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# The Impact of the ESG Ratings on Returns: an Event Study Perspective

**Supervisor**

Ch. Prof. Davide Raggi

**Graduand**

Leonardo Bordignon

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# Introduction

This thesis aims at analysing and deepening the most interesting and significant aspects of Environmental, Social and Governance (ESG) issues. In the last few years, concerns about ESG factors have become fundamental and asset managers need to consider their impact on companies value. In particular, the publication of a company's ESG rating could induce some abnormal returns in the stock market. The event study methodology can be used to verify the statistical significance of abnormal returns in the observation period, i.e. when ESG ratings are made public. The event study is a powerful statistical tool used in several disciplines for empirical research. For the purpose of this thesis the so called short-term event study methodology is used. The standard version of the event study methodology is presented, both in its simple but elegant formalization as well as in more advanced versions.

Since the last decade, many rating agencies began publishing ESG scores of listed companies on an annual basis. Two of the most popular agencies are Bloomberg and MSCI, that will be used in this thesis. In this thesis, a sample of one hundred and fifty listed firms that have received an annual ESG rating by Bloomberg and MSCI, from December 2014 to February 2022, is collected. These listed companies belong to the Dow Jones Sector Titans market index. Stock prices are taken from the Bloomberg database. Empirical findings demonstrate the presence of abnormal returns for the day the ESG scores are published. This phenomenon is consistent with the semi-strong form of the Efficient Market Hypothesis. However, abnormal returns are observable a few days before the publication of the ESG scores and persist for a few days thereafter. This behaviour of abnormal returns is common in several cases of event studies analysis provided in the literature and represents a violation of the semi-strong form of the Efficient Market Hypothesis. In particular, abnormal returns before the event date indicate a breach of insider trading rules, i.e. some investors exploited insider information to beat the market. Whilst the persistence of abnormal returns after the date of publication of the ESG ratings proves the stock market is not readily integrating the ESG factors' news to adjust stock prices accordingly.

In an increasingly complex financial world, investors face many questions about the ethics of their investments, and the concept of Socially Responsible Investment (SRI) is particularly relevant. SRI is sustainable development applied to finance. It is an investment strategy consisting of systematically mainstreaming factors linked to Environmental, Social and Governance (ESG) issues alongside financial criteria. When market participants are considering investing in a company, they may consider two main issues. They may look at financial criteria as profitability, business models, sector, and competitiveness, but also to ESG criteria, that is considered a proxy for social responsibility in financial markets. The Environmental side explores the environmental footprint of companies. In particular, it points out initiatives for energy saving and the reduction of polluting emissions. The Social part examines working conditions, relationships with clients and suppliers, and human resources management. The Governance portion investigates the governance structure to assess if it is transparent and independent and if there is respect for shareholders. Many productive firms, companies in the services and energy sector, asset management companies and investment firms, which are well diversified and operate worldwide, are pioneers in the SRI framework. They have been integrating ESG factors into their investment decisions. Such a great number of companies have been proving that the integration of ESG issues is fundamental to the sustainable performance of the business. Considering ESG factors in the fundamental analysis reduces the risk of an investment and decreases the cost of capital. Moreover, this approach helps to identify risks upstream and better assess them, recognise long-term investment opportunities, and create value. This SRI approach gives meaning to investing by ensuring the sustainable performance of investments. Socially Responsible Investment or Impact investing are terms that identify ESG investing. It considers how ESG issues affect the financial performance of the companies, and world data suggest a growing interest in ESG factors. In fact, according to a recent Morningstar report, more than 45 billion dollars flowed into Global Sustainable Funds in the first quarter of 2020. Moreover, the interest in Sustainable Investing among the general population of world investors jumped from 71% in 2015 to 85% in 2019.

The ESG investing was first mentioned in a 2004 letter from former United Nations secretary-general Kofi Annan. He wrote to 255 CEOs of the world's leading financial institutions, inviting them to participate in an initiative that would bridge the gap between investors and significant environmental, social and governance issues. The group formed what is known as the Principles for Responsible Investments. Its members are required to report Responsible Investment activities each year. The most notable money managers like BlackRock, Morgan Stanley and JP Morgan have signed on. However, at that time, ESG investing was not widely considered by investors as an interesting factor for financial management.

However, in 2020, Larry Fink, the CEO of BlackRock, the world's largest money manager, released a letter to its investors that stunned Wall Street. In this document, he stressed that climate change and investment decisions surrounding it would "*lead to a fundamental reshaping of finance.*" Fink wrote: "*As a fiduciary, our responsibility is to help clients navigate this transition. Our investment conviction is that sustainability- and climate-integrated portfolios can provide better risk-adjusted returns to investors. And with the impact of sustainability on investment returns increasing, we believe that sustainable investing is the strongest foundation for client portfolios going forward.*"[1]

[1] Larry Fink, BlackRock CEO, 2020.

In this respect, it appears that the ESG paradigm results as a significant factor that should be considered while taking financial decisions. However, some criticisms raised concerning ESG investing.

The most significant ESG criticism is that some companies use it as a marketing ploy. They make grand promises to become more inclusive or environmentally friendly, only to attract investors and improves their public standing. But some companies do not end up following through on these promises. Clear examples are the very well-known scandals of Volkswagen cars' carbon emissions or Equifax's breach of data privacy and cybersecurity. These are just two examples of the practice of greenwashing. In this context, it became crucial to track firms' achievements of the ESG goals stated in their corporate sustainability reports.

The European Union law mandates that public companies, asset managers and pension funds must disclose the Environmental, Social and Governance risks of their investments. The US does not have the same level of transparency, but in the last ten years, more firms have begun self-reporting their ESG performances besides their financial statements each year.

Third-party rating agencies, research firms and institutional investors take self-reporting data and other public information to rate companies based on a range of ESG issues. Principles may vary from how firms treat their employees to how sustainable their corporate culture is or how diverse their board is. Some evidence demonstrate that companies that genuinely understand and integrate ESG issues, not for box-ticking or greenwashing, but actually integrating, in the long-run, tend to be better-performing companies. Especially those that detect ESG risks and improve risk assessment methods within their industry.[2]

So far, there is not a single standard in place to measure ESG commitments that companies can uniquely follow. Financial data and media companies as

[2] Capelle-Blancard, G., & Petit, A. (2017). The Weighting of CSR Dimensions: One Size Does Not Fit All. Business and Society, 56(6), 919–943.

Bloomberg and MSCI have been helping investors quantify the data and make informative decisions by focussing on a number of different factors. Concerning the assessment of ESG scores, they look at a variety of variables, including where the company operates and the nature of its business. For example, for an oil company, the environmental footprint and the safety of its employees are crucial factors. In the technology sector, critical issues are data privacy and cybersecurity. For the retailer sector, analysts examine the supply chain and how retail firms manage their suppliers.

A large and increasing number of asset managers are integrating ESG factors to understand the risks and opportunities of investing in a company. An ESG lens can help stakeholders identify risks not spotted by conventional financial analysis. Such risks can impact a firm’s performance because of operational or litigation costs. Different ESG risks can harm various industries and sectors. The ESG rating system focuses on what is significant to a company’s bottom line and comparable with its peer group. Third-party rating agencies look at a firm’s exposure to industry-specific risks, which are based on its business activities, the size of its operations and where it operates. Then they examine how a company is managing its risk exposure. Indeed, companies that failed to cope with ESG risks have historically experienced a higher cost of capital, more volatility and accounting irregularities. The ESG scoring activity is not about hammering companies for all of their data, nor is it about asking for their opinion.

Scoring agencies collect the most relevant, publicly available data and use a precision approach designed to ensure that ESG scores pinpoint the most significant risks a company may face. Rating agencies collect data from thousands of sources and consider controversies that may indicate performance failures. To calculate ESG scores, rating companies assign percentage weights to each ESG risk according to their time horizon and impact. Then, ESG scores are combined and normalised relative to industry peers to achieve the overall rating. For example, a low ESG score assigned to a given company implies mismanagement of resources, waste, and emissions. It can demonstrate severe lapses in safety or the inappropriateness of the board of directors. The ESG ratings help investors identify companies that are leading or, on the opposite side, lagging within their industry or sector, which may flag opportunities or risks not captured by conventional financial analysis. Several institutional investors employ ESG scores for fundamental or quant analysis, portfolio construction and risk management and benchmarking index-based products.

Bloomberg is a third-party provider of reports and ratings. It can be considered a tool that allows institutional investors, fund managers, asset managers, financial institutions, and private investors to rely on its analyses to assess and evaluate the ESG performance of companies over time. Bloomberg has a partnership with MSCI to construct and control the ESG rating system aligning their factors and scores. The ESG rates can be computed as an overall indicator, or can be splitted into every single component, namely, Environment, Social and Governance. The Bloomberg ESG score is on a scale from zero to one hundred, whereas the MSCI scoring system uses rates similar to credit risk rates, that range from CCC at the bottom to AAA at the top. The two evaluation methods are perfectly superimposable. In fact, both scales can be divided into laggard companies at the bottom, average companies, and leading companies at the top. The ESG rating system focuses on a two-dimensional framework that captures the exposure of a firm to industry-specific risks and the way a firm is managing those risks. The ESG scores aim at rating companies yearly based on their disclosure of quantitative and policy related ESG data. In particular, it gathers public ESG information on firms, sustainability reports and annual reports. Such data is checked and standardised.

The Bloomberg ESG dataset provides information and scores for approximately 14000 firms worldwide. It covers self-reported data of companies and sector-specific and country-specific analyses. Bloomberg has built its ESG rating system focusing on key sustainability topics, including air quality, climate change, energy saving, waste disposal, health and safety of employees, compensation system, diversity, board independence, and shareholders’ rights.

This thesis uses the event study methodology to capture the reaction of the stock market when companies’ ESG ratings are published and the behaviour of abnormal returns before and after the event day.

Under the Efficient Market Hypothesis, securities prices should incorporate all currently available information. Thus price changes should include new information in the marketplace. Hence, it appears reasonable that it is possible to capture the importance of an event of interest by studying price changes throughout the period in which such an event occurs. The event study is a powerful methodology common in empirical financial research that allows one to assess the impact of a given event on a company’s stock prices.

Financial analysts are often asked to capture the effects of micro- or macro-economic events affecting the value of companies. In general, the event study technique has several applications; in the literature, there are examples in accounting and finance, earnings announcements or mergers and acquisitions. Many works are dated, but the method used has been improved over the years. Everyday stock prices reflect a variety of economic, social, or political news. Singling out the portion of stock prices’ variation attributable to a given event is the core of event study methodology. The most common approach begins with a Proxy for what stock prices would have been in the absence of the event under observation. Then, stock returns are computed. The method should be applied to excess returns, stock returns in excess of the risk-free rate, for example, the US Treasury Bill. The abnormal returns caused by the event under observation are assessed as the difference between stock excess returns in the event period and a benchmark. The single-factor model builds a stock’s abnormal returns as its returns minus that of a market index. In particular, the returns are influenced by a firm-specific factor and a market factor. The market model is a flexible method.

Nevertheless, the analyst should be careful to correctly estimate the regression parameters. In particular, they should be assessed using financial data before the relevant event and not overlapping it to separate pre-event returns from during-event returns. The pre-event period is called the estimation window and the event period is the event window. This design gives estimators for the single-factor model, which are not influenced by the excess returns close to the event date. Indeed including the estimation window in the event window would cause a misleading measure of the abnormal returns.

Estimating the abnormal returns of a stock, or a set of stocks, allows capturing the impact of the event under observation at the moment the information is disclosed to the market participants. The analyst should precisely define the announcement date as the date on which the information is made public. Then, the abnormal returns of each stock around the announcement date are estimated, and it is analysed the statistical significance of every abnormal return capturing the relevance of the information just made available. For an in-depth study of the model, an improved indicator could be the cumulative abnormal return (CAR). It is the sum of all the abnormal returns in the event window. The cumulative abnormal returns of a group of stocks show the overall firm-specific stock shift for the event window when the market is answering to the information under study.

It would be relevant to distinguish the news introduced on the market according to its nature. In particular, it is common practice to distinguish between “good news” and “bad news”. The core of the event study could be to demonstrate that the “good news” on the announcement date, defined as day 0, will lead to a substantial increase of cumulative abnormal returns of stocks under observation. Moreover, right after the day of the announcement, it is expected the cumulative abnormal returns stop increasing or decreasing. This phenomenon reflects the informationally Efficient Market Hypothesis. When the released information is incorporated into the marketplace, stock prices are adjusted accordingly to the news. Once stock prices have stabilised and absorbed the effect of the event made public, there is an equal chance that the abnormal returns will be negative or positive. In case a fluctuation of abnormal returns persists, the semi-strong form of the Efficient Market Hypothesis is violated. A further investigation could be to observe the trend of abnormal returns in the days before the announcement. If insider trading rules are followed, there should be no abnormal returns, as no disclosures have been made to the public before the announcement date. If, on the other hand, there is a breach of the insider trading rules, the presence of abnormal returns is observed before the announcement date. It means that some market participants know the news before the day it is made public. Both phenomena are common in the literature on the event study methodology, and they try to provide insights to contextualise the event under observation.

This thesis is structured as follows.

Chapter 1 explores the cornerstones of ESG investing, its relevance, and its critical issues, such as greenwashing. In particular, it frames the importance of sustainable investing by focusing on global ESG funds. It also delves into the development and purpose of the method for evaluating companies' ESG practices. The framework of the ESG rating system is based on the research and collaboration of two of the most prestigious companies in the field of data analysis and the production of reports and company assessments: Bloomberg and MSCI. Chapter 2 sets out the event study methodology and its most common variants in the literature. It is frequently used to ascertain and measure the impact of a given event on the value of a company and its stock price. The event under observation can be news officially released, in the specific case of this thesis, the annual publication of the ESG rating of listed companies. The formulas that make up the event study research technique are shown and explained. The market model used to analyse the excess returns of a company, or a group of companies is presented. For the purpose of the event study, abnormal returns, and cumulative abnormal returns (CAR) are particularly remarkable, and they are the core of the methodology applied in the data analysis. Chapter 3 organizes and illustrates the results of the event study with the help of tables and graphs. In particular, the data analysis focuses on the behaviour of abnormal returns and cumulative abnormal returns (CAR). The dataset for the event study is composed of a sample of one hundred and fifty listed companies belonging to the Dow Jones Sector Titans Index. Firms' stock prices and ESG ratings are downloaded from the Bloomberg database, and they cover the period from December 2014 to February 2022. Chapter 4 provides an explanation of the results of the previous chapter. It grasps their statistical meaning emphasizing their financial relevance. The chapter contextualizes the findings of the event study in the framework of ESG investing. The Appendix contains the script from the Python notebook used to perform the event study and the complete list of tables and graphs resulting from the data analysis.

# Chapter 1: The ESG Framework

Just few years ago, it was a niche investment strategy. Now Environmental, Social and Governance (ESG) has entered the mainstream. What has brought about this change? On one side, globally agreed principles driven by international organizations, stronger regulations, and growing evidence that an ESG strategy need not compromise the company's financial performance. On the other side, greater awareness of ESG issues and their importance for future generations, as well as for the global economy.

