MSc. in Corporate Finance

Department of Business and Management

Chair of Asset Pricing

# *"The Impact of ESG Ratings on Default Probability" Empirical Analysis on Credit Default Swap Spread.*

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Academic Year 2019/2020

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# Introduction

In recent years, the importance of green and sustainable aspects of investments has gained increased importance in markets, with the credit market being the pioneer of this trend. In 2017 and 2018 bonds issuer have collected respectively \$252bn. and \$315bn., selling green and sustainable bonds. In 2019 these numbers have grown further, reaching more than \$400bn., and it is expected that they will continue to grow in the coming years (Mutua e Poh 2019). ESG investments and ESG thematic funds represent definitely one of the "megatrends" that will shape markets, financial sector and asset management industry in the next years. The growing impact of sustainability in fixed income market is proven by the rising interest of credit rating agencies in acquiring companies that provide ESG data, as environmental, social and governance choices are steadily important in assigning and updating credit ratings.

Moreover, ESG is increasingly becoming an important topic for institutional and retail investors and from an Asset Management perspective, we see a secular shift of ESG adoption within funds managers. ESG flows continue to accelerate with total ESG focused funds approaching almost \$1.3tn globally, which represent 1% of global Asset-under-Management. Moreover, it is clear that ESG trend is still in the early stages of its development: whilst today ESG focused funds are a small percentage of total Assets under Management, the share of net flows continues to grow and all asset managers are looking to integrate ESG factors into their investment processes (Giblat, et al. 2020).

At the same time, attention to ESG aspects and climate change issues are gaining more consideration both in the public debate and in the new guidelines and regulations that governments issue towards companies, which have to inform and report their choices in terms of governance, social and environmental sustainability. MSCI Inc. reported that between 2010 and 2019 governments and regulatory authorities have enacted about 600 ESG-related standards globally.

Therefore, public attention, disclosure transparency, regulatory and investors increasing pressure raise several interesting questions. Do markets incorporate companies' ESG choices? If so, to what extent sustainable choices are assessed by the market? How much an ESG practice or an increase in ESG Score affect a company’s credit risk?

This research is aimed at answering these questions by using credit default swap (CDS) spreads as an indicator of credit risk, to analyze whether U.S. credit market reflects the firms’ choices in terms of environmental, social and governance sustainability. In the first chapter, various definitions and concepts that are part of the world of sustainable finance will be explored and clarified. It will explore the regulatory framework and the reasons why ESG investments and choices will shape the financial sector in the coming years. In addition, past literature relevant to the topics will be reviewed. The second chapter will be devoted to the structure of the empirical analysis: the regression model, the data and the methodology used for the research will be examined. Finally, the third chapter will comment on the results obtained in the research and on the statistical significance of the empirical analysis.

# CHAPTER 1 - ESG Conceptual Framework

## 1.1 Definitions and ESG Investing Insights

The term ESG investing is often used as a synonym for many other concepts, such as social responsible investing (SRI), sustainable investing, impact investing or screening. This is especially the case with SRI. The original development of the term SRI was linked to the practice of investors to exclude certain companies from their portfolios, for ethical or ideological based reasons. This original form of SRI is now called “exclusions” or “negative-screen” investing. Other SRI strategies have been developed, including positive screen or thematic investing, where only companies aligned to the investors’ values are included. More recently, impact investing has become popular; here investors provide capital to specific projects, funds and companies which work to improve a wide range of social issues, such as literacy and unemployment; and environmental issues, such as deforestation, scarcity of water and other natural resources; and many other globally widespread problems. In most cases, impact investing is used by companies to reduce or eliminate their carbon footprint. For instance, a company that produces negative externalities, like a certain amount of Co2 production in a year, can balance this emission by investing in a fund or project that uses the capital raised for reforestation or for the implementation of renewable energy. SRI has expanded to the extent that some have relabeled it from “socially responsible investing” to “sustainable, responsible and impact investing”. These terms are often used interchangeably.

Although the concepts mentioned above are very similar to each other and belong to the same area of discussion, it is important to clarify the different definitions, especially between ESG and SRI.

For many, the term ESG is closely linked to the debate on environmental issues, like climate change, clean energy transition and lack of resources (PricewaterhouseCoopers 2017). Following the definition suggested by Remi Briand, Managing Director of MSCI, we can define ESG investing as the explicit investors' inclusion of other factors such as environmental, social and governance, alongside financial factors in the capital allocation process (MSCI ESG Research LLC s.d.). Looking closer at this definition, we can analyze the three pillars that together form the concept of ESG:

- Environmental factors are those that include a company's contribution to climate change by reducing carbon emissions and other greenhouse gases, along with waste management and energy efficiency. Recently, the companies' contribution to biodiversity, reforestation and the issue of scarcity of water and other natural resources are also considered.
- Social factors cover an extremely wide range of potential issues. They concern human rights, supply chain labor standards, exposure to illegal child labor and other routine issues such as respecting health and safety in the workplace. A social score also increases if a company is well integrated with its local community and therefore has a "social license" to operate consensually. Among these factors, it is also important to mention customer satisfaction, gender equality, the acceptance of diversity in all its possible forms and finally the security and protection of customer data.
- Governance refers to a set of rules or principles that define rights, responsibilities and expectations among the various stakeholders in the governance of companies. A well-defined corporate governance system can be used to balance or align interests among stakeholders and can function as a tool to support a company's long-term strategy. Some of the most important specific factors to consider are board of directors (BoD) composition, audit committee structure, executive compensation, company's

controversies linked to bribery and corruption, company's lobbying activities and political contributions (CFA Institute s.d.).

Differently, the definition of SRI has a broader meaning, as it concerns the incorporation of ethical and social factors with a more general meaning and which often concerns the subjective evaluation by the investor, linked to his individual values (MSCI ESG Research LLC s.d.). In fact we can say that whilst on one hand ESG investing usually aim to maximize financial return with respect to the risk taken, on the other hand Social Responsible Investments consider financial return only after the investor's individual and personal values have been satisfied.

Confusion arises in cases where economic and individual values overlap; for instance, CO2 emission is a risk to a company's profits and to a person's health. It makes perfect sense to avoid polluting companies for either reason. Many investors will do it for both. In these cases, an investment could be called ESG and SRI (Adams 2018)

Summarizing, if individual values are more important to the investors than financial value, SRI might fit. If the investor wants to maximize value, but invest in a way that considers sustainable criteria, ESG investing might fit.

## 1.2 ESG: a "Megatrend" in Global Markets

The universe of ESG investments and SRI is clearly changing and growing rapidly; new players, new products, new assets, new investment strategies and new regulatory obligations are coming into the picture. Speaking of the sustainable financial market more generally, it has already existed for many years, but only in the last 3-5 years has undergone a profound change and growth. Thanks to this, nowadays sustainable finance has much more impact on risks and financial returns. In few words, ESG is moving from niche to mainstream (Apex Group Ltd.

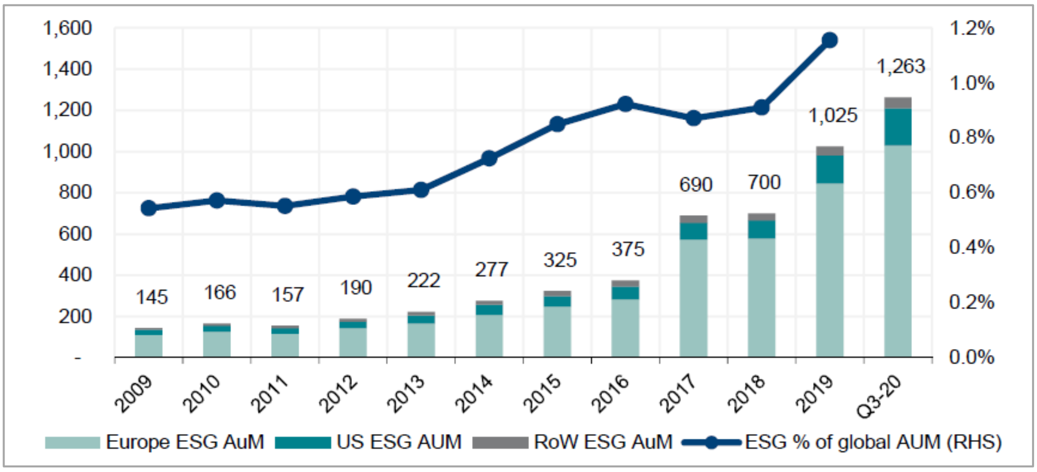
2020). These changes are accelerated by institutions, which are developing new rules and regulations that will influence all market players: banks, institutional and retail investors, regulated markets, companies and rating agencies.

It is important to talk about the asset management and diversified financial sector, as it plays a key role for the society: its main objective is to ensure an efficient allocation and management of capital, maximizing returns for investors and maximizing resources for the society. Therefore, this sector plays a crucial role in financing the economy and in ensuring the liquidity of the markets (Mason, et al. 2020) and that is one of the main reason why it is important to test wether the market prices enclose and valuate the ESG choices of companies. The question we ask ourselves is therefore whether this sector, and in general the investment chain from savers to companies, are serving society in the best possible way. We also wonder how asset managers are directing savers towards more sustainable investments in the short and long term. Finally, we ask how these managers expose their portfolios performance to the ESG trend across equity asset class. In this section of the thesis we will try to answer these questions, analyzing how this sector is shaping itself with respect to the trend of sustainability, talking about some new investment products that asset managers offer and reporting the words of some important figures in the industry.

In this context, we can say that there is a secular shift in the adoption of ESG within asset management industry. It has been estimated that today the ESG focused funds represent almost 1% of global Asset-under-Management, which corresponds to approximately $1.3tn. (Giblat, et al. 2020). The following figure shows the huge global increase in AuM’s inflows into ESG funds. The global AuM used in the figure is calculated considering Mutual Funds’ and ETF’s AuM.

**Figure 1.0: Global ESG AuM Growth Trend.**

ESG Global AuM in $ billion versus % of Global Mutual Funds' and ETF's AuM.



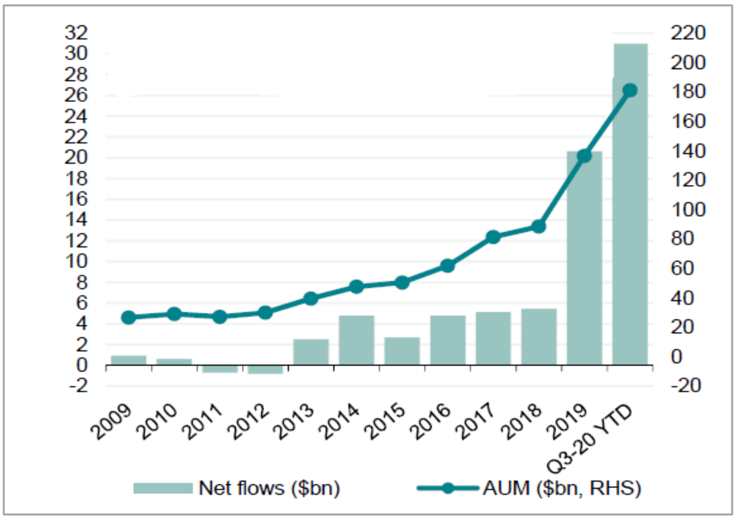

Source: Morningstar, Exane estimates

Although ESG funds are only a small portion of the total global AuM, discussion of ESG issues is on the daily agenda among institutional investors and all asset managers are looking to integrate ESG factors in their capital allocation process. Many new funds are emerging, both passive and active, as asset managers want to take advantage of this new opportunity: active ESG investment strategies are nearly 80% of the total, whilst passive and benchmark-replication strategies represents a 20% (Giblat, et al. 2020), but its growth curve is very steep. Considering that this trend is still in its infancy, those who today will be exposed to these factors will be able to experience outsized growth in the years to come. What has just been said is certainly proven by the net flows that the ESG funds register, like sustainable mutual funds or ESG thematic ETFs. For example, Morningstar estimated that in 2019 flows in Europe nearly tripled compared to the previous year, reaching around $120bn, which is a 22% share of all European net flows and a 21% net flow rate. In the first three quarters of 2020 these numbers have grown further, reaching $148bn (23% net flow rate). As for the US, we can see the same kind of trend. In 2019, flows to ESG funds quadrupled with respect to 2018, reaching $21bn and bringing the AuM in US to around $137bn. Equally, in 2020 the trend accelerated with $31bn in net flows and $181bn in AuM. Surely, these numbers attract attention, even if they represent respectively only 2.7% and 0.5% of total US asset management net flows and AuM in a year (Morningstar Inc. 2020).  Evidence of the enormous acceleration of this trend is Impax Asset Management, which specializes in sustainable investments. In 2015 Impax AM was a microcap asset manager listed in London with an AuM less than £3bn; in recent years it has experienced great growth and at the end of 2019 it had an AuM of £16bn (Source: ShareAction) (Mason, et al. 2020).

Notably, ESG practices are much more widespread in Europe than in US, with a 4-5% market share compared to 0.5% in the US. Probably this is due to the fact that European regulatory entities care much more the issue of environmental, social and governance sustainability and have issued an higher number of rules and guidelines for all industries, in addition to the fact that European companies are usually withstood by more transparency obligations regarding the sustainability of their business practices. The below figure demonstrates the large increase of Net Flows and AuM in Sustainable Mutual Funds and Sustainable ETFs in US, showing that the ESG trend had a great acceleration in in last 2 years, reaching the 0.5% of the total funds in US in terms of AuM.

**Figure 1.1: Net Flows and AuM of ESG Funds in US**

Flows into ESG are accellerating (market share is almost 0.5% of total funds)




Source: Morningstar, Exane estimates, Datastream

Moreover, as a plus to the high ESG inflows growth rate just showed in the figures, it must be taken into account that the ESG mega trend is still taking its first steps, so the numbers and data observed today are expected to increase consistently in the coming years. Bloomberg suggests that within five years almost 60% of assets managed by mutual funds will have the ESG label (Marsh 2020). This means that in a few years we will no longer talk about ESG and non-ESG investments, but rather we will talk about different levels of ESG for each investment or asset. In fact, the goal of this research is to understand if the ESG Scores, nowadays provided by companies such as Refinitiv or MSCI, have already such importance as to influence market prices and financial performance, which in our case is represented by CDS spread, i.e. the probability of default and credit risk. Financial data provider companies are among all those that could benefit most from this ESG trend, especially MSCI and London Stock Exchange (given exposure to FTSE Russell and the Dataset of Refinitiv) as they will exploit the advantage of the first mover. Looking at their revenues, other companies that are well positioned for ESG data are S&P Global, Morningstar, Moody's and even BlackRock, given the opportunity to integrate ESG data/ratings into its Aladdin platform (Source: Optimas) (Giblat, et al. 2020).
A further factor that has pushed the growth of the ESG trend even more is attributable to the global pandemic of COVID-19. In fact, the pandemic has on the one hand increased the interest of investors in socially responsible investments, not only in the search for a higher risk-adjusted return, but also because many investors have understood the importance of sustainable investments as a solid basis to better contain future social, economic and financial crises. Therefore, investments of a sustainable nature not only are at the base of today's economic recovery but also create the foundations for a future economy that can better face global challenges. It is no coincidence that many financial and economic professionals and experts believe that ESG factors will play a crucial role in restructuring the post-pandemic world, especially for global fixed income markets (Hasenstab 2020). For instance, during and after

the pandemic, many social responsible bonds were issued, in order to raise funds for projects specifically targeted at economic recovery. On the other hand, the pandemic has pushed international institutions to provide new capital, which will probably be directed towards assets labeled ESG. Just think of all the new financing initiatives that are emerging, such as the Green Deal, the Recovery Fund or the Next Generation Fund, all of which have particular attention to ESG issues and which will have the role of accelerator and catalyst of capital towards investments more sustainable from an environmental and social point of view. Previously, investors and supra-government agencies had also been paying attention to these important issues, but surely the global pandemic has pushed even more towards a more sustainable economy. However, while previously the main focus was on the environmental issue linked to climate change, today the aspect of social sustainability has also become the focus of the interests of investors and legislators.

From the point of view of financial return, also in this case ESG investments have performed better than the others, despite the global pandemic has created a strong crisis in financial markets and has caused volatility to reach very high peaks, even reaching 40 basis points, which is almost double its long-term average (Samson, Hodgson e Henderson 2020). The companies most attentive to ESG issues have therefore performed better on the markets in this period of global crisis. In fact, in the first quarter of 2020, as suggests Luca Giorgi , Head of iShares and Wealth at BlackRock Italy, around 94% of ESG indices recorded a better return than "traditional" indices, demonstrating that investing in sustainability does not necessarily mean giving up a better risk-return ratio (FundsPeople 2020). At the same time it does not mean that ESG investments have a better financial performance than the others. In fact, although almost all asset managers are increasingly exposing their portfolios to these factors, it is not proven that there is a persistent “sustainability alpha” in the market or, more specifically, an “ESG alpha”. They are certainly less risky than many other assets, but usually these investments are associated with a long-term return. This good risk-return ratio trend is also confirmed by the Association Forum for Sustainable Finance, as in an article stated that during 2020, in the months of high market volatility, ESG investments have better balanced and contained losses. The association also argued that during the recovery phase of the markets, the flow of sustainable investments recorded much higher growth rates than the average and that the SRIs, previously focused mainly on the climate and renewable energy issues, are now evolving with greater attention towards the social and governance aspects (FundsPeople 2020). In terms of risk, it is much easier to talk about climate risk, represented by the environmental pillar of ESG universe, as it is more easily measurable as a company's downside risk. However, especially in the last period, investors are more attentive to social risk, probably also driven by the global pandemic, and to the risk of controversies related to corporate governance, although it is more difficult to assess them in quantitative terms.

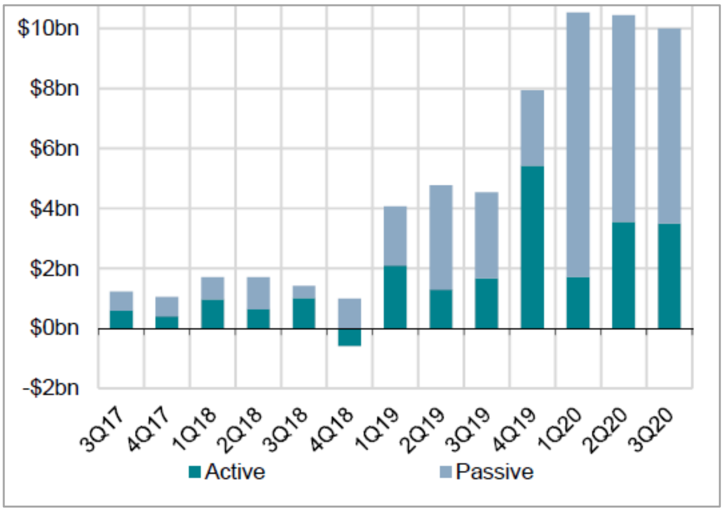
Until now, efforts have been made to demonstrate that ESG investments are shaping the asset management, the wealth management industry and the market as a whole. Therefore it is also important to ask what new products are being offered by asset managers to those seeking exposure to ESG factors and what are the new investment approaches. Furthermore, the fact that capital management companies are offering more and more products of this type does not mean that they are proactively embracing the process towards sustainability. Offering new products is not enough, and therefore another question we ask ourselves is what these companies are doing to be more sustainable in the true sense of the term, that is from the point of view of impact in the economy and in the real world. Sustainability is obviously a process that cannot stop at the mere offer of a sustainable investment product or the adoption of an ESG benchmark, but it concerns every business process, starting from top management decisions, passing through risk management up to the work of analysts, sales and obviously all the other stakeholders involved. Many asset managers have been offering investment strategies linked to sustainable finance for some time, but only in 2018 there was a sharp increase in interest in these products, also linked to new regulations and guidelines. The growth rate of ESG-labeled funds has gone from 2-3% in 2018 to around 10% today (FundsPeople 2020).

As for the offer of new ESG investment products, the ones that are offered the most to the public are both active and passive thematic equity funds, such as thematic investment funds and thematic ETFs, funds with impact on the real economy, funds that invest in ESG instruments of different asset classes and finally those that balance traditional investments with those labeled as sustainable.

As mentioned previously, the trend of large inflows into ESG-labeled AuM is positive both for active and passive funds managers, as described by the following figure.

**Figure 1.2: US ESG Active and Passive Funds Flows**

Trend is positive both but the chart shows an higher flow for passive in last year




Source: Morningstar

Thematic equity funds are those that raised the most in Italy in 2019 and 2020, especially those linked to the achievement of the SDGs. In fact, when deciding which companies to include in the portfolio, asset managers do not look only at the ESG ratings, but rather they choose those companies that are most likely to achieve the goals set by the U.N. within 2030.

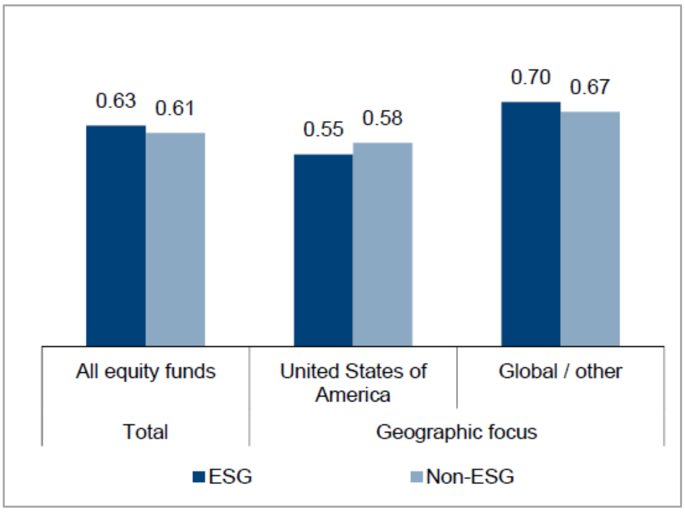
Therefore, we can say that the work of these companies has become even more difficult, as now, in addition to a quantitative financial performance analysis, a qualitative "extra-financial" analysis is also needed, to understand which companies are implementing an efficient plan of energy and environmental transition. This trend is growing especially for passive funds that replicate the benchmark, even creating a paradox in the asset management industry.

In fact, what is more surprising is that passive funds, which historically are less expensive than active ones in terms of fees and active management costs, have fees almost three times higher than non-ESG funds, as far as funds are concerned with the ESG label. Hence, suprisingly ESG funds have similar fees to non-ESG ones for active managers, whilst fees are higher for passive funds.

The following charts show this extraordinary difference between funds' expense ratio.

**Figure 1.3: Asset Weighted Average Total Expense Ratio for Active US Equity Mutual Funds**

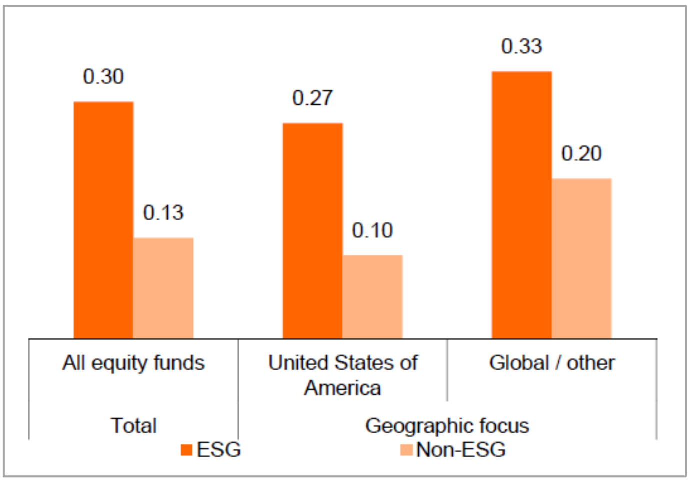
In the Active Asset Management space ESG and non-ESG Funds have similar fees




Source: Bllomberg

**Figure 1.4: Asset Weighted Average Total Expense Ratio for Passive US Equity Mutual Funds**

In the Passive Asset Management space ESG Funds have fee margin 2-3x higher than non-ESG




Source: Bloomberg

As for equity funds with an active strategy, there are different investment approaches to have greater exposure to ESG factors. The first approach is called "avoid", as it aims to exclude from the portfolio all those companies that have a low ESG rating, that create many negative externalities, that do not have an energy transition plan or that are involved in controversies from a social and governance point of view. In some cases this approach tends to exclude entire sectors, especially as they are harmful from an environmental point of view, such as the oil extraction and refining industry or from a social point of view, such as the weapons and ammunitions manufacturing industry or the tobacco industry. The second approach is called "advance", as it usually aims to include companies that have a virtuous behavior, regardless of the sector they belong to, thus going to reward the best-in-class of the various industries. This type of approach is called advanced “broad”, as it involves all sectors and all sustainability issues: every virtuous behavior in general, not tied to a single topic, such as environmental or good governance issues, is rewarded. There are also other types of "broad" approaches: for instance if an investor wants to be exposed to the future of the transportation sector, not only the companies that produce electric cars will be included in the portfolio, but also all the other entities involved in the production process and in the supply chain. The sectors that have registered greater interest are those of car electrification and self-driving cars and that of clean energy. Even real impact funds today arouse great interest, as a large part of investors not only seek economic returns but also want to contribute practically to the process towards a sustainable economy. In this context we can consider one of the last funds launched by BNP Paribas Asset Management, namely the Theam Quant Europe Climate Carbon Offset Plan or the Theam Quant World Climate Offset Plan (Hamlin 2020). These funds invest in shares of companies with a high ESG score and use part of the returns obtained to finance a reforestation project in Kenya, with the aim of offsetting carbon emissions (BNP Paribas Asset Management 2019). Specifically, the Kasigau Corridor REDD + (Reducing Emission from Deforestation and Degradation) project issues Verified Emission Reduction certificates (VERs) aimed at proving the balancing of CO2 emissions under the Verified Carbon Standard (VCS) and the Climate, Community and Biodiversity Standard (CCB) (Wildlife Works s.d.). Ultimately we could name those fund managers who place ESG assets in their "traditional" portfolios, both equity and multi-asset portfolios, within which many assets have low sustainability ratings. In this way, a sort of hedging of these portfolios is carried out, as different risks are balanced, such as climate risk, and losses are better contained.

