; Demers et al. (2020), Avramov et al (2009). The abnormal returns, used in this paper to address hypothesis 2, are obtained by subtracting the expected returns from the actual returns. The expected returns per each individual firm are calculated via the following formula:

$$E(R)_{it} = R_{ft} + \beta_{i1} \times (R_{mt} - R_{ft}) + \beta_{i2}(SMB_t) + \beta_{i3}(HML_t) + \beta_{i4}(MOM_t) \quad (6)$$

Where $E(R)_{it}$ are the expected returns of stock i in month t based on the Fama French 3 plus momentum factors. R_{ft} is the risk free rate in month t, $((R_{mt} - R_{ft})$ represents the market risk premium, SMB_t represents the size factor premium during month t (small minus big firms), HML_t represents the value factor premium during month t (high minus low value firms), whilst MOM_t represents the premium of monthly winners over losers. The β_{ix} coefficients are obtained by regressing each firm's returns on the four factors from the period of 2019 until 2022.

The cumulative abnormal returns during the priorly established COVID-19 crisis period are calculated for each firm. Subsequently, the Baron and Kenny method under 4.1.1 is repeated with cumulative abnormal returns instead of cumulative returns.

4.2 Returns inside vs outside the Crisis Period

To address the third hypothesis, three panel ordinary least squares models (OLS), based on the 4 step Baron and Kenny method, are employed with fixed and random effects. Subsequently, a Hausman test is used to assess if a fixed-effects model (FEM) or random-effects model (REM) is more appropriate. Following Lins et al. (2017), a dummy variable that assumes the value of 1 during the COVID period (02/2020 – 05/2020) is generated and controlled for the in the three OLS models. Additionally, the interaction effect between the main regressor of each OLS model and the dummy variable are controlled for as well (ESG for path a and ICR for path b)

4.2.1 Fixed Effects vs Random Effects model

Both FEM and REM are commonly used in panel OLS regressions, the however entail different assumptions (Nikolakopoulou et al., 2014). The FEM assumes traits that are unique to each entity (in this case firms) and correlated with the independent variables. It thus assumes individual specific coefficients to eliminate omitted variable bias (OVB). On the other hand, REM assumes that entity specific effects are uncorrelated with the independent variables and distributed randomly, and thus allows the intercepts to be randomly distributed across entities.

Since REM consequently considers both within-group and between-group variation, it has higher statistical efficiency. However, if entity specific effects are indeed correlated with independent variables, a REM is biased (OVB) and thus violates the OLS assumptions, making FEM more favourable. A Hausman test, which tests for this correlation, is thus contingent to decide which model to use. In literature regarding ESG and Credit Default Swaps, fixed effects models are popular as they condition out time invariant economy traits and industry differences, and thus allow to better isolate the impact of COVID-19 on stock prices (Ding et al., 2021).

4.2.2 Comparing Returns Inside and Outside of the Crisis Period

To test whether the mediation effect of ICR on ESG ratings on Stock returns was stronger during the COVID-19 crisis, and to see the general effects that the crisis had on these three variables, the following three OLS are employed:

$$Return_{it} = \varphi_{1i} + \gamma ESG_{it} + \gamma_1^x X_{it} + \gamma_1^C DCOVID_t + \gamma_1^i ESG_{it} \times DCOVID_t + \varepsilon_{1i} \quad (7)$$

$$ICR_{it} = \varphi_{2i} + \alpha ESG_{it} + \gamma_2^x X_{it} + \gamma_2^C DCOVID_t + \gamma_2^i ESG_{it} \times DCOVID_t + \varepsilon_{2i} \quad (8)$$

$$Return_{it} = \varphi_{3i} + \gamma_3 ESG_{it} + \beta ICR_{it} + \gamma_3^x X_{it} + \gamma_2^C DCOVID_t + \gamma_2^i ICR_{it} \times DCOVID_t + \varepsilon_{3i} \quad (9)$$

Where $Return_{it}$ denotes the returns of stock i in month t, φ_{1i} is the firm specific intercept, ESG_{it} is the ESG score of firm i in month t, ICR_i the implied credit rating of firm i in month i, X_{it} is a vector of control variables, $DCOVID_t$ is a dummy variable assuming the value of 1 from the period of 02/2020 until 05/2020 and $\gamma_1^i ESG_{it} \times DCOVID_t$ and $\gamma_2^i ICR_{it} \times DCOVID_t$ are the interaction effects. Equations (7) until (9) resemble FEM; these are tested against REM where, for x = (1,3) the intercept of any cross section resembles:

$$\varphi_{xi} = \varphi_x + u_i \quad (10)$$

The Hausman test tests for a correlation between φ_{xi} and u_i.