But what is ESG investing? It sums up the significant areas in which investors should act to align the global financial system with the needs of society, such as carbon emissions, water usage, and pollution, but also employees' health and safety, supply chain labour standards, privacy, and data security. Furthermore, ESG relates also on business ethics, corruption control and political instability, and conflicts of interest. Institutional investors know that valuation is about more than the profit potential, and ESG is not just a list of investment principles. It is about the impact a company has on its employees, shareholders, and community. It is a statement of ambition for the world as it should be. How can ESG investing add purpose to performance? ESG asset managers offer four main approaches. Exclusionary screening is about avoiding investments in companies or sectors that do not align with investors' values or meet norms or standards. Positive screening concerns of actively seeking out companies deemed well-performing on ESG measures. Thematic screening focuses on investments according to interest in specific ESG themes, such as clean and renewable energy. Impact investing examines investments in companies or funds intending to generate positive, measurable ESG impact and a financial return.

ESG investing is one of the actual trendiest phenomena in finance. Supporters say that being ethical and being profitable need not be mutually exclusive, benefitting shareholders, society, and the planet. However, critics argue that ESG products are not that different from other investments and complain that it can be hard to measure whether a company is doing the right thing. So, is ESG simply good branding? The idea of investment based on a set of principles and not merely for profit is as old as the concept of investing itself. For example, it is recognized that the pressure to avoid giving capital to South African companies between the 1970s and the 1990s was a factor that contributed to the end of apartheid. More recently, the impact of people's day-to-day lives on the environment has been the centre of attention. And that is affecting how investors allocate their capital. There is increasing understanding in society that people need to care about the climate, energy saving, and social conditions of workers. So, this attitude has shifted the focus of investment management firms. Moreover, evidence from academic research proved that the integration of ESG factors into portfolio management generates higher performance and lower risk. Such awareness has led fund managers to create financial products which invest in companies that meet their standards of being ESG-friendly. More investors are adding ESG funds and ESG ETFs to their portfolios. Only in the US, the share of investors that applied ESG principles to at least a quarter of their total investments jumped from 48% in 2017 to 75% in 2019. And just US professional investors are expected to expand their holdings in ESG assets from 12 trillion dollars in 2018 to 35 trillion by 2025, which is equivalent to 50% of their total investments. These forecasts were calculated before the Coronavirus pandemic, but the health emergency could further accelerate this trend. Somehow, Covid19 put a spotlight on the way companies operate or what is called company purpose. It underlined the needs of stakeholders, amplifying the idea of company risks and opportunities. The investment profile of the world's most significant ESG funds has changed over time, in particular, after Covid. About a decade ago, for example, they included substantial shares in major oil firms. In 2017, the composition of the MFS Value Fund, the world's largest ESG fund, was 13% of total investments in companies such as Shell, Total, and ExxonMobil. This allocation has fallen over the years and was less than 3% at the end of 2020.

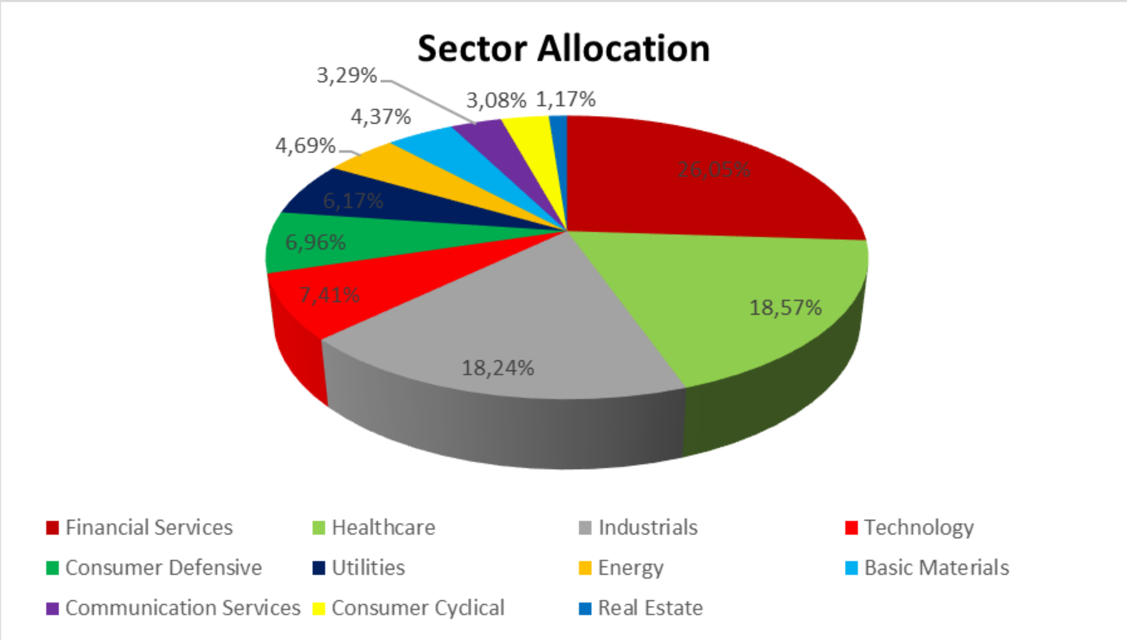


Figure 1: the MFS Value Fund Class I in 2022. Data source: Bloomberg.


Figure 2: the MFS Value Fund Class I in 2022. Data source: Bloomberg.

Anyway, several fund managers claim to promote sustainability, and, at the same time, they persevere in investing in oil companies, which are widely responsible for soaring levels of pollution and environmental damage. Investors need to bear in mind that ESG funds are portfolios devoted to getting a financial return. So they can be inclined to invest in groups of firms, industries or sectors that may or may not relate to the ESG framework. Definitely, ESG funds, as well as other investments, need to generate a profit. In fact, ESG funds have, on average, slightly outperformed non-ESG funds during the pandemic, and after the peak of Covid, they kept the trend. In part due to their holdings in tech stocks, which went strong during the pandemic. And ESG products have lower exposure in the energy sector, which was heavily hit by Covid19.

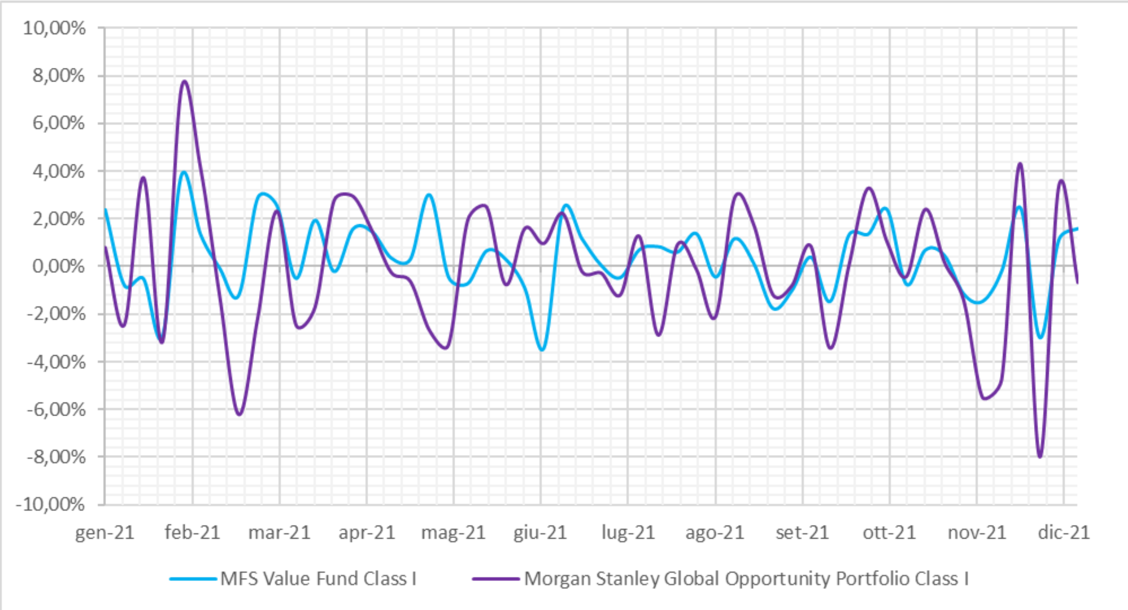


Figure 3: the returns of the ESG fund (MFS Value Fund Class I) and the non-ESG fund (Morgan Stanley Global Opportunity Portfolio Class I) in 2021. Data source: Bloomberg.

Take the online retail giant Amazon as an example. It is considered an ESG-friendly firm, even though Amazon registered a carbon footprint of over 50 million metric tons of $CO_2$ in 2019. With emissions rising by 15% compared to the previous year, the environmental concerns are not going away. Analysts specify that they do not have clear standards on what is positive or negative in the ESG framework. This translates into a lack of certainty for investors when allocating their capital to ESG funds. Always keeping Amazon as an example, a fund manager could consider it a positive investment in ESG terms. Conversely, another fund manager may consider it a negative investment as it does not meet the expected ESG standards. Beyond that, several popular ESG funds share portfolios with fashionable stocks with the same duality as Amazon. Some asset managers consider the Amazon's commitment to reduce its carbon emissions and become carbon neutral by 2040 as a reason it complies with the definition of an ESG-friendly firm. Fund managers could look at some firms complaining that, at the current state, their carbon footprint is not acceptable. The old-fashioned way investors addressed this problem was to divest their capital from all those companies that they did not consider ESG-friendly. Nowadays, asset managers do not consider divestment as the right way to induce firms to change. In fact, they prefer active engagement and step-by-step improvement of ESG goals. Additionally, investors and fund managers are pushing for companies to disclose a timeline of ESG achievements. What has just been said seems reasonable; however, critics find the yardstick too subjective. So they complain about a lack of transparency in the field of ESG investments. External analysts consider thousands of data points at the firm level. The problem is that companies either do not publish all these data points or the data they disclose does not tell relevant insights about how firms implement ESG principles. International organizations such as the United Nations and the European Commission are promoting common standards to remedy the companies' lack of transparency in disclosing ESG issues. And coming to the framework of ESG investing, fund managers should actively justify why their portfolios are considered ESG-friendly. Investors, on their own, should actively do some research and consultation work to ensure they are allocating their capital to funds that meet their ethical purposes. In this context, research, and rating agencies such as MSCI and Bloomberg play a fundamental role, which is discussed later in this chapter regarding the ESG rating system.

During the Covid19 crisis in 2020, one of the most popular ESG ETFs, the iShares ESG MSCI USA ETF, mimicked and barely outpaced the S&P 500.

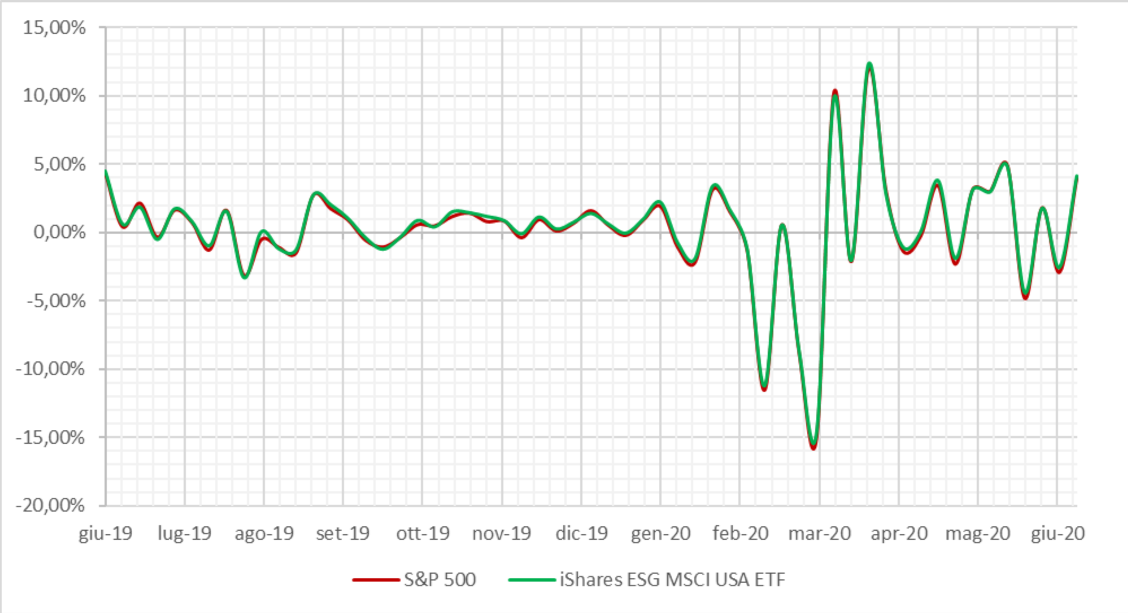


Figure 4: the returns of the iShares ESG MSCI USA ETF and the S&P 500 over the period from June 2019 to June 2020. Data source: Bloomberg.

So, who values ESG factors? Statistical interviews prove millennials, women, and high-net-worth individuals agree that ESG factors play a crucial role in their investment decisions. Millennials are the share of the world population that will generate wealth over the next couple of decades. Women are increasingly heads of households and are often in charge of investment decisions for their families. Wealthy individuals are the portion of the population that controls the largest proportion of assets today. According to research in the US[3], millennials alone will inherit and create wealth for about 80 trillion dollars over the next twenty years. To give an idea, a quarter of such wealth, 20 trillion dollars, was the size of the S&P 500 in 2020. The global pandemic of Covid19 highlighted a disconnection between the financial market and real everyday life. Millions lost their jobs, thousands went out into the street in protest, and the stock market surged. But there was a positive aspect, ESG investments also surged in 2020. While the stock market was volatile, investors were flocking to ESG investing strategy. The primary focus of investors has been and continues to be the "E" side in specific

[3] Bank of America, “US Trust Wealthy and Worth Survey”, 2018.

climate change issues. However, the pandemic has pushed interest in the "S" part, social issues such as labour conditions, the safety of workers, and the supply chain.

The data show that the capital injected into ESG funds peaked in 2020.[4] ESG fund managers explain they aim to attract investors looking for an ethical investing approach. In particular, it was clear that several of these funds outperformed the most relevant global market indexes. But regulators claim that sometimes ESG funds are not what they seem. The tension around such investment opportunities is motivated by the strategy used to build portfolios. Experts expose a few methods: exclusionary, single-theme, and best-in-class. When a portfolio manager takes on an exclusionary approach to construct an ESG fund, he decides what category of companies he does not want to include in a portfolio. The most commonly excluded are weapons manufactures, tobacco enterprises, and casino operators. When ESG funds follow a single-theme strategy, they choose a reference model, such as companies with female figures on the board of directors or companies that produce renewable energy. These funds help investors allocate capital to companies that may improve the environment and society. ESG funds can support investors in reaching their moral goals, but these funds have earned solid financial returns in recent years. A Wall Street Journal analysis of ESG equity funds found that 75% of such funds outpaced the average return of their benchmarks. According to the study, tech stocks have driven better performance. Typically ESG funds focus on these stocks, and half of the funds under observation hold Microsoft, Visa, and Apple. In other words, they are betting on big tech companies, but critics question these companies' inclusion in funds. Big tech firms are an interesting problem because several have established environmental practices; for example, Microsoft stated to become carbon negative by 2030. On the other hand, they may have severe problems with the social component of

[4] Bank of America, "10 Reasons to Care About ESG Investing", 2020.

ESG factors. For instance, some companies went through a scandal for the breach of data privacy security. Others have been criticised for the way they treat contractors and third-party workers. The last of the three approaches, a fund manager can use to build a portfolio, fits into this context. According to the best-in-class method, a fund manager may choose some companies that perform better overall than their peers in the ESG framework. For example, oil and gas firms can belong to an ESG fund if they perform better than their competitors in pursuing ESG principles. Following the best-in-class approach means that a company only needs to be better on ESG principles than other companies in the same sector, but investors do not know how the entire fund is structured. On average, investors do not care how the fund manager builds the fund and what companies make it up. Tickers of notable firms get their attention, or the well-known name of the fund is a certainty for them. It appears that a given fund is in line with an investor's moral and investment goals, but beneath the fund's surface are companies that are not aligned with ESG factors.