Going back to the question we asked ourselves earlier, it must be said that the mere offering of new products ESG-labelled cannot be enough to embrace the transition to a sustainable sector. Therefore it is also important to understand what are the initiatives that asset and fund managers are carrying out to contribute to a more sustainable economy, to follow the guidelines of the European authorities and to reach the SDGs as soon as possible. Many Asset Managers are already trying to minimize carbon emissions related to offices and business travel, balancing these emissions with positive environmental impact investments. Moreover, others have already structured long-term plans that aim at total carbon neutrality and climate neutrality of all financial assets managed in their portfolios. A positive example in this context is Candriam Investors Group, which managed to achieve carbon neutrality two years ago, as stated by Daniela Usai, Head of Retail Italy at Candriam, allocating part of the returns obtained in green investments. Moreover, Candriam is one of the first savings managers trying to create a culture on sustainable finance. In fact, it has established the Candriam Academy, which is a digital path open to professional and non-professional clients, which deals with the issues of sustainability and ESG investments. Furthermore, this path also concerns another fundamental theme connected to ESG, that of the circular economy. The Candriam Academy deals with this theme both from the point of view of real sustainability and from the point of view of new economic and financial opportunities. In fact, it is estimated that by 2030, the circular economy will be a market worth more than $4 trillion and therefore today it is important to transfer financial resources to those companies that are transforming their processes towards circularity (Usai 2020). Another example that deserves to be mentioned is that of NN Investment Partners, which is not only a market leader, with about 3 billion euros invested in green bonds and one of the most important green projects database, but is also implementing an internal policy aimed at including ESG factors in the risk management process at 100% (Merzagora 2020). This means that the sustainability theme will affect all business processes and all products offered to investors. Nordea Asset Management also made its contribution, since it opted for a total divestment of the "Stars" funds in Brazilian bonds, as the government has no hint of blocking or limiting deforestation activity (Caiani 2020). Hence, as its Managing Director said, Nordea AM has given a great proof of ideological coherence towards its customers and the market in general.

In this section of the thesis we have tried to review all the main reasons why sustainable and responsible investments are shaping the industry, both on the demand and on the supply side.

To conclude, it is appropriate to consider one last aspect that is even more related to the topic of this research. In fact, almost all fund management firms are now using internally developed ESG ratings or sustainability scores. Therefore, not only the largest financial data providers, such as Refinitiv, Bloomberg or MSCI, but also all the major companies in the sector have now understood the importance of having an ESG filter, which enables them to carry out a sustainability screening of the various assets and firms being analyzed. In this regard, it is important to say that the different filters that companies are developing are not only 'traditional' ESG scores, but also innovative and more specific ratings. For instance, Generali Investment Partners has developed two alternative metrics in addition to the standard ESG analysis (Alberici 2020). These are the Net Environment Contribution (NEC), which measures the contribution of a company's activities to the energy and environmental transition, and the Good Jobs Rating, which measures how much the company contributes to the creation of new jobs according to three dimensions: quantity of jobs created, quality in terms of inclusion and salary, and jobs geographical distribution. Therefore, as demonstrated by what has just been said, also from the point of view of sustainability ratings, attention is being focused on social human aspects, and not only to environmental ones.

## 1.3 Regulatory Framework

Since both ESG investors and financial sustainable products are increasing, a substantial proliferation of ESG related definitions and standards has arisen. The market need for greater transparency and standardization on sustainable investments has clashed with an underlying lack of data and a confusion on local and international definitions and regulations. Retail and institutional investors therefore face a major obstacle: it is almost impossible to compare the ESG credentials of companies that declare information and data according to different reporting standards. Furthermore, because these standards are "voluntary", they allow companies to choose which data to share and often avoided those that put the company in a bad light. Overall, it is clear that there is general investor concern about the reliability of sustainability reporting. In recent years there have been many attempts to introduce global standards, aimed at standardizing ESG reporting. However, these attempts did not solve the problem as they led to different and sometimes competing guidelines ( Cleary Gottlieb Steen & Hamilton LLP 2020). All the initiatives that aim to regulate and standardize ESG practices are listed below.

- Global Reporting Initiative (GRI) of 1997, taken as a reference by almost 40% of US companies and 60% of European companies (Global Sustainability Standards Board s.d.).
- United Nations-backed Principles for Responsible Investing of 2006, which signatories have signed up to six principles for sustainable investing (United Nation Global Compact & Finance UNEP Initiative s.d.).
- Carbon Disclosure Standards Board (CDSB) of 2007, linked to Carbon Disclosure Project (CDP), is a guideline for incorporate climate change related information in financial reports (Carbon Disclosure Project s.d.).
- Workforce Disclosure Initiative born in 2008, a project that attracted 141 companies to join in 2020 (Share Action 2020).
- Sustainability Accounting Standards Board (SASB) of 2011, which guides companies of each industry in reporting the impact of climate and environmental change on accounting (Sustainability Accounting Standards Board 2018).
- United Nations Sustainable Development Goals (UN SDGs) of 2015, which are 17 objectives and 169 related targets that should be achieved by 2030. In order to reach this goals, according to UN, it is necessary to harmonize three dimentions: economic

growth, social inclusion and environmental protection (United Nations Department of Economic and Social Affairs s.d.)

- Paris Agreement of 2015, which is the first universal and legally binding agreement on climate change. The EU and its member states are among the 190 parties that took part in the Agreement. Even United States, which leaved the Agreement few years ago, with Biden's new presidency mandate are managing to rejoin the Agreement's member states. In few words, the Agreement aims at the cooperation of governments in being able to keep the increase in the Earth's temperature below 2 ° C. The long-term goal is to achieve an average temperature increase of at least 1.5 °C, which would greatly reduce the Earth's impact of climate change (United Nations Framework Convention on Climate Change s.d.).
- Task Force on Climate-related Financial Disclosure (TCFD) of 2017, that is a voluntary initiative with the aim of providing clear guidance to estimate companies' exposure to climate change risk. This initiative is supported by G20's Financial Stability Board (Task Force on Climate-related Financial Disclosures s.d.).

During 2020, the EU regulators authorities increased their activities aimed at aligning the general regulatory framework relating to ESG and sustainable finance. Unlike other guidelines issued by global institutions, those of the EU have a much stronger impact, being binding and not discretionary. Globally, the main bodies that are working for harmonization, apart from the UN, are the International Accounting Standard Board (IASB) and the International Organization of Securities COmmission (IOSCO). The International Business Council (IBC) of the World Economic Forum has also issued a series of ESG metrics that try to summarize the other guidelines, such as those of GRI, SASB, TCFD and CDSB ( Cleary Gottlieb Steen & Hamilton LLP 2020). A series of new European regulations or updates of old regulations is at the starting blocks, many companies and asset managers are already working to immediately implement the new guidelines, therefore soon there will be new developments regarding the alignment of ESG standards. A series of new European regulations or updates of old regulations is at the starting blocks, many companies and asset managers are already working to immediately implement the new guidelines, so soon there will be new developments regarding the alignment of ESG standards, at least in Europe. The new rules in question are Taxonomy Regulation, Sustainable Finance Disclosures Regulation (SFDR) and Non-Financial Reporting Directive (NFRD) (European Commission Technical Expert Group on sustainable finance (TEG) 2020). The new regulatory developments will affect companies, investors, funds and advisers not only in Europe, as surely the other regulatory authorities will follow the advancement in our continent and will probably implement their regulatory framework in the wake of the European one.

## 1.4 Literature Review

The starting point of this research is represented by the ambiguous relationship between firm's ESG choices and credit risk. On the one hand, high levels of ESG should reduce a company's risk through a better perception of investors in terms of sustainability, future robustness of performance and by achieving higher and less volatile earnings. On the other hand, investments in ESG may be a waste of scarce resources resulting in lower cash flows and higher firm risk (Goss e Roberts 2011). Hence, the existing link between ESG and firm risk adds an additional factor influencing the valuation of credit risk and therefore also a firm's probability of default. According to Merton higher and less volatile flows determined by ESG practices result in an improvement in company valuation, i.e. in higher overall value of assets, which in turns means lower probability of default and, thus, lower credit spreads (Merton 1974).

The previous literature that analyses the influence of ESG on credit risk focuses mainly on financial instruments and estimates related to tradable debt, such as corporate bonds and credit ratings (Menz 2010), (Jiraporn, et al. 2014). In 2015 also z-spreads have been taken into account by Stellner et al., who found that z-spreads decrease for greater levels of ESG, but this evidence holds only for companies listed in high sustainable countries (Stellner, Klein e Zwergel 2015). This research makes an important contribution to the past academic literature, focusing on tradable debt, but analyzing CDS Spread as an output variable. In this context the use of CDS Spreads is particularly interesting, as they represents a precise indicators of credit risk, that is easily comparable across firms and accounts for the majority of the firm level determinants of default risk (Forte e Peña 2009), (Tang e Yan 2010). Existing literature and researches carried out so far on the U.S. bond market indicate a positive impact of ESG choices, demonstrated by a better credit rating or a lower bond yield spread (Oikonomou, Brooks e Pavelin 2014), (Ge e Liu 2015).

Given that the majority of past literature focuses on bond data, the use of CDS spreads offers an interesting alternative to investors and academics. CDS are much more liquid instruments than corporate bonds (Ederington, Guan e Yang 2015) and they are updated more frequently than credit ratings (Finnerty, Miller e Chen 2013). Moreover, bond prices can also be affected by others factors, like embedded options (Barth, Hubel e Scholz 2020), specific characteristics of that bond issuance or Central Banks short-term policies, making comparison across firms rather difficult. On the contrary, CDS have a standardize structure and this characteristic allows to compare probability of default across firms more easily (Norden e Weber 2009).

Another important contribution of this thesis refers to the literature that analyzes the determinants of CDS spreads. Credit Default Swaps are contracts traded over-the-counter (OTC) between two counterparties in order to transfer the credit exposure of the underlying company. Before CDS, there were no instruments capable of transferring the risk of insolvency, i.e. the risk of default, or other credit events, from one investor to another. Single-name CDS refer to a single underlying instrument, which can be a corporate bond, bank credits, loans or specific government and treasury bonds. Instead, Multi-name CDS have as underlying a bespoke portfolio of credit instruments, agreed by the counterparties. Basically, a single-name CDS is similar to an insurance contract: the buyer of the instrument has to pay to the seller the CDS premium every quarter (short credit exposure), which depends on the annual spreads; the seller has to compensate the buyer if a credit event occurs at the underlying firm (long credit exposure), as the buyer must be protected against any credit and insolvency events (Tavakoli 2001), (PIMCO 2017). The most traded single-name CDS is the 5-year maturity one, which is taken into consideration in this thesis, but also 1-year and 10-year CDS have a high liquidity. Previous studies suggest credit ratings, stock return, firm's leverage and stock return volatility as factors which significantly influence CDS Spread (Barth, Hubel e Scholz 2020). This thesis aims to understand whether even a company's ESG Score can be considered as additional factor that determine CDS spreads.

Given the results obtained from past researches, from the output of our analysis on one hundred U.S. firms we expect a higher ESG score to result in lower credit risk and therefore a lower CDS spread, i.e. a lower probability of default of the company. In fact, we expect our results to confirm the risk mitigation view of sustainable and ESG practices (Goss e Roberts 2011), which relates higher ESG ratings to lower spreads. The determining factors can be many, such as the fact that clients of a long-term sustainable company may accept to pay a "premium" for products and services, suppliers would accept more favorable payment terms or investors would be more motivated to make long-term investments (Barth, Hubel e Scholz 2020). Companies that adopt a transition towards sustainability do not only benefit all the stakeholders involved, but are able to obtain a better perception from the entire market and are more resilient to innovations and regulatory changes. The risk mitigation view also argues that an increase in

ESG performance has larger impact on risk weakening for companies with a modest ESG score with respect to companies with a very high or very low ESG score (Barth, Hubel e Scholz 2020). Some academic researches state that the risk-reducing effect is approximately double for modest ESG firms with respect to very high or very low sustainable firms, which means that the marginal return on ESG investments decreases as the amount invested increases (Flammer 2015), (Meier, Naccache e Schier 2019).

As mentioned previously, as opposed to the risk mitigation view, we take into account the overinvestment view, since it considers ESG investments as a waste of scarce resources, which is why low ESG score would be linked to a lower credit risk (Goss e Roberts 2011). Moreover, substantial investments in ESG can lead to agency conflicts between managers and shareholders (El Ghoul, Guedhami e Kim 2017): the management consider them as a business improvement and a long-term opportunity for the company whilst shareholders have to bear the costs of the investments and do not accept an increase in firms fixed costs (Perez-Batres, et al. 2012).

This research instead is based on the idea that companies that are sustainable or that have started a transition process towards business sustainability have a lower credit risk; the aim is therefore to understand if the credit market evaluates the level of ESG and how much this impacts on the risk of default, i.e. on the CDS spreads. In order to assess the value of a company's debt, we can use the credit-risk model provided by Merton, according to which debt's value is equal to a portfolio composed by a risk-free loan and a short position in a put option on the company's asset (Merton 1974). The strike price of the option has to be equal to the loan's nominal value. Hence, if at expiration date the assets value will be lower than the strike price, i.e. lower than the loan's value, the investor who held the portfolio will not repay the loan, as it is more convenient to exercise the option. This means that the investor default on the loan. Accordingly, if investments made in ESG result in a higher value of the company's assets, all other things being equal, the company should obtain lower probability of default (Barth, Hubel e Scholz 2020). In addition, investors would be more inclined to invest in a company with a better reputation and better compliancy to the regulatory framework (Franklin 2008), which means a lowering of the costs of raising capital for the company, that in turn is again correlated with higher value of assets and low default probability, i.e. lower credit spread (Chava 2014).

The strand of literature that we take into consideration in the development of this thesis is related to the connection between ESG practices and credit market, as we analyze the impact in the CDS market. On the other hand, there are many other studies, researches and conference proceedings that differ from this one, as they examine non-tradable debt, U.S. corporate bond yields and credit ratings (Oikonomou, Brooks e Pavelin 2014), (Ge e Liu 2015), (Jiraporn, et al. 2014), (Frooman, Zietsma e Mcknight 2008). These studies predominantly confirm that there is evidence of a lower credit risk associated with greater ESG level. Following, there are other articles and working papers that focus on the impact of a single ESG pillar (dealing with all three pillars, from an environmental, governance and employee treatment perspective), which confirm once again an effective mitigation of credit risk (Cremers, Nair e Wei 2007), (Bauer e Hann 2012), (Chen, Chen e Yang 2019). Surprisingly, the literature that focuses on European companies does not show the same results, arguing that greater level of ESG does not translate into higher bond yield spreads (Menz 2010), (Stellner, Klein e Zwergel 2015).

This thesis aims to make a contribution to existing literature, as there are few studies that focus on CDS spreads and / or that use as an explanatory variable ESG ratings, which have now become commonly used by all those who intend to invest in sustainable businesses. However, Barth, Hubel and Scholz's paper finds importance results on European firms for the 2007-2019 period. They find evidence of the risk mitigation view, i.e. they sustain that a higher ESG score affects a company's probability of default, decreasing the CDS spread (Barth, Hubel e Scholz 2020). This study connects to their results, providing further evidence for U.S. listed companies based on two different types of ESG ratings provided by Refinitiv (Thomson Reuters Eikon Datastream).

Lastly, another strand of the existing literature does not focus on ESG impact in the credit markets but rather in equity markets (Lins, Servaes e Tamayo 2017) or in the funds management sector (Renneboog, Ter Horst e Zhang 2008), (Borgers, et al. 2015), but in this thesis we will not discuss their results.

The choice to use single-name CDS spreads is driven by several reasons and there are numerous advantages over the use of credit ratings and bond yields. First of all single-name CDS are the most traded and liquid credit derivatives on the market (Longstaff, Mithal e Neis 2005), (PIMCO 2017). Since CDS are traded on the market at a much higher frequency, they are a better indicator of credit risk, as they absorb market news and changes in credit risk much faster than bond prices and credit ratings of the largest rating agencies (Ericsson, Jacobs e Oviedo 2019), (Blanco, Brennan e Marsh 2005). Secondly, single-name CDS are more connected to the distinctive elements of the company (such as leverage structure, profitability, volatility, environmental, social and governance sustainability) with respect to bond yields, which instead are more affected by term structure movements and Central Bank's monetary policies. In addition, CDS have a standardized structure as of maturities, secured or unsecured debt, as well as debt seniority levels (Barth, Hubel e Scholz 2020). These mentioned above are the main reasons why in this thesis we have decided to examine single-name 5-Y CDS spreads: summarizing, CDS give a more correct measure of a company's credit risk, through the probability of default, and they make it easier and more immediate to compare credit risk between different companies in the U.S. market.

# CHAPTER 2 - Variables and Panel Data Models

This chapter provides an in-depth look at the quantitative research methodology used to test the hypothesis that will be discussed in the first section of the chapter. The second section gives a detailed explanation of the variables examined, distinguishing between the main variable of interest, i.e. ESG scores, and the other explanatory variables, i.e. the control variables. The statistical sample and the panel of data downloaded to carry out the regression will also be explored. Finally, the last section will cover in detail the panel regression models and the pool of data construction in two dimensions, cross sectional and time series.

## 2.1 Hypothesis Construction

This research aims to investigate the relationship between the credit risk of US companies and their commitment to being sustainable environmentally, socially and at a corporate governance level. The relationship in question has always been considered ambiguous in academic and extra-academic researches. The existing literature has not demonstrated conclusive evidence of better financial performance for sustainable firms, nor has shown that investing in business sustainability is a waste of scarce resources. The results of past empirical analyses are different and vary according to the dependent and independent variables taken into account, the sample used, the reference years of the data points observed, the countries or continent where the data are being observed and finally on the basis of the different types of ESG scores taken into consideration.

This research can contribute to the existing literature by investigating the overall impact of ESG ratings on CDS spreads, i.e. on the probability of corporate default, rather than by considering individually each ESG pillar. Therefore, the contribution of this thesis is important both for future research focusing on the impact of ESG scores in financial variables and for those investigating the factors and determinants that influence CDS spreads. Furthermore, the topic of the research and the results we will obtain from our quantitative analysis are in the interest of academics but also of investors, who may have a greater awareness of the implications of sustainable or unsustainable investing. The construction of the hypothesis that will be tested follows a deductive approach, referring to previous studies focusing on the bond and credit markets, in the context of the sustainability performance of companies listed in the US or Europe. As mentioned earlier, in the section reviewing the existing literature, this research is a supporter of that part of the literature, which argues that higher corporate sustainability, and thus a higher ESG score, is inversely correlated with credit risk and probability of default. Empirical evidence should therefore show that a higher ESG rating corresponds to a lower CDS spread. Based on this belief, we will construct the hypothesis that this thesis aims to test.

The analysis will be performed on 100 companies listed in the United States on different regulated stock markets and belonging to different equity indices. The 100 companies in the sample are part of different industries and sectors, including sectors that are sustainable by nature, such as renewable energy production or electric cars, and non-sustainable sectors, such as oil extraction or weapons production. The aim is to investigate whether exists a medium-term relationship between environmental, social and governance responsibility and corporate credit risk, ceteris paribus. The hypothesis to test is therefore the following:

$H_0$: *Companies' ESG Scores and ESG Combined Scores have a negative impact on US Single-Name CDS Mid Spreads, i.e. coefficients $\beta$ are negative.*

This hypothesis means that more sustainable companies and companies with higher ESG Score have a lower credit risk and less default probability and thus their CDS Spread quoted on the market is lower with respect to less sustainable companies or companies with lower ESG Score (both standard and combined). In addition, a second hypothesis will be tested:

$H_1$: *ESG Combined Score has a stronger impact on CDS Spreads with respect to standard ESG Score.*

The latter hypothesis is tested as it is in our interest to understand which of the two scores has a greater impact on the dependent variable and if the market news affecting the Combined score have an amplifying effect with respect to the CDS spreads, as these are as well influenced in some way by news and published reports.

## 2.2 Sample, Descriptive Statistics and Time Horizon

The sample consists of 100 firms listed in different US stock exchanges, including the New York Stock Exchange (NYSE), The National Association of Securities Dealers Automated Quotation (NASDAQ), The American Stock Exchange (AMEX) and the Chicago Mercantile Exchange (CME). Each of them is represented by the corresponding Single-Name 5Y CDS Spread.

The companies that compose the sample are selected from different industries, such as Healthcare; Manufacturing; Construction; Utilities; Mining (including Renewable & non-Renewable Energy; Mineral & Gold Mining; Oil & Gas Drilling, Extraction and Distribution); Wholesale & Retail Trade; Transportation & Airlines; Finance, Banking & Insurance; Information & Technology; Telecommunications Services; Administration, Management & Advisory; Accommodation & Food Services; Automotive and Other

Services. The decision to create a basket of companies from different industries is driven by the idea of avoiding possible biases, due to a different environmental and social impact, regulatory environment, corporate governance engagement across sectors and macro industry-related trends.  This choice allows to achieve not distorted sample by industry specificity and more heterogeneous. Considering the attention that the ESG topic is acquiring, there is no reason why some industries should be considered less affected. For instance, news regarding major corporate governance disputes can have the same market impact in different industries. At the same time there is no reason to believe that CDS spreads and CDS liquidity should be differently affected by ESG scores based on the industry they belong to. Indeed, the panel of companies included 52 different sectors, some of which were been listed above. The 27.3% of the sample belong to an industry that weight only 1% on the total sectors, i.e. 27 companies over 99 belongs to a sector different from the others. Moreover, two sectors weight more than others (Electric Utilities and Healthcare Facilities & Services), but they account only for 6.1% and 5.1% of the sample branches respectively. All companies, sectors and industries' weight (expressed in percentage) are listed in the table below. The industry assignment to each company is developed following the indications of Thomson Reuters, consistently with the other variables of the analysis.

The construction of our basket of companies is clearly driven also by the availability of data points for the variables that compose the panel, especially for the scarce availability of past CDS Mid Spreads and recent ESG Scores on the Refinitiv platforms. In particular, in Refinitiv CDS Data time series are available only for previous five years, whilst ESG Data only until 2019 (except few companies for which there are already available 2020 data to calculate the rating). The following table describes the sector concentration, their weight on the sample and lists each company and its related reference sector.

[Insert Table 01 here]

The time horizon in which the analysis is realized is from 31 December 2015 to 31 December 2019. The choice is on the one hand conditioned by the availability of data, as mentioned previous, on the other hand this period of time is interesting for the sharp increase in ESG policies, regulations, reporting guidelines, accounting standards and others, especially after the 2015 Paris Agreement, and also for the huge amount of ESG investments made by institutional and private investors. This increased consideration is a consequence of three main reasons: the growing conviction that ESG performance and value creation are correlated, the confidence that in the long term only sustainable businesses will be able to raise easily capital from the market, and the certainty that within a few years all active and passive asset managers will build almost exclusively ESG-labeled funds, portfolios and investment strategies.

## 2.3 Credit Default Swap Spread

Credit Default Swaps are the most liquid credit derivative on the market and for this reason they were chosen for the purpose of this research. The high liquidity of the instrument allows us to have quickly updated market valuations and therefore also the market information (included ESG scores and news related to corporate's sustainability) are faster embedded in the price (in the spread in this case, as the market quotes CDS Spreads). The price (spread) quoted in basis points (bps) represents the amount that the investor has to pay to insure against the company's default. Usually those who have a long position on a CDS want to hedge against the risk of default of a company as they hold a certain number of bonds of that company. If the CDS spread is 80 bps for instance, means that the investor pays $80,000 a year to buy protection on $10 million worth of the company's debt. As default risk rises, so does the cost of CDS, i.e. the spread, as it is more likely that the company will default on its debt obligations.

The CDS dataset is downloaded from Refinitiv EIKON (formally Thomson Reuters). In this research Single-Name 5-Years CDS Mid Spread represent the dependent variable of the regression model. The choice to use the Mid spread CDS is driven by previous reference research and is considered a practice in the academic study of CDS in general. The decision to study the 5-year CDS is linked to the central variable of this thesis, i.e. the ESG scores. In fact, since the topic of our thesis is linked to the sustainability of US companies, choosing a 1-year CDS might distort the results, as it could not correctly evaluate the sustainable investments of the reference company, which usually give average benefits in the medium-long period. Similarly, a maturity of 5 years versus 10 or 30 years is sufficient for the correct embedment of the company's ESG choices. CDS Mid Spreads are downloaded for the period 2016-2020 and the choice is driven by the data availability in Refinitiv. All CDS in our sample belong to US companies and are denominated in US Dollars. They are quoted under modified restructuring clause and refer to senior-unsecured debt. As all data have monthly observation frequency, composite month-end Mid Spreads are acquired and rely on quotes from numerous valuation sources. The total number of data points for this variable, limited by the availability of data on the Refinitiv platform, is 4851. The data cleaning process consists in removing all extraordinary evaluations, i.e. removing all Mid Spreads which are equal or higher to 4000 basis points (bp), in order to avoid distorted results due to high instrument illiquidity, severe valuation or data errors (Zhang, Yibin Zhou e Zhu 2019). The following table shows the sample's average CDS Mid Spread for each year.

[Insert Table 02 here]

Alternatively, the below table provides average CDS Mid Spreads for each year, in order to assess their trend over years. They are obtained first calculating the mean of each monthly observation for each company, and then calculating the mean of the values obtained for each year.

**Table 03: Average, Max & Min CDS Mid Spread**

| Year | Average CDS Mid Spread | Max Spread | Min Spread |
|---|---|---|---|
| 2015 | 135.451 | 1998.55 | 13.91 |
| 2016 | 98.286 | 2396.93 | 11.44 |
| 2017 | 98.684 | 871.18 | 13.57 |
| 2018 | 117.509 | 1346.68 | 14.62 |
| 2019 | 89.567 | 2142.26 | 13.76 |

## 2.4 Stock Return, Volatility and Leverage

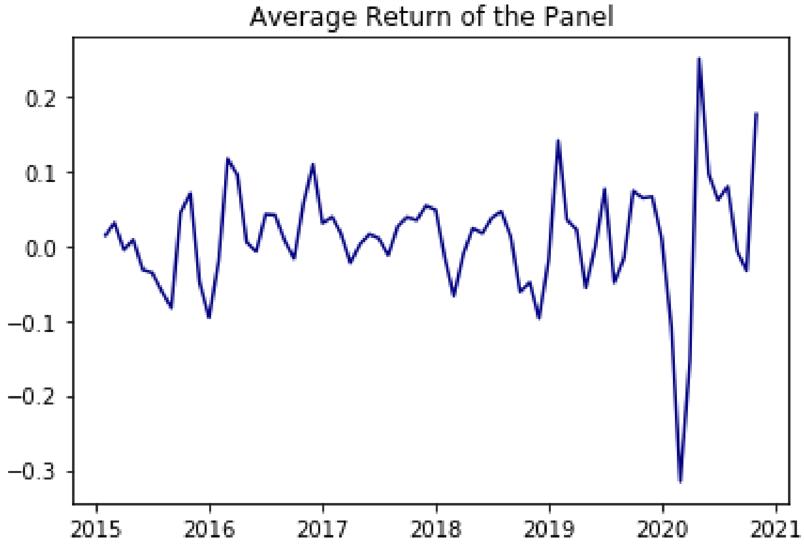
Stock Return, Volatility and Leverage are three of the five independent variable in the regression. These factors are defined in this thesis as control variables, as soon as the focus is on the ESG scores. Credit Rating is another variable that will be discussed further, as it is considered more as a structural variable of CDS spreads rather than a control one.