With regards to the interaction effects, a significant γ_1^i coefficient would mean that the effect of ESG ratings on returns is different during the COVID period. A significant γ_2^i coefficient would mean that the effect of ESG ratings on ICR is different during the COVID period (path a). A significant γ_3^i coefficient would mean that the effect of ICR on returns is different during the COVID period (path b). If both γ_2^i and γ_3^i are significant, it could be that the mediation effect is stronger during the COVID-19 period, thus a Sobel test would be employed to analyse if the indirect path is significantly higher during the COVID period:

$$z = \frac{\widehat{\gamma_2^i} * \widehat{\gamma_3^i}}{Standard\ Error} \quad (11)$$

Where:

$$Standard\ Error = sqrt(\widehat{\gamma_2^i}^2 \times s^2_{\widehat{\gamma_3^i}^2} + \widehat{\gamma_3^i}^2 \times s^2_{\widehat{\gamma_2^i}^2}) \quad (12)$$

4.3 Robustness test: Controlling for Past Returns

In financial markets, returns can often exhibit temporal dependencies, which may introduce temporal dynamics or autocorrelation. Including a lag of the dependent variable as a regressor partially accounts for this potential autocorrelation. Additionally, this helps establish a temporal precedence, allowing for a more causal assessment of the mediation pathway. Consequently, as a robustness test, equations 7 to 9 are altered by adding the 1-month lag of returns:

$$Return_{it} = \varphi_{1i} + \gamma ESG_{it} + \gamma_1^x X_{it} + \gamma_1^C DCOVID_t + \gamma_1^i ESG_{it} \times DCOVID_t + \varepsilon_{1i} + Return_{it-1} \tag{7}$$

$$ICR_{it} = \varphi_{2i} + \alpha ESG_{it} + \gamma_2^x X_{it} + \gamma_2^C DCOVID_t + \gamma_2^i ESG_{it} \times DCOVID_t + \varepsilon_{2i} \tag{8}$$

$$Return_{it} = \varphi_{3i} + \gamma_3 ESG_{it} + \beta ICR_{it} + \gamma_3^x X_{it} + \gamma_2^C DCOVID_t + \gamma_2^i ICR_{it} \times DCOVID_t + \varepsilon_{3i} + Return_{it-1} \tag{9}$$

Where the variable $Return_{it-1}$ resembles the returns of stock i in month t-1. The rest of the variables are identical to those under chapter 4.2.2.

CHAPTER 5 Results

This section encompasses the results obtained following the methodology from Chapter 4. Firstly, the results of the cross-sectional analysis that revolve around hypotheses 1 and 2 are presented. Secondly, the results from the panel data analysis revolving around hypothesis 3 is presented.

5.1 Mediation during the COVID-19 crisis period

This section covers the mediation effect of implied credit ratings on the effect of ESG on stock returns during the COVID-19 crisis period as per section 3.1. To establish whether the OLS regressions from equations (1) – (6) (corresponding to the Baron and Kenny 4 step method for normal and abnormal returns) should be run robust to heteroskedasticity or not, the Breusch Pagan test is employed on the regressions. As shown in table 5, only the OLS regressions from equation (3) are significant in the BP test for both normal and abnormal returns. Therefore, for these regressions, the null hypothesis that the variance of the error terms is not correlated with the regressors is rejected, and the regressions are consequently run heteroskedasticity robust. For the other regressions this is not the case, as the null hypothesis cannot be rejected.

Table 5: Breusch-Pagan test results for each of the OLS regressions with regards to the mediation on cumulative stock returns and cumulative abnormal stock returns during the COVID-19 period (Equation 1-6). Equation (2) from section 4.1.1 is identical for normal and abnormal returns and thus only included once here.