The noticeable problem is the lack of regulation and common standards in building an ESG fund. These details matter because they can influence how the fund performs. Critics say new ESG rules can compromise the funds' mission of getting profits for their too-high ethical standards. In the last months of 2019, the Securities and Exchange Commission (SEC) put US ESG funds under scrutiny. The SEC observed how fund managers evaluate the companies for composing the portfolios. The labelling is often based on incomplete information, sometimes distorted to attract the public towards investments that are not entirely sustainable or ESG based. Both EU and US Regulators are considering whether or not to change any rules. Several think there should be more standardisation across ESG global funds to prevent investors from being misled, and such a process is a step in the right direction to get the financial market thinking about sustainability. Analysts from MSCI expect ESG investing to be a standard option in portfolio construction for fund managers. And they pursue the aim of full transparency on ESG factors both for companies and for funds. So investors can feel comfortable when allocating their capital to align their financial and moral goals using improved tools and datasets.

**The Phenomenon of Greenwashing and the Voluntary Carbon Offset Market**

The growing interest of both professional and non-professional investors in ESG investing is now clear and evident in global finance. Indeed, global investment in sustainable ESG funds reached 35 trillion dollars in 2020. However, the high demand for ESG investments is balanced by a healthy dose of scepticism. That is because of concerns about greenwashing, where ESG funds' credentials are exaggerated and inflated. And their impact is neither sustainable nor beneficial.[5] Investment specialists of MSCI and Bloomberg believe that it is possible to see through the problem of greenwashing, but it takes time and effort, especially for passive tracker funds. The analysts of these two agencies observe that some important index trackers, labelled as either ESG or sustainable, attract many investors. But when they have a look inside these funds, there are firms that should not be there. And it is the moral duty of investors to ask themselves how such names could have ended up in a fund advertised as ESG. Specialists answer that the fundamental problem is the lack of common standards to identify ESG factors for portfolio construction. This industry is overloaded with hundreds of ESG ratings and rankings, most of which are self-reported by companies or funds. Firms and funds have their measurement mechanism, and many rating agencies do not share the same evaluation principles; such frameworks do make not meaningful the ESG scores that are produced. Independent agencies like MSCI and Bloomberg strongly believe that ESG ratings are a helpful starting point under two conditions. Agencies need to support investors in understanding and evaluating the sense of ESG scores and what they are telling about a company. And for more accurate measuring of the impact of an ESG fund, ESG scores should

[5] Lyon, T., & Maxwell, J. (2011). Greenwash: Corporate Environmental Disclosure Under Threat of Audit. Journal of Economic and Management Strategy, 20(1), 3–41.

be seen under the light of the United Nations Sustainable Development Goals (SDGs). The framework provided by the United Nations is a powerful tool for investors and rating agencies because it is a binary mean. A company under scrutiny can invest some capital to achieve the SDGs, or it can row against the SDGs away from the goal of pursuing sustainable development.

So far, digging into individual funds to check their ESG credentials has widely been up to investors, but financial watchdogs and ranking agencies are breaking new ground to combat greenwashing. The European Union's Sustainable Finance Disclosure Regulation pushes asset managers to meet strict standards to market their funds as ESG or sustainable. And the International Organisation of Securities Commissions based in Madrid wants members to review their rules and policies. The feeling is that regulations are becoming stricter and more enforceable, and a much more rigorous regime is coming. Specialists explain that technology is being harnessed to track and check the impact of ESG companies and funds. In particular, external ranking agencies are perfecting methods to see what fund managers are doing in terms of reporting and measuring the impact of ESG investments and compliance. MSCI and Bloomberg agree that data technology is making information gathering more comfortable for investors. They could find out firms with concrete sustainable projects and count on the truthfulness of information to construct portfolios with ESG solutions.

In the first nine months of 2021, global investors allocated 477.4 billion dollars into sustainable funds, well above the 366.6 billion dollars in 2020. But is this ongoing investing in ESG making a difference? CO2 emissions have more than doubled since 1970 and continue to accelerate, and the international commitment to limit global warming to 1.5 degrees by the end of the century is falling well short. Meanwhile, the output from oil, gas, coal, and other so-called "sunset industries" is still in high demand, and ironically, they are needed to produce new green technologies. Specialists believe a break will arrive, but it is a balancing act. Investors cannot just pull money out from their portfolios or companies close their businesses. Experts are inclined to persevere in achieving the objectives that have been outlined. The expertise of third-party agencies and analytical methods to avoid greenwashing are increasing and improving for those investors willing to scratch the surface to distinguish between genuine ESG opportunities and cheating ones.

Multinational agreements concerning environmental issues produce the expression "net zero", which means to cease raising greenhouse gases in the air. The first step to reaching the objective is lowering carbon emissions. But, in a 2022 essay, the UN Intergovernmental Panel on Climate Change (IPCC) stated that large-scale carbon dioxide removal is crucial to reach the goal of restricting global warming to 1.5 °C. The ways stated comprise planting trees, working soil to absorb more carbon, and installing devices that capture carbon dioxide from the atmosphere. Businesses and supporters of the IPCC are designing a new framework: the Voluntary Carbon Offset Market.[6] For each tonne of carbon dioxide participants withdraws from the environment, they can market a one-tonne carbon credit. Then, companies can offset their carbon emissions by purchasing these credits and proclaiming to be carbon neutral. However, carbon removal projects constitute about 3% of all undertakings publishing credits from January 2021 to April 2022. Today, most carbon credits on the marketplace are related to undertakings that seek to avoid emissions. For example, in an avoidance-based scheme, a supporter may purchase an extent of woodland and certify to maintain it. The supporter can trade carbon credits as a reward for the felling of trees prevented, only if the deforestation practice is lower than the local average. Avoidance-linked carbon credits are less expensive than those related to carbon dioxide removal, and several firms are exploiting them to declare carbon neutrality. Detractors state that several of these undertakings have far less effect than they assert. For instance, protecting one site from illegal

[6] Financial Times Moral Money, “Scrutiny of the Carbon Offset Market Is Growing”, 2022.

deforestation does not preserve the site just next to it, with identical environmental damage from its destruction.

The outcome of COP26 in November 2021 highlighted that a zero-emissions planet is coming. The Glasgow Climate Pact, arranged by almost 200 nations, radically cuts coal use, stops fossil-fuel subsidies, and engages governments to carbon emissions decreases. While many claim that the deal is excessively ambitious without an extreme conversion of the industrial sector, favourable ones say it is a good starting point. Carbon and its pricing persist in earning considerable importance as governments and businesses pursue reducing carbon emissions by buying carbon offset credits. The analysts of Bloomberg investigate possible market developments founded on various regulatory systems for carbon offsets, described as verified lowering in climate-warming gases employed to balance for emissions that happen elsewhere. Investigation outcomes show that an oversupplied voluntary market may stimulate a protracted price increase. On the other side, only carbon-removal projects may generate a pricing wave of more than 3000% by the end of 2029.

The COP26 environment panel encouraged a multinational motivation to diminish emissions. Nevertheless, the law of carbon-cutting projects is a recent notion afflicted by greenwashing, i.e. producing a faulty image or misleading statement about how a firm’s behaviour is environmentally friendly. Solely a part of projects extract carbon dioxide from the atmosphere, and regulations change from nation to nation, with carbon emissions frequently unregulated. Nowadays, also the voluntary offset market is unregulated, and accusations of greenwashing are extending against firms employing low-quality offsets to declare carbon neutrality. A new-born entity, the Integrity Council for the Voluntary Carbon Market is planning new measures to support offset customers to recognise high-quality projects which satisfy specific conditions, such as longevity and measurability. The Council's experts say that it is not straightforward to detect projects that provide the advantages they declare. The Integrity Council plans to formalise the arrangements for offsets, making them smoothly exchangeable on the marketplace, but assessing the comparative advantage of different projects is complicated. Enhancing the efficacy of the offset market is challenging, but when the regulatory regime is implemented, businesses will require to be careful when selecting their offsets.

**The ESG Rating System: MSCI and Bloomberg Reporting and Scoring Activity**

Those favourable to ESG investing believe there is a way to align corporate interests and profits with protecting the planet. In theory, the ESG system should help. Analysts build the whole framework on the idea that investing in companies that perform well allows investors to profit by doing something good for the world. The volume of ESG investments and historical data show that this could be the best opportunity for future investing. Underneath this entire system there are ESG ratings that look like credit ratings of companies but are based on unregulated data. Talking about ESG also means knowing what is inside ESG scores and scores are what underlie the decision-making process of institutional and non-institutional investors. The ESG ratings focus on what is significant to a company's bottom line. Bloomberg specialists explain that they found the foundation of such a multi-trillion-dollar game appears to be something that, in reality, is not. And investors have a vague idea of what an ESG score is.

Nowadays, there are about 160 different agencies that sell data, reports, and ratings of publicly listed companies on ESG factors. There are so many providers because it is an unregulated framework based on subjective parameters and methods of evaluation. However, there is one company that appear to be dominating in such a business, that is, MSCI. In this context, Bloomberg explains why it has chosen to collaborate constructively with MSCI. In fact, this company offers a rating system built on multifactor scores converted into ratings familiar to investors as they appear like credit ratings. In particular, AAA is at the top of the rating scale, and CCC is at the bottom. By mimicking the credit rating system, which is regulated internationally, MSCI has created an aura of respectability and confidence for investors.[7]

| ESG Ratings | | |
|---|---|---|
| **MSCI** | **Bloomberg** | **Category** |
| AAA | 90 ⟶ 100 | |
| AA | 80 ⟶ 90 | **Leader** |
| A | 70 ⟶ 80 | |
| BBB | 60 ⟶ 70 | **Average** |
| BB | 40 ⟶ 60 | |
| B | 20 ⟶ 40 | |
| CCC | 0 ⟶ 20 | **Laggard** |

Figure 5: the scale of MSCI and Bloomberg ESG ratings.

MSCI has been in the business for two decades, and it started as a company that arranged stocks in an electronic index. Since then, they began providing indexes for a wide range of aspects on financial activities, and because of the increasing demand of social responsibility indicators, they built up a proprietary ESG metric. According to a recent estimate, 40 cents on every dollar spent on ESG ratings is owned by MSCI. Considering a large company listed and belonging to a world index such as one of the sector indices of the Dow Jones or the S&P 500, the ESG score can significantly impact the company's trend line lowering the cost of capital. Moreover, a rating considered "leader" can help the company enter an ESG world fund. When a firm's score goes up, MSCI produces an updated report showing the relevant factors that led the company to increase its rating. Bloomberg specialists find that half of the companies out of a sample of 150 got upgraded just for sitting, still because MSCI changed the way it weighted the score or the method for assessing the rating.

A typical example is McDonald’s. If considering total emissions it appears the company run a business that is not *sustainable*, since it produces emissions

[7] Berg, F., Heeb, F., & Kölbel, J., F. (2022). The Economic Impact of ESG Ratings. Available at SSRN.

compared with the whole Portugal. The larger part of these emission are related to the production and use of beef. But when MSCI gave McDonald's an ESG rating upgrade from BB to BBB in April 2021, it did that by reducing the assessment of emissions from 5% to nothing. MSCI underlined a new initiative that McDonald's launched around recycling. The recycling initiative came from installing bins in selected locations in France and the UK. But, looking carefully, in France and the UK, there was an upcoming regulation forcing fast food companies to install recycling bins in given locations. So, McDonald's got a score upgrade for doing the bare minimum that it should have done anyway, leaving aside the fact of responsibility for emissions into the atmosphere. McDonald's declined to comment on its ESG rating from MSCI. In practice, change in ratings may just depends on expectations or announcements regarding future company's policies, and not on real improvements in their best practices.

This example is not unique and ties in perfectly with Bloomberg's study of 150 upgrades in the ESG score. The 150 listed companies belong to the S&P 500 Index and the relevant period is from January 2020 to June 2021. Nearly half of the companies got upgraded in their ESG rating without even fully disclosing their carbon emissions. Analysts listed the factors that led to such upgrades: corporate behaviour, employment practices, data protection, structure of boards, and carbon emissions reduction. Only one company out of the 150 received an upgrade thanks to a significant lowering in carbon emissions. The rating system and the pure scores create the opposite framework that many investors believe they are looking at when seeing a leader-rated company. They think the company has robust Environmental, Social and Governance practices with a significant positive impact on sustainability. But what scores measure is the other side of the coin. Is the firm sustainable? Is the value to shareholders sustainable? What is the impact of water shortage, pollution, and climate change on the company? The MSCI Chairman and CEO Henry Fernandez explains: "*MSCI is the leading provider of investment tools in the world.*" He goes on to say: "*Our raw materials are* *sophisticated models, big data, and advanced technology.*" At COP26, world governors met the significant businesses playing a role in fighting climate change and are fully integrated into the ESG rating system. Fernandez was asked if the average investor has any idea that the lens of the system is *the impact of the world on the company and not the impact of the company on the world*. He replied: "*The average investor has no idea about it.*" And he added: "*Even investment managers putting together stocks into funds do not grasp it.*"

By the start of 2019, it was clear that millennials and their pension funds stimulated a massive shift from conventional investments to ESG investing. This new way of thinking about investing was taking hold and was creating the demand for investment managers to build funds to make the world a better place. In recent years, ESG scores have been under the scanner, and the rating system appears to be the "Wild West". International Regulators are trying to figure out a way to standardise the ESG rating assessment method and be sure that ESG scores do not end up greenwashing a company's activities. The Securities and Exchange Commission (SEC) has produced a regulatory agenda to bring more regulation concerning ESG factors disclosure.[8] In the future, it will be critical to see the effects of SEC standards and whether or not they can crack down on some of the claims to strengthen ESG investing for what it is. There is no question that the action of shareholders can influence companies to move away from practices that cause damage to the planet or society. The new generations of investors are demanding that their investments and pensions not be allocated to funds that destroy the world in which they live.

[8] Washington D.C., June 11, 2021: "The Office of Information and Regulatory Affairs today released the Spring 2021 Unified Agenda of Regulatory and Deregulatory Actions. The report, which includes contributions related to the Securities and Exchange Commission, lists short- and long-term regulatory actions that administrative agencies plan to take."

## Chapter 2: The Event Study Methodology

In this section, the econometric methodology labelled as event study is described.[9] Several times it is necessary to measure the effect of a given economic, financial, social, or political event on the companies' stock price. The short-term event study may provide a reliable measure of such effect. This methodology takes as input financial market outputs to explore the trend of firms' security prices before and during the event under observation. The final goal is to define a statistical test in which, the null hypothesis is the event under observation does not affect the distribution of excess returns of a number of selected companies, i.e. not causing any abnormal returns. In a nutshell,

$$\begin{cases} H_0 : AR_{it} = 0 \\ H_1 : AR_{it} \neq 0 \end{cases}$$

Where $H_0$ is the null hypothesis and $H_1$ is the alternative hypothesis. $AR_{it}$ is the abnormal return of stock $i$ at time $t$ with $T_1 \leq t \leq T_2$, i.e. in the event window.