Control variables are included to better study the impact of ESG score on the credit risk, which is the goal of this research, and to better isolate the ESG effect on credit spreads. These variables are known to be correlated to CDS spreads. In past important studies and in several structural credit risk models, asset value, asset volatility and leverage are included as determinants of corporate credit risk (Merton 1974) and that is the main reason why these variables are included in this model. The data are retrieved from Refinitiv EIKON and data points are observed on a monthly basis. The decision to use Refinitiv as a data source is dictated by reasons of consistency and continuity with the CDS Spreads dataset.

In order to obtain Stock Returns, we downloaded the monthly stock price of each company in the sample from 2015 to 2020. From stock prices we obtained monthly stock returns on the same time period. Each data is denominated in US Dollar currency and reflect the perspective of US investors.

Then, we calculated the Excess Returns by subtracting to Stock Returns the Risk Free Rate. Since all companies in the sample are US-based, the Risk Free is the US 10-Year Treasury Rate observed on a monthly frequency for the 5-years time horizon. Risk Free Data are downloaded from DataHub and come from the Long-term Interest Rate Release of the Federal Reserve on "Selected Interest Rate Daily" (10 Year Nominal Yields on US Government Bonds). The following Table describes the trend of the average return of the sample across the reference time horizon. As we can see in the chart, the average return of the entire sample varies almost in the range from 0.1 to -0.1 over the first years, whilst it registers a much higher volatility during the last years, probably due to the financial market crisis related with the global pandemic and sanitary emergency.

**Figure 2.0: Sample's Average Return Trend**

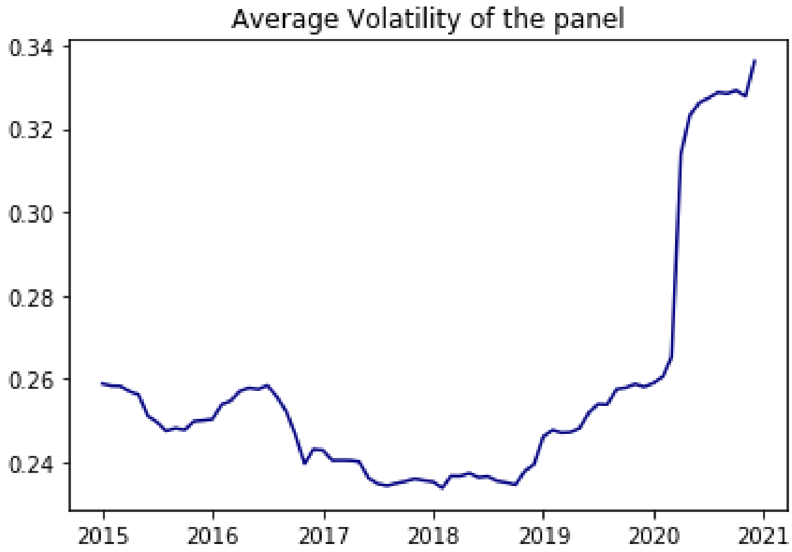



The horizontal axis represents time, the vertical axis the returns, expressed in numbers.

Volatility is defined as the 180-day rolling window volatility of the stock return (Campbell e Taksler 2003). This variable is included in the model since the volatility of the market value of firm's assets can be considered correlated with the credit and insolvency risk of the company. The volatility time series is downloaded in percentage format and not in bp.

The following chart shows the sample's average volatility trend over time. The figure tells that the average volatility of the sample over the period 2015-2019 is almost stable, has a low standard deviation and has a value close to the Volatility Index (VIX) long-term average (which has a value between 25 and 26 bps). Instead, in the two final years the average volatility registers a strong rise, consistent with the lower average return of the sample and with the level reached by VIX during the global pandemic. It is appropriate to refer to the VIX as it describes the volatility of the returns of US companies that are part of the S&P500 Index, which includes many of the companies that compose our sample.

**Figure 2.1: Sample's Average Volatility Trend**




The horizontal axis represents time, the vertical axis the volatility, expressed in numbers.

Finally, Leverage is defined as the firm's leverage ratio, i.e. the sum of the long-term and the short-term debt, divided by the total asset value (Ericsson, Jacobs e Oviedo 2019). The sample's Average Leverage value across the reference time horizon registers a decreasing trend over the initial three years, while the trend is growing in the following periods. This is consistent with the trend that the whole US market had during the global health emergency, a period in which US companies recorded a record increase in the percentage of leverage.

## 2.5 Model Generated Credit Rating

In this thesis Credit Rating is considered on one hand as a control variable, as the focus relies on ESG score, but on the other hand it's important to discuss it deeply, since it is a structural determinant for CDS Spreads and could be an alternative reliable measure for credit risk.

We apply the last updated valuation of the month-end rating (consistent with the last updated month-end CDS Mid Spread) and we remove the default-rating data, i.e. we remove the credit ratings with 100% default probability, since if a company defaults such that ESG score has no relevant impact on the credit risk, there is no reason to include the rating in our dataset.

The initial idea was to rely on the credit ratings of traditional rating agencies, such as Standard & Poor's, Moody's, Fitch. However, it was decided to opt for a different solution, since the ratings of the agencies listed above are not available for all the companies in our sample and as they are updated occasionally (for some companies, we found credit ratings updated only 2 or 3 times in our reference 5 years horizon). This aspect contrasts with our objective: since we want to understand the impact of ESG scores on corporate credit risk, for our study we need a credit rating that is more responsive to market news and companies' sustainability reporting and that is updated frequently, as our data is observed on a monthly basis.

For those reasons mentioned above, the choice fell on one of the Thomson Reuters Starmine Quantitative Credit Risk Models suite. StarMine SmartRatios model generates on a daily-updating basis default probability (or bankruptcy probability) estimates, letter ratings, 1-100 percentile rankings, and component scores on over 35,000 global companies. Hence, for the thesis purpose is chosen the SmartRatios Credit Risk Model provided by Thomson Reuters. This model is an intuitive and robust default prediction model that provides a view of a firm's credit condition and financial health by analyzing a wide array of accounting ratios that are predictive of credit risk. The model produces daily updated estimates of the probability of default or bankruptcy within one year for 35,000 companies globally, including Financials. The default probabilities are also mapped to traditional letter ratings and ranked to produce 1-100 percentile scores (Thomson Reuters 2013)  The Smart Ratios taken into consideration, i.e. accounting ratios along with industry-specific metrics, are grouped into five main components: Profitability, Liquidity, Leverage, Coverage and Growth, which are combined in a logistic regression. The final output is the default probability, which is also function of geographic region. In this context, the default probability definition includes debt service default, i.e. failure to pay interest or principal, and filing for bankruptcy.

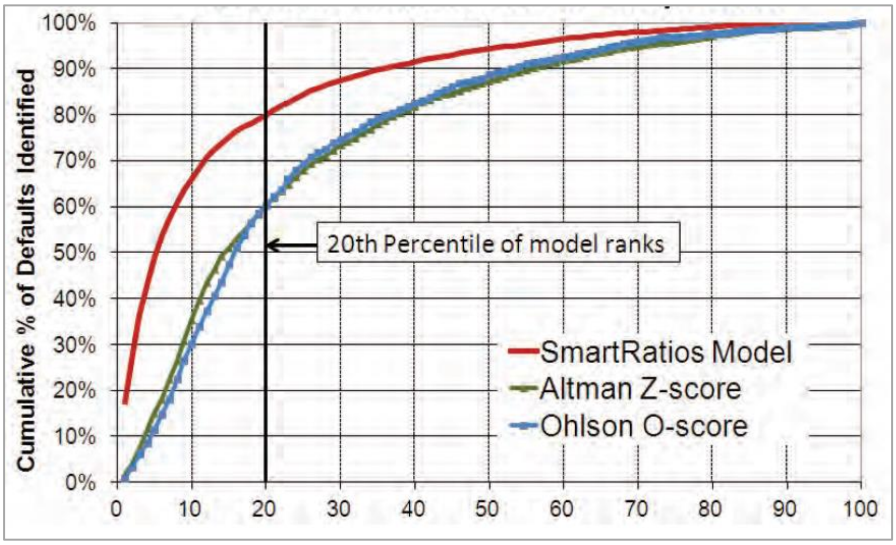
The main advantages of the SmartRatios model over traditional accounting-based credit models are:

- embedding information from both reported actuals and forward-looking estimates via StarMine's proprietary SmartEstimate;
- exploiting industry-based metrics for companies in different industries (expecially Banking, Insurance, Utility, Retail, Airline and Oil & Gas industries;
- combining the accounting ratios in a weighting structure that ensures the most determinant ratios for a given sector receive the most weight;
- handling outliers and missing data seamlessly and smartly.

Consequently, the StarMine model considerably outperforms traditional accounting-based credit risk models on default prediction. In addition, it can provide incremental value in an investment strategy. Finally, it can also serve as a reliable measure of future changes in agency ratings when there is a wide spread between SmartRatios rating and the agency rating (Thomson Reuters 2013).

Thomson Reuters also stated that its Credit Risk Model esitmates have more explanatory power in predicting potential defaults with respect to reported actuals alone and its model is more accurate than usual alternatives such as the Altman Z-score and the Ohlson O-score. The model properly predicts about 80% of default events at the 20th percentile of model scores compared to 60% for the others two scores, as shown by the following figure.

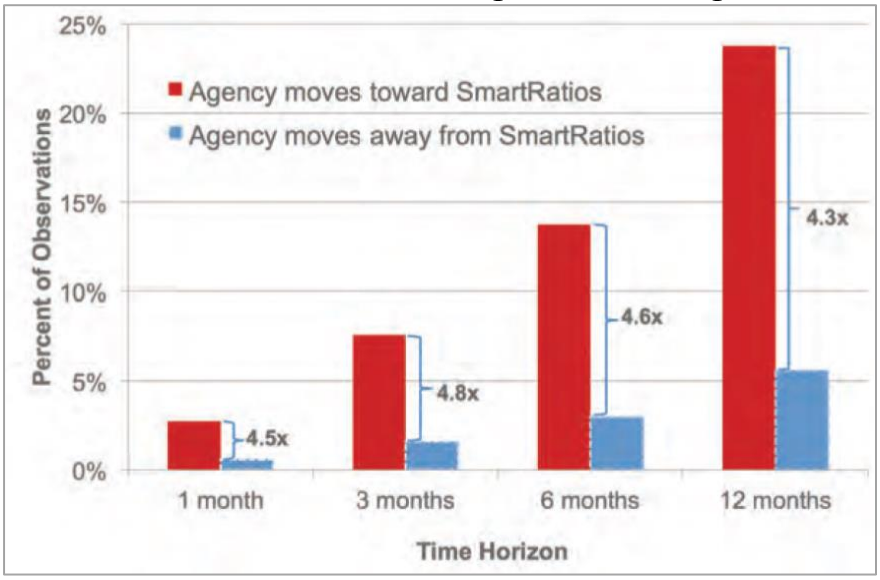
**Figure 2.2: Default Prediction Power Comparison**




Source: Thomson Reuters – StarMine Credit Risk Models

To facilitate comparability to agency ratings, the SmartRatios default probability is delineated to letter ratings by analysing the historical distribution of agency ratings on a standard basket of companies. The StarMine SmartRatios default probabilities is then mapped to letter ratings such that the distribution of model-generated ratings is consistent with those of agency ratings. In case that the SmartRatios rating differs from the agency rating, the agency rating moves toward the model-generated rating at least 80% of the times that it moves. In few words, the agency ratings are 4-5 times as likely to move toward the SmartRatios rating as they are to move away from it. The following chart describes what has been said above and why the SmartRatios model can be used as a reliable indicator of the future moves in agency ratings.

**Figure 2.3: Direction of future changes in agency ratings when they differ significantly from SmartRatios Model generated Ratings**




Source: Thomson Reuters – StarMine Credit Risk Models

Model-generated credit ratings assume a value within the range 0-100, in which a score of 100 corresponds to a probability of default equal to 0%, while a score equal to or similar to 0 corresponds to a probability of default of approximately 100%. The difference in score between each rating level is equal to 4.167, therefore the scale of ratings grows linearly from "C-" to "AAA" (as the traditional credit rating), generating 25 overall possible ratings. As mentioned previously, the ratings are based on five main accounting and financial components that vary across different industries. Each component has several determinants, that is worth investigating for a clearer view of the model. Profitability component depends on Return on Tangible Capital, Net Profit Margin, Unrealized Losses over Tangible Capital, Unrealized Losses over Revenues and the Delta of LIFO Reserve. Leverage depends on Equity-Asset Ratio, Net Debt-Equity Ratio, Underfunded Pension Liability over Equity and Intangible-Assets Ratio. The Coverage component is determined by EBIT over Interest Expense, EBITDA over Interest Expense and Free Cash Flow over Total Debt. Then, Liquidity score is based on Cash over Total Debt, ST Debt over Total Debt, Quick Ratio and

Delta Reserves. Finally, Growth & Stability component depends on the ROE Growth Rate, the EPS St. Dev and the Revenues St. Dev. Each component has a score divided into 5 percentile keys: 1-10, 11-30, 31-70, 71-90, 91-100.

For instance the company Best Buy Co. Inc., which is in the Computer & Electronics Retail industry, has a 77 score in profitability, 54 in leverage, 80 in coverage, 50 in liquidity and 99 in growth and stability, achieving a model-generated Credit Rating of "A". Instead, Xerox Holdings Corp, which operates in a similar industry, has all components scoring in the range 31-70, except for leverage, that scores 17. Therefore, Xerox has a final Credit Rating of "BB".

## 2.6 ESG Rating and ESG Combined Rating

Despite the numerous new regulations and standards that are emerging, there is still a lot of confusion on the firm's sustainable reporting mandatory obligations, especially for non-European companies. Furthermore, it is not clear which ESG criteria are taken into consideration in the companies' data disclosure and reporting. For these reason, it is not easy at all to find ESG scores for the entire US stock universe. However, several rating agencies and data providers have contributed to the development of ESG data and ratings, but the several valuation structures and standards differs from agency to agency, causing a lack of reliability for public data and ratings.

Almost all ESG rating providers use different methods to assign scores and in many cases asset managements, insurance companies and other institutionals have developed internal and not-disclosed ESG rating, in order to assess the sustainability level of their investments.

Usually, agencies collect and evaluate data from different sources, such as corporate annual reports, corporate websites, NGO reports, CSR reports, market news and media news, articles and reports. The standard practice is to assign an annual score to each different ESG category to calculate the final ESG score. Obviously, there are exceptions, which in most cases are represented by significant news that change the score assigned to a particular company. The different models and methodologies used to assign the various scores mean that there may be different scores for the same company, and this is one of the reasons of lack of data reliability; it is therefore important to use the same data provider for all ESG ratings of our sample. At the same time, this absence of a standard methodology between rating providers is understandable due to the particular multi-dimensionality of the sustainability rating. The difficult comparability of the indicators between the various industries is a further drawback related to the ESG issue, since the ESG choice determinants may differ from one sector to another. For instance, regulations linked to climate change challenge could affect more sectors such as Energy industry or Oil & Gas industry. Equally, the corporate governance practices may be affected by sector-specific determinants (Jhonson, Moorman e Sorescu 2009).

In order to ensure data transparency, reliability and to be consistent with the other variables included in the model (CDS Spreads, Stock Returns, Volatilities, Leverage ratios and Credit Ratings), the ESG scores are retrieved from Refinitiv EIKON database. Refinitiv provides ESG data on more than 9,000 listed companies, including many of the primary US and global indices, such as MSCI World, NASDAQ 100, S&P 500 and Russell 100. The information is manually collected and audited by Refinitiv ESG analysts based on publicly available sources. Moreover, since there is no global mandatory standard by which listed companies must report their ESG data, it is often the case that figures are reported in different units of measure or currency. For these reasons, Refinitiv provides both “as reported” data and standardized ESG values for all companies across at least 5 years. The rating process is constructed as follow: the overall company ESG score comes from the score in each pillar (E, S and G). The score of each pillar is based on the score of different categories incorporated in all three pillars; for instance Emission or Innovation for the Environmental pillar, Human Rights and Product Responsibility for the Social one, Board composition and CSR Strategy for the Governance pillar. Then, every score assigned to each category has several determinants, i.e. more than 70 key performance indicator (KPI), which are in turn calculated from more than 400 data points value (including datapoints linked to United Nation SDGs). The Refinitiv ESG score is updated usually every year, but is monitored and adjusted on a daily basis in case of controversies, relevant events and significant media news. Therefore, annual ratings are collected from Refinitiv and each rating is assigned for each month of the reference year, in order to have monthly datapoints.

Further, it is important to disclose the definition that the data provider gives to the three individual pillars score. The Environmental pillar is defined as a measure of the company's impact on living and non-living natural system, including the air, land and water, as well as complete ecosystem. It reflects how well a company uses best management practice to avoid environmental risks and capitalize on environmental opportunities in order to generate LT shareholder value. The Social pillar measures a company's capacity to generate trust and loyalty with its workforce, customers and society, through its use of best management practices. It is a reflection of the company's reputation and the health of its license to operate, which are the key factors in determining its ability to generate LT shareholder value. Finally, Governance pillar is defined as the measure of a company's systems and processes, which ensure that its board members and executives act in the best interests of its LT shareholders. It reflects a company's capacity, through its use of best management practices, to direct and control its rights and responsibilities through the creation of incentives, as well as checks and balances in order to generate LT shareholder value.

Each ESG score can take a value from 0 to 100, i.e. a rating from "D-" to "A+". Hence, every rating has a spread with others always equals to 8.333. For instance, if a company has a score from 100 to 91.666, it has a rating of "A+", whilst if a company has a score in the range 91.666-83.333 it has a rating of "A", and so on until the last score range, which is from 8.333 to 0 and corresponds to the rating "D-". In total there are 12 possible ESG ratings for each firm in the sample.

For the purpose of this research, it was decided to include in the model two different types of ESG scores provided by Refinitiv:

- ESG Score, which is an overall company score based on the self-reported information in the environmental, social and governance pillars, and which assigns different weights to each pillar according to different company's industries.
- ESG Combined Score, which is an overall company score based on the self-reported information in the environmental, social and governance pillars, with an ESG Controversies overlay and negative events reflected in global media.

The choice to include two different ESG scores is driven by the possibility of differentiating this thesis from previous literature and by the fact that it could be very interesting to study the differences in the impact of the two scores on credit risk, caused by the inclusion of controversies and global media news. The ESG Score is basically a weighted average of the three pillars scores, and the weight assigned to each pillar depends on the company's industry. For instance, for an electric utilities company as Southern Co. the Environmental pillar accounts for 42.5%, the Social pillar for 32.5% and the Governance one for 25%; whereas for an IT services and consulting company the E pillar accounts only for 13.9%, the S pillar for 39.8% and the G for 46.3%. Usually in industries like Energy, Construction or Oil

& Gas the E pillar has an higher weight with respect to the other pillars (usually from 40% to 55%), whilst in industries like Telecommunication, Healthcare, Financials or Food Retail & Distribution the social factor is the one that weights the most (usually from 35% to 45%). The standardized structure allows to have numeric score also for some KPIs that are qualitative and not quantitative. For instance, one of the most important KPI for the E score is the Policy Water Efficiency, and answer to the question "does the company have a policy to improve its water efficiency?". In this case, Refinitiv provides numerical answer to this question firstly by assessing if it is true or false that the company has this kind of policy and secondly by comparing the scores of the company's peer group. The following table shows both ESG and ESG Combined Scores of the sample over the period 2015-2019.

[Insert Table 04 here]

Moreover the following table provides average values of both ESG Scores and the correspondent average rating for each year.

**Table 05: Average ESG and ESG Combined Ratings**

| Year | ESG Rating | | | | | | ESG Combined Rating | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Avg | | Max | | Min | | Avg | | Max | | Min | |
| 2015 | 64.72 | B | 86.85 | A | 20.24 | D+ | 56.61 | B- | 93.18 | A+ | 20.24 | D+ |
| 2016 | 66.01 | B | 87.96 | A | 17.69 | D+ | 58.48 | B | 93.22 | A+ | 17.69 | D+ |
| 2017 | 66.8 | B+ | 89.77 | A | 19.59 | D+ | 56.64 | B- | 91.49 | A | 19.59 | D+ |
| 2018 | 68.4 | B | 87.74 | A | 13.34 | D | 56.07 | B- | 91.22 | A | 13.34 | D |
| 2019 | 68.8 | B+ | 89.64 | A | 20.76 | D+ | 56.15 | B- | 93.06 | A+ | 20.76 | D+ |

## 2.7 Panel Data Model: Fixed and Random Effects

Data panel in econometrics is employed when it is necessary to embody in the analysis information across both time and space. Thus, the panel of data has two dimensions, one represented by the data points of each firm for each variable (like cross-sectional data, panel data contains observations across a collection of individuals) and the other dimension represented by data points of each firm for each month in the period (like time series data, panel data contains observations collected at a regular frequency, chronologically). For this reason, panel data is also called longitudinal data or cross-sectional time-series data. In fact, the panel methodology allows to consider both cross-sectional and temporal variations simultaneously, i.e. it accounts for individual heterogeneity, and that is the main pros of using panel data as opposed to cross-sectional data. Indeed, any aspiration to infer a causal relationship from a cross-sectional parameter is limited by two main reasons: the unobserved variable bias (Berrington, Smith e Sturgis 2009), the endogeneity bias (Finkel 1995).
Unobserved variable bias is relevant when there is a bivariate (or partial) correlation between two variables, X and Y, which become conditionally independent, given a third variable (or vector of variables), Z, which has not been included in the model. Endogeneity issue arises when both X and Y influence each other causally but the model specifies the relationship as running in only one direction, say from X to Y. The inclusion of a temporal dimension to the time-static cross-sectional data delivers greater weight on questions of causality, in particular indeterminacy over the sequencing (ESRC National Centre for Research Methods Briefing Paper 2006).

Taking as an example the Pooled OLS estimator, it has several limitations when applied to data panel analysis. First, it would assume that the average values of the variables and their correlation are constant over time and over the cross-sections, i.e. across all firms in the sample. Second, could be interesting to analyze the relationship across variables, above all how variables change dynamically (over time). Third, the analysis of the dynamic behavior of a large sample at the same time can also help to avoid multicollinearity issues that appears when time series are considered individually (Brooks 2014).

However, the statistical models that fits for panel data are more complicated and complex to estimate than those used for cross-sectional observations. Specifically, panel data models account for the fact that data points for the same unit over time are improbably independent of one another, which is instead a standard assumption of cross-sectional estimators.

Some drawbacks of this methodology are data collection and sampling design issues, non-response in case of micro data panels or cross-country dependency in the case of macro panels, i.e. strong correlation across countries (Torres-Reyna 2007).

Economically speaking, the simplest panel regression would have the following structure:

$$y_{it} = \alpha + \beta x_{it} + u_{it} \qquad (1.0),$$

where:

- $y_{it}$ is the dependent variable,
- $\alpha$ is the intercept term,
- $\beta$ is the $k\ x\ 1$ vector of parameters to be estimated with respect to the explanatory variables,
- $x_{it}$ is a $1\ x\ k$ vector of explanatory variables observations over time,
- and $t$ = 1,…, T and $i$ = 1,…, N.

There are generally two types of panel estimator methods used in financial studies: fixed effects models (FE) and random effects models (RE). If the regression is developed via FE model, it is allowed the intercept to change between entities (cross-sectionally) but not across time, whereas the slopes are constant in both dimensions. This method is called the entity-fixed effect. In order to run this model, it is needed the decomposition of the error term $u_{it}$ into $\mu_i$, which represents the entity specific effect that varies only cross-sectionally, and $v_{it}$, which is the "remaining portion" of the error term that varies both across time and entities, capturing what the independent variables don't explain about $y_{it}$. Thus, $\mu_i$ incorporates all the determinants that impact CDS Spreads only cross-sectionally but not over time (like the industry in which a firm operates). Below the decomposition of the error term from the equation 1.0:

$$u_{it} = \mu_i + v_{it} \qquad (1.1).$$

Considering the last assumption, the equation 1.0 changes as:

$$y_{it} = \alpha + \beta x_{it} + \mu_i + v_{it} \qquad (1.2),$$

where:

- $y_{it}$, $\alpha$, $\beta$, and $x_{it}$ are the same of the equation 1.0,
- $\mu_i$ is the entity fixed-effect that varies cross-sectionally,
- $v_{it}$ is the error term that varies cross-sectionally and over time.

One of the approach to estimate this model is the Least Square Dummy Variable (LSDV), which will be discussed in the next paragraph (Brooks 2014).

Additionally, it is possible to estimate the time-fixed effect model, in which intercepts differ over time but are fixed cross-sectionally in each moment. Usually this model is selected when one thinks that the average value of the depend variable varies across time but not cross-sectionally, which is not the case of this analysis. This approach allows the intercept to vary only across time but not over entities, at each moment in time. In this case the error term $u_{it}$ of the equation 1.0 is decomposed into $\lambda_t$, which represents the time varying intercept that encloses all variables affecting $y_{it}$ across time but fixed across entities. and $v_{it}$, which is the remaining error as in the equation 1.2. Since $\lambda_t$ is fixed only cross-sectionally, it means that affect $y_{it}$ as time passes, but the entities of the sample are affected equally, in the same proportion, such that the time fixed-effect varies only over time. Following this approach the equation 1.0 becomes:

$$y_{it} = \alpha + \beta x_{it} + \lambda_t + v_{it} \qquad (1.3),$$

where:

- $y_{it}$, $\alpha$, $\beta$, and $x_{it}$ are the same of the equation 1.0,
- $\lambda_t$ is the time fixed-effect that varies across time,
- $v_{it}$ is the error term that varies cross-sectionally and over time.