	Value		
OLS Model	Chi^2	df	p value
(1) Total Returns	1.91	6	0.928
(2) ICR	4.22	6	0.647
(3) Direct Returns	19.8	7	0.00583
(4) Total FF3 + M returns	5.49	6	0.483
(6) Direct FF3 + M Returns	20.4	7	0.00479

Table 6 shows the results of the OLS models formulated in equations (1) to (3). When looking at the R^2, ESG and the vector of control variables as per section 4 only explain 14.2% of the variance in cumulative returns during the COVID-19 period. With the inclusion of implied credit ratings (ICR) in the regressors, the explanatory power of the regressors goes up to 16%. Model 2's R^2 is 0.343, meaning that 34.3% of the variance in ICR is explained by the independent variables in the model.

In terms of the effect of ESG scores on returns, both the total and direct effect, as seen under column (1) and column (3), are positive but insignificant, which is in line with the lack of consensus in findings explained by Pavlova and de Boyrie (2022). It is also noteworthy that after including ICR, the effect of an increase in ESG scores by 1 point on returns during the period goes down from +0.055% to +0.022% percent points in the sample. Although the significance of the total effect (path c) was a prerequisite as per the causal steps approach as per Baron and Kenny (1986), it is deemed by many statisticians today as unnecessary, and rather a test of joint significance can be made, only requiring significance of the indirect paths (Andrew Hayes, 2009). This test of joint significance is still analogous to the Baron and Kenny method, but is not contingent on the significance of path c.

In line with the findings of Chodnicka-Jaworska (2021) and Zhao and Zhu (2024), the effect of ESG scores on implied credit ratings, constituting path a, was indeed found to be significant and positive; an ESG score increase of 1 increases the ICR by 0.012. Additionally, the effect of ICR on returns, constituting indirect path b, is also positive and significant; an increase in the implied credit score by 1 increase returns by 2.91%. This means that a Sobel test can be done as per the joint significance causal steps approach.

With regards to the control variables, Profit/Assets has a significant positive effect in each regression, the logarithm of assets has a significant positive effect of implied credit ratings, but insignificant effects on returns. All the other control variables do not have significant effects on the dependent variables in the three models.

When observing table 7, it can be seen that the results with regards to returns controlled for the FF-3 + Momentum factors are the same as those of ordinary returns. The adjusted R^2 increased to 0.198 (19.8% of the variation in abnormal returns is explained by the regressors) in the model predicting abnormal returns without ICR as a regressor and 0.224 (22.4% of the variation in abnormal returns is explained by the regressors) when including ICR as a regressor. This increase in explanatory power makes sense as more is accounted for in the models when adjusting the returns based on the factors. Two major differences are that path b, the effect of an increase ICR by one on abnormal returns, increased to 3.81% and is even significant at a 0.01% significance level, and that the logarithm of assets also significantly and positively affects abnormal returns in the model without ICR (column 3).

Table 6: OLS model results regarding the effect of ESG scores on cumulative returns (Equation 1), the effect of ESG scores on implied credit ratings (Equation 2), and the effect of both ESG scores and implied credit ratings on cumulative returns (Equation 3). Cumulative returns signify the cumulative returns during the COVID-19 period.

	Dependent Variable		
	(1) Cumulative Returns	(2) ICR	(3) Cumulative Returns
Constant	-39.5%*** (15.1)	-1.92* (0.840)	-33.9%*** (12.7)
ESG	0.0553 (0.0677)	0.0115** (0.00376)	0.0217 (0.0650)
ICR	-	-	2.91* (1.12)
Log (Assets)	0.787 (0.0853)	0.396 *** (0.0473)	-0.366 (0.865)
Debt/Assets	-4.12 (6.52)	-0.337 (0.362)	-3.14 (-6.22)
BM Ratio	-0.822 (2.01)	-0.0951 (0.112)	-0.545 (2.19)
Profit/Assets	116*** (18.5)	4.92*** (1.02)	102*** (18.8)
Negative B/M	-7.72 (4.78)	-0.304 (0.265)	-6.83 (4.80)
Adjusted R^2	0.142	0.343	0.160
Observations	238	238	238

**** Notes: Standard errors are given in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001***

Table 7: OLS model results regarding the effect of ESG scores on cumulative abnormal returns (Equation 4), the effect of ESG scores on implied credit ratings (Equation 2), and the effect of both ESG scores and implied credit ratings on cumulative abnormal returns (Equation 6). Cumulative abnormal returns signify the cumulative abnormal returns, based on the Carhart 4 factor model, during the COVID-19 period.