Also note that, according to the semi-strong form of the Efficient Market Hypothesis (EMH), asset prices already reflect all publicly available information.[10] Thus it is impossible to earn abnormal (excess) returns using fundamental or technical analysis. Computing eventual abnormal (excess) returns with the event study methodology would prove the violation of the semi-strong form of the EMH. Excess returns are companies' stock returns minus a fixed risk-free rate, such as the US Treasury Bill, if we consider as benchmark an asset traded in the US market. The statistical issue is then to determine and compute abnormal returns. This is typically done by defining a statistical model that settles the *normal* return, and then the abnormal is computed as the difference between actual observations and the expected (or normal) ones.

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[9] MacKinlay, A. C. (1997). Event Studies in Economics and Finance. Journal of Economic Literature, 35(1), 13–39.

[10] Fama, E., Fisher, L., Jensen, M., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. International Economic Review, 10, 1–21.

The first task in this setting, is to define the timeline for the event, focusing on day 0, i.e. the date of the public event under scrutiny. On this date, an abnormal return may occur because the market is responding appropriately to the news or some public events. However, if the abnormal returns are lingering some days after the event date, it means that there may be an inconsistency with the semi-strong form of the Efficient Market Hypothesis. In fact, this feature may be caused by the market, that is not quickly incorporating the newly available information into stock prices. Sometimes it is also interesting to observe the behaviour of the abnormal returns some days before the event date. In this case, if abnormal returns are displayed before day 0, it means there may be an infringement of insider trading rules, where some investors could exploit insider information to anticipate the market. To capture the dynamics of the abnormal returns, the event study should be conducted through an observation period called the event window. The event window is centred on the event date and includes a specific time before and after such day.

A second task, necessary to implement the procedure, is to set an estimation window, that allows to measure normal returns in a timespan where it is expected no unusual news hit the market. This time in some way represents a benchmark. The average returns on a stock are the reference to evaluate the significance of the abnormal returns on the same stock.

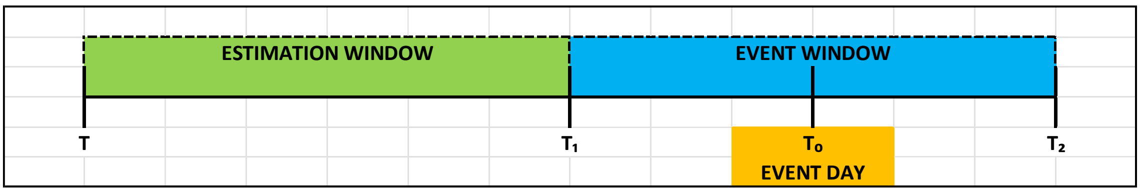


Figure 6: the timeline of the event study methodology.

In particular, $T_1$ is the opening date of the event window, $T_0$ is the event date, and $T_2$ is the closing date of the event window. T indicates the starting date of the estimation window, which closes in correspondence with the opening date of the event window, and they do not overlap.

**The Structure of the Event Study**

The initial steps of performing an event study are to determine the event of interest and specify the time over which the stock prices of the companies under observation are studied, i.e. the event window. Moreover, the stock prices are observed on a daily basis, so the event window includes the event date (day 0), some days before, and some days after the event date. The event window is more extensive than the exact date of interest and it allows investigation of periods enclosing day 0. So, the method aims at catching the impact of the news on the stock prices, which appear before and after the stock market closure on the event date. And the pre-event period is also relevant for the study. To evaluate the outcome of the event, it is necessary to calculate the abnormal returns. The abnormal return ($AR_{it}$) of stock $i$ at time $t$ is given by:

$$AR_{it} = R_{it} - E(R_{it}|X_t)$$

In particular, $R_{it}$ is the observed stock $i$ return in the event window and $E(R_{it}|X_t)$ is the stock $i$ normal return expected at $t$ from the estimation window. Moreover, $X_t$ is the conditional information of the normal return (information from the estimation window).

This chapter presents two different models to compute the abnormal returns of a stock: the simplest is the Constant Mean Return Model, whereas the most general one is the Market Model. The first one considers the average return of a stock constant across time, whereas the latter implies a linear relationship among stock and market returns. The analyst should choose the estimation window appropriately to get an accurate estimate of the normal returns. In case of enough daily data, the estimation period should contain several months, or the best option is the length of the trading year. Such a period is the benchmark for the estimation of the parameters in the Market Model. Estimation and event windows must not overlap to prevent the model to predict normal returns affected by the event itself.

Afterwards, the analyst should build the testing environment for the abnormal returns. Significant concerns are determining the null hypothesis and the methods to join the individual companies' abnormal returns. The representation of the practical outcomes follows the structure of the econometric skeleton. The analyst should make the statistical assumptions that the stock returns are independent and normally distributed in time. Such assumptions are valid for both the Constant Mean Return Model and the Market Model. Carrying out event studies with just one or two event observations implies that the outputs may be strongly affected by the behaviour of one or two companies. Understanding this, is crucial for measuring the significance of the outcomes. The study of empirical outputs give the possibility to capture the impact, if any, of the event under observation, its extent, origins, and reasons.

**The Constant Mean Return Model**

The Constant Mean Return Model is the simpler model, and according to this model the abnormal return ($AR_{it}$) of stock $i$ at time $t$ is:

$$AR_{it} = R_{it} - \bar{R}_i$$

Where $R_{it}$ is the return of stock $i$ at time $t$ in the event window and $\bar{R}_i$ is the average return of stock $i$ over the estimation window, i.e. the benchmark period not influenced by the event under observation.

Nevertheless, empirical studies found comparable outcomes to those of more complete models, such as the Market Model.[11] The most relevant issue is to consider models for the returns that allow for reduced estimated conditional variances. This helps on defining more accurate event tests. Obviously, the conditional variance diminishes when using more complex models. In case of daily data, the Constant Mean Return Model can employ nominal returns;

[11] Brown & Warner (1980, 1985).

however, the best choice should be to use returns in excess of the risk-free rate. Such a model is a functional step towards understanding the Market Model.

**The Market Model**

This method is based on the single-index model, which implies that the return ($R_{it}$) of stock $i$ at time $t$ is given by a firm-specific factor and a market factor.

$$R_{it} = \alpha_i + \beta_i R_{Mt} + \varepsilon_{it}$$

In this equation, the parameters $\alpha_i$ and $\beta_i$ are the average return the stock $i$ would have in time of a zero return on the market, and the sensitivity of the return of the market portfolio, respectively. $R_{Mt}$ is the market portfolio return at time $t$. The disturbance term ($\varepsilon_{it}$) is the portion of the return of stock $i$ at time $t$ deriving from a firm-specific event. The disturbance term ($\varepsilon_{it}$) represent a measure for abnormal returns and can be explained as the unexpected return resulting from the event. The computation of the abnormal return of stock $i$ at time $t$ is given rearranging the equation above.

$$\varepsilon_{it} = R_{it} - (\alpha_i + \beta_i R_{Mt})$$

Note that in the estimation window:

$$E(\varepsilon_{it}) = 0$$

$$\sigma^2(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$$

The disturbance term ($\varepsilon_{it}$) is the element due to the event under observation and it is the return of stock $i$ at time $t$ above the market portfolio return forecasted over the same period. In practice, it is common to use a broad market index as the market portfolio. The Market Model is a statistical improvement compared to the previous model. By removing the part of the stock return, which is due to the deviation of the market portfolio return, the variance of the abnormal return decreases. This solution drives increased knowledge to catch the impact of the event under study. The advantage of employing the Market Model relies on the $R^2$ of the market model regression via Ordinary Least Squares (OLS) estimation.

The larger the $R^2$, corresponds to a smaller variance of the abnormal return, improving the better accuracy of the test.

In particular, the parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimated via OLS regression of the return of stock $i$ at time $t$ ($R_{it}$) on the market portfolio return at time $t$ ($R_{Mt}$) over the estimation window. The estimator for the abnormal return of stock $i$ at time $t$ is given by:

$$\widehat{AR}_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{Mt})$$

It can be observed that the abnormal returns estimators are normally distributed. In particular, $\widehat{AR}_{it} \sim N\left[0, \sigma^2(\widehat{AR}_{it})\right]$, where the conditional mean is zero and the conditional variance is:

$$\sigma^2\left(\widehat{AR}_{it}\right) = \sigma^2_{\varepsilon_i} + \frac{1}{T_1 - T}[1 + \frac{(R_{Mt} - \hat{\mu}_{Mt})^2}{\hat{\sigma}^2_{Mt}}]$$

Here, $\sigma^2_{\varepsilon_i}$ is the disturbance variance and $T_1 - T$ is the extension of the estimation window. The wider the extension of the estimation window, the lower the second part of the equation. When it is reasonably close to zero, the sampling error of the model's parameters disappears. So, the variance of the abnormal return is just equal to: $\sigma^2\left(\widehat{AR}_{it}\right) = \sigma^2_{\varepsilon_i}$.

Moreover, the analyst can consider the abnormal returns independent over the event window. Empirically can be useful to select the extension of the estimation window sufficiently wider to consider the impact of the second part of the equation on the abnormal return's variance not significant. For instance, a wise choice is extending the estimation window, i.e. the benchmark period, for the number of days of trade in a calendar year.

The natural candidate for the test statistic of the abnormal return estimator ($\widehat{AR}_{it}$) of stock $i$ at time $t$ is thus given by:

$$\widehat{SAR}_{it} = \begin{cases} \widehat{AR}_{it} / \sqrt{\sigma^2(\widehat{AR}_{it})} & for\ T \leq t \leq T_2 \\ \dfrac{\widehat{AR}_{it} / \sqrt{\sigma^2(\widehat{AR}_{it})}}{\sqrt{\sigma^2\left(\widehat{AR}_{it} / \sqrt{\sigma^2(\widehat{AR}_{it})}\right)}} & for\ t = T_0 \end{cases}$$

The test statistic ($\widehat{SAR}_{it}$) denotes the standardised abnormal return, in particular, it is distributed as a standard normal: $\widehat{SAR}_{it} \sim N(0,1)$. For stock $i$, the standardised abnormal return is computed according to the first option for each day in the estimation window and in the event window ($T \leq t \leq T_2$). And it is calculated following the second option on the event date, i.e. the day 0 ($t = T_0$).

An interesting generalization of the testing procedure implies the aggregation of the abnormal returns over the event window. This help understanding the impact of the event not just on a single day, but in the complete event time interval.

The aggregation is made for each stock through a given period. This is the notion of the cumulative abnormal return (CAR) for stock $i$ across the event window. So, for $T_1 \leq t \leq T_2$, the cumulative abnormal return estimator is given by:

$$\widehat{CAR}_i(T_1, T_2) = \sum_{t=T_1}^{T_2} \widehat{AR}_{it}$$

The cumulative abnormal return included in the interval [$T_1$, $T_2$] is obtained summing the abnormal returns in the event window. Moreover, knowing that $\sigma^2(\widehat{AR}_{it}) = \sigma^2_{\varepsilon_i}$ and it is constant in time, the variance of $\widehat{CAR}_i(T_1, T_2)$ is computed as:

$$\sigma^2\left(\widehat{CAR}_i(T_1, T_2)\right) = (T_2 - T_1 + 1)\sigma^2_{\varepsilon_i}$$

As the estimator for the variance relies on the conditional variance of the abnormal return ($\sigma^2(\widehat{AR}_{it}) = \sigma^2_{\varepsilon_i}$), the estimation window should be wide enough to decrease as possible the estimation error for the parameters.

Under the null hypothesis the cumulative abnormal return is normally distributed as follows:

$$\widehat{CAR}_i(T_1, T_2) \sim N[0, (T_2 - T_1 + 1)\sigma^2_{\varepsilon_i}]$$

Also for the $\widehat{CAR}_i(T_1, T_2)$ is provided an adequate test statistic over the event window [$T_1$, $T_2$]:

$$\widehat{SCAR}_i(T_1, T_2) = \frac{\widehat{CAR}_i(T_1, T_2)}{\sqrt{\sigma^2\left(\widehat{CAR}_i(T_1, T_2)\right)}}$$

The test statistic ($\widehat{SCAR}_i(T_1, T_2)$) denotes the standardised cumulative abnormal return distributed as a standard normal: $\widehat{SCAR}_i(T_1, T_2) \sim N(0, 1)$.

Finally, the analyst can examine the average abnormal return for the sample of stocks over the event window [$T_1$, $T_2$]. In particular, the average and its variance are given by:

$$\widehat{AAR}_t = \frac{1}{n}\sum_{i=1}^{n} \widehat{AR}_{it}$$

$$\sigma^2(\widehat{AAR}_t) = \frac{1}{n^2}\sum_{i=1}^{n} \sigma^2(\widehat{AR}_{it})$$

Where $t$ is included in the interval [$T_1$, $T_2$] and $n$ is the number of stocks in the sample of the study. Once again, the test statistic for the average abnormal return is computed as:

$$\widehat{SAAR}_t = \frac{\widehat{AAR}_t}{\sqrt{\sigma^2(\widehat{AAR}_t)}}$$

On a date $t$ in the event window: $\widehat{SAAR}_t \sim N(0, 1)$.

It is worth noting that the assumptions for the Market Model are strictly related to the regression and the formulas presented in the chapter. First, the benchmark period and the sample of stocks are sufficiently wide to imply the normal distribution. Second, the abnormal returns and the cumulative abnormal returns are independent across stocks over the event window. And third, the variances computed are constant over the event window.

The most remarkable event studies have been performed in the field of corporate finance. The empirical analysis in this area of finance can count on a reliable and tested methodology. The survey of corporate events generally centres on the behaviour of the abnormal returns in a period close to the date of the announcement. A fundamental factor for conducting a meaningful event study is the opportunity to exactly detect the date of the event under observation, i.e. day 0. Moreover, also building an appropriate event window and estimation window is functional for the good performance of the study. The analyst should remember to construct the event window not too large but, at the same time, consider the movements of a rational marketplace, i.e. the behaviour of investors. So, it is common practice to include in the event window a few days before and after the event date in order to grasp the presence of any abnormal returns. On the other side, the estimation window should be large enough to assume such a period as a statistically significant benchmark for the regression of the parameters of the Market Model. The optimal choice would be the number of trading days in a year. Both the number of stocks in the sample and the number of days in the estimation window must be high enough to use the normal distribution assumption.

Empirical evidence proves that stock prices react to the news, so the metrics to judge the significance of abnormal returns (if any) is given by the cumulative abnormal returns and the average abnormal returns. The first is an aggregate measure for each stock of the sample over the relevant period, i.e. the event window. The latter is an average measure of the returns of a set of stocks over the same period. Finally, according to the Market Model, the market portfolio on which each stock of the sample is regressed is usually a market index. In particular, often the stocks of the study belong to this broad market index.

This chapter has presented the short-term event study methodology. Namely, the event window closes just a few days after the day 0. The two models that have been outlined show the comparable worths of the parametric model against the non-parametric model. The Market Model fits for event studies with daily data for stock prices and a sample of stocks belonging to relevant market indexes, like the S&P 500 or Dow Jones indexes. The Constant Mean Return Model is useful for providing to the analyst an immediate and effective measure of the abnormal returns in the event window with respect to the benchmark period. Lastly, empirical research demonstrates that event studies focused on the impact of a single event, without the overlapping of multiple events, avoid the issue of cross sectional correlation between the returns of the stocks in the sample.