As with entity FE model, the time FE model can be estimated using Dummy Variables, but there is a difference: now dummies don't capture cross-sectional variations but only time ones.

The random effects model is similar to the FE model, as it allows changes in the intercepts cross-sectionally, but fixed at each point in time. The difference between the two models is that in the RE model the intercepts that change between entities originate from a common intercept, constant cross-sectionally and temporally, plus a random variable, which is fixed over time but not across entities (Brooks 2014). Hence, this method accounts for random variation of each firms' intercept starting from the common intercept value. In this case the equation 1.0 can be rewrited following the RE panel model:

$$y_{it} = \alpha + \beta x_{it} + \omega_{it} \qquad (2.0).$$

The term $\omega_{it}$ can be decomposed into two terms:

$$\omega_{it} = \epsilon_i + u_{it} \quad (2.1),$$

Where:

- $y_{it}$, $\alpha$, $\beta$, and $x_{it}$ are the same of the equation 1.0,
- $u_{it}$ is the error term varying over time and cross-sectionally,
- $\epsilon_i$ which measures the distance of each entity's intercept from the common intercept term.

Summarizing, this approach includes the common intercept term $\alpha$ which is constant for each entity both cross-sectionally and over time, plus a random term $\epsilon_i$ that varies only cross-sectionally. Thus, $\epsilon_i$ captures the deviation of each entity from the starting point of the common intercept $\alpha$ and the final intercept of each company is composed by both terms, the fixed one plus the random one.

Even if $x_{it}$ is still a *1xk* vector, the heterogeneity aspect of the entities, i.e. the cross-sectional variation, is not captured using LSDV, but through the $\epsilon_i$ random error term of entities.

## 2.8 Further Descriptive Statistics

In this paragraph further descriptive statistics are discussed. The focus is on the correlations between variables, in particular between ESG Scores, ESG Combined Scores and CDS Mid Spreads, and on summary statistics of our panel data.

The summary statistics for each variable are reported in the following table.

**Table 06: Summary Statistics**

| ***Summary Statistics*** | *Exc.Return* | *Leverage* | *Volatility* | *Credit Rat.* | *ESGscore* | *C.ESGscore* | *CDS Spr.* |
|---|---|---|---|---|---|---|---|
| Mean | 0.007 | -10 | 0.24 | 55 | 67 | 57 | 112 |
| Standard Error | 0.001 | 25 | 0.00 | 0 | 0 | 0.23 | 2 |
| Median | 0.008 | 103 | 0.22 | 54 | 69 | 57 | 62 |
| Mode | 0.000 | 94 | 0.21 | 54 | 72 | 41 | 98 |
| Standard Deviation | 0.082 | 1714 | 0.10 | 11 | 15 | 16 | 167 |
| Sampling Variance | 0.007 | 293754 | 0.01 | 128 | 225 | 250 | 27818 |
| Kurtosis | 5.933 | 72 | 3.23 | 0 | 0 | -1 | 40 |
| Skewness | 0.274 | -7 | 1.74 | 0 | -1 | 0 | 5 |
| Interval | 1.169 | 27313 | 0.55 | 67 | 74 | 70 | 2385 |
| Minimum | -0.477 | -20606 | 0.11 | 17 | 20 | 20 | 11 |
| Maximum | 0.692 | 6707 | 0.66 | 83 | 93 | 90 | 2397 |
| Sum | 33.404 | -48401 | 1171.66 | 268108 | 322594 | 276317 | 543254 |

It is interesting to note that the average ESG Combined Score is “B-“ , which corresponds to a score of 57, whilst the average ESG Score is “B+”, attributed to a score of 67. This is consistent which the construction itself of the two scores, as it is expected that the Combined Score is lower in average with respect to the standard Score, as it is affected also by market and media news and not only buy the structural model of the score construction. Also, it is interesting to note that the average Credit Rating correspond to “BB”, which is similar to other two scores. Finally, it is necessary to highlight that leverage has a negative average value and a huge standard deviation. This is due to the fact that there are several leverage ratio in the sample that have a negative value, far below zero. This could be a problem for the regression analysis, as the regression result could be biased by these characteristics.

In the next section of the paragraph, the focus will be on relation between all variables of the panel, to analyse whether their relations is in line with what one should expect from the real economy and markets. In particular, the central focus is on the main variables in our interest: both CDS Scores and CDS Mid Spreads.

In this paragraph it is also important to focus on the relation between ESG Scores and CDS Mid Spreads, as they are the central variables of this research thesis. Hence, the correlation matrix of variables observed annually and the correlation matrix of variables observed monthly are reported below. In order to do that, firstly the correlation matrix of variables observed monthly and the correlation matrix of the variables observed each year are showed below.

**Figure 2.4: Correlation matrix of variables observed monthly**

| ***Correlations*** | Exc.Return | CDS | Leverage | Volatility | Cr.Rating | ESG Score | C.ESG Score |
|---|---|---|---|---|---|---|---|
| Exc.Return | 1.00 | -0.08 | 0.00 | -0.01 | 0.04 | 0.01 | 0.01 |
| CDS | -0.08 | 1.00 | -0.13 | 0.69 | -0.44 | -0.32 | -0.19 |
| Leverage | 0.00 | -0.13 | 1.00 | -0.09 | 0.10 | 0.05 | 0.08 |
| Volatility | -0.01 | 0.69 | -0.09 | 1.00 | -0.38 | -0.41 | -0.24 |
| Cr.Rating | 0.04 | -0.44 | 0.10 | -0.38 | 1.00 | 0.31 | 0.13 |
| ESG Score | 0.01 | -0.32 | 0.05 | -0.41 | 0.31 | 1.00 | 0.59 |
| C.ESG Score | 0.01 | -0.19 | 0.08 | -0.24 | 0.13 | 0.59 | 1.00 |

In the figure 2.4 correlations between explanatory variables and CDS Spreads are consistent with what expected, except for Leverage. For Excess Return, Credit Rating, Volatility and both ESG Scores, the correlation with dependent variable is negative, as we expected. As expected, higher Stock Return means a lower CDS Spread and a better Credit Rating or ESG Scores means a lower probability of default and less credit risk. Instead, volatility is as expected positively correlated with credit risk, as it is a measure of risk for the markets and for investors. Leverage usually should be positive correlated with credit risk, as high leverage could be considered as a measure of firm's assets risk, but our panel data don't suggest this. Again Leverage represents deviate values from what one should expect, that have few sense statistically and economically speaking.

As mentioned in the previous paragraph, often when dealing with data panels, problems arise of collinearity between the variables, i.e. when two variables are highly correlated or partly depend on the same determinants. It could be argued that when two variables depend on the same determinants, it is more likely that collinearity problems arise and that therefore some of these determinants are double-counted in their impact on the dependent variable. In the case of this analysis, this possibility exists mainly due to the collinearity between the two ESG ratings and the collinearity between Credit Ratings and ESG ratings, both standard and combined. In the first case, the problem is easily avoided, as two distinct regressions are performed, one using the standard ESG and the other using the combined ESG score. In the second case, however, it is necessary to understand whether the determinants that make up the Credit Rating are actually associated with the ESG ones.

As we downloaded data for these two variables on Thomson Reuters, it is worth discussing which variables the data provider considers when assigning their ratings. Thomson Reuters' model-generated Credit Ratings are assigned primarily on the basis of accounting determinants, disclosed in the income statement or balance sheet of the company in question, plus a peer comparison. The five macro-areas, that in turn contain other variables, which make up the Credit Rating are Profitability, Leverage, Coverage, Liquidity and Growth. Hence, the Rating will depend on value as Net Profit Margin (Profitability), Net Debt divided by Assets (Leverage), percentage of EBIT used to cover interest expenses (Coverage), and many others mentioned in variables description of previous paragraphs. None of these variables has an impact on the assignment of the ESG score, which is considered much more on a qualitative rather than quantitative or accounting level. In fact, the determinants of ESG scores depend above all on the environmental, social and governance choices of the company and answer different questions. To cite few relevant environmental examples, some important KPIs of ESG scores, both combined and standard, are Policy Water and Energy Efficiency, CO2 Emission level, Materials used for Packaging, Presence of Green Buildings, Production of Toxic Chemicals, Biodiversity Impact, and so on. Thomson Reuters uses more than 70 KPIs calculated from more than 400 data points, and they can be can be categorized into ten areas: Resource Use, Emission and Innovation for the E pillar, Workforce, Human Rights, Community and Product Responsibility for the S pillar, Management, CSR strategy and Shareholders for the G pillar. In addition, for the ESG Combined, 23 more controversy measures are included as a plus to the KPIs mentioned, e.g. controversies related specific business area: Accounting, Tax Fraud, Customer Health and Safety, Environmental, Anti-Competition, Working Conditions, and many others.

Thus, we can conclude that the collinearity issue should not affect our analysis as determinants of variables are different and not correlated within each other.

Heterogeneity and Multicollinearity are not the only obstacles to face: using panel data there could be also an issue of Reverse Causality between variables in our interest, i.e. between CDS Spreads and ESG Ratings. We know that both variables change between the reference time horizon, but we do not necessarily know which one drives the effect. Reverse causality is a widespread problem for many research questions, but rarely discussed in practical applications and this problem also affects OLS estimations but could be more severe in FE estimations because the latter solely rely on intertemporal variation. As far as the ESG standard score is concerned, this issue can be considered as irrelevant, as no determinant of the Thomson Reuters' ESG model is considered as a factor influencing Default Probability. However, this cannot be 100% asserted for ESG Combined Scores, as news regarding company-relevant sustainability disputes could affect the ESG Score as much as the Credit Risk. This last point is certainly one of the limitations of this analysis, considering however that, as opposite to the well-known issue of unobserved heterogeneity, it is much less clear for researchers how to deal with reverse causality (Leszczensky, Wolbring 2019). Surely it would be very interesting to improve our analysis using one of the methods discussed by the literature to overcome the problem of reverse causality, for example using the First-Difference Model with Lagged Independent Variables or the more recent Cross-Lagged Panel Models with Fixed Effects (Allison, Williams, and Moral-Benito 2017).

The next figure exhibits the correlation matrix also of variables which data points are calculated as the mean of monthly data, to obtain annual data.

**Figure 2.5: Correlation matrix of variables observed annually**

| ***Correlations*** | Exc.Return | CDS | Leverage | Volatility | Cr.Rating | ESG Score | C.ESG Score |
|---|---|---|---|---|---|---|---|
| Exc.Return | 1.00 | -0.12 | 0.03 | 0.03 | 0.08 | 0.08 | 0.03 |
| CDS | -0.12 | 1.00 | -0.12 | 0.72 | -0.47 | -0.33 | -0.18 |
| Leverage | 0.03 | -0.12 | 1.00 | -0.11 | 0.11 | 0.07 | 0.11 |
| Volatility | 0.03 | 0.72 | -0.11 | 1.00 | -0.39 | -0.39 | -0.23 |
| Cr.Rating | 0.08 | -0.47 | 0.11 | -0.39 | 1.00 | 0.30 | 0.13 |
| ESG Score | 0.08 | -0.33 | 0.07 | -0.39 | 0.30 | 1.00 | 0.57 |
| C.ESG Score | 0.03 | -0.18 | 0.11 | -0.23 | 0.13 | 0.57 | 1.00 |

Using annual observations there is a slightly higher correlation of ESG Score with CDS and a slightly lower for Combined ESG Score and as expected they are in line with expectations, except for leverage.

The next figure shows the Delta between the two correlation matrices, in order to assess if there is a large discrepancy between the values observed at a different frequency. As we want to use both panel (with annual and monthly data points) we ask whether there is a difference between the data correlations with the dependent variable.

**Figure 2.6: Delta of Correlation Matrices**

| ***Correlations*** | Exc.Return | CDS | Leverage | Volatility | Cr.Rating | ESG Score | C.ESG Score |
|---|---|---|---|---|---|---|---|
| Exc.Return | 0.00 | 0.04 | -0.03 | -0.04 | -0.04 | -0.07 | -0.02 |
| CDS | 0.04 | 0.00 | -0.01 | -0.03 | 0.03 | 0.01 | -0.01 |
| Leverage | -0.03 | -0.01 | 0.00 | 0.02 | -0.01 | -0.02 | -0.03 |
| Volatility | -0.04 | -0.03 | 0.02 | 0.00 | 0.01 | -0.02 | -0.01 |
| Cr.Rating | -0.04 | 0.03 | -0.01 | 0.01 | 0.00 | 0.01 | 0.00 |
| ESG Score | -0.07 | 0.01 | -0.02 | -0.02 | 0.01 | 0.00 | 0.02 |
| C.ESG Score | -0.02 | -0.01 | -0.03 | -0.01 | 0.00 | 0.02 | 0.00 |

All delta correlations are lower than 0.05, except one values which is still below 0.08. These findings are positive for this research, as they indicate that the correlation between variables does not change for the purposes of our objective and that use annual observations for our empirical research will not affect significantly our results. Furthermore, the evidence demonstrated by the data collected on the leverage variable is not convincing and does not seem to make sense neither for our empirical research nor from the point of view of the economic and financial reality. For these reasons, it is decided not to include the variable in the panel regression.

Both ESG Scores Data have a significant correlation with CDS Spreads. On one hand, ESG Score has an higher correlation compared to ESG Combined Score. On the other hand, if we calculate the average of sample's annual observation, obtaining only five observation of each variable, i.e. each variable has one observation for each years, ESG Combined Score seems to be highly correlated with CDS Spreads with respect to ESG standard Score. In fact, while the ESG Score has a growing trend between the time horizon, the ESG Combined has a trend inversely correlated with CDS Spreads: in 2016 spread decreases and score increases, and in 2018 spread increases and score decreases turning back to its 2016 level. The ESG score instead registers a growing trend over years with an increase of 6.3%. This is however consistent with the structure of the score taken into account. The increase of ESG scores over years is highly expect for the reasons we discuss in the Chapter 1: the growing issue of regulations and standards both nationally and internationally, the greater attention to social, environmental and managerial sustainability and the risk that unsustainable companies face, considering what the global trend is today and what are the estimates for the future.

The ESG Combined has the difference of being affected by market news and media and in this context it is similar to CDS market movements generated by news on companies' controversies and relevant events.

# CHAPTER 3 - *Empirical Methodology and Results*

## 3.1 Empirical Methodology

For the purpose of this thesis, the entity fixed-effect model is selected to run our empirical analysis. It is preferable to use this method as in our model there are more entities than moments in time in which the variables are observed, and this is valid both for monthly and annual observations of the variables that determine our regression analysis. As the panel data is not perfectly balanced, both monthly and annual data will be taken into account. Unbalanced panel in this case means that on one hand data points at a monthly frequency are observed, on the other hand ESG variables data are updated usually every year, except for events particularly resonant events. This issue create a divergence between variance of data observed at a different frequency and in turn could create a bias in the analysis. For this reason, the LSDV approach will be performed using both panel and results will be compared. Annual data are obtained as average of monthly data for each sample's company. Starting from the equation 1.2 and applying the LSDV approach, the equation modifies as follow:

$$y_{it} = \alpha + \beta x_{it} + \mu_i D1_i + \mu_i D2_i + \mu_i D3_i + \cdots + \mu_N DN_i + v_{it} \qquad (3.0),$$

where:

- $D1_i$ is a dummy variable that takes the value of 1 for all observations on the first company in the sample and zero otherwise,

- $D2_i$ is a dummy variable that takes the value of 1 for all observations of the second company in the sample and zero otherwise,
- and so on until the Nth company in the sample which is multiplied by $DN_i$ that takes the value of 1 for the Nth company in the sample and zero otherwise.

This method is performed for monthly and annual frequency data, obtained through average of monthly values of excess returns, volatility, credit ratings and CDS mid spreads. ESG scores and ESG combined scores are not included: as they are observed annually, the average of monthly observation is the annual rating itself.

Moreover, can be interesting to compare the FE model results with a Pooled OLS approach, in order to assess if the two approaches presents divergent results. In order to run also an OLS model estimator, the so-called "within transformation" is executed (Brooks 2014). It necessitates to subtract from the values of the variable the time-mean of each company observations. Thus, we calculate the mean of each variables (explanatories and dependent) for cross-sectional unit "$i$". The example for variable $y$ that follows is repeated for each explanatory variable:

$$\bar{y}_i = \frac{1}{T} \sum_{t=1}^{T} y_{it} \qquad (3.1).$$

Hence, starting from equation 1.0 the below is obtained:

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i \qquad (3.2),$$

that can be re-wrote as:

$$\ddot{y}_{it} = \beta \ddot{x}_{it} + \ddot{u}_{it} \qquad (3.3),$$

where the double dots above variables represent the demeaned values. Note that after these adjustments the regression does not need an intercept any more as dependent variable have now zero mean by construction.

## 3.2 Panel Data Regression

Given what has been said in the previous paragraph and in Chapter 2, this section developes the Analysis' Panel Data Regression Model construction and description for both monthly observation panel and annual observation panel. Starting from equation 1.0 we can write our model as:

$$y_{it} = \alpha + \beta X + u_{it} \qquad (4.0),$$

where:

- $y_{it}$ is a *1x4851* vector of monthly observation of Single-Name CDS Mid Spreads,
- $\alpha$ is the intercept term
- $\beta$ is a *1x5* vectors of coefficients
- $u_{it}$ is a *1x4851* vector of errors, containing also the time or the entity fixed effect
- $X$ is a *5x4851* matrix of explanatory variables observations in which each column represents a variable and each row a monthly observation of cross-sections.

We can say that each vector *1x4851* composing the matrix X is built as follows: we can imagine each vector as composed by several vectors. These vectors contain entity observations for each month, hence 99 companies times 49 observation create the 4851 rows vector. Then, we can create the matrix X containing these five vectors. The totality of data points using monthly data are 29,106.

Using annual observations, the equation 4.0 has the below structure:

- $y_{it}$ is a *1x495* vector of annual observation of Single-Name CDS Mid Spreads,
- $\alpha$ is the intercept term
- $\beta$ is a *1x5* vector of coefficients for each variable
- $u_{it}$ is a *1x495* vector of errors, containing also the time or the entity fixed effect
- $X$ is a *5x495* matrix of explanatory variables observations in which each column represents a variable and each row a monthly observation of cross-sections.

In this case, the vectors composing matrix X have five observation (one for each year) for all the companies of the sample. Thus, we have 495 observations for each variable and the totality is 2,970 data points.

The equation 4.0 can be decomposed in order to show all variables composing the matrix X:

$$CDS_{it} = \alpha + \beta^{ESG} ESG_{it} + \beta^{cESG} cESG_{it} + \beta^{R} R_{it} + \beta^{Vol} Vol_{it} + \beta^{CR} CR_{it} + u_{it}$$

(4.1).

Following the enitity FE method we can re-write the equation 4.1 as:

$$CDS_{it} = \alpha + \beta^{ESG} ESG_{it} + \beta^{cESG} cESG_{it} + \beta^{R} R_{it} + \beta^{Vol} Vol_{it} + \beta^{CR} CR_{it} + \mu_i + v_{it}$$

(4.2).

Instead, using the time FE, the structure would have been:

$$CDS_{it} = \alpha + \beta^{ESG} ESG_{it} + \beta^{cESG} cESG_{it} + \beta^{R} R_{it} + \beta^{Vol} Vol_{it} + \beta^{CR} CR_{it} + \lambda_i + v_{it}$$

(4.3).

Since CDS Mid Spread are quoted in bps, they can reach very high values in terms of data observed. For this reason, it is calculated the logarithm of CDS Mid Spread, as it allows to have all variables almost in the same scale and to avoid huge difference in value observed. For the same reason, it is decided to convert the range of both ESG Scores and Credit Rating from the range 0-100 to the range 0-1. Through this amendment, we are able to achieve that all variable are in the same scale, i.e. all variables' value vary in the range -2/+1. For the same reason we decided to exclude Leverage from our empirical analysis, as it is the only variable with different scale and not varying in the range mentioned above. Taking the natural logarithm of CDS Mid Spreads, the next equation is obtained:

$$\ln(CDS_{it}) = \alpha + \beta^{ESG} ESG_{it} + \beta^{cESG} cESG_{it} + \beta^{R} R_{it} + \beta^{Vol} Vol_{it} + \beta^{CR} CR_{it} + \mu_i + v_{it}$$

(4.4).

## 3.3 Pooled OLS Regression

This paragraph presents the model used to obtain the coefficients of the explanatory variables using the OLS estimator. Since the panel in question is longitudinal, the so-called Pooled OLS estimator is used. This further analysis is developed in order to compare the findings achieved through panel regression. The empirical methodology used for pooling the panel data is previously described in the first paragraph of this chapter.

Starting from equation 3.2, the regression model becomes:

$$\ln(CDS)_{it} - \overline{\ln(CDS)}_i = \beta^{ESG}(ESG_{it} - \overline{ESG}_i) + \beta^{cESG}(cESG_{it} - \overline{cESG}_i) + \beta^{R}(R_{it} - \bar{R}_i) + \beta^{Vol}(Vol_{it} - \overline{Vol}_i) + \beta^{CR}(CR_{it} - \overline{CR}_i) + (u_{it} - \bar{u}_i)$$

(5.0).

Note again that this model has no intercept as the variable ln(CDS) have zero mean by construction.

The equation 5.0 can be also described as:

$$\ln(\ddot{CDS})_{it} = \beta^{ESG}\ddot{ESG}_{it} + \beta^{cESG}c\ddot{ESG}_{it} + \beta^{R}\ddot{R}_{it} + \beta^{Vol}\ddot{Vol}_{it} + \beta^{CR}\ddot{CR}_{it} + \ddot{u}_{it}$$

(5.1).

The results of the Pooled OLS estimations are discussed in the following paragraph.

# 3.4 Results & Findings

Once the final variables are selected and the empirical model's structure is defined, the panel data regression can be performed, following the methods discussed previously, i.e. the fixed effect model. Indeed, the results of four different regression will be described in this paragraph. All regression are completed using the statistical software *Stata15*.

The first two are performed following the standard entity FE, whilst the other two are the same regression with clustered errors. In this analysis is very import to use both these approaches to see whether we have biased results or instead they are consistent with both approaches. Fixed effect approach aims to avoid non-observed heterogeneity across different group in panel data. As soon as non-observable variables vary across panel groups, each variable's coefficient could be biased if correlated with this variation. Hence, the assumption that errors $v_{it}$ are identically and independently distributed (i.i.d.), is clearly violated in many cases. For that reason we assume in third and fourth regressions that errors are clustered, i.e. that observations between entities have unknown correlation, but different groups in the sample have no correlated errors (Nichols e Schaffer 2007). Thus, clustered standard errors account for non i.i.d. errors within each group (and not across groups). Even if we account for entity-level FE, there is still some variation in the dependent variable not captured by the effect and correlated across time (Miller 2017).

Therefore, both entity FE model are employed to run the regressions and then other two regressions are developed with clustering errors approach, so that results can be compared. In particular, the comparison focus is on the ESG variables coefficients estimation with and without clustered standard errors. In addition, other four regressions are developed following the same path but using annual data for each variable. The next table shows the results for these regressions:

1- Panel Data Entity Fixed-Effect with monthly observations and ESG Combined Score;
2- Panel Data Entity Fixed-Effect with monthly observations and ESG Score;
3- Panel Data Entity Fixed-Effect with monthly observation, ESG Combined Score and clustered errors
4- Panel Data Entity Fixed-Effect with monthly observation, ESG Score and clustered errors.

**Table 07: Monthly Panel Empirical Results**

| | (1) ln(cds) | (2) ln(cds) | (3) ln(cds) | (4) ln(cds) |
|---|---|---|---|---|
| Excess Return | -0.364*** | -0.368*** | -0.364*** | -0.368*** |
| | (-7.24) | (-7.32) | (-6.91) | (-6.99) |
| Volatility | 0.818*** | 0.840*** | 0.818*** | 0.840*** |
| | (17.92) | (18.49) | (4.87) | (4.91) |
| Cr. Rating | -0.651*** | -0.663*** | -0.651*** | -0.663*** |
| | (-17.30) | (-17.77) | (-3.94) | (-4.08) |
| ESG C. Score | -0.128*** | | -0.128 | |
| | (-4.65) | | (-1.26) | |
| ESG Score | | -0.253*** | | -0.253 |
| | | (-4.86) | | (-1.48) |
| Intercept | 8.595*** | 9.216*** | 8.595*** | 9.216*** |
| | (49.02) | (35.93) | (11.53) | (9.24) |
| Observations | 4851 | 4851 | 4851 | 4851 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Analysing the results obtained on the first two regressions, i.e. Panel Data Entity Fixed-Effect with monthly observations and ESG Combined Score and Panel Data Entity Fixed-Effect with monthly observations and ESG Score, all coefficient's estimations are significant. Statistically speaking, these coefficients are significant as described by low p-values, all lower than 0.001, which is an important finding as it means that the variable of our model affect CDS Spreads in the reference time horizon. Looking at the results more in depth, it is interesting to note that all coefficients values are consistent with expectation: excess return impact negatively on CDS Spread, as Credit Rating and ESG Score do; Volatility impact positively the spreads, i.e. the company's credit risk, which is in line with suppositions. However, even if these results are significant, the coefficients estimated tell us that these variables do not affect CDS strongly, as all of them are lower than zero.

Focusing on the main variables of this research, ESC Combined Scores variation over years impact CDS only for the 0.12%, whilst ESG Score for 0.25%. The reason of this slight impact could be several and will be discussed in next paragraphs. Also, Betas estimated for other variables are all higher than ESG ones. In particular note that Credit Rating has a much higher impact on CDS spread with respect to both sustainability ratings. ESG and ESG Combined have respectively a delta with Credit Rating equal to 0.41 and 0.52. The delta is even higher if compared with Volatility coefficient. Therefore, within all the variables of the model, the ESG ones have the least influence on the corporates' probability of default.