	Dependent Variable		
	(1) FF3 + Momentum Abnormal Returns	(2) ICR	(3) FF3 + Momentum Abnormal Returns
Intercept	-75.3%	-1.92*	-67.9%*
	(0.167)	(0.840)	(0.127)
ESG	0.106	0.0115**	0.0616
	(0.0747)	(0.00376)	(0.0650)
ICR	-	-	3.81***
			(1.12)
Log (Assets)	2.11*	0.396 ***	0.602
	(0.940)	(0.00473)	(0.865)
Debt/Assets	-2.67	-0.337	-1.39
	(7.19)	(0.362)	(6.22)
BM Ratio	1.23	-0.0951	1.59
	(2.22)	(0.112)	(2.19)
Profit/Assets	148***	4.92***	129***
	(20.4)	(1.02)	(18.8)
Negative B/M	-8.66	-0.304	-7.50
	(5.27)	(0.265)	(4.80)
Four-factor loadings	Yes	No	Yes
Adjusted R^2	0.198	0.326	0.224
Observations	238	238	238

***** ***Notes: Standard errors are given in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001***

Table 8 shows the Sobel tests for ICR as a mediator for the effect of ESG ratings on returns under panel A, and for ICR as a mediator for the effect of ESG ratings on abnormal returns under panel B. For both panels, the indirect effect of ESG scores on returns is higher than the direct effect, which is in line with the fact that the direct effect is insignificant for both. The Sobel values are 1.98 and 2.27 respectively, which are significant given the 5% 2 tailed critical value of 1.96. Consequently, both hypothesis 1 and hypothesis 2 are confirmed as ICR is found to be a mediator in both models. Nevertheless, it must be noted this is not a traditional mediation but rather an indirect-only mediation, since the direct and total effects are insignificant as priorly mentioned. This means that although it can’t be said that ESG has a total or direct effect on returns during the COVID-19 crisis period, ESG is found to indirectly and positively affect returns and abnormal returns through the implied credit ratings channel during the COVID-19 period.

Table 8: Panel A displaying the results of the Sobel test testing ICR scores as a mediator for the effect of ESG scores on cumulative returns during the COVID-19 period. Panel B displaying the results of the Sobel test testing ICR scores as a mediator for the effect of ESG scores on cumulative abnormal returns during the COVID-19 period. SE is an abbreviation for standard error.

Value	Panel	
	(A) Returns	(B) FF-3 + Momentum Abnormal Returns
Indirect Effect (a*b)	0.0335	0.0852
Direct Effect (c)	0.0217	0.0634
SE	0.0169	0.0193
Sobel Value	1.98*	2.27*
N	238	10272

***** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$**

5.2 Mediation inside vs outside of the crisis period

This section shows the results of the panel regressions with the COVID time dummy to analyse whether mediation effect (if existent) is stronger during the COVID period than outside the COVID period.

After the OLS models are both estimated for random effects and fixed effect, the Hausman test is utilized. As shown in table 9, the p values are all below the critical value of 5%, meaning that the the null hypothesis that corr (φ_{xi},u_i) = 0, is rejected. Hence, the FE model is used for each regression. Subsequently, the Breusch Pagan test is used for all three models, with a p value below the critical value of 5% for each, meaning that regressions are run robust to heteroskedasticity.