# Chapter 3: The Reaction of the Stock Market Following the Disclosure of ESG Ratings

As the first step, in this analysis, 150 listed companies that belong to the Dow Jones Sector Titans Index are selected. The sample of firms is in line with the interest in the ESG issues discussed in Chapter 1, as they represent high-capitalisation companies committed to maintaining a virtuous image while operating in the ESG framework. In this context, the event under observation for performing the event study is picked out. In particular, it has been chosen the annual disclosure date of the ESG ratings of the 150 listed companies. Every year on December 31, Bloomberg, in collaboration with MSCI, publishes the ESG scores of listed companies. Such a date is taken as the relevant event date, i.e. the day 0, for the event study. The stock returns, as well as the ESG ratings, came from the Bloomberg database, and they include more than seven years of trading from December 2014 to February 2022. After selecting the sample of stocks and the event under observation, the first task for proceeding with the event study is to specify the period over which the stock returns are examined. The event window opens twenty days before the event date and closes twenty days after it. The estimation window covers 253 trading days before the opening of the event window. In particular, according to NYSE and NASDAQ, 253 is the average number of trading days per year. The estimation window closes when the event window opens, so the two windows do not overlap, ensuring the independence between the excess returns during the benchmark period and the event period.

The event study investigates the behaviour of stock prices over a few days before and after the ESG ratings release. This methodology assesses the response of investors to the announcement, judging the published score of each company positively or negatively. The underlying concept is the Efficient Market Hypothesis saying that when further knowledge becomes public, market participants completely take it. Therefore, stock price’s shifts incorporate the discounted value of actual and future company’s cash flows. The fundamental notion applied in the methodology is that the answer of investors to a given news can be captured by comparing each observed return in the event period with each return expected, or predicted, in the benchmark or estimation period. Such a difference is the abnormal return. If market participants respond (un) favourably to the ESG announcement, (negative) positive significant abnormal returns are predicted. This method is founded on the broad judgment of a statistically considerable number of investors, who readily elaborate the news to evaluate a company's market value. The analysis that has been performed and is presented in this chapter employs the Market Model discussed in chapter 2. All the computations have been done through Python, especially by using the libraries `pandas` and `statsmodels`.

The daily prices of the 150 stocks in the sample over the seven years period are obtained from Bloomberg. Then, excess returns are computed as the difference between each stock return and the risk-free asset, i.e. the US Treasury Bill. For the Market Model, also the excess returns of the Dow Jones Sector Titans Index (ticker: DJTSEC) over the relevant period are calculated.


Figure 7: the excess returns of the 150 stocks and the DJTSEC index over the period from December 2014 to February 2022.

The ESG ratings over the seven years period are published on December 31 of the following years: 2015, 2016, 2017, 2018, 2019, 2020, and 2021. So, to grasp the impact of the disclosure on stock prices year-by-year, are performed seven different event studies. The estimation window lasts 253 days, and the event window includes 41 days, i.e. 20 days before the day 0, the event date, and 20 days after the day 0. The structure of the relevant periods is the same each year across the study.

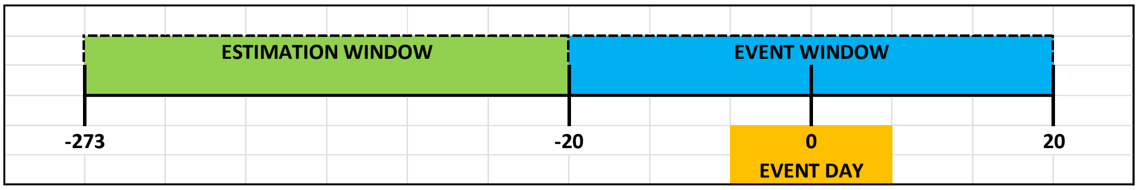

Figure 8: the timeline of the seven event studies.

Here, T = -273, $T_1$ = -20, (T - $T_1$) = -253, and $T_2$ = 20. Some experiments with narrower event windows, symmetrical and asymmetrical with respect to day 0, have been performed. The regression's result is basically the same. After imposing the restrictions of figure 8, the Python routine has been run. It extracted the excess returns of the 150 stocks and the DJTSEC market index over the estimation window. The Market Model has been implemented for each stock in the sample as follows:

$$R_{it} = \alpha_i + \beta_i R_{DJTSECt} + \varepsilon_{it}$$

The excess returns of the stocks and the DJTSEC market index are given ($R_{it}$ and $R_{DJTSECt}$). The parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimated via OLS, by regressing each $R_{it}$ on $R_{DJTSECt}$. After executing 150 regressions, the abnormal return for each stock over the event window has been computed according to:

$$\widehat{AR}_{i[-20,20]} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{DJTSECt})$$

This formula provided the abnormal return for each stock over the event window, i.e. 41 days. The width of the estimation window (253 trading days) is statistically significant to assume:

$$\widehat{AR}_{it} \sim N\left[0, \sigma_{\varepsilon_i}^2\right]$$

Because: $\sigma^2\left(\widehat{AR}_{it}\right) = \sigma_{\varepsilon_i}^2 + \frac{1}{T_1 - T}\left[1 + \frac{(R_{Mt} - \hat{\mu}_{Mt})^2}{\hat{\sigma}_{Mt}^2}\right]$

With: $\frac{1}{253}\left[1 + \frac{(R_{Mt} - \hat{\mu}_{Mt})^2}{\hat{\sigma}_{Mt}^2}\right] \cong 0$

Once obtained the abnormal return for each stock on each day of the event window, the analysis need to be performed on two measures: the cumulative abnormal return (CAR) and the average abnormal return (AAR). The CAR is an aggregate measure of the abnormal returns stock-by-stock over the event period. The AAR is an average measure of the abnormal returns of all the stocks in the sample day-by-day over the event window.

**The Procedure for the Event Study of the AAPL Stock for the First Year of the Seven Years Period Under Study**

Apple Inc. (ticker: AAPL) is the first company of the sample of listed companies belonging to the Dow Jones Sector Titans Index. The methodology implemented in this thesis is described in detail for this time series. Then, the generalization to the other stocks is trivial, and implemented recursively. In particular, the AAPL stock is taken as an example of the methodology that has been applied for all the stocks of the sample over the seven years under study. The relevant event is the disclosure of the ESG rating on December 31, 2015. The event window counts 41 trading days from 2015-12-02 to 2016-01-29. The estimation window lasts 253 trading days and closes on 2015-12-02. Once computed the excess returns of the AAPL stock and DJTSEC market index over the seven years of the study, have been extracted those in the estimation window year-by-year. The Market Model for the AAPL stock is given by:

$$R_{AAPLt} = \alpha_{AAPL} + \beta_{AAPL} R_{DJTSECt} + \varepsilon_{AAPLt}$$

Where $R_{AAPLt}$ and $R_{DJTSECt}$ are the excess returns of the AAPL stock and DJTSEC market index. The abnormal returns of the AAPL stock over the event window, i.e. ([-20, 20]) are calculated as:

$$\widehat{AR}_{AAPL[-20,20]} = R_{AAPL[-20,20]} - (\hat{\alpha}_{AAPL} + \hat{\beta}_{AAPL} R_{DJTSEC[-20,20]})$$

In particular, the AAPL stock's abnormal returns are normally distributed as:

$$\widehat{AR}_{AAPL[-20,20]} \sim N\left[0, \sigma^2_{\varepsilon AAPL}\right]$$

The parameters $\hat{\alpha}_{AAPL}$ and $\hat{\beta}_{AAPL}$ are estimated over the 253 days estimation window, i.e. ([-273, -20]) via OLS, by regressing $R_{AAPLt}$ on $R_{DJTSECt}$.

```
Dep. Variable:                   AAPL   R-squared:                       0.548
Model:                            OLS   Adj. R-squared:                  0.546
Method:                 Least Squares   F-statistic:                     304.2
Date:                Sat, 21 Jan 2023   Prob (F-statistic):           3.68e-45
Time:                        14:22:08   Log-Likelihood:                 660.99
No. Observations:                 253   AIC:                            -1318.
Df Residuals:                     251   BIC:                            -1311.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0003      0.001      0.237      0.813      -0.002       0.002
DJTSEC         0.7686      0.044     17.440      0.000       0.682       0.855
==============================================================================
Omnibus:                       21.044   Durbin-Watson:                   1.943
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               77.914
Skew:                           0.065   Prob(JB):                     1.21e-17
Kurtosis:                       5.715   Cond. No.                         39.3
```

Figure 9: the result of the AAPL stock OLS estimation.

The program gave back the abnormal returns of the AAPL stock day-by-day over the event window, i.e. $\widehat{AR}_{AAPL[-20,20]}$. Then, the test statistic for each abnormal return and the corresponding p-value are computed.

$$\widehat{SAR}_{AAPL[-20,20]} = \widehat{AR}_{AAPL[-20,20]} \Big/ \sqrt{\sigma^2\left(\widehat{AR}_{AAPL[-20,20]}\right)}$$

Where the variance of each abnormal return in the event period is given by:

$$\sigma^2\left(\widehat{AR}_{AAPL[-20,20]}\right) = \sigma^2_{\varepsilon_{AAPL}}$$

The variance-covariance matrix has been developed using the program. It is a useful tool for calculating the variance of each stock over the entire period of the study. Moreover, a graphical representation of the variance-covariance matrix, i.e. the diagonal of the matrix, has been constructed, providing an immediate image of the distribution of the variance, of its maximum and minimum values, and of its average in the period of the seven years under observation. The typing of the program, all the computations, and the complete list of results for the seven years under observation are shown in the Appendix. To provide an idea of the study, the data of the AAPL stock from 2015-12-02 to 2016-01-29 (the first year under study) are presented as an example.

| Date | AAPL | SAR(AAPL) | p-SAR(AAPL) | | Date | AAPL | SAR(AAPL) | p-SAR(AAPL) |
|---|---|---|---|---|---|---|---|---|
| 2015-12-02 | 0.009733 | 0.546270 | 0.584880 | | 2016-01-01 | 0.005997 | 0.336594 | 0.736423 |
| 2015-12-03 | -0.009677 | -0.543111 | 0.587053 | | 2016-01-04 | -0.002188 | -0.122809 | 0.902259 |
| 2015-12-04 | 0.009414 | 0.528339 | 0.597264 | | 2016-01-05 | -0.009291 | -0.521446 | 0.602056 |
| 2015-12-07 | -0.012537 | -0.703603 | 0.481680 | | 2016-01-06 | -0.015909 | -0.892869 | 0.371927 |
| 2015-12-08 | 0.020552 | 1.153483 | 0.248712 | | 2016-01-07 | -0.058892 | -3.305283 | 0.000949 |
| 2015-12-09 | -0.025999 | -1.459185 | 0.144514 | | 2016-01-08 | 0.014301 | 0.802638 | 0.422184 |
| 2015-12-10 | 0.002225 | 0.124858 | 0.900636 | | 2016-01-11 | 0.006126 | 0.343845 | 0.730963 |
| 2015-12-11 | -0.039107 | -2.194851 | 0.028174 | | 2016-01-12 | 0.021847 | 1.226167 | 0.220136 |
| 2015-12-14 | 0.002668 | 0.149743 | 0.880968 | | 2016-01-13 | -0.039627 | -2.224046 | 0.026145 |
| 2015-12-15 | -0.027459 | -1.541126 | 0.123286 | | 2016-01-14 | 0.016554 | 0.929069 | 0.352853 |
| 2015-12-16 | 0.005300 | 0.297432 | 0.766137 | | 2016-01-18 | -0.002685 | -0.150690 | 0.880221 |
| 2015-12-17 | -0.025525 | -1.432547 | 0.151987 | | 2016-01-19 | -0.008971 | -0.503473 | 0.614632 |
| 2015-12-18 | -0.016020 | -0.899110 | 0.368594 | | 2016-01-20 | 0.011336 | 0.636203 | 0.524644 |
| 2015-12-21 | 0.032284 | 1.811901 | 0.070002 | | 2016-01-21 | 0.013265 | 0.744484 | 0.456584 |
| 2015-12-22 | 0.007433 | 0.417182 | 0.676546 | | 2016-01-22 | 0.052991 | 2.974086 | 0.002939 |
| 2015-12-23 | 0.025112 | 1.409369 | 0.158726 | | 2016-01-25 | -0.012571 | -0.705531 | 0.480480 |
| 2015-12-25 | -0.000569 | -0.031956 | 0.974507 | | 2016-01-26 | -0.000890 | -0.049966 | 0.960150 |
| 2015-12-28 | -0.010100 | -0.566868 | 0.570804 | | 2016-01-27 | -0.079069 | -4.437686 | 0.000009 |
| 2015-12-29 | 0.026924 | 1.511089 | 0.130766 | | 2016-01-28 | -0.006381 | -0.358102 | 0.720267 |
| 2015-12-30 | -0.024435 | -1.371401 | 0.170250 | | 2016-01-29 | 0.038342 | 2.151903 | 0.031405 |
| 2015-12-31 | -0.003903 | -0.219069 | 0.826596 | | | | | |

Figure 10: the abnormal returns, the test statistic for each abnormal return, and the p-value of the test statistic over the event window for the AAPL stock.

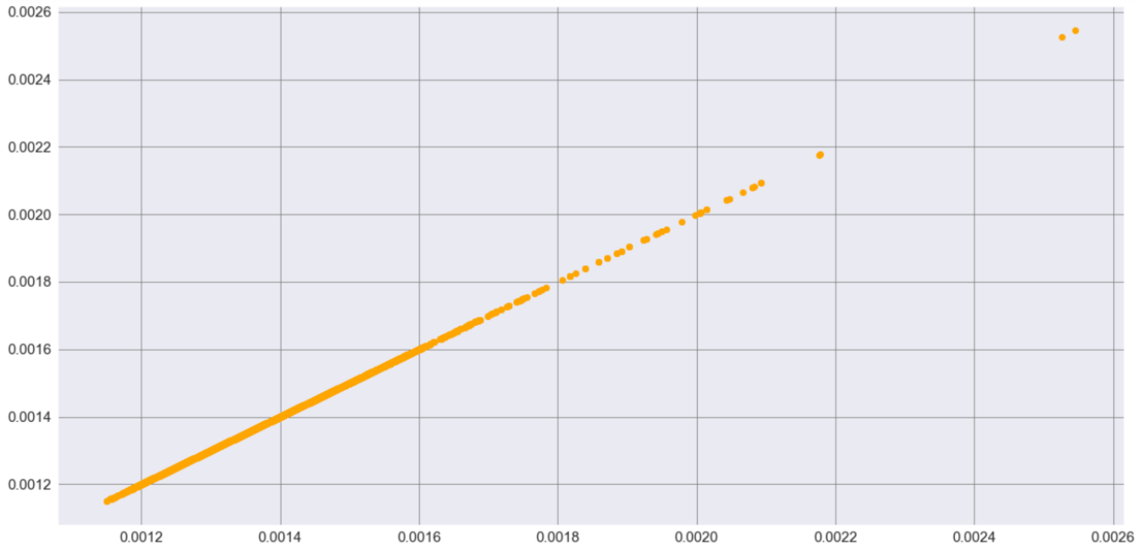


Figure 11: the diagonal of the variance-covariance matrix representing graphically the values of the variance for each stock in the sample.

For each stock, the variance is computed and has been used throughout the event study methodology into the formulas thus allowing for a statistical test on $\widehat{AR}_{it}$. In particular, the event study methodology has been implemented through a recursive algorithm performed across two dimensions: on a stock-by-stock basis, for the 150 stocks in the sample, and on a year-by-year basis, for the seven years under observation. Taking into account these preliminary remarks about the methodology, and the results available above, the hypotheses to be tested are developed, and the core analysis of the event study can be defined.