Switching to other two regressions, where clustered errors approach is included, the results change completely for the ESG variables, but remain the same for other variables. Excess Return, Credit Rating and Volatility still have strong significance and p-values below 0.01. This is not the case for ESG Combined and ESG Score, as they register p-values above 0.05 and hence rejected for a 95% standard confidence level. Clearly, coefficients estimated for the three control variables vary when we switch from one ESG score to the other. That is because the coefficient represents not only the covariance of the variable $x$ and $y$, divided by the variance of $x$, but this value is also adjusted for the covariance that the variable $x$ has with the others explanatory variables. For this reason, we also decided to run two different regressions: one with Combined score and the other with standard score, since these two variables are highly correlated as shown in figure 2.4 and 2.5 and we don't want this affect the results. Also, statistically speaking, include two variables in the same regression which are very correlated is not so useful for our objective.

As can be seen in Table 07, the robust or clustered error approach implies a lower significance of the estimated coefficients for ESG variables, given that this approach allows for heteroscedasticity and correlation in the error term within a cluster. This means that the model allows the correlation between the error terms of variables of the same cluster.

Specifically, clustering errors means considering them not i.i.d. for the entities of the same cluster, as there could be a correlation given by specific characteristics of the cluster itself. In the case of this research, the entities are obviously the companies of our sample and the clusters are the various industries to which they belong. Therefore, we can say that it is correct to use a method that takes into account the relationship between specific unobservable of a sector, especially when dealing with sustainability thematics that have a different weight in the industries. Therefore, using CSE is on the one hand more correct, as it imposes a more restrictive assumption on errors correlation within a cluster, on the other hand it therefore implies a lower significance of the estimated results. Therefore, for the third and fourth regression listed in Table 07, we reject the coefficients estimated for both ESG variables as p-values are higher than 0.05 for a 95% confidence interval, whilst the other three independent variables' coefficients are still significant.

The next step of the empirical process involves other four regression following exactly the same approach just described, but using annual data panel. Then we will compare the results obtained using different data frequency.

The table below shows the results for the listed regressions:

1- Panel Data Entity Fixed-Effect with annual observations and ESG Combined Score;
2- Panel Data Entity Fixed-Effect with annual observations and ESG Score;
3- Panel Data Entity Fixed-Effect with annual observation, ESG Combined Score and clustered errors
4- Panel Data Entity Fixed-Effect with annual observation, ESG Score and clustered errors

**Table 08: Annual Panel Empirical Results**

| | (1) ln(cds) | (2) ln(cds) | (3) ln(cds) | (4) ln(cds) |
|---|---|---|---|---|
| Excess Return | -1.591** | -1.642*** | -1.591** | -1.642** |
| | (-3.31) | (-3.43) | (-3.04) | (-3.16) |
| Volatility | 0.608*** | 0.635*** | 0.608** | 0.635** |
| | (4.02) | (4.25) | (3.14) | (3.24) |
| Cr. Rating | -0.794*** | -0.794*** | -0.794*** | -0.794*** |
| | (-5.95) | (-6.09) | (-4.08) | (-4.24) |
| ESG C. Score | -0.0888 | | -0.0888 | |
| | (-0.94) | | (-0.69) | |
| ESG Score | | -0.382* | | -0.382* |
| | | (-2.29) | | (-2.12) |
| Intercept | 8.678*** | 9.962*** | 8.678*** | 9.962*** |
| | (14.81) | (11.75) | (9.95) | (9.48) |
| Observations | 495 | 495 | 495 | 495 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

The table above shows results for panel data regression using annual observation of variables. On one hand, results obtained are very similar to previous ones for Credit Rating and Volatility, as coefficients estimated have the same statistical significance and similar values. Excess return's coefficients estimation has slightly less significance, with p-values higher than 0.01 in two regressions over three and also coefficients' value is more than three times higher versus the estimation using monthly observation. The great achievement in this case is that statistical significance of coefficients for standard ESG score is not lost when we cluster errors in the third regression. In fact, the coefficient has a value of -0.382 and a p-value lower than 0.05 and hence still significant for 95% confidence interval. Unfortunately, this is not true for Combined score, as it loses significance when we cluster errors, as per monthly data panel discussed previously. Summarizing, results obtained with annual observation seems to be better with respect to monthly, and probably the main reason is that we have a balanced panel, as all variables are observed at the same frequency, in contrast with panel data used for the estimation in Table 05.

Going beyond panel data regressions, this section discuss results achieved via Pooled OLS estimator. The regression in this case in performed using Excel. The table below shows the findings.

**Table 09: OLS Estimator Empirical Findings**

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* |
|---|---|---|---|---|
| Intercept | 0 | 0 | 0 | 0 |
| Exc.Return | -0.45720727 | 0.09461555 | -4.83226 | 0.00 |
| Volatility | 1.12551290 | 0.024328997 | 46.2622 | 0.00 |
| Cr.Rating | -1.23381824 | 0.037239433 | -33.132 | 0.00 |
| ESG Score | -0.43980968 | 0.039681272 | -11.0836 | 0.00 |
| ESG C. Score | 0.00593010 | 0.033297549 | 0.178094 | 0.86 |

Comparing results with Panel Data regression, we can see that all coefficients are higher in the latter table, except for Excess Return and ESG Combined. Looking at p-values, it is interesting to note that once again results estimated are significant, but surprisingly we have no significance for ESG Combined score at 95% confidence level. The positive aspect of those findings is that Betas estimated seem to have higher impact on CDS Spreads, with respect to coefficients estimated previously. We can say that, apart for ESG Combined, the OLS regression presents consistent results compared with those listed in Table 05 and Table 06. Note that to run this regression, monthly observations were employed as model data. The following table shows further OLS regression statistics.

**Table 10: OLS Regression Statistics**

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.766076136 |
| R Square | 0.586872646 |
| Adjusted R Square | 0.586325172 |
| Standard Error | 0.53700378 |
| Observations | 4851 |

From Table 08, it is important to discuss the R-Square values resulted. The most common interpretation of R-squared is how well the regression model fits the observed data. In our model, nearly 60% of the data fits the model and this is a further significant achievement. We can rewrite equation

# Limitations

Despite the statistical significance of the results discussed above, the analysis carried out has several limitations. First of all, starting from the research outputs, the evidence obtained for the two ESG variables is less significant when the standard errors are clustered. This means that when the model accounts for non i.i.d. errors over entities, the model's ability to predict fails. Surely a further limitation is represented by the scarcity of data available from accessible sources. In particular, the ESG Ratings are provided by a few agencies and main data sources, which still use different models for assigning the score. In this sense, the lack of clear legislation and guidelines is also a disadvantage for this analysis. ESG scores are also available for a few years, usually updated annually and potentially have a very large number of qualitative and quantitative determinants, as there are no commonly used standards.
Moreover, a further limit to consider is the short time horizon on which the analysis is carried out, since ESG is relatively young as a trend with scarce data available. Finally, the limitation of having an unbalanced panel data is once again due to the difference between monthly observations of excess return, volatility and CDS spread against annual observations for ESG ratings and sometimes non-monthly observations for credit ratings.
Nevertheless, the research has also several points of strength and significance. The results obtained are significant and consistent with expectations and the first hypothesis discussed in Chapter 2 has never been rejected. The coefficients estimated for the ESG scores are consistent and even following the approach that clusters the errors, the results remain significant for the standard ESG score, but to a lesser extent. The analysis is also supported by previous literature and bibliographic references in the objective and method. At the same time, this differs from previous similar researches, mainly for two reasons: first because it

focuses on US companies, where the ESG trend is growing at a slower rate than in Europe and is less frequently on the agenda for both regulations issued and for the evidence on the market; second because it uses two different sustainability ratings, combining both the deterministic aspect of corporate sustainability choices and that linked to disputes, resonant management decisions, market news and the media reports. Moreover, this research work differs from the previous ones also because it does not study the impact of sustainability in the credit market from the point of view of bonds, loans, yields or term structure, but instead from the point of view of the derivatives market, or CDS, which are the most liquid and traded instrument among credit derivatives.

# Conclusions

The thesis has statistically and econometrically achieved positive and significant results, both for future literature and for investors, as the ESG trend is growing fast in the economy and this is clearly reflected in global markets for all asset classes. The estimations are consistent with expectations and significant in terms of p-values, even if clustered errors are taken into accounts. We can summarize our results re-writing the two main equation of the research, i.e. equation 4.3 and equation 5.0.

Starting from the Panel Regression that includes ESG Combined Score and monthly frequency observations, equation 4.3 presents the following Betas estimation:

$$\ln(CDS_{it}) = 8.595 - 0.128cESG_{it} - 0.364R_{it} + 0.818Vol_{it} - 0.651CR_{it}$$

(6.0).

Next equation shows results of the same regression, but using standard ESG Scores:

$$\ln(CDS_{it}) = 9.216 - 0.253ESG_{it} - 0.368R_{it} + 0.840Vol_{it} - 0.663CR_{it}$$

(6.1).

Clustering errors, we obtained results that are not statistically significant for both ESG scores, as demonstrated by p-values discussed in Chapter 3.

Given the findings obtained for equation 6.0 and 6.1, $H_0$ is not rejected whilst $H_1$ is rejected, at 95% confidence level.

Then, we ran other four regression following the same model but using different observation frequency, i.e. annual data. The results obtained are the following:

$$\ln(CDS_{it}) = 8.678 - 0.088cESG_{it} - 1.591R_{it} + 0.608Vol_{it} - 0.794CR_{it}$$

(6.2);

$$\ln(CDS_{it}) = 9.962 - 0.382ESG_{it} - 1.642R_{it} + 0.635Vol_{it} - 0.794CR_{it}$$

(6.3).

Following errors clustering approach, we obtained significant results for ESG standard Score using annual data, in contrast with monthly panel regressions. $\beta^{ESG}$ is still consistent at 95% confidence level as p-value stands between 0.05 and 0.01. Betas estimated are equal to those in equation 6.3, but the ESG coefficient has less significance with clustered errors, since its p-value is higher, but still below 0.05. These findings confirm that once again $H_0$ is not rejected, whilst $H_1$ is rejected.

In summary, the most significant and relevant coefficient estimated in this research is the $\beta^{ESG}$ of the equation 6.3 developed using annual panel data and following the errors clustering method. The $\beta^{ESG}$equal to -0.382 means that an improving in corporates' ESG Score, e.g. from C+ to B-, creates a decrease in CDS Spread of 0.382%. Considering the entire range of ESG ratings (from D- to A+), the total spread of scores from 0 to 1 accounts in average for 3.82% of CDS Spreads. Hypothetically, if a company improves its sustainable rating from the lowest score to the highest, it would tightens its probablity of default by 3.82%. The estimate of this impact is large and very significant, expecially if its considered how muchi it can grows, given that ESG trend is still in its early stages.

Lastly, the results of OLS coefficient estimation are presented in the below equation. Note that $\beta^{cESG}$ of Combined ESG is not significant in this case and that the regression has no intercept by construction. Other independent variables' coefficients are coherent with expectations and significant. Therefore, Equation 5.0 can be rewritten as:

$$\ln(CDS)_{it} - \overline{\ln(CDS)}_i = -0.439(ESG_{it} - \overline{ESG}_i) - 0.457(R_{it} - \bar{R}_i) + 1.125\big(Vol_{it} - \overline{Vol}_i\big) - 1.233(CR_{it} - \overline{CR}_i)$$

(6.4).

For the latter regression, $H_0$ is not rejected for ESG Score but it is for the ESG Combined; in turn $H_1$ is automatically rejected.

Even if results are coherent with expectations and significant, the ESG Betas estimated have relatively low values with respect to other independent variables. As our main objective is to assess the magnitude of ESG scores' impact on CDS spread for US companies, our finding tells us that this impact is significant and that in few years it could be even more powerful. At the moment, the ESG impact is still not completely perceived by the market for several reasons. In the US, regulations and standards are still not improved by authorities, companies' reporting has no clear mandatory guidelines and often rules overlap. In addition, the rating agencies and data providers use different methods to estimate sustainability ratings, because there is no common rules to follow both from the authorities side and companies' side (even for those adhering to SDGs objective or TCFD guidelines, since they often omit information in reports or share only those that are most convenient to). Moreover, even if own proprietary rating agencies and data providers are investing in this context, the subject is too broad and determinants of the ESG rating are potentially infinite. This research is however important for many purposes: for the climatic and social challenges the world is facing, and for investors, who must have the opportunity to make conscious investments and the ability to know in a standardized manner the level of sustainability of the company in which they are investing. Finally, considering that today the ESG branded AUM accounts for \$1.3tn only in US and that the macro-trend is only at its infancy, we can say that in the coming years it could grow at important levels, and hence global standards have to keep up with expansion.

The analysis carried out is significant not only for the assessment of the impact of ESG ratings but also for highlighting the determinants of CDS Spreads in the American market, and this is certainly a further relevant aspect of this study.

To conclude, some suggestions are discussed for future research that will focus on the topics covered in these theses. First of all, it would be intriguing to carry out the same type of research for listed companies in Europe, in order to compare the results and understand whether the legislation and the greater European attention to the issue of sustainability is reflected in the credit market or not (obviously the hypothetical research should focus on the same sectors that have been taken in the account in this thesis and sector concentration as similar as possible to those included in Table 01). Furthermore, it would be very interesting to control for different ESG scores, provided by another reliable source, to understand if their impact on CDS is consistent with the findings of the empirical analysis. Finally, over time much more data will be available and firms' practices and reporting will be standardized by new regulations, thus a research focused on growth rate of ESG impact in credit market would be important to address.

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# Appendix

## Tables

**Table 01: Companies, Sectors' weight and industries, as reported in Thomson Reuters (2020)**

| # | Company | Sector | Sector Concentration |
|---|---|---|---|
| 1 | OMNICOM GROUP INC | Advertising & Marketing | 1,0% |
| 2 | BOEING CO | Aerospace & Defense | 2,0% |
| 3 | TEXTRON INC | Aerospace & Defense | |
| 4 | AMERICAN AIRLINES GROUP INC | Airlines | 3,0% |
| 5 | DELTA AIR LINES INC | Airlines | |
| 6 | SOUTHWEST AIRLINES CO | Airlines | |
| 7 | WHIRLPOOL CORP | Appliances, Tools & Housewares | 1,0% |
| 8 | AUTOZONE INC | Auto Vehicles, Parts & Service Retailers | 1,0% |
| 9 | BORGWARNER INC | Auto , Truck & Motorcycle Parts | 3,0% |
| 10 | CUMMINS INC | Auto , Truck & Motorcycle Parts | |
| 11 | FORD MOTOR CO | Auto , Truck & Motorcycle Parts | |
| 12 | CITIGROUP INC | Banks | 4,0% |
| 13 | JPMORGAN CHASE & CO | Banks | |
| 14 | WELLS FARGO & CO | Banks | |
| 15 | BANK OF AMERICA CORP | Banks | |
| 16 | AIR PRODUCTS AND CHEMICALS INC | Commodity Chemicals | 3,0% |
| 17 | RPM INTERNATIONAL INC | Commodity Chemicals | |
| 18 | SHERWIN-WILLIAMS CO | Commodity Chemicals | |
| 19 | MOTOROLA SOLUTIONS INC | Communications & Networking | 1,0% |
| 20 | BEST BUY CO INC | Computer & Electronics Retailers | 1,0% |
| 21 | VULCAN MATERIALS CO | Construction Materials | 1,0% |
| 22 | 3M CO | Consumer Goods Conglomerate | 2,0% |
| 23 | GENERAL ELECTRIC CO | Consumer Goods Conglomerate | |
| 24 | AMERICAN EXPRESS CO | Consumer Lending | 1,0% |
| 25 | UNITED PARCEL SERVICE INC | Courier, Postal, Air Freight & Land-Based Logistics | 1,0% |
| 26 | TJX COMPANIES INC | Discount Stores | 1,0% |

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|---|---|---|---|
| **27** | **RITE AID CORP** | Drug Retailers | 1,0% |
| **28** | **AES CORP** | Electric Utilities | 6,1% |
| **29** | **AMERICAN ELECTRIC POWER COMPANY INC** | Electric Utilities | |
| **30** | **EXELON CORP** | Electric Utilities | |
| **31** | **NEXTERA ENERGY INC** | Electric Utilities | |
| **32** | **SOUTHERN CO** | Electric Utilities | |
| **33** | **XCEL ENERGY INC** | Electric Utilities | |
| **34** | **AVNET INC** | Electornics Equipment & Parts | 1,0% |
| **35** | **REPUBLIC SERVICES INC** | Environmental Services & Equipment | 2,0% |
| **36** | **WASTE MANAGEMENT INC** | Environmental Services & Equipment | |
| **37** | **ARCHER-DANIELS-MIDLAND CO** | Food Processing | 5,1% |
| **38** | **HERSHEY CO** | Food Processing | |
| **39** | **KELLOGG CO** | Food Processing | |
| **40** | **TYSON FOODS INC** | Food Processing | |
| **41** | **CAMPBELL SOUP CO** | Food Processing | |
| **42** | **WALMART INC** | Food Retail & Distribution | 1,0% |
| **43** | **LOUISIANA-PACIFIC CORP** | Forest & Woods Products | 1,0% |
| **44** | **NORFOLK SOUTHERN CORP** | Ground Freights & Logistics | 3,0% |
| **45** | **RYDER SYSTEM INC** | Ground Freights & Logistics | |
| **46** | **UNION PACIFIC CORP** | Ground Freights & Logistics | |
| **47** | **CVS HEALTH CORP** | Healthcare Facilities & Services | 5,1% |
| **48** | **LABORATORY CORP. OF AMERICA HOLD.** | Healthcare Facilities & Services | |
| **49** | **QUEST DIAGNOSTICS INC** | Healthcare Facilities & Services | |
| **50** | **TENET HEALTHCARE CORP** | Healthcare Facilities & Services | |
| **51** | **UNIVERSAL HEALTH SERVICES INC** | Healthcare Facilities & Services | |
| **52** | **CATERPILLAR INC** | Heavy Machinery & Vehicles | 2,0% |
| **53** | **NAVISTAR INTERNATIONAL CORP** | Heavy Machinery & Vehicles | |
| **54** | **MARRIOTT INTERNATIONAL INC** | Hotel, Motels & Cruise Lines | 1,0% |
| **55** | **STANLEY BLACK & DECKER INC** | Industrial Machinery & Equipment | 1,0% |
| **56** | **GOLDMAN SACHS GROUP INC** | Investment Banking & Brokerage Services | 2,0% |
| **57** | **MORGAN STANLEY** | Investment Banking & Brokerage Services | |
| **58** | **UNITED STATES STEEL CORP** | Iron & Steel | 1,0% |
| **59** | **INTERNATIONAL BUSINESS MACHINES CORP** | IT Services & Consluting | 2,0% |
| **60** | **UNISYS CORP** | IT Services & Consluting | |
| **61** | **HUMANA INC** | Managed Healthcare | 1,0% |
| **62** | **AMERISOURCEBERGEN CORP** | Medical Equipment, Supplies & Distribution | 1,0% |
| **63** | **CMS ENERGY CORP** | Multiline Utilites | 2,0% |
| **64** | **SEMPRA ENERGY** | Multiline Utilites | |
| **65** | **COCA-COLA CO** | Non-Alcoholic Beverages | 2,0% |
| **66** | **PEPSICO INC** | Non-Alcoholic Beverages | |
| **67** | **SEALED AIR CORP** | Non-Paper Cantainers & Packaging | 1,0% |
| **68** | **XEROX CORP** | Office Equipment | 1,0% |

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|---|---|---|---|
| **69** | **NABORS INDUSTRIES INC** | Oil & Gas Drilling | 2,0% |
| **70** | **TRANSOCEAN INC** | Oil & Gas Drilling | |
| **71** | **APACHE CORP** | Oil & Gas Exploration and Production | 4,0% |
| **72** | **MURPHY OIL CORP** | Oil & Gas Exploration and Production | |
| **73** | **OCCIDENTAL PETROLEUM CORP** | Oil & Gas Exploration and Production | |
| **74** | **PIONEER NATURAL RESOURCES CO** | Oil & Gas Exploration and Production | |
| **75** | **CHEVRON CORP** | Oil & Gas Refining And Marketing | 3,0% |
| **76** | **EXXON MOBIL CORP** | Oil & Gas Refining And Marketing | |
| **77** | **MARATHON PETROLEUM CORP** | Oil & Gas Refining And Marketing | |
| **78** | **KINDER MORGAN INC** | Oil & Gas Transportation Services | 1,0% |
| **79** | **PACKAGING CORP OF AMERICA** | Paper Packaging | 1,0% |
| **80** | **JOHNSON & JOHNSON** | Personal Products | 3,0% |
| **81** | **PROCTER & GAMBLE CO** | Personal Products | |
| **82** | **COLGATE-PALMOLIVE CO** | Personal Products | |
| **83** | **AMGEN INC** | Pharmaceuticals | 2,0% |
| **84** | **BRISTOL-MYERS SQUIBB CO** | Pharmaceuticals | |
| **85** | **APPLE INC** | Phones & Handheld Devices | 1,0% |
| **86** | **BRUNSWICK CORP** | Recreational Products | 1,0% |
| **87** | **MCDONALD'S CORP** | Restaurants & Bars | 3,0% |
| **88** | **WENDY'S INTERNATIONAL LLC** | Restaurants & Bars | |
| **89** | **YUM! BRANDS INC** | Restaurants & Bars | |
| **90** | **INTEL CORP** | Semiconductors | 1,0% |
| **91** | **MICROSOFT CORP** | Software | 3,0% |
| **92** | **ORACLE CORP** | Software | |
| **93** | **SABRE HOLDINGS CORP** | Software | |
| **94** | **COOPER TIRE & RUBBER CO** | Tires & Rubbers Products | 2,0% |
| **95** | **GOODYEAR TIRE & RUBBER CO** | Tires & Rubbers Products | |
| **96** | **PHILIP MORRIS INTERNATIONAL INC** | Tobacco | 1,0% |
| **97** | **HASBRO INC** | Toys & Children's Products | 1,0% |
| **98** | **UNITED STATES CELLULAR CORP** | Wireless Telecommunications Services | 2,0% |
| **99** | **AT&T INC** | Wireless Telecommunications Services | |

Source: Thomson Reuters

## Table 02: Sample's CDS Mid Spreads Average Values

| # | Sample | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|
| **1** | **3M CO** | 424.34 | 21.23 | 22.57 | 25.69 | 27.72 |
| **2** | **AES CORP** | 69.88 | 271.28 | 184.13 | 126.36 | 81.56 |
| **3** | **AIR PRODUCTS AND CHEMICALS INC** | 354.08 | 54.64 | 43.24 | 36.64 | 37.12 |
| **4** | **AMERICAN AIRLINES GROUP INC** | 18.81 | 427.14 | 303.58 | 314.28 | 237.80 |
| **5** | **AMERICAN ELECTRIC POWER COMPANY INC** | 217.51 | 25.43 | 26.74 | 41.63 | 30.26 |
| **6** | **APACHE CORP** | 24.12 | 176.04 | 100.32 | 99.22 | 135.75 |
| **7** | **APPLE INC** | 78.29 | 28.96 | 26.69 | 18.99 | 20.88 |
| **8** | **ARCHER-DANIELS-MIDLAND CO** | 56.08 | 76.96 | 75.09 | 73.31 | 71.60 |
| **9** | **AVNET INC** | 19.46 | 83.48 | 83.02 | 89.92 | 86.82 |
| **10** | **BOEING CO** | 114.69 | 36.51 | 22.14 | 31.42 | 45.28 |
| **11** | **BORGWARNER INC** | 80.87 | 93.34 | 87.87 | 76.09 | 86.64 |
| **12** | **BRUNSWICK CORP** | 88.2 | 85.90 | 82.73 | 100.42 | 92.53 |
| **13** | **CATERPILLAR INC** | 70.38 | 76.50 | 41.03 | 44.66 | 41.74 |
| **14** | **CHEVRON CORP** | 54 | 92.04 | 51.67 | 28.41 | 37.51 |
| **15** | **CMS ENERGY CORP** | 26.06 | 57.87 | 56.22 | 47.29 | 32.70 |
| **16** | **COCA-COLA CO** | 162.75 | 27.17 | 26.58 | 25.71 | 30.32 |
| **17** | **COOPER TIRE & RUBBER CO** | 53.95 | 171.01 | 142.15 | 164.64 | 148.27 |
| **18** | **CUMMINS INC** | 81.33 | 54.29 | 45.43 | 45.44 | 53.49 |
| **19** | **CITIGROUP INC****** | 29.36 | 88.23 | 54.68 | 56.28 | 56.87 |
| **20** | **CVS HEALTH CORP** | 281.47 | 29.73 | 51.44 | 69.44 | 74.20 |
| **21** | **DELTA AIR LINES INC** | 37.18 | 224.59 | 128.78 | 119.98 | 107.13 |
| **22** | **EXELON CORP** | 23.25 | 36.83 | 33.83 | 43.99 | 29.14 |
| **23** | **EXXON MOBIL CORP** | 121.17 | 40.21 | 35.73 | 35.18 | 35.70 |
| **24** | **FORD MOTOR CO** | 41.31 | 156.68 | 119.63 | 162.60 | 211.98 |
| **25** | **GENERAL ELECTRIC CO** | 83.97 | 44.38 | 38.27 | 105.33 | 105.43 |
| **26** | **GOLDMAN SACHS GROUP INC** | 161.3 | 100.57 | 69.68 | 69.32 | 68.96 |
| **27** | **GOODYEAR TIRE & RUBBER CO** | 86.25 | 181.53 | 141.57 | 207.73 | 272.09 |
| **28** | **HASBRO INC** | 35.06 | 85.00 | 88.97 | 110.92 | 146.61 |
| **29** | **HERSHEY CO** | 35.18 | 36.20 | 37.71 | 45.53 | 50.12 |
| **30** | **HUMANA INC** | 40.52 | 37.18 | 40.52 | 43.37 | 42.06 |
| **31** | **INTEL CORP** | 44.12 | 69.94 | 52.10 | 32.85 | 42.20 |
| **32** | **INTERNATIONAL BUSINESS MACHINES CORP** | 19.01 | 57.78 | 36.69 | 42.27 | 47.91 |
| **33** | **JOHNSON & JOHNSON** | 71.33 | 17.45 | 18.54 | 19.35 | 28.09 |
| **34** | **JPMORGAN CHASE & CO** | 77.34 | 68.56 | 48.91 | 48.60 | 43.76 |
| **35** | **KELLOGG CO** | 392.35 | 80.63 | 69.67 | 75.20 | 89.78 |
| **36** | **KINDER MORGAN INC** | 112.8 | 252.13 | 93.19 | 89.79 | 69.72 |