Table 9: The p values of the Hausman test, and the subsequent Breusch Pagan test for the panel data regression models regarding the effect of ESG scores on monthly returns (Equation 7), the effect of ESG scores on implied credit ratings (Equation 8), and the effect of both ESG scores and implied credit ratings on monthly returns (Equation 9). The time-period is from 2019 to 2022.

	p value	
OLS Model	Hausman test	Breusch Pagan test
(7) Total Returns	0.000377	>0.000001
(8) ICR	0.000002	>0.000001
(9) Direct Returns	>0.000001	>0.000001

Table 10 shows the OLS models corresponding to equations (7) to (9) from the years 2019 until 2022, with all models having the same vector of control variables as before, in addition to the COVID_19 period time dummy and the interaction of the dummy with the ESG score. Similarly to the section 5.1, ESG does not have a significant effect on returns with (path c) and without the inclusion of ICR as a control, the value of the effect is however negative. The COVID dummy is significant and negative for all models, which signifies that returns and credit ratings are lower during the COVID-19 period, which is in line with common intuition.

Path a, ie the effect of ESG scores on ICR, is not significant, meaning that the priorly analysed mediation effect does not exist from the period of 2019 until 2022. On the other hand, path b, ie the effect of ICR on returns, is significant; monthly returns are found to go up by 1.57% as the credit rating increases by 1. This positive relationship is in line with Dichev (1998) and Campbell et al. (2008). Additionally, the interaction effect between credit ratings and the COVID dummy is positive yet insignificant. This does not correspond the findings of Ahmed et al. (2022), who find that the COVID period mediates for the effect of credit ratings on stock returns.

The interaction effect between ESG scores and the COVID-19 dummy is also insignificant in models 7 and 9 meaning that the effect of ESG scores on returns is not stronger during the COVID-19 period, which contradicts the findings of Lins et al. (2017). Due to this the Sobel test does not have to be done, as it would have tested for the joint significance between the interaction effect of path a and the COVID dummy and the interaction effect of path b and the COVID dummy, both of which are insignificant by themselves. From this, it can be extrapolated that the mediation effect is not stronger during the COVID period compared to outside the COVID period.

Table 10: Displaying the regression results regarding the effect of ESG scores on monthly returns (Equation 7), the effect of ESG scores on implied credit ratings (Equation 8), and the effect of both ESG scores and implied credit ratings on monthly returns (Equation 9). The time-period is from 2019 to 2022. Each regression also controls for the COVID-19 time dummy and its interactions with the relevant regressors. The time-period is from 2019 to 2022.

	Dependent Variable		
	(7) Returns	(8) ICR	(9) Returns
Constant	FE	FE	FE
ESG	-0.00578 (0.0169)	0.00107 (0.000829)	-0.00410 (0.0129)
ICR	-	-	1.57*** (0.220)
COVID dummy	-6.47*** (1.56)	-0.323*** (0.0764)	-5.96*** (1.41)
COVID dummy*ESG	-0.0313 (0.0261)	-	0.0291 (2.32)
COVID dummy*ICR	-	0.00142 (0.00128)	0.00209 (0.00250)
Log (Assets)	-3.51*** (0.946)	0.857*** (0.0464)	-4.86*** (0.716)
Debt/Assets	0.0526 (2.37)	0.991*** (0.116)	-1.50 (2.07)
BM Ratio	-2.26*** (0.418)	-0.130*** (0.0205)	-2.05* (0.831)
Profit/Assets	11.8* (5.21)	2.61*** (0.256)	7.65 (7.30)
Negative B/M	0.118 (0.0261)	-0.155** (0.0506)	0.361 (0.842)
Observations	10272	10272	10272

**** Notes: Standard errors are given in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001***

5.3 Robustness Checks

5.3.1 Controlling for lag of returns

As shown in table 11, when controlling for lagged returns, the results do not change. Path remains slightly positive but insignificant, path b remains significant and positive. Path c, resembling the overall effect of ESG on Returns without controlling for ICR, remains insignificant aswell. Finally, the interaction effects between the regressors in question and the COVID dummy also remain insignificant.

Table 11: Analogous to table 10, with lagged returns as a control variable for Equation 7 and equation 9.