*Hypothesis 1*: the disclosure of companies' ESG ratings has a significant impact on companies' stock prices. In particular, the abnormal returns on stocks around the release date are positive or negative, i.e. significantly different from zero.

*Hypothesis 2*: there is a significant presence of abnormal returns a few days before the day of disclosure of companies' ESG ratings, indicating some form of anticipation.

*Hypothesis 3*: the impact of the disclosure of companies' ESG ratings on companies' stock prices is larger for downgrades than for upgrades.

In order to proceed with the hypothesis testing, the cumulative abnormal returns (CAR) and the average abnormal returns (AAR) need to be determined. For a smoother analysis, the average abnormal returns have been calculated first. In the first year under study, the 2015, they are the average of the abnormal returns of all the 150 stocks in the sample, on a day-by-day basis over the event window, i.e. from 2015-12-02 to 2016-01-29. Note that the first year under observation (2015) is used as a model for the other years of the study. In particular, each average abnormal return has been obtained as:

$$\widehat{AAR}_{[-20,20]} = \frac{1}{150}\sum_{i=1}^{150} \widehat{AR}_{i[-20,20]}$$

Where [-20, 20] is the event window, $i$ is each stock of the sample, and $\widehat{AR}_{i[-20,20]}$ is each abnormal return stock-by-stock in the event window. Moreover, the program provided the test statistic for each average abnormal return and the relevant p-value according to:

$$\widehat{SAAR}_{[-20,20]} = \frac{\widehat{AAR}_{[-20,20]}}{\sqrt{\sigma^2\left(\widehat{AAR}_{[-20,20]}\right)}}$$

Where the variance of each average abnormal return in the event period is:

$$\sigma^2\left(\widehat{AAR}_{[-20,20]}\right) = \frac{1}{150^2}\sum_{i=1}^{150} \sigma^2\left(\widehat{AR}_{i[-20,20]}\right)$$

With the variance of each abnormal return equals to: $\sigma^2\left(\widehat{AR}_{i[-20,20]}\right) = \sigma^2_{\varepsilon_i}$ as has been demonstrated above. The sorted list of results of the last step about the average abnormal returns (AAR) will be shown in chapter 4. Having reached this point of the methodology that has been applied, it is necessary to collect significant outcomes to test the first hypothesis. In particular, hypothesis 1, i.e. the core hypothesis of the event study, can be discussed by observing the relevant data of the AAR. According to the basic methodology of an event study, the hypothesis looks like this:

$$\begin{cases} H_0 : AR_{it} = 0 \\ H_1 : AR_{it} \neq 0 \end{cases}$$

It can be slightly modified to align with the needs of the method applied for this specific study, using precisely the average abnormal returns estimated above.

$$\begin{cases} H_0 : \widehat{AAR}_{[-20,20]} = 0 \\ H_1 : \widehat{AAR}_{[-20,20]} \neq 0 \end{cases}$$

Under the null hypothesis, the disclosure of companies' ESG ratings, i.e. the event under observation, does not affect the distribution of excess returns of the selected companies, and it does not cause any abnormal returns. The AAR are estimated over the event window ([-20, 20]). They have been used to assess the validity of hypothesis 1. The test statistic for each AAR and the corresponding p-value have been observed to state the statistical significance of the hypothesis testing. The procedure that has been followed above for testing hypothesis 1 can be expanded to verify hypothesis 2, i.e. the statistical significance of abnormal returns before the day of disclosure of companies' ESG ratings. In particular, the typical structure of the short-term event study methodology with anticipation implies a pre-event period and a post-event period. They have the same weight on the impact of the observed event on the distribution of abnormal returns. For hypothesis 2 what is relevant is the pre-event period, so the null hypothesis may be interpreted as follows:

$$\begin{cases} H_0 : \widehat{AAR}_{[-20,0]} = 0 \\ H_1 : \widehat{AAR}_{[-20,0]} \neq 0 \end{cases}$$

The behaviour of the AAR in the twenty days preceding the publication of companies' ESG ratings ([-20, 0]) will be discussed in chapter 4.

The second part of this chapter aims to extend and deepen this empirical research. For this purpose, the cumulative abnormal returns (CAR) have been used. Each cumulative abnormal return is an aggregate measure of the abnormal returns, on a stock-by-stock basis, over the event window ([-20, 20]). Taking once again the AAPL stock as an example, the relevant CAR is given by:

$$\widehat{CAR}_{AAPL}(T_1, T_2) = \sum_{t=T_1}^{T_2} \widehat{AR}_{AAPL[-20,20]}$$

Where $T_1$ and $T_2$ are the opening and closing dates of the event window, respectively. And $\widehat{AR}_{AAPL[-20,20]}$ are the abnormal returns of the AAPL stock over the event window, which have been computed at the beginning of the procedure for the event study. This is the calculation to obtain the AAPL stock's CAR, it has been repeated for all the 150 stocks within the sample. Moreover, knowing that $\sigma^2\left(\widehat{AR}_{AAPL[-20,20]}\right) = \sigma^2_{\varepsilon_{AAPL}}$ and it is constant through time, the variance of $\widehat{CAR}_{AAPL}(T_1, T_2)$ is computed as:

$$\sigma^2\left(\widehat{CAR}_{AAPL}(T_1, T_2)\right) = (T_2 - T_1 + 1)\sigma^2_{\varepsilon_{AAPL}}$$

The estimator for the variance of each CAR relies on the conditional variance of each abnormal return, the estimation window is wide enough to decrease as possible the estimation error for the parameters. So, as it has been assumed for the average abnormal returns, also the cumulative abnormal returns are normally distributed. In particular, for the AAPL stock:

$$\widehat{CAR}_{AAPL}(T_1, T_2) \sim N[0, (T_2 - T_1 + 1)\sigma^2_{\varepsilon_{AAPL}}]$$

As happened for the AAR, also for the CAR the program has been implemented to providing the test statistic and the corresponding p-value for each cumulative abnormal return in the event period. The test statistic is obtained as follows:

$$\widehat{SCAR}_{AAPL}(T_1, T_2) = \frac{\widehat{CAR}_{AAPL}(T_1, T_2)}{\sqrt{\sigma^2\left(\widehat{CAR}_{AAPL}(T_1, T_2)\right)}}$$

As an example, the standardised cumulative abnormal return of the AAPL stock has been computed over the event window, and it is distributed as a standard normal: $\widehat{SCAR}_{AAPL}(T_1, T_2) \sim N(0, 1)$. The methodology just described above has been applied through a recursive process for all the stocks under study.

The last part of this chapter is devoted to explaining how to make inference on CAR, in order to find a relationship between the CARs stock-by-stock and the ESG ratings, still stock-by-stock. The program presented the relevant data in ordered tables, which have been used for the preliminary analysis.

| | AAPL | MSFT | V | NVDA | UNH | JNJ | GOOGL |
|---|---|---|---|---|---|---|---|
| CAR | -0.109401 | 0.052933 | -0.02512 | -0.11213 | 0.03961 | 0.10369 | -0.016449 |
| SCAR | -0.958919 | 0.463969 | -0.220177 | -0.982836 | 0.347186 | 0.90886 | -0.144177 |
| p-value | 0.3376 | 0.64267 | 0.825734 | 0.325688 | 0.728451 | 0.363424 | 0.885361 |

Figure 12: the cumulative abnormal return stock-by-stock, its test statistic, and the corresponding p-value, for the first few stocks of the DJTSEC market index. In chapter 4, this outcome will be used to verify the statistical significance of each CAR, and then to expand and test hypothesis 3.

**The Relation Between the Cumulative Abnormal Return and the ESG Rating Stock-by-stock Over the Event Window**

The last insight of the event study performed in this thesis aims to assess the impact of upgrades and downgrades in ESG score on company's stock price. In chapter 1, the rating activity of different agencies, such as MSCI and Bloomberg, has been explained. The annual publication of this score for listed companies has been taken as the relevant event for the event study methodology. In the marketplace, such an occurrence can be interpreted as a news disclosure. In particular, it is common practice to distinguish the news introduced on the market according to its nature. A rating, from one year to the next one, can undergo an upgrade or a downgrade. For example, a firm has the possibility to go from BBB (lower rank) to A (top rank). Conversely, another firm could be downgraded from BB to B. For the purpose of this last analysis, each upgrade has been evaluated as a "good news", while each downgrade has been evaluated as a "bad news".

The goal of hypothesis 3 is exploring the consequences of what investors may judge as a positive or negative ESG news. Moreover, it investigates the weights assigned to upgrades and downgrades measured through shifts in stock prices. The hypothesis states that investors give more weight to "bad news" than to "good news", so downgrades affect stock prices more than upgrades. Assuming that market participants are rational, empirical results from the recent literature show that in correspondence with a positive event, companies' stock prices tend to increase. Conversely, when a negative event occurs, stock prices decrease.[12] To test the above hypothesis, it seems reasonable to assume that investors believe the only reliable source of ESG ratings is the MSCI-Bloomberg rating system. Furthermore, market participants do not consider the self-reported ratings from companies or the scoring activity of NGOs. The study is based on the behaviour of cumulative abnormal returns. As explained in Chapter 2, abnormal returns can be aggregated across time. So, over the event window ([-20, 20]), each cumulative abnormal return is assessed on a stock-by-stock basis.

As exemplified in figure 12, for each of the 150 stocks CAR have been computed, together with the related test statistic, and the p-value. After evaluating the statistical significance of each cumulative abnormal return, the analysis of the ESG ratings is performed. First of all, they come from the Bloomberg's database, and the numerical format of Bloomberg's own rating system has been chosen. As illustrated in figure 5 of Chapter 1, MSCI and Bloomberg manage two visually different but conceptually similar scoring systems. The first mimics the credit risk rating system from CCC to AAA. The latter is based on a numerical scale from 0 to

[12] Capelle-Blancard, G., & Petit, A. (2019). Every Little Helps? ESG News and Stock Market Reaction. Journal of Business Ethics, 157, 543–565.

100. The two assessments are superimposable, and the choice of one rather than the other does not affect the final analysis.[13]

The ESG scores over the seven years under observation are enclosed within a range between 0 and 80. Moreover, according to the view of MSCI, they fluctuate between CCC and A.

| | CCC-B | BB | BBB-A |
|---|---|---|---|
| **Date** | **<40** | **40≤x<60** | **≥60** |
| **31/12/2015** | 82 | 65 | 3 |
| **31/12/2016** | 79 | 67 | 4 |
| **31/12/2017** | 68 | 73 | 9 |
| **31/12/2018** | 52 | 91 | 7 |
| **31/12/2019** | 41 | 97 | 12 |
| **31/12/2020** | 31 | 100 | 19 |
| **31/12/2021** | 26 | 99 | 25 |

Figure 13: the ESG ratings over the seven years period of the study.

Figure 13 helps to understand how the ratings have changed over the years under observation. It is clear that there is a direct relationship between time and the growth of scores. The number of so-called laggard companies (CCC-B) has dropped over the years. As a result, more companies have received a BB rating (from 40 to 60). Finally, it can be seen that the number of BBB scores (from 60 to 70) has grown progressively. However, in the sample of companies, only a few exceptions have reached the rating A (greater than 70).

To validate hypothesis 3 two steps are necessary. The first entails proving the presence of significant cumulative abnormal returns over the event period. The second implies checking for a direct relationship between the ESG ratings and the CARs. As it has been done to test the presence of abnormal returns, the generic test can be expanded to CAR as follows:

[13] Berg, F., Heeb, F., & Kölbel, J., F. (2022). The Economic Impact of ESG Ratings. Available at SSRN.

$$\begin{cases} H_0 : \widehat{CAR}_i(-20, 20) = 0 \\ H_1 : \widehat{CAR}_i(-20, 20) \neq 0 \end{cases}$$

Here, according to the null, the CAR of stock $i$ in the event window ([$T_1$, $T_2$]) is not statistically significant.

Then, the idea is to visualise the ESG scores and the CARs in a cartesian plane. In particular, the role of the independent variable is given to each ESG score, whereas the dependent variable is the CAR of each stock in the sample. It could be interesting to ascertain a direct linear relationship between the two variables. However, these ratings, in addition to a precise numerical value, have a symbolic value that could drive the behaviour of investors. The rating system developed by MSCI is based on the confidence and familiarity investors have with credit risk ratings. Valuing each numerical value within intervals, such as the ones of Bloomberg's scoring system, could be more complex. On the contrary, investors are aware of what an upgrade from B to BB, or a downgrade from BBB to BB, means. They also know there is an intrinsic difference between going from CCC to B and going from BBB to A, i.e. the underlying value of the upgrade is higher in the second case.

As mentioned in chapter 1, the techniques of MSCI and Bloomberg are based on similar ESG pillars and lead to comparable empirical results. However, they are conceptually distinct, and investors approach them differently. This difference in the interpretation of ESG ratings affects the method of the final analysis. A regression with dummy variables has been performed to capture the impact of score changes on cumulative abnormal returns. Moreover, the divergence in the way MSCI and Bloomberg display their rating systems becomes more evident. First, a linear regression has been run, and then the one with dummy variables has been built. Finally, the regression that fits more suitable on CAR's shifts, if any, has been assessed. To fully understand this empirical finding, it is necessary to explain how the regression with dummy variables has been developed. In particular, four dummies have been selected, and each of them labels a progressive change in the ESG rating. Dummy 1 describes companies rated from CCC to B; dummy 2 from B to BB; dummy 3 from BB to BBB; and dummy 4 from BBB to A.

<table>
<tr><th>MSCI</th><th>CCC</th><th>B</th><th>BB</th><th>BBB</th><th>A</th></tr>
<tr><th>Bloomberg</th><th>[0, 20[</th><th>[20, 40[</th><th>[40, 60[</th><th>[60, 70[</th><th>[70, 80[</th></tr>
<tr><th>Dummy Variables</th><td></td><td></td><td></td><td></td><td></td></tr>
<tr><th>Dum1</th><td colspan="2">1</td><td>0</td><td>0</td><td>0</td></tr>
<tr><th>Dum2</th><td>0</td><td colspan="2">1</td><td>0</td><td>0</td></tr>
<tr><th>Dum3</th><td>0</td><td>0</td><td colspan="2">1</td><td>0</td></tr>
<tr><th>Dum4</th><td>0</td><td>0</td><td>0</td><td colspan="2">1</td></tr>
</table>

Figure 14: the dummy variables selected for the regression.

Figure 14 provides the regression pattern of cumulative abnormal returns of the 150 stocks on dummy variables. Each CAR has been regressed on the four dummy variables showing the relationship between CARs and ESG scores in the event window. In the cartesian plane, it visually resembles a scale, where the height of each step is proportional to the impact of each change in the ESG score on CARs. In particular, the regression has been built so that each shift is considered an upgrade. Finally, a more standard linear regression has been performed, and the resulting line has been included in the same plane to compare the results of both regressions and how they fit the distribution of CARs.

What has been achieved may be considered the core of the study and a reliable answer to hypothesis 3. The regression described above has been repeated recursively for each year under observation. In chapter 4, outputs and graphs obtained enable the analyst to compare the trend of cumulative abnormal returns year-by-year. Then, some inferences about the evolution of both CARs and ESG scores will be made.