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|---|---|---|---|---|---|---|
| **37** | **LABORATORY CORPORATION OF AMERICA HOLDINGS** | 147.44 | 115.52 | 75.98 | 67.15 | 75.16 |
| **38** | **LOUISIANA-PACIFIC CORP** | 140 | 126.07 | 82.06 | 90.40 | 132.52 |
| **39** | **MARATHON PETROLEUM CORP** | 47.12 | 232.67 | 171.01 | 102.53 | 69.73 |
| **40** | **MARRIOTT INTERNATIONAL INC** | 37.09 | 59.78 | 37.77 | 47.66 | 43.65 |
| **41** | **MCDONALD'S CORP** | 32.71 | 35.09 | 26.71 | 33.34 | 25.40 |
| **42** | **MICROSOFT CORP** | 85.32 | 33.96 | 29.32 | 24.48 | 25.43 |
| **43** | **MORGAN STANLEY** | 137.49 | 98.78 | 65.73 | 63.86 | 62.71 |
| **44** | **MOTOROLA SOLUTIONS INC** | 531.06 | 125.96 | 77.15 | 73.71 | 66.77 |
| **45** | **MURPHY OIL CORP** | 574.54 | 518.02 | 219.37 | 177.41 | 157.81 |
| **46** | **NABORS INDUSTRIES INC** | 620.11 | 466.49 | 351.93 | 395.68 | 638.62 |
| **47** | **NAVISTAR INTERNATIONAL CORP** | 78.84 | 622.81 | 624.30 | 613.05 | 589.54 |
| **48** | **NEXTERA ENERGY INC** | 24.55 | 87.57 | 70.63 | 72.93 | 68.35 |
| **49** | **NORFOLK SOUTHERN CORP** | 119.65 | 43.22 | 30.82 | 32.69 | 25.20 |
| **50** | **OCCIDENTAL PETROLEUM CORP** | 23.08 | 125.33 | 63.55 | 39.08 | 79.94 |
| **51** | **OMNICOM GROUP INC** | 30.13 | 35.82 | 30.89 | 58.23 | 44.67 |
| **52** | **ORACLE CORP** | 103.95 | 35.23 | 35.35 | 36.11 | 37.32 |
| **53** | **PACKAGING CORP OF AMERICA** | 42.54 | 87.33 | 43.45 | 57.90 | 45.86 |
| **54** | **PEPSICO INC** | 34.1 | 47.71 | 42.38 | 35.74 | 39.01 |
| **55** | **PHILIP MORRIS INTERNATIONAL INC** | 319.06 | 38.56 | 44.90 | 54.61 | 54.62 |
| **56** | **PIONEER NATURAL RESOURCES CO** | 25.02 | 158.34 | 70.62 | 54.62 | 65.81 |
| **57** | **PROCTER & GAMBLE CO** | 68.93 | 21.60 | 21.87 | 29.09 | 20.02 |
| **58** | **QUEST DIAGNOSTICS INC** | 59.03 | 57.04 | 38.54 | 44.48 | 42.74 |
| **59** | **REPUBLIC SERVICES INC** | 168.06 | 56.11 | 52.79 | 41.06 | 50.34 |
| **60** | **RITE AID CORP** | 100.97 | 158.68 | 488.35 | 842.76 | 1495.9 |
| **61** | **RPM INTERNATIONAL INC** | 110.77 | 101.04 | 87.07 | 87.44 | 95.86 |
| **62** | **RYDER SYSTEM INC** | 232.56 | 93.92 | 63.72 | 77.56 | 94.48 |
| **63** | **SABRE HOLDINGS CORP** | 136.97 | 163.55 | 155.60 | 192.00 | 102.42 |
| **64** | **SEALED AIR CORP** | 35.6 | 121.07 | 98.29 | 112.42 | 101.14 |
| **65** | **SEMPRA ENERGY** | 18.58 | 44.88 | 32.71 | 51.66 | 51.67 |
| **66** | **SHERWIN-WILLIAMS CO** | 53.52 | 65.85 | 66.75 | 83.29 | 76.44 |
| **67** | **SOUTHERN CO** | 35.84 | 54.93 | 62.14 | 63.57 | 47.82 |
| **68** | **SOUTHWEST AIRLINES CO** | 80.57 | 54.40 | 62.03 | 53.29 | 58.26 |
| **69** | **STANLEY BLACK & DECKER INC** | 605.4 | 91.05 | 76.29 | 74.08 | 100.77 |
| **70** | **TENET HEALTHCARE CORP** | 71.41 | 615.05 | 532.69 | 422.69 | 400.96 |
| **71** | **TEXTRON INC** | 56.01 | 76.76 | 49.03 | 44.46 | 77.92 |
| **72** | **TJX COMPANIES INC** | 1447.8 | 61.51 | 43.58 | 54.23 | 47.67 |
| **73** | **TRANSOCEAN INC** | 49.63 | 1076.9 | 503.49 | 380.50 | 621.01 |
| **74** | **TYSON FOODS INC** | 20.07 | 59.56 | 49.57 | 63.33 | 51.23 |
| **75** | **UNION PACIFIC CORP** | 399.8 | 26.17 | 18.94 | 29.53 | 24.74 |
| **76** | **UNISYS CORP** | 17.49 | 631.43 | 533.42 | 475.06 | 373.75 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **77** | **UNITED PARCEL SERVICE INC** | 231 | 20.84 | 19.14 | 33.22 | 37.58 |
| **78** | **UNITED STATES CELLULAR CORP** | 1998.5 | 207.25 | 144.71 | 146.33 | 128.92 |
| **79** | **UNITED STATES STEEL CORP** | 110.76 | 992.04 | 405.45 | 268.29 | 514.32 |
| **80** | **UNIVERSAL HEALTH SERVICES INC** | 84.78 | 94.30 | 93.55 | 78.23 | 57.30 |
| **81** | **VULCAN MATERIALS CO** | 31.06 | 78.04 | 56.21 | 57.72 | 61.57 |
| **82** | **WALMART INC** | 68.96 | 39.51 | 36.02 | 32.57 | 22.65 |
| **83** | **WASTE MANAGEMENT INC** | 53.88 | 58.31 | 51.11 | 41.26 | 50.17 |
| **84** | **WELLS FARGO & CO** | 172.97 | 57.76 | 45.32 | 53.24 | 47.80 |
| **85** | **WENDY'S INTERNATIONAL LLC** | 101.95 | 163.93 | 132.70 | 192.29 | 189.15 |
| **86** | **WHIRLPOOL CORP** | 34.23 | 90.97 | 64.97 | 100.80 | 97.60 |
| **87** | **XCEL ENERGY INC** | 168.77 | 35.97 | 35.04 | 62.09 | 88.31 |
| **88** | **XEROX CORP** | 203.61 | 221.24 | 126.92 | 193.32 | 186.63 |
| **89** | **YUM! BRANDS INC** | 38.24 | 195.40 | 87.16 | 98.71 | 79.57 |
| **90** | **AMERICAN EXPRESS CO** | 37.97 | 46.22 | 27.52 | 37.02 | 34.42 |
| **91** | **AMERISOURCEBERGEN CORP** | 44.13 | 44.50 | 50.85 | 80.81 | 95.45 |
| **92** | **AMGEN INC** | 85.25 | 56.22 | 38.34 | 44.96 | 47.05 |
| **93** | **AT&T INC** | 24.79 | 93.79 | 75.13 | 89.88 | 90.03 |
| **94** | **AUTOZONE INC** | 72.59 | 35.33 | 61.44 | 61.61 | 44.16 |
| **95** | **BANK OF AMERICA CORP** | 13.91 | 87.87 | 53.82 | 53.47 | 48.43 |
| **96** | **BRISTOL-MYERS SQUIBB CO** | 33.1 | 17.28 | 25.67 | 34.01 | 33.79 |
| **97** | **CAMPBELL SOUP CO** | 23.07 | 40.72 | 35.42 | 97.42 | 80.92 |
| **98** | **BEST BUY CO INC** | 217.05 | 28.66 | 30.64 | 34.54 | 36.25 |
| **99** | **COLGATE-PALMOLIVE CO** | 19.5 | 198.51 | 137.16 | 94.65 | 83.45 |

Source: Thomson Reuters

**Table 04: ESG Scores and ESG Combined Scores of the Sample**

| # | Sample | 2019 | | 2018 | | 2017 | | 2016 | | 2015 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | ESG | ESG COMB. | ESG | ESG COMB. | ESG | ESG COMB. | ESG | ESG COMB. | ESG | ESG COMB. |
| 1 | 3M CO | A | B- | A | B | A | A | A | A- | A | A |
| 2 | AES CORP | B+ | B+ | B | B | B- | B- | B | B- | B- | B- |
| 3 | AIR PRODUCTS AND CHEMICALS INC | A- | A- | A | A | A- | A- | B+ | B+ | A- | A- |
| 4 | AMERICAN AIRLINES GROUP INC | B+ | C | B+ | C | B+ | C+ | B+ | B+ | B+ | B- |
| 5 | AMERICAN ELECTRIC POWER COMPANY INC | B | B | B | B | B | B | B | B | B | B |
| 6 | APACHE CORP | B | B | B | B | B | B | B- | B- | C+ | C+ |
| 7 | APPLE INC | B+ | C | B+ | C | B+ | C+ | B | C | B- | C- |
| 8 | ARCHER-DANIELS-MIDLAND CO | A- | B+ | A- | A- | A- | A- | B- | B- | B- | B- |
| 9 | AVNET INC | C | C | C | C | C+ | C+ | B | B | C+ | C+ |
| 10 | BOEING CO | A- | C | A- | C | A- | B- | B+ | B+ | B+ | B- |
| 11 | BORGWARNER INC | B- | B- | C+ | C+ | B- | B- | B- | B- | B- | B- |
| 12 | BRUNSWICK CORP | B+ | B+ | B+ | B+ | B | B | B | B | B- | B- |
| 13 | CATERPILLAR INC | B+ | B+ | B+ | B+ | B | B | B+ | B+ | A- | A- |
| 14 | CHEVRON CORP | A- | B | A | C+ | A | B+ | A- | C+ | A- | B+ |
| 15 | CMS ENERGY CORP | B- | B- | B- | B- | B- | B- | B | B | C+ | C+ |
| 16 | COCA-COLA CO | B | B | B+ | C | B+ | C | A- | A- | B+ | B- |
| 17 | COOPER TIRE & RUBBER CO | C+ | C+ | C+ | C+ | B- | B- | B- | B- | C+ | C+ |
| 18 | CUMMINS INC | B+ | B+ | B+ | B+ | B+ | B+ | A- | A- | B+ | B+ |
| 19 | CITIGROUP INC**** | A | C+ | A | C+ | A | C+ | A- | C+ | A- | C+ |
| 20 | CVS HEALTH CORP | A- | C+ | A- | B- | A- | B+ | A- | B- | A | A- |
| 21 | DELTA AIR LINES INC | B+ | C | B+ | C | B+ | B+ | B+ | C+ | B+ | B+ |
| 22 | EXELON CORP | B | B | B | B | B+ | B+ | B | B | B | B |
| 23 | EXXON MOBIL CORP | B+ | C | B+ | C | A- | C | B+ | C | A- | B- |
| 24 | FORD MOTOR CO | A- | C+ | A- | B- | A- | C+ | A- | C+ | A- | B |
| 25 | GENERAL ELECTRIC CO | A- | C | A- | C+ | A- | B | A- | A- | A- | C+ |
| 26 | GOLDMAN SACHS GROUP INC | A- | C+ | B+ | C | B | C+ | B | C- | B+ | C |
| 27 | GOODYEAR TIRE & RUBBER CO | B | B- | B | B- | B- | C+ | B- | B- | B- | B- |
| 28 | HASBRO INC | A- | A- | A- | A- | A | A | A | B+ | A | A |
| 29 | HERSHEY CO | A- | A- | B+ | B+ | B+ | B | A- | B+ | B+ | B+ |
| 30 | HUMANA INC | A | A | A | A | A | A | A | C+ | A | A- |
| 31 | INTEL CORP | A | B- | A | C+ | A | A- | A | A | A | A |
| 32 | INTERNATIONAL BUSINESS MACHINES CORP | B+ | B+ | A- | A- | A- | A- | A- | A- | A- | B+ |
| 33 | JOHNSON & JOHNSON | A- | C | A | C+ | A | C+ | A | B- | A+ | A- |
| 34 | JPMORGAN CHASE & CO | A- | C | B+ | C | A- | C+ | A- | C+ | A- | C |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **35** | **KELLOGG CO** | **A-** | **A-** | **A-** | **A-** | **A-** | **A-** | **A-** | **C+** | **B+** | **B+** |
| **36** | **KINDER MORGAN INC** | **A-** | **A-** | **B** | **B** | **B-** | **B-** | **C** | **D+** | **C** | **C** |
| **37** | **LABORATORY CORP OF AMERICA HOLDING** | **A-** | **A-** | **A-** | **A-** | **B** | **B** | **B-** | **B-** | **B-** | **B-** |
| **38** | **LOUISIANA-PACIFIC CORP** | **C-** | **C-** | **C-** | **C-** | **C-** | **C-** | **C** | **C** | **C** | **C** |
| **39** | **MARATHON PETROLEUM CORP** | **B+** | **B+** | **B** | **B** | **B** | **B** | **B** | **B-** | **B** | **B** |
| **40** | **MARRIOTT INTERNATIONAL INC** | **A-** | **C** | **A-** | **C** | **B+** | **B+** | **A-** | **A-** | **B+** | **B+** |
| **41** | **MCDONALD'S CORP** | **B+** | **C** | **B+** | **C** | **B+** | **C** | **B+** | **C** | **B** | **C-** |
| **42** | **MICROSOFT CORP** | **A+** | **C+** | **A+** | **C+** | **A** | **C+** | **A** | **B-** | **A+** | **A** |
| **43** | **MORGAN STANLEY** | **B** | **C** | **B** | **C** | **B+** | **C** | **B+** | **C+** | **B+** | **C** |
| **44** | **MOTOROLA SOLUTIONS INC** | **A-** | **B+** | **A-** | **B+** | **A-** | **A-** | **A-** | **A-** | **A-** | **A-** |
| **45** | **MURPHY OIL CORP** | **C** | **C** | **C** | **C** | **C** | **C** | **C** | **C** | **C** | **C** |
| **46** | **NABORS INDUSTRIES INC** | **B** | **B** | **B-** | **B-** | **B-** | **B-** | **C** | **C** | **C** | **C** |
| **47** | **NAVISTAR INTERNATIONAL CORP** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **B-** | **B-** |
| **48** | **NEXTERA ENERGY INC** | **A-** | **A-** | **B+** | **B+** | **B+** | **B+** | **B+** | **B+** | **B+** | **B+** |
| **49** | **NORFOLK SOUTHERN CORP** | **B** | **B** | **B+** | **B+** | **B+** | **B+** | **B+** | **B+** | **B** | **B** |
| **50** | **OCCIDENTAL PETROLEUM CORP** | **A-** | **B-** | **A-** | **A-** | **B+** | **B+** | **B+** | **B+** | **B+** | **B+** |
| **51** | **OMNICOM GROUP INC** | **B+** | **B+** | **B-** | **B-** | **B-** | **B-** | **C+** | **C+** | **B-** | **B-** |
| **52** | **ORACLE CORP** | **B-** | **C+** | **B-** | **B-** | **B-** | **C+** | **C+** | **C+** | **C+** | **C** |
| **53** | **PACKAGING CORP OF AMERICA** | **B+** | **B+** | **B+** | **B+** | **B-** | **B-** | **B-** | **B-** | **C+** | **C+** |
| **54** | **PEPSICO INC** | **A** | **B+** | **A** | **A-** | **A-** | **A-** | **A-** | **B** | **B+** | **B+** |
| **55** | **PHILIP MORRIS INTERNATIONAL INC** | **A** | **C+** | **A** | **A-** | **A** | **A** | **A-** | **B+** | **B** | **B** |
| **56** | **PIONEER NATURAL RESOURCES CO** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C-** | **C-** |
| **57** | **PROCTER & GAMBLE CO** | **B+** | **B+** | **B** | **B** | **B** | **C** | **B+** | **B+** | **B+** | **C** |
| **58** | **QUEST DIAGNOSTICS INC** | **A-** | **A-** | **B+** | **B+** | **B** | **B** | **B+** | **B+** | **B+** | **B+** |
| **59** | **REPUBLIC SERVICES INC** | **B+** | **B-** | **A-** | **A-** | **B+** | **B+** | **B** | **B** | **B** | **B** |
| **60** | **RITE AID CORP** | **B-** | **B-** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C-** |
| **61** | **RPM INTERNATIONAL INC** | **C** | **C** | **C** | **C** | **C-** | **C-** | **C-** | **C-** | **C-** | **C-** |
| **62** | **RYDER SYSTEM INC** | **B+** | **B-** | **B+** | **B-** | **B+** | **B+** | **B** | **B** | **B** | **B** |
| **63** | **SABRE HOLDINGS CORP** | **B-** | **C** | **C+** | **C+** | **C** | **C** | **B-** | **B-** | **C+** | **C+** |
| **64** | **SEALED AIR CORP** | **C** | **C-** | **C-** | **C-** | **C** | **C** | **C+** | **C+** | **C+** | **C+** |
| **65** | **SEMPRA ENERGY** | **B+** | **B** | **A-** | **A-** | **A** | **A-** | **B+** | **C+** | **B+** | **B** |
| **66** | **SHERWIN-WILLIAMS CO** | **B+** | **B+** | **B** | **B** | **B** | **B** | **B** | **B** | **B** | **B** |
| **67** | **SOUTHERN CO** | **B+** | **B-** | **B+** | **B-** | **B+** | **B+** | **B+** | **B+** | **B-** | **B-** |
| **68** | **SOUTHWEST AIRLINES CO** | **B+** | **B** | **B+** | **B+** | **B** | **B** | **B** | **B-** | **B** | **C+** |
| **69** | **STANLEY BLACK & DECKER INC** | **B+** | **B+** | **B** | **B** | **C+** | **C+** | **C** | **C** | **C** | **C** |
| **70** | **TENET HEALTHCARE CORP** | **C** | **C** | **C+** | **C+** | **C+** | **C-** | **B** | **B** | **B+** | **B+** |
| **71** | **TEXTRON INC** | **B+** | **B+** | **B+** | **B+** | **B** | **B** | **B** | **B** | **B** | **B** |
| **72** | **TJX COMPANIES INC** | **B+** | **B+** | **B+** | **B+** | **B+** | **B+** | **B** | **B** | **B-** | **B-** |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **73** | **TRANSOCEAN INC** | **B** | **B** | **B** | **B** | **B-** | **B-** | **B** | **B** | **C+** | **C+** |
| **74** | **TYSON FOODS INC** | **B+** | **C** | **B-** | **B-** | **B-** | **B-** | **B-** | **C+** | **B-** | **C** |
| **75** | **UNION PACIFIC CORP** | **B** | **B** | **B** | **B** | **B+** | **B+** | **B+** | **B+** | **B** | **B** |
| **76** | **UNISYS CORP** | **B** | **B** | **B** | **B** | **B** | **B** | **B-** | **B-** | **C** | **C** |
| **77** | **UNITED PARCEL SERVICE INC** | **B+** | **C** | **B+** | **C+** | **B+** | **B-** | **B+** | **C+** | **B+** | **C+** |
| **78** | **UNITED STATES CELLULAR CORP** | **D+** | **D+** | **D+** | **D+** | **D+** | **D+** | **D+** | **D+** | **D+** | **D+** |
| **79** | **UNITED STATES STEEL CORP** | **B-** | **C-** | **C+** | **C+** | **C+** | **C-** | **C** | **C** | **C+** | **C+** |
| **80** | **UNIVERSAL HEALTH SERVICES INC** | **C** | **C** | **C** | **C** | **C-** | **C-** | **C** | **C** | **C+** | **C+** |
| **81** | **VULCAN MATERIALS CO** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C+** | **C** | **C** |
| **82** | **WALMART INC** | **A-** | **C+** | **B+** | **C** | **A-** | **C** | **A-** | **A-** | **A-** | **C** |
| **83** | **WASTE MANAGEMENT INC** | **A** | **A** | **A** | **A** | **A** | **A** | **A-** | **A-** | **A** | **A** |
| **84** | **WELLS FARGO & CO** | **B+** | **C** | **A-** | **C** | **A-** | **C** | **A-** | **C** | **A-** | **C+** |
| **85** | **WENDY'S INTERNATIONAL LLC** | **B+** | **B-** | **B-** | **B-** | **B-** | **B-** | **B-** | **C** | **B** | **C+** |
| **86** | **WHIRLPOOL CORP** | **B+** | **C** | **B+** | **B+** | **B** | **B** | **B** | **B** | **B-** | **B-** |
| **87** | **XCEL ENERGY INC** | **A-** | **A-** | **A-** | **A-** | **B+** | **B+** | **B+** | **B+** | **B+** | **B+** |
| **88** | **XEROX CORP** | **B+** | **C+** | **B+** | **C+** | **B+** | **B+** | **B+** | **B-** | **B+** | **B+** |
| **89** | **YUM! BRANDS INC** | **B+** | **B+** | **A-** | **A-** | **A-** | **A-** | **B** | **B** | **B** | **C** |
| **90** | **AMERICAN EXPRESS CO** | **A-** | **A-** | **B+** | **B-** | **B+** | **B+** | **B+** | **B+** | **B-** | **C** |
| **91** | **AMERISOURCEBERGEN CORP** | **B** | **C-** | **B** | **C-** | **B-** | **B-** | **B-** | **B-** | **C+** | **C+** |
| **92** | **AMGEN INC** | **B+** | **C+** | **B+** | **B+** | **B+** | **B+** | **B** | **B** | **B+** | **B+** |
| **93** | **AT&T INC** | **B+** | **C** | **B** | **C** | **B** | **C** | **B** | **C** | **B** | **C** |
| **94** | **AUTOZONE INC** | **B** | **B** | **B-** | **B-** | **B** | **B** | **B** | **B** | **B** | **B** |
| **95** | **BANK OF AMERICA CORP** | **A-** | **C+** | **B+** | **C+** | **B+** | **C+** | **B+** | **C** | **B+** | **C** |
| **96** | **BRISTOL-MYERS SQUIBB CO** | **B+** | **B** | **B+** | **B** | **B+** | **B+** | **B+** | **B+** | **B+** | **B+** |
| **97** | **CAMPBELL SOUP CO** | **A** | **A** | **A** | **A** | **A** | **A** | **A** | **A** | **A** | **A** |
| **98** | **BEST BUY CO INC** | **A** | **A** | **A** | **A** | **A-** | **A-** | **A-** | **A-** | **A-** | **A-** |
| **99** | **COLGATE-PALMOLIVE CO** | **A** | **A-** | **A** | **A-** | **A** | **A** | **A** | **C+** | **A-** | **A-** |