	Dependent Variable		
	(7) Returns	(8) ICR	**(9)** Returns
Constant	FE	FE	FE
ESG	-0.00446 (0.0144)	0.00107 (0.000829)	-0.00283 (0.0145)
ICR	-	-	1.73*** (0.236)
COVID dummy	-7.18*** (1.60)	-0.323*** (0.0764)	-6.64*** (1.55)
COVID dummy*ESG	-0.0352 (0.0262)	0.00142 (0.00128)	0.0329 (0.0253)
COVID dummy*ICR	-	0.00142 (0.00128)	0.00321 (0.00387)
Log (Assets)	-3.21*** (0.808)	0.857*** (0.0464)	-4.68*** 0.757
Debt/Assets	0.938 (2.12)	0.991*** (0.116)	-0.730 (2.28)
BM Ratio	-2.44* (1.13)	-0.130*** (0.0205)	-2.22* (1.07)
Profit/Assets	13.7* (8.58)	2.61*** (0.256)	9.21 (8.08)
Negative B/M	0.270 (0.916)	-0.155** (0.0506)	5.42 (8.95)
Lag of Returns	-0.105*** (0.0135)	-	-0.107*** (0.0136)
Observations	10058	10058	10058

Notes: Standard errors are given in parentheses, * p < 0.05, ** p < 0.01, *** p < 0.001

5.3.2 ViF test

One potential statistical problem that could arise in this analysis is that of multicollinearity, which arises when two or more independent variables are too highly correlated, this can make the coefficient estimates unstable and high in variance. To address this, the Variance-in-Inflation factor (ViF) is obtained from each independent variable employed in section 5.1. The ViF tells how much the variance of a regression coefficient is increased due to multicollinearity. As displayed in table 12, the ViF does not exceed 5, which is a reasonable threshold for multicollinearity (databasecamp, 2024).

Table

Table 12: ViF test results for based on the OLS regression corresponding to equation 1

Dependent Variable	ESG Score	Credit Rating	Log (Assets)	Debt/Assets	BM ratio	Profit/Assets	Negative B/M
ViF	1.13	1.52	1.35	1.26	1.35	1.17	1.45

CHAPTER 6 Discussion & Conclusion

6.1 General Discussion

This paper aimed to address the following questions:

1) Do CSR scores mediate for the effect of ESG scores on stock returns during the COVID-19 crisis?
2) How does this effect differ inside vs outside of the COVID-19 crisis?

Indeed, based on the results, the answer to the first question is yes for both normal returns and abnormal returns. Regarding the second question, no significant difference was identified, although a mediation through the ICR channel was found during the COVID-19 period and not found using the broader time period of 2019 to 2022.

The paper finds that, during the COVID-19 crisis, ESG indirectly positively affects returns via the credit risk channel, which confirms hypothesis 1. This builds onto much of the previous existing literature that has tried to explain the mechanisms behind the effect of ESG on stock returns. Godfrey et al find that high ESG protects firms from negative reactions when firms perform badly. Given this paper's findings, it very much possible that this downside protection is achieved through ESG investors placing a higher importance on the credit risk of firms during financial downturns when making decisions. By the same token, it seems intuitive that the Albuquerque et al's. (2021) positive mechanisms of customer loyalty and investor segmentation are strengthened during uncertain periods like the COVID-19 crisis, due to investors placing more importance on stable firms. This paper however finds that both the effect of ESG and credit ratings on stock returns not significantly higher during the COVID-19 crisis, yet the effect of credit ratings on stock returns are. This however would be in line with the following: the two resiliency mechanisms are channelled through credit ratings during the COVID-19 period.

Hypothesis 2 is also confirmed as the Sobel test testing for the mediation effect of implied credit ratings on the effect of ESG on abnormal returns was significant, and in fact yielded a higher z value than that of normal returns. This comes as somewhat surprising, since the CAPM factor adjusts for the volatility and thereby also the riskiness of firms, and a lot of the mechanisms regarding ESG and ICR explored in the theoretical framework involved risk and credit risk. Possible reasons behind this are market efficiency issues or that credit ratings may have a more muted impact on stock returns, which could be isolated via the pricing models. It is also noteworthy that ESG is found to not affect stock returns during the COVID-19 period, therefore, the observed mediation is an indirect-only mediation, as opposed to complementary or competitive mediation.

Additionally, whilst it was expected the indirect path a, ie the effect of ESG on ICR was significant during the COVID period, it was rather unexpected for it to be insignificant when looking at a broader time period, as this contradicts the findings of Chodnicka-Jaworska (2021) and Zhao and Zhu (2024). Additionally, insignificance of the interaction effects between the COVID dummies and paths a and b reject hypothesis 3. This is also rather surprising, as when looking at previous literature that studied the effect of COVID-19 on these paths, Lins et al (2017) and Ahmed et al (2022) find these to be positive.