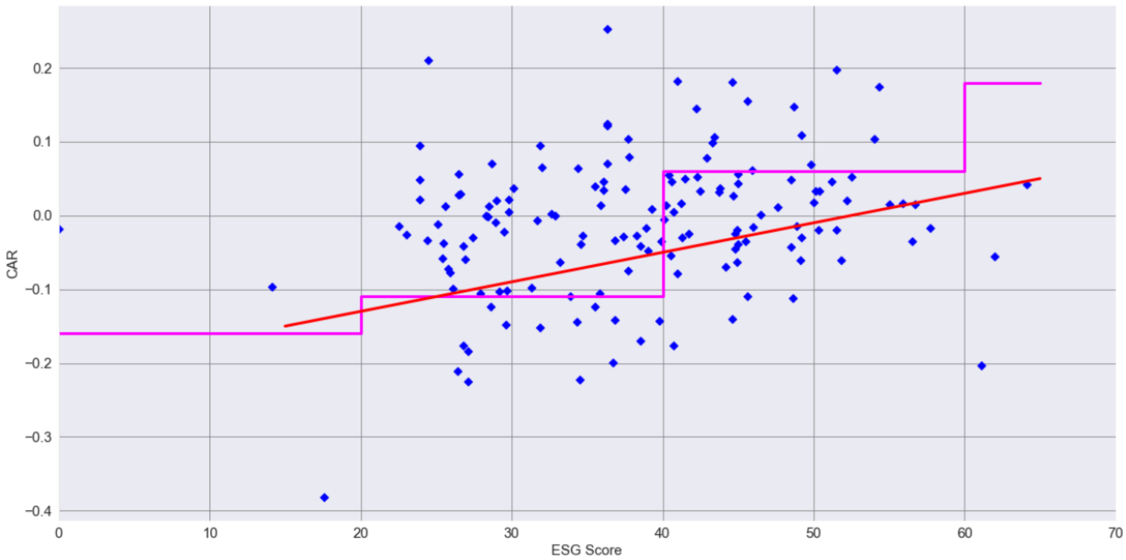


Figure 15: the output of the regressions of CARs on ESG scores over the event window for the first year under study (2015). The red line represents the linear regression. The magenta “scale” shows the outcome of the regression with the four dummy variables.

## Chapter 4: Analysis of Empirical Results

In this chapter, the main focus is on analysing the results of the event study implemented. The relevant empirical findings have been used to provide evidence on the three hypotheses formulated in the previous chapter. First, a few considerations should be made. The 150 companies under study are well-known firms with high capitalisation, and several are blue-chip companies. Furthermore, the Dow Jones Sector Titans is one of the most relevant, since it is widespread followed and mimicked compared to other market indexes. There is no doubt that, as illustrated in chapter 1, the reshaping of finance through the increasing interest on ESG investment opportunities is a matter of fact. However, it is relevant not to forget that selected companies are multinational corporations dedicated to earning a profit and growing their market value. It is not the aim of this thesis to focus on the strategies and choices in the ESG field of individual companies, nor to judge the evaluation methods of the rating agencies, agreeing or not, on the final ESG scores. Therefore, it is appropriate to treat the data used in the analysis as raw material to perform the event study. The financial data and the ESG ratings are obtained from the Bloomberg database and are taken for granted.

A preliminary investigation on the data has been first implemented. The DJTSEC index gathers information on leading companies from different market sectors. A correlation matrix is a practical tool for ascertaining the degree of correlation between firms. The correlation matrix for the stocks in the sample has been built using the program. But, being a 150 by 150 matrix, its direct observation is hardly interpretable. However, it is possible to visualise the matrix graphically in a so-called heat map. The lighter spots of colour indicate the stocks with more significant correlation. In fact, the diagonal of the matrix, which by definition is made up of as many 1s as there are stocks, is white. Conversely, the darker spots highlight the companies with a lower correlation. It can be seen that most firms are nearly uncorrelated (less than 0.4), several have an average correlation (around 0.5), and a few have a higher-than-average correlation (greater than 0.6). It is due to the substantially heterogeneous set of stocks concerning their market sector. However, some groups of companies in the DJTSEC index belong to the same business, such as Apple, Microsoft, and Google, or Chevron, Exxon Mobil, and ConocoPhillips. So, their respective correlations are above average.

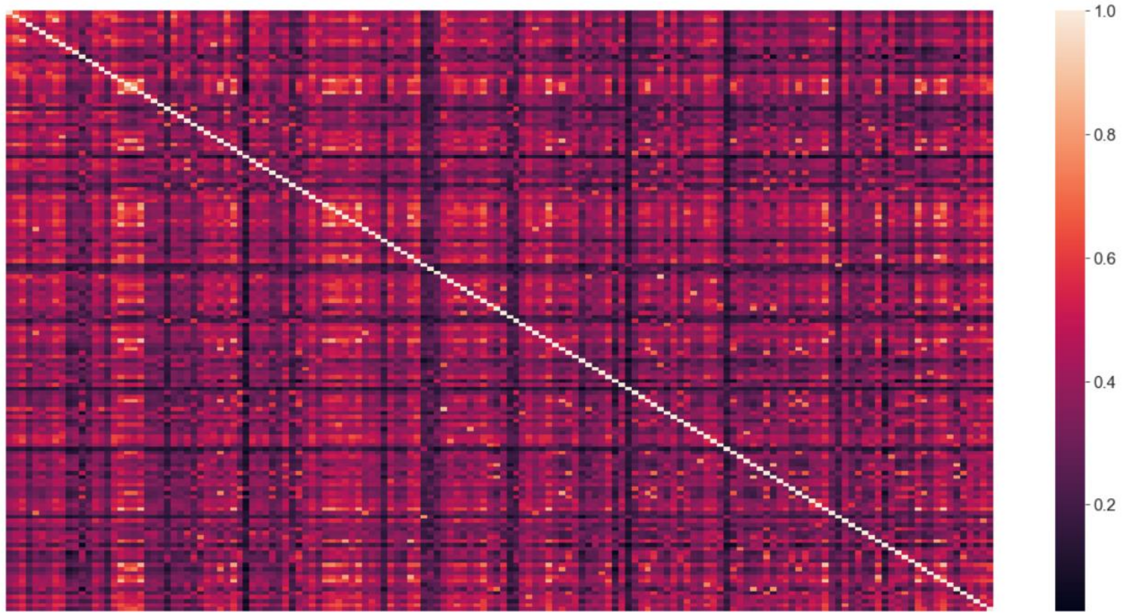


Figure 16: the graphical representation of the correlation matrix (heat map). On the right, the colour gradations identify the degree of correlation.

A further preliminary analysis concerns the volatility of excess returns for the 150 companies, and as above, a matrix has been constructed. The variance-covariance matrix provides, on the diagonal, the values of the variance stock-by-stock. A graphical representation of the volatility dynamics is functional for catching the pattern describing the variance's dynamics. The square root of the variance is the standard deviation, and the latter is the measure of volatility. In particular, one can visualise shifts in the volatility of each stock over the seven years under study. It seems that the companies have undergone the same periods of high volatility, as the trend of the variance is almost synchronous. However, several groups of companies have experienced spikes in volatility over some periods. The peaks are concentrated and defined, and a few companies have encountered above-average volatility. The same inference, from a different perspective, can be obtained from figure 7 in chapter 3. The distribution of excess returns in the seven years window undergoes sharp peaks during defined periods. What happened during the Covid19 global pandemic will be discussed later in this chapter.

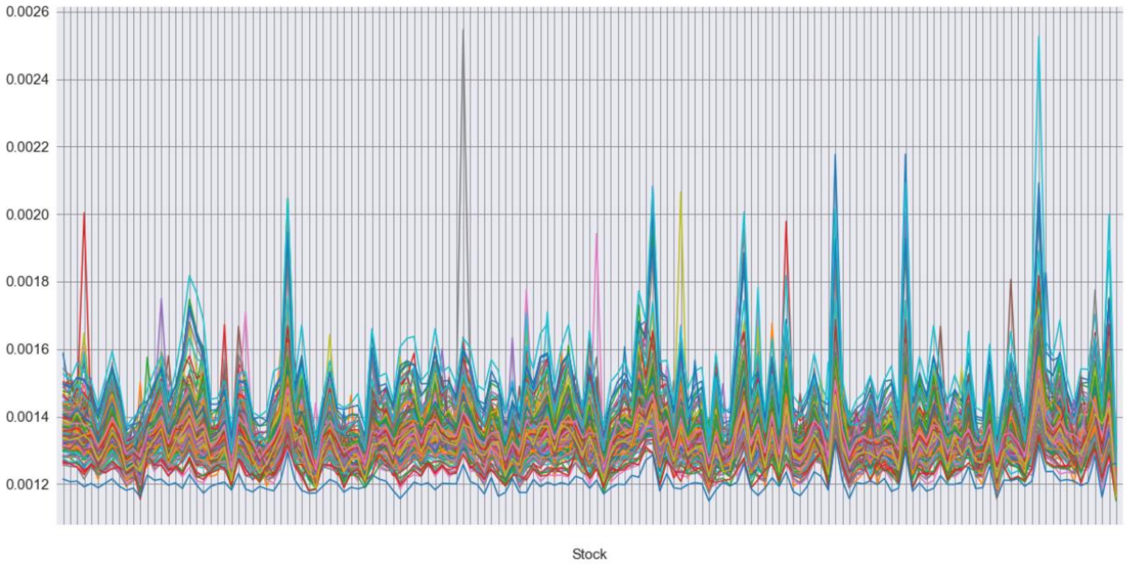


Figure 17: the graphical representation of the variance-covariance matrix.

As stressed before, the procedure for the event study has been applied separately for each year under observation. The recursive analysis allows the analyst to grasp the relevant features of the study year-by-year, compare them across the years, and exploiting the cross sectional dependencies to perform inferences. The methodology has been described step-by-step in chapter 3. Moreover, the significant hypotheses of the study have been stated in the previous chapter. In this chapter, the three hypothesis tests will be commented and analysed, and then, an interpretation of empirical outcomes will be provided.

According to hypothesis 1, the disclosure of the ESG ratings on December 31 affects stock prices either positively or negatively. Following the Market Model, such a hypothesis should be tested using abnormal returns for the 150 stocks over the event window. In particular, it should be assessed if abnormal returns are significantly different from zero. The optimal choice is to compute the average of all abnormal returns of stocks, day-by-day across the event period. So, 41 average abnormal returns (AARs) have been obtained, i.e. 20 days before the disclosure, December 31, and 20 days after. For each year, the formal hypothesis to be tested is:

$$\begin{cases} H_0 : \widehat{AAR}_{[-20,20]} = 0 \\ H_1 : \widehat{AAR}_{[-20,20]} \neq 0 \end{cases}$$

Here, according to the null, average abnormal returns are equal to zero over the event window, i.e. [-20, 20].

For each year under observation, the Python routine proposed provides a table with the AAR on a day-by-day basis, the relevant test statistics, and the corresponding p-values. As illustrated in figure 18, for the first year of the study, namely 2015, such an output allows to assess the validity of the first hypothesis. The p-value is statistically equivalent to zero, so the null hypothesis has been rejected. In particular, the average abnormal returns over the event window are not equal to zero. Figure 19 exemplifies, again for the first year under scrutiny, the second test to validate hypothesis 1. It is a graphical representation of AARs across the event period. The x-axis shows the days of the event window, while the y-axis displays the values of average abnormal returns. The table and the graph have been implemented through the seven years to compare the outcomes and offer some extra insights. First, for each year, the p-values are roughly equal to zero, so the null hypothesis has been rejected for all seven years under study. Moreover, all the graphs show the average abnormal returns shifting away from the x-axis, confirming to be significantly different from zero. However, the analysis is not complete. It has been said that the impact of the announcement of ESG scores may cause a positive or negative reaction in the stock market. It has been empirically proved that this effect exists, so it is necessary to investigate the "sign" of this reaction, i.e. whether the AARs are, overall, positive, or negative. The average of AARs computed along the event window has been calculated for each year under observation. Observing this single value, it is possible to state that AARs are barely negative over the event period.

However, a couple of remarks should be emphasised. First, what is the behaviour of the average abnormal return on the day of disclosure? Second, what is the behaviour of AARs over the twenty days after December 31?

| Date | AvgAR | SAvgAR | p-SAvgAR | Date | AvgAR | SAvgAR | p-SAvgAR |
|---|---|---|---|---|---|---|---|
| 2015-12-02 | 0.618451 | 449.535492 | 0.0 | 2016-01-01 | 0.354791 | 257.888110 | 0.0 |
| 2015-12-03 | -0.978402 | -711.174419 | 0.0 | 2016-01-04 | -1.283888 | -933.223732 | 0.0 |
| 2015-12-04 | -0.409757 | -297.841227 | 0.0 | 2016-01-05 | 1.217541 | 884.998152 | 0.0 |
| 2015-12-07 | -0.768811 | -558.828428 | 0.0 | 2016-01-06 | -0.712685 | -518.031537 | 0.0 |
| 2015-12-08 | 0.853004 | 620.026167 | 0.0 | 2016-01-07 | -2.431333 | -1767.271178 | 0.0 |
| 2015-12-09 | -0.703277 | -511.193304 | 0.0 | 2016-01-08 | -0.173788 | -126.322004 | 0.0 |
| 2015-12-10 | -0.053977 | -39.234314 | 0.0 | 2016-01-11 | -0.529466 | -384.855014 | 0.0 |
| 2015-12-11 | -1.995039 | -1450.140506 | 0.0 | 2016-01-12 | 0.934251 | 679.082156 | 0.0 |
| 2015-12-14 | 0.585468 | 425.560776 | 0.0 | 2016-01-13 | -2.116930 | -1538.740182 | 0.0 |
| 2015-12-15 | 0.291460 | 211.854585 | 0.0 | 2016-01-14 | 0.280580 | 203.945998 | 0.0 |
| 2015-12-16 | 0.701507 | 509.906882 | 0.0 | 2016-01-18 | -0.096739 | -70.316674 | 0.0 |
| 2015-12-17 | -0.791793 | -575.533226 | 0.0 | 2016-01-19 | 0.063118 | 45.878477 | 0.0 |
| 2015-12-18 | -0.333938 | -242.730500 | 0.0 | 2016-01-20 | -0.343609 | -249.760461 | 0.0 |
| 2015-12-21 | 1.539656 | 1119.134697 | 0.0 | 2016-01-21 | 1.517348 | 1102.919491 | 0.0 |
| 2015-12-22 | 1.000014 | 726.883232 | 0.0 | 2016-01-22 | 1.276143 | 927.594712 | 0.0 |
| 2015-12-23 | 1.620584 | 1177.959304 | 0.0 | 2016-01-25 | -0.314665 | -228.721406 | 0.0 |
| 2015-12-25 | 0.286061 | 207.930296 | 0.0 | 2016-01-26 | 0.355200 | 258.185154 | 0.0 |
| 2015-12-28 | -0.088114 | -64.047492 | 0.0 | 2016-01-27 | -1.209530 | -879.174798 | 0.0 |
| 2015-12-29 | 1.274922 | 926.706964 | 0.0 | 2016-01-28 | -0.820383 | -596.314628 | 0.0 |
| 2015-12-30 | -1.047259 | -761.225013 | 0.0 | 2016-01-29 | 1.807079 | 1313.517550 | 0.0 |
| 2015-12-31 | 0.417070 | 303.157286 | 0.0 | | | | |

Figure 18: average abnormal returns day-by-day over the event window, the relevant test statistic, and the corresponding p-value, for the first year under observation (2015).