Source: Thomson Reuters

# Stata Code

```
remove(list=ls())
library(readxl)
library(tidyverse)
library(data.table)
library(lubridate)
library(reshape2)
library(writexl)
library(dplyr)
library(readxl)
# x1 <- read_excel("~/Doc/rip/covariate_1.xlsx", sheet = "excess_return")
# x2 <- read_excel("~/Doc/rip/covariate_1.xlsx", sheet = "leverage")
# x3 <- read_excel("~/Doc/rip/covariate_1.xlsx", sheet = "volatility")
x4 <- read_excel("~/Doc/rip/covariate_2.xlsx", sheet = "credit_ratings")
x5 <- read_excel("~/Doc/rip/covariate_2.xlsx", sheet = "esg_score")
x6 <- read_excel("~/Doc/rip/covariate_2.xlsx", sheet = "esg_combined_score")
y <- read_excel("~/Doc/rip/y_var.xlsx")
#reshape
exc_return<-reshape2::melt(data = x1, id.vars = c("DATE"), measure.vars = 2:100)
lev<-reshape2::melt(data = x2, id.vars = c("DATE"), measure.vars = 2:100)
vol<-reshape2::melt(data = x3, id.vars = c("DATE"), measure.vars = 2:100)
credit_rat<-reshape2::melt(data = x4, id.vars = c("DATE"), measure.vars = 2:100)
esg_score<-reshape2::melt(data = x5, id.vars = c("DATE"), measure.vars = 2:100)
esg_c_score<-reshape2::melt(data = x6, id.vars = c("DATE"), measure.vars = 2:100)
cds<-reshape2::melt(data = y, id.vars = c("DATE"), measure.vars = 2:100)
#rename
names(exc_return)[3] <- "exc_return"
names(lev)[3] <- "lev"
names(vol)[3] <- "vol"
names(credit_rat)[3] <- "credit_rat"
names(esg_score)[3] <- "esg_score"
```

```
names(esg_c_score)[3] <- "esg_c_score"
names(cds)[3] <- "cds"
#merge
#covariates
step1 <-merge(exc_return,lev, by=c("DATE","variable"))
step2<-merge(step1,vol, by=c("DATE","variable"))
step3<-merge(step2,credit_rat, by=c("DATE","variable"))
step4<-merge(step3,esg_score, by=c("DATE","variable"))
step5<-merge(step4,esg_c_score, by=c("DATE","variable"))
#y
step6<-merge(step5,cds, by=c("DATE","variable"))
names(step6)[2] <- "id"
#date format
step6$DATE<-as.Date(step6$DATE, origin = "1900-01-01")
#step6[order("id", "DATE"),]
df<-step6[order(step6$id,as.Date(step6$DATE, format="%d/%m/%Y")),]
names(df)[1] <- "time"
###########
df$lev<-as.numeric(df$lev)
df<-df[complete.cases(df), ]
############
df$year<-year(df$time)
############
# Annual df
annual_panel_df<- df %>%
          group_by(id,year) %>%
          summarise(mean_exc_return=mean(exc_return),
                    mean_cds=mean(cds),
                    mean_lev=mean(lev),
                    mean_vol=mean(vol),
                    mean_credit_rat=mean(credit_rat),
                    mean_esg_score=mean(esg_score),
                    mean_esg_c_score=mean(esg_c_score))
```

```
##########
annual_panel_df<-annual_panel_df[complete.cases(annual_panel_df), ]

time_df<- annual_panel_df %>%
          group_by(year) %>%
          summarise(mean_exc_return1=mean(mean_exc_return),
                    mean_cds1=mean(mean_cds),
                    mean_lev1=mean(mean_lev),
                    mean_vol1=mean(mean_vol),
                    mean_credit_rat1=mean(mean_credit_rat),
                    mean_esg_score1=mean(mean_esg_score),
                    mean_esg_c_score1=mean(mean_esg_c_score))
############
#analisi di correlazione
df_corr<-df[,3:9]
df_corr<-df_corr[,c("exc_return","cds","lev","vol","credit_rat",
                    "esg_score","esg_c_score")]
panel_corr<-round(cor(df_corr),2)
panel_corr<-as.data.frame(panel_corr)
annual_panel_corr<-annual_panel_df[complete.cases(annual_panel_df), ]
annual_panel_corr<-annual_panel_df[,3:9]
annual_panel_corr2<-round(cor(annual_panel_corr),2)
annual_panel_corr2<-annual_panel_corr2[     ,c("mean_exc_return","mean_cds",
                                               "mean_lev","mean_vol",
                                               "mean_credit_rat","mean_esg_score",
                                               "mean_esg_c_score")]

annual_panel_corr2<-as.data.frame(annual_panel_corr2)
delta_corr=as.data.frame(panel_corr-annual_panel_corr2)
############
#str(df
#Summary Statistics
# total_freq_status_azione<- datiT %>% mutate(TOT=sum(n())) %>%
```

```
#   group_by(Evento_Prima_Notifica,Status_Prima_Notifica,
#            Evento_Seconda_Notifica,Status_Seconda_Notifica,
#            Evento_Ultima_Notifica,`Status_-_Ultima_Notifica`) %>%
#   summarise(freq=n(), TOT=mean(TOT)) %>%
#   mutate(freq_rel=freq/TOT, freq_rel_by_group = freq/sum(freq))
#
#scatterplot<-
ggplot(data = df, mapping = aes(x = esg_score, y = cds))
library(ggplot2)
ggplot(data=df, aes(x=esg_score, y=time)) +
  geom_line(linetype = "dashed")+
  geom_line(color="red")+
  geom_point()
clear all
import excel "E:\df.xlsx", sheet("Sheet1") firstrow
encode id, generate(id1)
sort id time
by id: gen time_month= _n
xtset id1 time_month
xtreg cds exc_return vol credit_rat esg_score
gen lcds=ln(cds)
gen lvol=ln(vol)
gen lcredit_rat=ln(credit_rat)
gen lesg_score=ln(esg_score)
gen lesg_c_score=ln(esg_c_score)
xtreg lcds exc_return lvol lcredit_rat lesg_c_score, fe
est store m1
xtreg lcds exc_return lvol lcredit_rat lesg_score, fe
est store m2
xtreg lcds exc_return lvol lcredit_rat lesg_c_score, fe cl(id)
est store m3
xtreg lcds exc_return lvol lcredit_rat lesg_score, fe cl(id)
est store m4
```

```
esttab m1 m2 m3 m4

############

clear all

import excel "E:₩annual_panel_df.xlsx", sheet("Sheet1") firstrow clear

encode id, generate(id1)

 sort id year

xtset id1 year

gen lmean_cds=ln(mean_cds)

gen lmean_vol=ln(mean_vol)

gen lmean_credit_rat=ln(mean_credit_rat)

gen lmean_esg_score=ln(mean_esg_score)

gen lmean_esg_c_score=ln(mean_esg_c_score)

*xtreg lmean_cds mean_exc_return lmean_vol lmean_credit_rat lmean_esg_score, fe
vce(robust)

*xtreg lmean_cds mean_exc_return lmean_vol lmean_credit_rat lmean_esg_c_score, fe
vce(robust)

xtreg lmean_cds mean_exc_return lmean_vol lmean_credit_rat lmean_esg_c_score, fe

est store m1

xtreg lmean_cds mean_exc_return lmean_vol lmean_credit_rat lmean_esg_score, fe

est store m2

xtreg lmean_cds mean_exc_return lmean_vol lmean_credit_rat lmean_esg_c_score, fe cl(id)

est store m3

xtreg lmean_cds mean_exc_return lmean_vol lmean_credit_rat lmean_esg_score, fe cl(id)

est store m4

esttab m1 m2 m3 m4
```

# Abbreviations

AuM = Asset under Management

ESG = Environmental, Social & Governance

SRI = Social Responsible Investing

AM = Asset Management

WM = Wealth Management

CDS = Credit Default Swap

SDG = Social Development Goals

REDD = Reducing Emission from Deforestation and forest Degradation

VER = Verified Emission Reductions

VCS = Verified Carbon Standard

CCB = Climate, Community and Biodiversity standard

NEC = Net Environment Contribution

GRI = Global Reporting Initiative

PRI = Principle for Responsible Investment

CDSB = Carbon Disclosure Standards Board

CDP = Carbon Disclosure Project

WFI = Work Force disclosure Initiative

SASB = Sustainability Accounting Standards Board

UNFCCC: United Nations Framework Convention on Climate Change

TCFD = Task Force on Climate-related Financial Disclosure

FSB = Financial Stability Board

IASB = International Accounting Standard Board

IOSCO = International Organization of Securities COmmission

IBC = International Business Council

WEF = World Economic Forum

SFDR = Sustainable Finance Disclosures Regulation

NFRD = Non-Financial Reporting Directive

TEG = Technical Expert Group

OTC = Over The Counter

NYSE = New York Stock Exchange

NASDAQ = National Association of Securities Dealers Automated Quotation

AMEX = American EXchange

CME = Chicago Mercantile Exchange

bp/bps = Basis point/s

EPS = Earnings Per Share

St.D = Standard Deviation

NGO = Non Governative Organisations

CSR = Corporate Social Responsability

KPI = Key Performance Indicator

FE = Fixed Effects

RE = Random Effects

VIX = Volatility Index (Cboe S&P 500 Volatility Index)

LSDV = Least Squared Dummy Variable

iid = indipendent identically distributed

CSE = Clustered Standard Errors

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MSc. in Corporate Finance

Department of Business and Management

Chair of Asset Pricing

# *"The Impact of ESG Ratings on Default Probability" Empirical Analysis on Credit Default Swap Spread.*

## *Summary*


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# Introduction

In recent years, the importance of green and sustainable aspects of investments has gained increased importance in markets, with the credit market being the pioneer of this trend. In 2017 and 2018 bonds issuer have collected respectively $252bn. and $315bn., selling green and sustainable bonds. In 2019 these numbers have grown further, reaching more than $400bn., and it is expected that they will continue to grow in the coming years (Mutua e Poh 2019). ESG investments and ESG thematic funds represent definitely one of the “megatrends” that will shape markets, financial sector and asset management industry in the next years. The growing impact of sustainability in fixed income market is proven by the rising interest of credit rating agencies in acquiring companies that provide ESG data, as environmental, social and governance choices are steadily important in assigning and updating credit ratings. Moreover, ESG is increasingly becoming an important topic for institutional and retail investors and from an Asset Management perspective, we see a secular shift of ESG adoption within funds managers. ESG flows continue to accelerate with total ESG focused funds approaching almost $1.3tn globally, which represent 1% of global Asset-under-Management. Moreover, it is clear that ESG trend is still in the early stages of its development: whilst today ESG focused funds are a small percentage of total Assets under Management, the share of net flows continues to grow and all asset managers are looking to integrate ESG factors into their investment processes (Giblat, et al. 2020).
At the same time, attention to ESG aspects and climate change issues are gaining more consideration both in the public debate and in the new guidelines and regulations that governments issue towards companies, which have to inform and report their choices in terms of governance, social and environmental sustainability. MSCI Inc. reported that between 2010 and 2019 governments and regulatory authorities have enacted about 600 ESG-related standards globally.
Therefore, public attention, disclosure transparency, regulatory and investors increasing pressure raise several interesting questions. Do markets incorporate companies' ESG choices? If so, to what extent sustainable choices are assessed by the market? How much an ESG practice or an increase in ESG Score affect a company’s credit risk? This research is aimed at answering these questions by using credit default swap (CDS) spreads as an indicator of credit risk, to analyze whether U.S. credit market reflects the firms’ choices in terms of environmental, social and governance sustainability.

# CHAPTER 1 - ESG Conceptual Framework

## 1.1 Definitions and ESG Investing Insights

The term ESG investing is often used as a synonym for many other concepts, such as social responsible investing (SRI), sustainable investing, impact investing or screening. This is especially the case with SRI. The original development of the term SRI was linked to the practice of investors to exclude certain companies from their portfolios, for ethical or ideological based reasons. This original form of SRI is now called “exclusions” or “negative-screen” investing. Other SRI strategies have been developed, including positive screen or thematic investing, where only companies aligned to the investors’ values are included. More recently, impact investing has become popular; here investors provide capital to specific projects, funds and companies which work to improve a wide range of social issues, such as literacy and unemployment; and environmental issues, such as deforestation, scarcity of water and other natural resources; and many other globally widespread problems. Although the concepts mentioned above are very similar to each other and belong to the same area of discussion, it is important to clarify the different definitions, especially between ESG and SRI. For many, the term ESG is closely linked to the debate on environmental issues, like climate change, clean energy transition and lack of resources (PricewaterhouseCoopers 2017). Following the definition suggested by Remi Briand, Managing Director of MSCI, we can define ESG investing as the explicit investors' inclusion of other factors such as environmental, social and governance, alongside financial factors in the capital allocation process (MSCI ESG Research LLC s.d.). Looking closer at this definition, we can analyze the three pillars that together form the concept of ESG:

- Environmental factors are those that include a company's contribution to climate change by reducing carbon emissions and other greenhouse gases, along with waste management and energy efficiency.
- Social factors cover an extremely wide range of potential issues. They concern human rights, supply chain labor standards, exposure to illegal child labor and other routine issues such as respecting health and safety in the workplace.
- Governance refers to a set of rules or principles that define rights, responsibilities and expectations among the various stakeholders in the governance of companies.

Differently, the definition of SRI has a broader meaning, as it concerns the incorporation of ethical and social factors with a more general meaning and which often concerns the subjective evaluation by the investor, linked to his individual values (MSCI ESG Research LLC s.d.).

Summarizing, if individual values are more important to the investors than financial value, SRI might fit. If the investor wants to maximize value, but invest in a way that considers sustainable criteria, ESG investing might fit.

## 1.2 ESG: a "Megatrend" in Global Markets

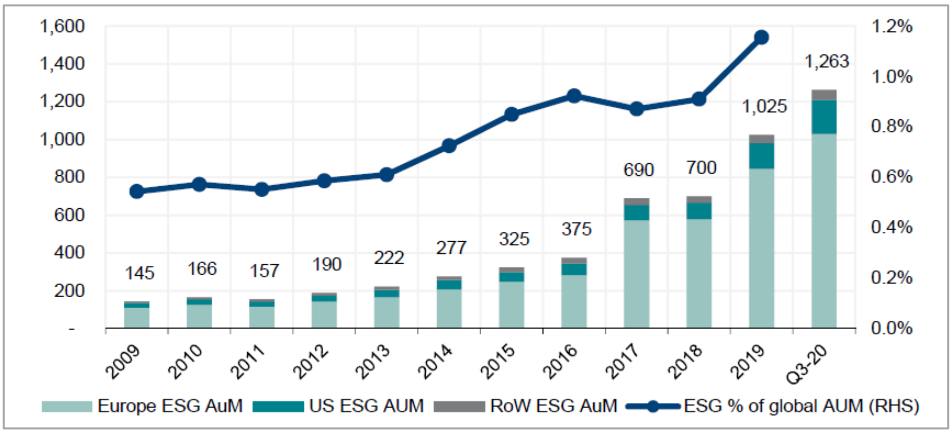
The universe of ESG investments and SRI is clearly changing and growing rapidly; new players, new products, new assets, new investment strategies and new regulatory obligations are coming into the picture. Speaking of the sustainable financial market more generally, it has already existed for many years, but only in the last 3-5 years has undergone a profound change and growth. Thanks to this, nowadays sustainable finance has much more impact on risks and financial returns. In few words, ESG is moving from niche to mainstream (Apex Group Ltd. 2020). These changes are accelerated by institutions, which are developing new rules and regulations that will influence all market players: banks, institutional and retail investors, regulated markets, companies and rating agencies.

It is important to talk about the asset management and diversified financial sector, as it plays a key role for the society: its main objective is to ensure an efficient allocation and management of capital, maximizing returns for investors and maximizing resources for the society. Therefore, this sector plays a crucial role in financing the economy and in ensuring the liquidity of the markets (Mason, et al. 2020) and that is one of the main reason why it is important to test wether the market prices enclose and valuate the ESG choices of companies. The question we ask ourselves is therefore whether this sector, and in general the investment chain from savers to companies, are serving society in the best possible way. We also wonder how asset managers are directing savers towards more sustainable investments in the short and long term. Finally, we ask how these managers expose their portfolios performance to the ESG trend across equity asset class. In this context, we can say that there is a secular shift in the adoption of ESG within asset management industry. It has been estimated that today the ESG focused funds represent almost 1% of global Asset-under-Management, which corresponds to approximately \$1.3tn. (Giblat, et al. 2020). The following figure shows the huge global increase in AuM's inflows into

ESG funds. The global AuM used in the figure is calculated considering Mutual Funds' and ETF's AuM.

**Figure 1.0: Global ESG AuM Growth Trend.**

ESG Global AuM in $ billion versus % of Global Mutual Funds' and ETF's AuM.




Source: Morningstar, Exane estimates

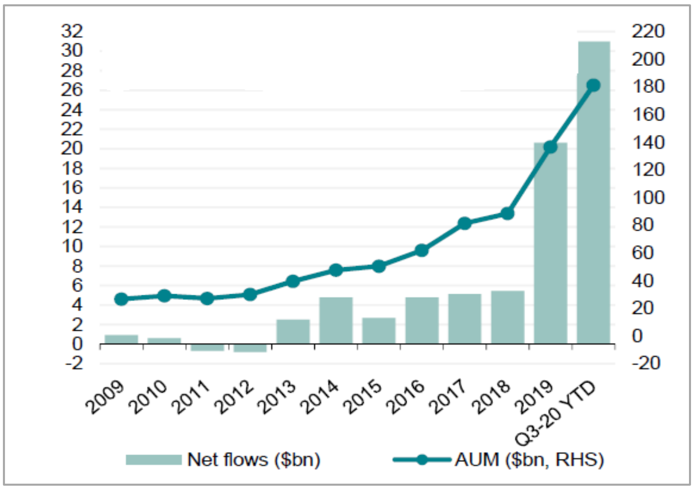
Although ESG funds are only a small portion of the total global AuM, discussion of ESG issues is on the daily agenda among institutional investors and all asset managers are looking to integrate ESG factors in their capital allocation process. Many new funds are emerging, both passive and active, as asset managers want to take advantage of this new opportunity: active ESG investment strategies are nearly 80% of the total, whilst passive and benchmark-replication strategies represents a 20% (Giblat, et al. 2020), but its growth curve is very steep. Considering that this trend is still in its infancy, those who today will be exposed to these factors will be able to experience outsized growth in the years to come. What has just been said is certainly proven by the net flows that the ESG funds register, like sustainable mutual funds or ESG thematic ETFs. For example, Morningstar estimated that in 2019 flows in Europe nearly tripled compared to the previous year, reaching around $120bn, which is a 22% share of all European net flows and a 21% net flow rate. In the first three quarters of 2020 these numbers have grown further, reaching $148bn (23% net flow rate). As for the US, we can see the same kind of trend. In 2019, flows to ESG funds quadrupled with respect to 2018, reaching $21bn and bringing the AuM in US to around $137bn. Equally, in 2020 the trend accelerated with $31bn in net flows and $181bn in AuM. Surely, these numbers attract attention, even if they represent respectively only 2.7% and 0.5% of total US asset management net flows and AuM in a year (Morningstar Inc. 2020).

Evidence of the enormous acceleration of this trend is Impax Asset Management, which specializes in sustainable investments. In 2015 Impax AM was a microcap asset manager listed in London with an AuM less than £3bn; in recent years it has experienced great growth and at the end of 2019 it had an AuM of £16bn (Source: ShareAction) (Mason, et al. 2020). Notably, ESG practices are much more widespread in Europe than in US, with a 4-5% market share compared to 0.5% in the US. Probably this is due to the fact that European regulatory entities care much more the issue of environmental, social and governance sustainability and have issued an higher number of rules and guidelines for all

industries, in addition to the fact that European companies are usually withstood by more transparency obligations regarding the sustainability of their business practices.
The below figure demonstrates the large increase of Net Flows and AuM in Sustainable Mutual Funds and Sustainable ETFs in US, showing that the ESG trend had a great acceleration in in last 2 years, reaching the 0.5% of the total funds in US in terms of AuM.

**Figure 1.1: Net Flows and AuM of ESG Funds in US**

Flows into ESG are accellerating (market share is almost 0.5% of total funds)




Source: Morningstar, Exane estimates, Datastream

Moreover, as a plus to the high ESG inflows growth rate just showed in the figures, it must be taken into account that the ESG mega trend is still taking its first steps, so the numbers and data observed today are expected to increase consistently in the coming years. Bloomberg suggests that within five years almost 60% of assets managed by mutual funds will have the ESG label (Marsh 2020). This means that in a few years we will no longer talk about ESG and non-ESG investments, but rather we will talk about different levels of ESG for each investment or asset. In fact, the goal of this research is to understand if the ESG Scores, nowadays provided by companies such as Refinitiv or MSCI, have already such importance as to influence market prices and financial performance, which in our case is represented by CDS spread, i.e. the probability of default and credit risk.

## 1.3 Regulatory Framework

Since both ESG investors and financial sustainable products are increasing, a substantial proliferation of ESG related definitions and standards has arisen. The market need for greater transparency and standardization on sustainable investments has clashed with an underlying lack of data and a confusion on local and international definitions and regulations. Overall, it is clear that there is general investor concern about the reliability of sustainability reporting. In recent years there have been many attempts to introduce global standards, aimed at standardizing ESG reporting. However, these attempts did not solve the problem as they led to different and sometimes competing guidelines ( Cleary Gottlieb Steen & Hamilton LLP 2020). All the initiatives that aim to regulate and standardize ESG practices are listed below. Global Reporting Initiative (GRI) of 1997, United Nations-backed Principles for Responsible Investing of 2006, Carbon Disclosure Standards Board (CDSB) of 2007, Workforce Disclosure Initiative born in 2008, Sustainability Accounting Standards Board (SASB) of 2011, United Nations Sustainable Development Goals (UN SDGs) of 2015, Paris Agreement of 2015, Task Force on Climate-related Financial Disclosure (TCFD) of 2017.

### 1.4 Literature Review

The starting point of this research is represented by the ambiguous relationship between firm's ESG choices and credit risk. On the one hand, high levels of ESG should reduce a company's risk through a better perception of investors in terms of sustainability, future robustness of performance and by achieving higher and less volatile earnings. On the other hand, investments in ESG may be a waste of scarce resources resulting in lower cash flows and higher firm risk (Goss e Roberts 2011). Hence, the existing link between ESG and firm risk adds an additional factor influencing the valuation of credit risk and therefore also a firm's probability of default. According to Merton higher and less volatile flows determined by ESG practices result in an improvement in company valuation, i.e. in higher overall value of assets, which in turns means lower probability of default and, thus, lower credit spreads (Merton 1974).

The previous literature that analyses the influence of ESG on credit risk focuses mainly on financial instruments and estimates related to tradable debt, such as corporate bonds and credit ratings (Menz 2010), (Jiraporn, et al. 2014). In 2015 also z-spreads have been taken into account by Stellner et al., who found that z-spreads decrease for greater levels of ESG, but this evidence holds only for companies listed in high sustainable countries (Stellner, Klein e Zwergel 2015). This research makes an important contribution to the past academic literature, focusing on tradable debt, but analyzing CDS Spread as an output variable. In this context the use of CDS Spreads is particularly interesting, as they represents a precise indicators of credit risk, that is easily comparable across firms and accounts for the majority of the firm level determinants of default risk (Forte e Peña 2009), (Tang e Yan 2010). Existing literature and researches carried out so far on the U.S. bond market indicate a positive impact of ESG choices, demonstrated by a better credit rating or a lower bond yield spread (Oikonomou, Brooks e Pavelin 2014), (Ge e Liu 2015). Given that the majority of past literature focuses on bond data, the use of CDS spreads offers an interesting alternative to investors and academics. CDS are much more liquid instruments than corporate bonds (Ederington, Guan e Yang 2015) and they are updated more frequently than credit ratings (Finnerty, Miller e Chen 2013). Moreover, bond prices can also be affected by others factors, like embedded options (Barth, Hubel e Scholz 2020), specific characteristics of that bond issuance or Central Banks short-term policies, making comparison across firms rather difficult. On the contrary, CDS have a standardize structure and this characteristic allows to compare probability of default across firms more easily (Norden e Weber 2009).

# CHAPTER 2 - Variables and Panel Data Models

### 2.1 Hypothesis Construction

This research aims to investigate the relationship between the credit risk of US companies and their commitment to being sustainable environmentally, socially and at a corporate governance level.The analysis will be performed on 100 companies listed in the United States on different regulated stock markets and belonging to different equity indices. The aim is to investigate whether exists a medium-term relationship between environmental, social and governance responsibility and corporate credit risk, ceteris paribus. The hypothesis to test is therefore the following:

*$H_0$: Companies' ESG Scores and ESG Combined Scores have a negative impact on US Single-Name CDS Mid Spreads, i.e. coefficients $\beta$ are negative.*

This hypothesis means that more sustainable companies and companies with higher ESG Score have a lower credit risk and less default probability and thus their CDS Spread quoted on the market is lower with respect to less sustainable companies or companies with lower ESG Score (both standard and combined). In addition, a second hypothesis will be tested:

*$H_1$: ESG Combined Score has a stronger impact on CDS Spreads with respect to standard ESG Score.*
The latter hypothesis is tested as it is in our interest to understand which of the two scores has a greater impact on the dependent variable and if the market news affecting the Combined score have an amplifying effect with respect to the CDS spreads, as these are as well influenced in some way by news and published reports.

## 2.2 Credit Default Swap Spread

Credit Default Swaps are the most liquid credit derivative on the market and for this reason they were chosen for the purpose of this research. The high liquidity of the instrument allows us to have quickly updated market valuations and therefore also the market information (included ESG scores and news related to corporate's sustainability) are faster embedded in the price (in the spread in this case, as the market quotes CDS Spreads). The price (spread) quoted in basis points (bps) represents the amount that the investor has to pay to insure against the company's default. Usually those who have a long position on a CDS want to hedge against the risk of default of a company as they hold a certain number of bonds of that company. If the CDS spread is 80 bps for instance, means that the investor pays $80,000 a year to buy protection on $10 million worth of the company's debt. As default risk rises, so does the cost of CDS, i.e. the spread, as it is more likely that the company will default on its debt obligations. The CDS dataset is downloaded from Refinitiv EIKON (formally Thomson Reuters). In this research Single-Name 5-Years CDS Mid Spread represent the dependent variable of the regression model.

## 2.3 Stock Return, Volatility and Leverage

Stock Return, Volatility and Leverage are three of the five independent variable in the regression. These factors are defined in this thesis as control variables, as soon as the focus is on the ESG scores. Credit Rating is another variable that will be discussed further, as it is considered more as a structural variable of CDS spreads rather than a control one. Control variables are included to better study the impact of ESG score on the credit risk, which is the goal of this research, and to better isolate the ESG effect on credit spreads. These variables are known to be correlated to CDS spreads. The data are retrieved from Refinitiv EIKON and data points are observed on a monthly basis. The decision to use Refinitiv as a data source is dictated by reasons of consistency and continuity with the CDS Spreads dataset.

## 2.4 Model Generated Credit Rating

The initial idea was to rely on the credit ratings of traditional rating agencies, such as Standard & Poor's, Moody's, Fitch. However, it was decided to opt for a different solution, since the ratings of the agencies listed above are not available for all the companies in our sample and as they are updated occasionally (for some companies, we found credit ratings updated only 2 or 3 times in our reference 5 years horizon). This aspect contrasts with our objective: since we want to understand the impact of ESG scores on corporate credit risk, for our study we need a credit rating that is more responsive to market news and companies' sustainability reporting and that is updated frequently, as our data is observed on a monthly basis. For those reasons mentioned above, the choice fell on one of the Thomson Reuters Starmine Quantitative Credit Risk Models suite. StarMine SmartRatios model generates on a daily-updating basis default probability (or bankruptcy probability) estimates, letter ratings, 1-100 percentile rankings, and component scores on over 35,000 global companies. Hence, for the thesis purpose is chosen the SmartRatios Credit Risk Model provided by Thomson Reuters.

## 2.5 ESG Rating and ESG Combined Rating

Despite the numerous new regulations and standards that are emerging, there is still a lot of confusion on the firm's sustainable reporting mandatory obligations, especially for non-European companies. In order to ensure data transparency, reliability and to be consistent with the other variables included in the model (CDS Spreads, Stock Returns, Volatilities, Leverage ratios and Credit Ratings), the ESG scores are retrieved from Refinitiv EIKON database. Refinitiv provides ESG data on more than 9,000 listed companies, including many of the primary US and global indices, such as MSCI World, NASDAQ 100, S&P 500 and Russell 100. The information is manually collected and audited by Refinitiv ESG analysts based on publicly available sources. For the purpose of this research, it was decided to include in the model two different types of ESG scores provided by Refinitiv:

- ESG Score, which is an overall company score based on the self-reported information in the environmental, social and governance pillars, and which assigns different weights to each pillar according to different company's industries.
- ESG Combined Score, which is an overall company score based on the self-reported information in the environmental, social and governance pillars, with an ESG Controversies overlay and negative events reflected in global media.

## 2.6 Panel Data Model: Fixed and Random Effects

Econometrically speaking, the simplest panel regression would have the following structure:

$$y_{it} = \alpha + \beta x_{it} + u_{it} \qquad (1.0),$$

where $y_{it}$ is the dependent variable, $\alpha$ is the intercept term, $\beta$ is the $k \ x$ 1 vector of parameters to be estimated with respect to the explanatory variables, $x_{it}$ is a 1 $x \ k$ vector of explanatory variables observations over time, and $t$ = 1,…, T and $i$ = 1,…, N.