6.2 Limitations

The use of the Sobel test in this study represents a limitation due to its reliance on the causal steps approach, which is heavily criticized for its low statistical power and indirect inference of mediation effects (Hayes, 2009). The causal steps approach infers the presence of an indirect effect based on the significance of separate paths (a and b), rather than directly quantifying the effect itself, which is contrary to traditional scientific practices that emphasize direct hypothesis testing and quantification. Additionally, simulation studies have shown that this method is among the least effective at detecting true indirect effects (MacKinnon et al., 2002). The possibility of a type 1 error, which occurs when the H_0 is falsely rejected, is quite high when using the Sobel test, thus hypotheses 1 and 2 may have only been confirmed due to this error. It is also very hard to test the normality of the distribution of indirect effects in a mediation analysis, which is an assumption required for the Baron and Kenny method.

For these reasons, the bootstrapping method is often used for mediation analyses instead, as it does not require a normality of the distributions of the indirect effects. Additionally, bootstrapping has higher explanatory power and does not entail a lower possibility of a type 1 error compared to the method used. Thus, there is space for future researchers to repeat this analysis using the bootstrapping method.

Additionally, there may have been endogeneity issues in both the panel regressions and the cross-section regressions. This could be due to omitted variable bias or reverse causality in any of the direct or indirect paths. A common solution for this is the usage of instrumental variables for the mediator, which for instance was done by Bardos et al. (2020), who considered product market perception as a mediator between ESG and financial performance. In this paper, finding an instrumental variable was redundant as it was tough to find a variable that met both the relevance assumption and the exclusion assumption for internal credit ratings on returns. The usage of lagged variables for the panel regressions as a robustness measure may have limited the endogeneity due to the inclusion of temporal dynamics, but it does not completely solve for it, and it was not possible to include in the cross-sectional portion of the methodology.

The panel data section that addressed hypothesis 3 had a broader time period than the cross-sectional section which only considered the COVID-19 period, leading to further companies that had to be omitted just for hypothesis 3. This may explain why COVID-19 was not found to not pronounce the mediation effect despite mediation being found within the COVID-19 period but not in the broader time-period (2019-2020). Furthermore, the distribution of the debt control variable was slightly skewed to the right, which violates the OLS assumption of normality for the regressions. Nevertheless, each variable was optimized to be minimally skewed, hence this most probably did not affect the accuracy of the results.

6.3 Conclusion

This paper successfully finds credit ratings of firms, specifically implied credit ratings, to be a mediator for the effect of ESG scores on both returns and abnormal returns as per the Carhart 4 factor model during the COVID-19 pandemic in the US. More specifically, a unit increase in the ESG score of a firm approximately causes its COVID period returns and abnormal returns to increase by 0.055% and 0.106% respectively, although these effects are insignificant. The direct effect stays insignificant and narrows down to increases of 0.0217% and 0.0634%. Meanwhile, the indirect effect channelled through implied credit ratings is significant, constituting 0.0335% and 0.0852% increases in COVID-19 returns and abnormal returns respectively.

Nevertheless, looking at a broader time period, stock returns are solely affected by implied credit ratings, with a unit increase generally increasing monthly returns by 1.57%. Additionally, none of the individual effects within the mediation significantly differ during the COVID-19 pandemic compared to outside of this period. Thus, it is found that the mediation effect via internal credit ratings does not significantly differ during the COVID-19 period.

The effect of ESG on stock returns is very contradictory across papers and our understanding of it is very limited. The explanation that ESG affects stock returns due to its close correlation to credit ratings during pandemics thus shines more light on this complex relationship and adds to the literature regarding ESG investing. The results of this research highlight that there is a lot of room for future researchers to analyse investor behaviour and market sentiments towards ESG firms during financial crises. Finally, the fact that the mediation effect was found to only exist during this period has many implications for theorists that want to understand how the behaviour of investors and firm performance with regards to ESG can change given the macroeconomic environment.

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