There are generally two types of panel estimator methods used in financial studies: fixed effects models (FE) and random effects models (RE). If the regression is developed via FE model, it is allowed the intercept to change between entities (cross-sectionally) but not across time, whereas the slopes are constant in both dimensions. This method is called the entity-fixed effect. In order to run this model, it is needed the decomposition of the error term $u_{it}$ into $\mu_i$, which represents the entity specific effect that varies only cross-sectionally, and $v_{it}$, which is the "remaining portion" of the error term that varies both across time and entities, capturing what the independent variables don't explain about $y_{it}$. Thus, $\mu_i$ incorporates all the determinants that impact CDS Spreads only cross-sectionally but not over time (like the industry in which a firm operates). Below the decomposition of the error term from the equation 1.0:

$$u_{it} = \mu_i + v_{it} \qquad (1.1).$$

Considering the last assumption, the equation 1.0 changes as:

$$y_{it} = \alpha + \beta x_{it} + \mu_i + v_{it} \qquad (1.2),$$

where: $y_{it}$, $\alpha$, $\beta$, and $x_{it}$ are the same of the equation 1.0, $\mu_i$ is the entity fixed-effect that varies cross-sectionally, $v_{it}$ is the error term that varies cross-sectionally and over time.
One of the approach to estimate this model is the Least Square Dummy Variable (LSDV), which will be discussed in the next paragraph (Brooks 2014).
Additionally, it is possible to estimate the time-fixed effect model, in which intercepts differ over time but are fixed cross-sectionally in each moment. Usually this model is selected when one thinks that the average value of the depend variable varies across time but not cross-sectionally, which is not the case of this analysis. This approach allows the intercept to vary only across time but not over entities, at each moment in time. In this case the error term $u_{it}$ of the equation 1.0 is decomposed into $\lambda_t$, which represents the time varying intercept that encloses all variables affecting $y_{it}$ across time but fixed across entities. and $v_{it}$, which is the remaining error as in the equation 1.2. Since $\lambda_t$ is fixed only cross-sectionally, it means that affect $y_{it}$ as time passes, but the entities of the sample are affected equally, in the same proportion, such that the time fixed-effect varies only over time.
Following this approach the equation 1.0 becomes:

$$y_{it} = \alpha + \beta x_{it} + \lambda_t + v_{it} \qquad (1.3),$$

where $y_{it}$, $\alpha$, $\beta$, and $x_{it}$ are the same of the equation 1.0, $\lambda_t$ is the time fixed-effect that varies across time, $v_{it}$ is the error term that varies cross-sectionally and over time.
As with entity FE model, the time FE model can be estimated using Dummy Variables, but there is a difference: now dummies don't capture cross-sectional variations but only time ones.
The random effects model is similar to the FE model, as it allows changes in the intercepts cross-sectionally, but fixed at each point in time. The difference between the two models is that in the RE model the intercepts that change between entities originate from a common intercept, constant cross-sectionally and temporally, plus a random variable, which is fixed over time but not across entities (Brooks 2014). Hence, this method accounts for random variation of each firms' intercept starting from the common intercept value. In this case the equation 1.0 can be rewrited following the RE panel model:

$$y_{it} = \alpha + \beta x_{it} + \omega_{it} \qquad (2.0).$$

The term $\omega_{it}$ can be decomposed into two terms

$$\omega_{it} = \epsilon_i + u_{it} \qquad (2.1),$$

where $y_{it}$, $\alpha$, $\beta$, and $x_{it}$ are the same of the equation 1.0, $u_{it}$ is the error term varying over time and cross-sectionally, $\epsilon_i$ which measures the distance of each entity's intercept from the common intercept term.Summarizing, this approach includes the common intercept term $\alpha$ which is constant for each entity both cross-sectionally and over time, plus a random term $\epsilon_i$ that varies only cross-sectionally. Thus, $\epsilon_i$ captures the deviation of each entity from the starting point of the common intercept $\alpha$ and the final intercept of each company is composed by both terms, the fixed one plus the random one. Even if $x_{it}$ is still a *1xk* vector, the heterogeneity aspect of the entities, i.e. the cross-sectional variation, is not captured using LSDV, but through the $\epsilon_i$ random error term of entities.

## 2.7 Further Descriptive Statistics

The focus is on the correlations between variables, in particular between ESG Scores, ESG Combined Scores and CDS Mid Spreads, and on summary statistics of our panel data.

**Figure 2.4: Correlation matrix of variables observed monthly**

| ***Correlations*** | Exc.Return | CDS | Leverage | Volatility | Cr.Rating | ESG Score | C.ESG Score |
|---|---|---|---|---|---|---|---|
| Exc.Return | 1.00 | -0.08 | 0.00 | -0.01 | 0.04 | 0.01 | 0.01 |
| CDS | -0.08 | 1.00 | -0.13 | 0.69 | -0.44 | -0.32 | -0.19 |
| Leverage | 0.00 | -0.13 | 1.00 | -0.09 | 0.10 | 0.05 | 0.08 |
| Volatility | -0.01 | 0.69 | -0.09 | 1.00 | -0.38 | -0.41 | -0.24 |
| Cr.Rating | 0.04 | -0.44 | 0.10 | -0.38 | 1.00 | 0.31 | 0.13 |
| ESG Score | 0.01 | -0.32 | 0.05 | -0.41 | 0.31 | 1.00 | 0.59 |
| C.ESG Score | 0.01 | -0.19 | 0.08 | -0.24 | 0.13 | 0.59 | 1.00 |

In the figure 2.4 correlations between explanatory variables and CDS Spreads are consistent with what expected, except for Leverage. For Excess Return, Credit Rating, Volatility and both ESG Scores, the correlation with dependent variable is negative, as we expected. As expected, higher Stock Return means a lower CDS Spread and a better Credit Rating or ESG Scores means a lower probability of default and less credit risk. Instead, volatility is as expected positively correlated with credit risk, as it is a measure of risk for the markets and for investors. Leverage usually should be positive correlated with credit risk, as high leverage could be considered as a measure of firm's assets risk, but our panel data don't suggest this. Again Leverage represents deviate values from what one should expect, that have few sense statistically and economically speaking. The next figure exhibits the correlation matrix also of variables which data points are calculated as the mean of monthly data, to obtain annual data.

**Figure 2.5: Correlation matrix of variables observed annually**

| ***Correlations*** | Exc.Return | CDS | Leverage | Volatility | Cr.Rating | ESG Score | C.ESG Score |
|---|---|---|---|---|---|---|---|
| Exc.Return | 1.00 | -0.12 | 0.03 | 0.03 | 0.08 | 0.08 | 0.03 |
| CDS | -0.12 | 1.00 | -0.12 | 0.72 | -0.47 | -0.33 | -0.18 |
| Leverage | 0.03 | -0.12 | 1.00 | -0.11 | 0.11 | 0.07 | 0.11 |
| Volatility | 0.03 | 0.72 | -0.11 | 1.00 | -0.39 | -0.39 | -0.23 |
| Cr.Rating | 0.08 | -0.47 | 0.11 | -0.39 | 1.00 | 0.30 | 0.13 |
| ESG Score | 0.08 | -0.33 | 0.07 | -0.39 | 0.30 | 1.00 | 0.57 |
| C.ESG Score | 0.03 | -0.18 | 0.11 | -0.23 | 0.13 | 0.57 | 1.00 |

Using annual observations there is a slightly higher correlation of ESG Score with CDS and a slightly lower for Combined ESG Score and as expected they are in line with expectations, except for leverage.

# CHAPTER 3 - Empirical Methodology and Results

## 3.1 Empirical Methodology

The LSDV approach will be performed using both panel and results will be compared. Annual data are obtained as average of monthly data for each sample's company. Starting from the equation 1.2 and applying the LSDV approach, the equation modifies as follow:

$$y_{it} = \alpha + \beta x_{it} + \mu_i D1_i + \mu_i D2_i + \mu_i D3_i + \cdots + \mu_N DN_i \; + \; v_{it} \qquad (3.0),$$

where $D1_i$ is a dummy variable that takes the value of 1 for all observations on the first company in the sample and zero otherwise, $D2_i$ is a dummy variable that takes the value of 1 for all observations of the second company in the sample and zero otherwise, and so on until the Nth company in the sample which is multiplied by $DN_i$ that takes the value of 1 for the Nth company in the sample and zero otherwise.

This method is performed for monthly and annual frequency data, obtained through average of monthly values of excess returns, volatility, credit ratings and CDS mid spreads. ESG scores and ESG combined scores are not included: as they are observed annually, the average of monthly observation is the annual rating itself.

Moreover, can be interesting to compare the FE model results with a Pooled OLS approach, in order to assess if the two approaches presents divergent results. In order to run also an OLS model estimator, the so-called "within transformation" is executed (Brooks 2014). It necessitates to subtract from the values of the variable the time-mean of each company observations. Thus, we calculate the mean of each variables (explanatories and dependent) for cross-sectional unit "$i$". The example for variable $y$ that follows is repeated for each explanatory variable:

$$\bar{y}_i = \frac{1}{T} \sum_{t=1}^{T} y_{it} \qquad (3.1).$$

Hence, starting from equation 1.0 the below is obtained:

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i \qquad (3.2),$$

that can be re-wrote as:

$$\ddot{y}_{it} = \beta \ddot{x}_{it} + \ddot{u}_{it} \qquad (3.3),$$

where the double dots above variables represent the demeaned values. Note that after these adjustments the regression does not need an intercept any more as dependent variable have now zero mean by construction.

## 3.2 Panel Data Regression

Following the enitity FE method we can re-write the equation 4.1 as:

$$CDS_{it} = \alpha + \beta^{ESG} ESG_{it} + \beta^{cESG} cESG_{it} + \beta^{R} R_{it} + \beta^{Vol} Vol_{it} + \beta^{CR} CR_{it} + \mu_i + v_{it} \qquad (4.2).$$

Since CDS Mid Spread are quoted in bps, they can reach very high values in terms of data observed. For this reason, it is calculated the logarithm of CDS Mid Spread, as it allows to have all variables almost in the same scale and to avoid huge difference in value observed. For the same reason, it is decided to convert the range of both ESG Scores and Credit Rating from the range 0-100 to the range 0-1. Through this amendment, we are able to achieve that all variable are in the same scale, i.e. all variables' value vary in the range -2/+1. For the same reason we decided to exclude Leverage from our empirical analysis, as it is the only variable with different scale and not varying in the range mentioned above. Taking the natural logarithm of CDS Mid Spreads, the next equation is obtained:

$$\ln(CDS_{it}) = \alpha + \beta^{ESG} ESG_{it} + \beta^{cESG} cESG_{it} + \beta^{R} R_{it} + \beta^{Vol} Vol_{it} + \beta^{CR} CR_{it} + \mu_i + v_{it} \qquad (4.4).$$

## 3.3 Pooled OLS Regression

This paragraph presents the model used to obtain the coefficients of the explanatory variables using the OLS estimator. Since the panel in question is longitudinal, the so-called Pooled OLS estimator is used. This further analysis is developed in order to compare the findings achieved through panel regression. The empirical methodology used for pooling the panel data is previously described in the first paragraph of this chapter. Starting from equation 3.2, the regression model becomes:

$$\ln(CDS)_{it} - \overline{\ln(CDS)}_i = \beta^{ESG}(ESG_{it} - \overline{ESG}_i) + \beta^{cESG}(cESG_{it} - \overline{cESG}_i) + \beta^{R}(R_{it} - \bar{R}_i) + \beta^{Vol}(Vol_{it} - \overline{Vol}_i) + \beta^{CR}(CR_{it} - \overline{CR}_i) + (u_{it} - \bar{u}_i) \qquad (5.0).$$

Note again that this model has no intercept as the variable ln(CDS) have zero mean by construction. The equation 5.0 can be also described as:

$$\ln(\ddot{CDS})_{it} = \beta^{ESG} \ddot{ESG}_{it} + \beta^{cESG} c\ddot{ESG}_{it} + \beta^{R} \ddot{R}_{it} + \beta^{Vol} \ddot{Vol}_{it} + \beta^{CR} \ddot{CR}_{it} + \ddot{u}_{it} \qquad (5.1).$$

The results of the Pooled OLS estimations are discussed in the following paragraph.

## 3.4 Results & Findings

Once the final variables are selected and the empirical model's structure is defined, the panel data regression can be performed, following the methods discussed previously, i.e. the fixed effect model. Indeed, the results of four different regressions will be described in this paragraph. All regression are completed using the statistical software *Stata15*.

**Table 07: Monthly Panel Empirical Results**

| | (1)<br>ln(cds) | (2)<br>ln(cds) | (3)<br>ln(cds) | (4)<br>ln(cds) |
|---|---|---|---|---|
| Excess Return | -0.364***<br>(-7.24) | -0.368***<br>(-7.32) | -0.364***<br>(-6.91) | -0.368***<br>(-6.99) |
| Volatility | 0.818***<br>(17.92) | 0.840***<br>(18.49) | 0.818***<br>(4.87) | 0.840***<br>(4.91) |
| Cr. Rating | -0.651***<br>(-17.30) | -0.663***<br>(-17.77) | -0.651***<br>(-3.94) | -0.663***<br>(-4.08) |
| ESG C. Score | -0.128***<br>(-4.65) | | -0.128<br>(-1.26) | |
| ESG Score | | -0.253***<br>(-4.86) | | -0.253<br>(-1.48) |
| Intercept | 8.595***<br>(49.02) | 9.216***<br>(35.93) | 8.595***<br>(11.53) | 9.216***<br>(9.24) |
| Observations | 4851 | 4851 | 4851 | 4851 |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Analysing the results obtained on the first two regressions, i.e. Panel Data Entity Fixed-Effect with monthly observations and ESG Combined Score and Panel Data Entity Fixed-Effect with monthly observations and ESG Score, all coefficient's estimations are significant. Statistically speaking, these coefficients are significant as described by low p-values, all lower than 0.001, which is an important finding as it means that the variable of our model affect CDS Spreads in the reference time horizon. Looking at the results more in depth, it is interesting to note that all coefficients values are consistent with expectation: excess return impact negatively on CDS Spread, as Credit Rating and ESG Score do; Volatility impact positively the spreads, i.e. the company's credit risk, which is in line with suppositions. However, even if these results are significant, the coefficients estimated tell us that these variables do not affect CDS strongly, as all of them are lower than zero. Focusing on the main variables of this research, ESC Combined Scores variation over years impact CDS only for the 0.12%, whilst ESG Score for 0.25%. The reason of this slight impact could be several and will be discussed in next paragraphs. Also, Betas estimated for other variables are all higher than ESG ones. In particular note that Credit Rating has a much higher impact on CDS spread with respect to both sustainability ratings. ESG and ESG Combined have respectively a delta with Credit Rating equal to 0.41 and 0.52. The delta is even higher if compared with Volatility coefficient. Therefore, within all the variables of the model, the ESG ones have the least influence on the corporates' probability of default.

Switching to other two regressions, where clustered errors approach is included, the results change completely for the ESG variables, but remain the same for other variables. Excess Return, Credit Rating and Volatility still have strong significance and p-values below 0.01. This is not the case for ESG Combined and ESG Score, as they register p-values above 0.05 and hence rejected for a 95% standard confidence level. Clearly, coefficients estimated for the three control variables vary when we switch from one ESG score to the other. That is because the coefficient represents not only the covariance of the variable *x* and *y*, divided by the variance of *x*, but this value is also adjusted for the covariance that the variable *x* has with the others explanatory variables. For this reason, we also decided to run two different regressions: one with Combined score and the other with standard score, since these two variables are highly correlated as shown in figure 2.4 and 2.5 and we don't want this affect the results. Also, statistically speaking, include two variables in the same regression which are very correlated is not so useful for our objective. As can be seen in Table 07, the robust or clustered error approach implies a lower significance of the estimated coefficients for ESG variables, given that this approach allows for heteroscedasticity and correlation in the error term within a cluster. This means that the model allows the correlation between the error terms of variables of the same cluster. Specifically, clustering errors means considering them not i.i.d. for the entities of the same cluster, as there could be a correlation given by specific characteristics of the cluster itself. In the case of this research, the entities are obviously the companies of our sample and the clusters are the various industries to which they belong. Therefore, we can say that it is correct to use a method that takes into account the relationship between specific unobservable of a sector, especially when dealing with sustainability thematics that have a different weight in the industries. Therefore, using CSE is on the one hand more correct, as it imposes a more restrictive assumption on errors correlation within a cluster, on the other hand it therefore implies a lower significance of the estimated results. Therefore, for the third and fourth regression listed in Table 07, we reject the coefficients estimated for both ESG variables as p-values are higher than 0.05 for a 95% confidence interval, whilst the other three independent variables' coefficients are still significant. The next step of the empirical process involves other four regression following exactly the same approach just described, but using annual data panel. Then we will compare the results obtained using different data frequency.

**Table 08: Annual Panel Empirical Results**

| | (1)<br>ln(cds) | (2)<br>ln(cds) | (3)<br>ln(cds) | (4)<br>ln(cds) |
|---|---|---|---|---|
| Excess Return | -1.591**<br>(-3.31) | -1.642***<br>(-3.43) | -1.591**<br>(-3.04) | -1.642**<br>(-3.16) |
| Volatility | 0.608***<br>(4.02) | 0.635***<br>(4.25) | 0.608**<br>(3.14) | 0.635**<br>(3.24) |
| Cr. Rating | -0.794***<br>(-5.95) | -0.794***<br>(-6.09) | -0.794***<br>(-4.08) | -0.794***<br>(-4.24) |
| ESG C. Score | -0.0888<br>(-0.94) | | -0.0888<br>(-0.69) | |
| ESG Score | | -0.382*<br>(-2.29) | | -0.382*<br>(-2.12) |
| Intercept | 8.678***<br>(14.81) | 9.962***<br>(11.75) | 8.678***<br>(9.95) | 9.962***<br>(9.48) |
| Observations | 495 | 495 | 495 | |

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

The table above shows results for panel data regression using annual observation of variables. On one hand, results obtained are very similar to previous ones for Credit Rating and Volatility, as coefficients estimated have the same statistical significance and similar values. Excess return's coefficients estimation has slightly less significance, with p-values higher than 0.01 in two regressions over three and also coefficients' value is more than three times higher versus the estimation using monthly observation. The great achievement in this case is that statistical significance of coefficients for standard ESG score is not lost when we cluster errors in the third regression. In fact, the coefficient has a value of -0.382 and a p-value lower than 0.05 and hence still significant for 95% confidence interval. Unfortunately, this is not true for Combined score, as it loses significance when we cluster errors, as per monthly data panel discussed previously. Summarizing, results obtained with annual observation seems to be better with respect to monthly, and probably the main reason is that we have a balanced panel, as all variables are observed at the same frequency, in contrast with panel data used for the estimation in Table 05.  Going beyond panel data regressions, this section discuss results achieved via Pooled OLS estimator. The regression in this case in performed using Excel. The table below shows the findings.

**Table 09: OLS Estimator Empirical Findings**

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* |
|---|---|---|---|---|
| Intercept | 0 | 0 | 0 | 0 |
| Exc.Return | -0.45720727 | 0.09461555 | -4.83226 | 0.00 |
| Volatility | 1.12551290 | 0.024328997 | 46.2622 | 0.00 |
| Cr.Rating | -1.23381824 | 0.037239433 | -33.132 | 0.00 |
| ESG Score | -0.43980968 | 0.039681272 | -11.0836 | 0.00 |
| ESG C. Score | 0.00593010 | 0.033297549 | 0.178094 | 0.86 |

Comparing results with Panel Data regression, we can see that all coefficients are higher in the latter table, except for Excess Return and ESG Combined. Looking at p-values, it is interesting to note that once again results estimated are significant, but surprisingly we have no significance for ESG Combined score at 95% confidence level. The positive aspect of those findings is that Betas estimated seem to have higher impact on CDS Spreads, with respect to coefficients estimated previously. We can say that, apart for ESG Combined, the OLS regression presents consistent results compared with those listed in Table 05 and Table 06. Note that to run this regression, monthly observations were employed as model data.  The following table shows further OLS regression statistics.

# Limitations

Despite the statistical significance of the results discussed above, the analysis carried out has several limitations. First of all, starting from the research outputs, the evidence obtained for the two ESG variables is less significant when the standard errors are clustered. This means that when the model accounts for non i.i.d. errors over entities, the model's ability to predict fails. Surely a further limitation is represented by the scarcity of data available from accessible sources. In particular, the ESG Ratings are provided by a few agencies and main data sources, which still use different models for assigning the score. In this sense, the lack of clear legislation and guidelines is also a disadvantage for this analysis. ESG scores are also available for a few years, usually updated annually and potentially have a very large number of qualitative and quantitative determinants, as there are no commonly used standards. Moreover, a further limit to consider is the short time horizon on which the analysis is carried out, since ESG is relatively young as a trend with scarce data available. Finally, the limitation of having an unbalanced panel data is once again due to the difference between monthly observations of excess return, volatility and CDS spread against annual observations for ESG ratings and sometimes non-monthly observations for credit ratings. Nevertheless, the research has also several points of strength and significance that will be discussed across conclusions of next paragraph

# Conclusions

The thesis has statistically and econometrically achieved positive and significant results, both for future literature and for investors, as the ESG trend is growing fast in the economy and this is clearly reflected in global markets for all asset classes. The estimations are consistent with expectations and significant in terms of p-values, even if clustered errors are taken into accounts. We can summarize our results re-writing the two main equation of the research, i.e. equation 4.3 and equation 5.0. Starting from the Panel Regression that includes ESG Combined Score and monthly frequency observations, equation 4.3 presents the following Betas estimation:

$$\ln(CDS_{it}) = 8.595 - 0.128cESG_{it} - 0.364R_{it} + 0.818Vol_{it} - 0.651CR_{it} \quad (6.0).$$

Next equation shows results of the same regression, but using standard ESG Scores:

$$\ln(CDS_{it}) = 9.216 - 0.253ESG_{it} - 0.368R_{it} + 0.840Vol_{it} - 0.663CR_{it} \quad (6.1).$$

Clustering errors, we obtained results that are not statistically significant for both ESG scores, as demonstrated by p-values discussed in Chapter 3.
Given the findings obtained for equation 6.0 and 6.1, $H_0$ is not rejected whilst $H_1$ is rejected, at 95% confidence level.
Then, we ran other four regression following the same model but using different observation frequency, i.e. annual data. The results obtained are the following:

$$\ln(CDS_{it}) = 8.678 - 0.088cESG_{it} - 1.591R_{it} + 0.608Vol_{it} - 0.794CR_{it} \quad (6.2);$$
$$\ln(CDS_{it}) = 9.962 - 0.382ESG_{it} - 1.642R_{it} + 0.635Vol_{it} - 0.794CR_{it} \quad (6.3).$$

Following errors clustering approach, we obtained significant results for ESG standard Score using annual data, in contrast with monthly panel regressions. $\beta^{ESG}$ is still consistent at 95% confidence level as p-value stands between 0.05 and 0.01. Betas estimated are equal to those in equation 6.3, but the ESG coefficient has less significance with clustered errors, since its p-value is higher, but still below 0.05. These findings confirm that once again $H_0$ is not rejected, whilst $H_1$ is rejected.
In summary, the most significant and relevant coefficient estimated in this research is the $\beta^{ESG}$ of the equation 6.3 developed using annual panel data and following the errors clustering method. The $\beta^{ESG}$equal to -0.382 means that an improving in corporates' ESG Score, e.g. from C+ to B-, creates a decrease in CDS Spread of 0.382%. Considering the entire range of ESG ratings (from D- to A+), the total spread of scores from 0 to 1 accounts in average for 3.82% of CDS Spreads. Hypothetically, if a company improves its sustainable rating from the lowest score to the highest, it would tightens its probablity of default by 3.82%. The estimate of this impact is large and very significant, expecially if its considered how muchi it can grows, given that ESG trend is still in its early stages.
Lastly, the results of OLS coefficient estimation are presented in the below equation. Note that $\beta^{cESG}$ of Combined ESG is not significant in this case and that the regression has no intercept by construction. Other independent variables' coefficients are coherent with expectations and significant. Therefore, Equation 5.0 can be rewritten as:

$$\ln(CDS)_{it} - \overline{\ln(CDS)}_i = -0.439(ESG_{it} - \overline{ESG}_i) - 0.457(R_{it} - \bar{R}_i) + 1.125\left(Vol_{it} - \overline{Vol}_i\right) - 1.233(CR_{it} - \overline{CR}_i) \quad (6.4).$$

For the latter regression, $H_0$ is not rejected for ESG Score but it is for the ESG Combined; in turn $H_1$ is automatically rejected. Even if results are coherent with expectations and significant, the ESG Betas estimated have relatively low values with respect to other independent variables. As our main objective is to assess the magnitude of ESG scores' impact on CDS spread for US companies, our finding tells us that this impact is significant and that in few years it could be even more powerful. At the moment, the ESG impact is still not completely perceived by the market for several reasons. In the US, regulations and standards are still not improved by authorities, companies' reporting has no clear mandatory guidelines and often rules overlap. In addition, the rating agencies and data providers use different methods to estimate sustainability ratings, because there is no common rules to follow both from the authorities side and companies' side (even for those adhering to SDGs objective or TCFD guidelines, since they often omit information in reports or share only those that are most convenient to). Moreover, even if own proprietary rating agencies and data providers are investing in this context, the subject is too broad and determinants of the ESG rating are potentially infinite. This research is however important for many purposes: for the climatic and social challenges the world is facing, and for investors, who must have the opportunity to make conscious investments and the ability to know in a standardized manner the level of sustainability of the company in which they are investing. Finally, considering that today the ESG branded AUM accounts for $1.3tn only in US and that the macro-trend is only at its infancy, we can say that in the coming years it could grow at important levels, and hence global standards have to keep up with expansion. The analysis carried out is significant not only for the assessment of the impact of ESG ratings but also for highlighting the determinants of CDS Spreads in the American market, and this is certainly a further relevant aspect of this study.

To conclude, some suggestions are discussed for future research that will focus on the topics covered in these theses. First of all, it would be intriguing to carry out the same type of research for listed companies in Europe, in order to compare the results and understand whether the legislation and the greater European attention to the issue of sustainability is reflected in the credit market or not (obviously the hypothetical research should focus on the same sectors that have been taken in the account in this thesis and sector concentration as similar as possible to those included in Table 01). Furthermore, it would be very interesting to control for different ESG scores, provided by another reliable source, to understand if their impact on CDS is consistent with the findings of the empirical analysis. Finally, over time much more data will be available and firms' practices and reporting will be standardized by new regulations, thus a research focused on growth rate of ESG impact in credit market would be important to address.