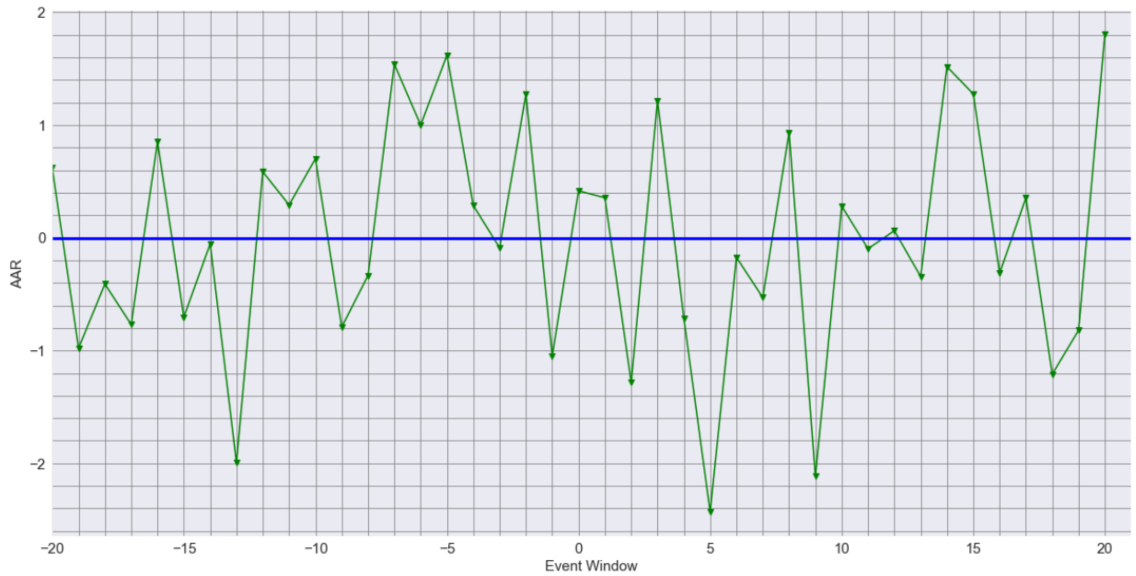


Figure 19: average abnormal returns over the event window, i.e. 20 days before the disclosure, day 0 (December 31), and 20 days after, (2015). The x-axis in blue.

The outcomes computed for the seven years under study denote that, on average, the day of disclosure of ESG ratings shows a positive AAR. A few event studies provide the opposite effect, a negative AAR on December 31. Excluding other factors beyond the control of this study, this result is likely due to the reaction of market participants. As outlined in this thesis, investors respond to macro- and micro-economic shocks, trying to align the idea of profit and their moral attitude. Therefore, sometimes, investors may interpret such events as beneficial for their portfolios, while on the contrary, some occurrences may conflict with their investment purposes. This is also the case for ESG scores, as they may flag a new investment opportunity or a risk for the entire portfolio, as presented in chapter 1.[14] A positive AAR on December 31 may signal that investors have incorporated the disclosure as "good news", causing positive abnormal returns on that day. A negative AAR may indicate that investors have integrated the publication as "bad news", generating negative abnormal returns.[15]

[14] Bank of America, "10 Reasons to Care About ESG Investing", 2020.
[15] Capelle-Blancard, G., & Petit, A. (2019). Every Little Helps? ESG News and Stock Market Reaction. Journal of Business Ethics, 157, 543–565.

The phenomenon of abnormal returns different than zero on the event day, i.e. December 31, is consistent with the semi-strong form of the Efficient Market Hypothesis. When information becomes public, stock prices fully reflect it and adjust accordingly.[16] However, it is relevant to note what happened over the twenty days after day 0. Again according to the semi-strong form of the Efficient Market Hypothesis, abnormal returns should cease the day after the disclosure of ESG ratings. But empirical results (in particular, figures 18 and 19 and their reiteration across the seven years under observation) prove the persistence of abnormal returns in the days after December 31. Moreover, average abnormal returns over the twenty days post-event are larger, in absolute value, than the AAR on the event date. So, the first considerable insight of this analysis is that AARs are lingering some days after the disclosure of ESG ratings with higher absolute values. Such behaviour may flag a delay in investors' interpretation of ESG ratings or in the stock market reaction.

The appendix provides the analytical tools of Python to perform the event study over the years and verify this first insight. In particular, this chapter does not report all relevant tables and graphical representations. However, the graph of average abnormal returns over the event window for the year 2017 is particularly suitable to strengthen what has been demonstrated above for the first hypothesis. Year 2017 is one of the few under study with a barely positive mean of average abnormal returns. It is around 0.033 during the 41 days event period. On the day of the disclosure of ESG ratings, i.e. 2017-12-31, the AAR is negative, with a value of around -0.64. This may flag investors integrated the publication of ESG scores of 2017 as "bad news". Nevertheless, AARs took twelve days to stabilise toward zero. AAR peaks at about 2.71 eight days after December 31, and some AARs after day 0 outclass the average value. So, the significant behaviour of AAR on the day of disclosure and the persistence of average abnormal returns

[16] Fama, E., Fisher, L., Jensen, M., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. International Economic Review, 10, 1–21.

after the event date have been confirmed. Above-average values after day 0 may indicate a lag in response to the publication of ESG scores of either investors or the stock market.

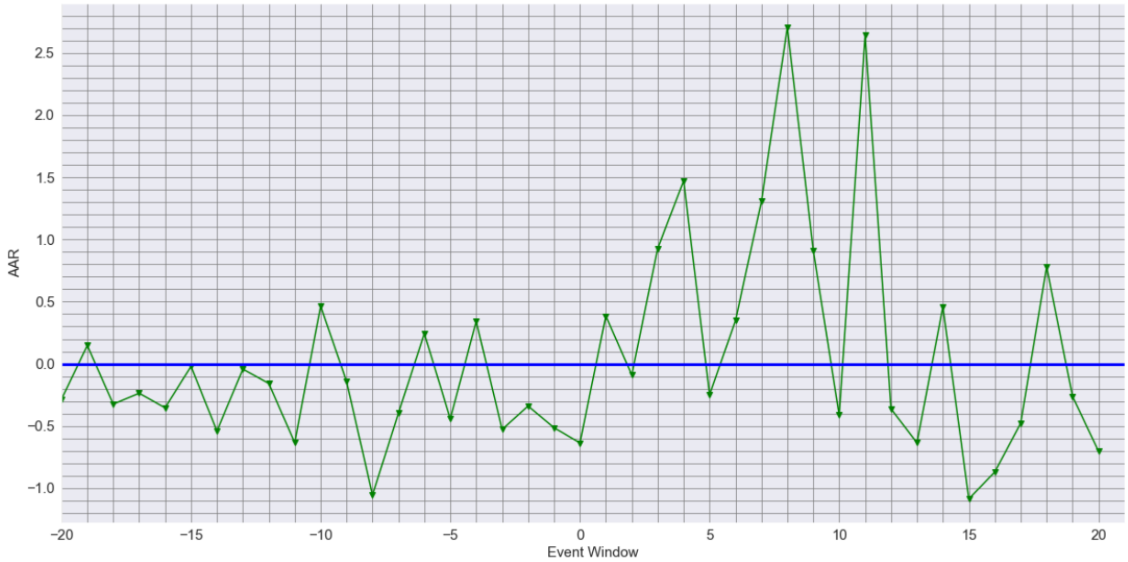


Figure 20: average abnormal returns over the event window, i.e. 20 days before the disclosure, day 0 (December 31), and 20 days after, (2017). The x-axis in blue.

According to hypothesis 2, abnormal returns a few days before the disclosure of ESG ratings are significantly different from zero. Such an assumption is voluntarily in contradiction with the semi-strong form of the Efficient Market Hypothesis and represents a violation of the insider trading rules. In particular, if insider trading rules are followed, there should be no abnormal returns, as no disclosures have been made to the public before December 31. Conversely, if there is a breach of the insider trading rules, abnormal returns are observed before day 0. It may indicate that some market participants knew the news before it was made public and used their advantage to beat the stock market. Some remarks concerning the specific case of ESG ratings will be proposed.

To validate the anticipated effect hypothesis, the hypothesis system is presented as follows:

$$\begin{cases} H_0 : \widehat{AAR}_{[-20,0]} = 0 \\ H_1 : \widehat{AAR}_{[-20,0]} \neq 0 \end{cases}$$

Here, the standard event window of hypothesis 1 ([-20, 20]) has been halved and made asymmetric. Average abnormal returns have been observed over the twenty days before the disclosure date. Under the null, AARs are equal to zero over the first half of the event window, i.e. [-20, 0].

After setting the new relevant event window, the testing procedure follows the same path as the first hypothesis. First, the statistical significance of average abnormal returns over the period [-20, 0] has been assessed. As above, such a step has been performed across the seven years under study through the program's output table (figure 18). Then, AARs over the first half of the event window are considered in the graphical representations (such as figures 19 and 20). Finally, observing the relevant p-values and the distribution of average abnormal returns over the event period, the null hypothesis has been rejected again.

The pair of hypotheses just tested represent the first part of the study involving the behaviour of average abnormal returns on the day of disclosure of ESG ratings and several days before and after day 0. Before moving to the third hypothesis concerning the analysis of cumulative abnormal returns and ESG scores, a couple of summary considerations have been expressed.

The first consideration concerns average abnormal returns over the entire event window. The study defined for the first two hypotheses has been performed across the seven years under scrutiny, and the final result is the same. The null hypothesis has always been rejected, and AARs are significantly different from zero over the event window. On average, the mean of AARs over the event period is barely negative. However, the AAR on day 0 is positive in some years and negative in others, meaning that investors have judged the ESG rating as "good news" and "bad news", respectively. The second consideration regards hypothesis 2 only. One of the theories to explain the presence of abnormal returns some days before the disclosure of ESG ratings is the violation of insider trading rules. Insider trading regulations are an overly complex field. In fact, US Securities and Exchange Commission is continuously working on these rules and trying to update them.[17] This interest from international regulators demonstrates that insider trading is a current issue.

However, the anticipation of abnormal returns is quite common in the literature of event studies. The research used the insider trading case as an assumption to show that "*all events induce variance*", even in pre-event time.[18] This thesis did not address the "*event-induced volatility*" issue, but in the first part of this chapter, the variance of the 150 stocks has been studied. The investigation has been conducted not through models but using empirical methods. As mentioned at the beginning of this chapter, the variance, or rather its square root, measures the volatility of any stock. A first method may use graphical representations of stocks' variance (figure 11 of chapter 3 and figure 17 of chapter 4). Focusing on short periods, it is possible to state that volatility tends to increase around the event date. No significant differences have been noted between the volatility a few days before the event date and that a few days after. A second method may apply the formula for the variance specified in chapter 3, thus actually computing the volatility indicators. Calculating the variance of each abnormal return day-by-day over the event window may exhibit similar behaviour of the volatility before and after day 0.

According to hypothesis 3, the impact of the disclosure of ESG ratings on the stock market is greater for downgrades than upgrades. To test such an assumption, cumulative abnormal returns have been used. The assessment procedure has been divided into two parts. First, it has been evaluated whether CARs over the

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[17] Washington D.C., Dec. 14, 2022: "The Securities and Exchange Commission today adopted amendments to Rule 10b5-1 under the Securities Exchange Act of 1934 and new disclosure requirements to enhance investor protections against insider trading. The amendments include updates to Rule 10b5-1(c)(1), which provides an affirmative defense to insider trading liability under Section 10(b) and Rule 10b-5. Collectively, the final rules aim to strengthen investor protections concerning insider trading and to help shareholders understand when and how insiders are trading in securities for which they may at times have material non-public information."

[18] Corrado, C., J. (2011). Event Studies: A Methodology Review. Accounting and Finance, 51, 207-234.

event window are significantly different from zero, as previously done with average abnormal returns. Then, CARs have been regressed on ESG scores to evaluate the type of relationship, if any, between them. As explained when the Market Model was expanded for the purpose of this study, cumulative abnormal returns are an aggregate measure of abnormal returns stock-by-stock across the event period. So, through Python, 150 CARs, one for each stock, have been obtained. Each company received its ESG rating on December 31 for the seven years under observation. Year after year, each company in the sample was assigned a CAR and an ESG score.

The relevant hypothesis system is presented as follows:

$$\begin{cases} H_0 : \widehat{CAR}_i(-20, 20) = 0 \\ H_1 : \widehat{CAR}_i(-20, 20) \neq 0 \end{cases}$$

Here, under the null, CAR of stock $i$ over the event window is not statistically significant.

Figure 12 of chapter 3 exemplifies part of the table provided by Python. The complete list of CARs stock-by-stock, the relevant test statistic, and the corresponding p-value has been used to assess the significance of each cumulative abnormal return. Across the seven years, only a restricted portion of stocks has a CAR significantly different from zero. This pattern changes during the last two years under scrutiny affected by the Covid19 pandemic and will be highlighted later in this chapter. The non-significance of CARs may depend on the parameters of the model used by the program, which provides quite-high p-values for each cumulative abnormal return, and p-values above average may drive the acceptance of the null hypothesis. However, since this is an aggregate measure, it is something we have to face while dealing with empirical methods. As shown in chapter 2, the cumulative abnormal return of stock $i$ is computed as the summation of abnormal returns of stock $i$ over the event period. It has been demonstrated above that all abnormal returns of companies in the sample are statistically significant across the event window. So, it is reasonable to assume that, however slightly positive or negative, CARs are different from zero. And Python has been able to compute them. In fact, in the first row of the output shown in figure 12, no CAR equals net zero.

The reasoning just developed gives an assist for the final part of the study. It concerns an empirical analysis based on a graphical representation of ESG scores as the independent variable and CARs as the dependent variable. A regression analysis introduced in chapter 3 have been performed. In the following, comparison between a standard linear regression and a more sophisticated regression with dummy variables is implemented. Figure 15 of chapter 3 summarises the relationship between the independent and the dependent variables fitted by a linear model and an augmented model with four dummy variables. The latter model is constructed by taking advantage of the so-called categorical variables. In the case of ESG scores, each upgrade falls into a category. The four upgrades taken into consideration are CCC-B, B-BB, BB-BBB, and BBB-A. Such a pattern has been assessed through the seven years under study. The Covid19 pandemic affected the last two years, and the outcome will be deepened in the final part of this chapter.

Overall, both regressions discreetly fit the behaviour of CARs and ESG scores. In particular, the linear relationship gives a straightforward idea of the trend. It does not match with several pairs of CAR-ESG score because of the presence of outliers. Sometimes the difference between cumulative abnormal returns with distinct ESG scores is negligible. Some stocks may have the same CAR value but different ratings. Other times, with the same ESG score, there may be a discrete difference in the CAR's values. For these reasons, the regression with the four dummy variables is considered an improvement of the model fitting. Each categorical variable tags an upgrade, and the graphical output resembles a scale with varying heights of steps. The step's height is proportional to the weight of each upgrade on cumulative abnormal returns. Due to the distribution of ESG scores in the sample, the most significant upgrades concern companies improving from a laggard to an average rating. Moreover, the majority of firms undergo upgrades from B to BB and from BB to BBB. Just a few businesses achieve a high-quality shift from BBB to A. The model with dummy variables indicates that investors give more weight to improvements from laggard to average ranks.

| Date | AAPL | MSFT | V | NVDA | UNH | JNJ | GOOGL |
|---|---|---|---|---|---|---|---|
| 2015-12-31 | 45.6 | 52.5 | 41.7 | 48.6 | 35.5 | 54.0 | 38.9 |
| 2016-12-31 | 49.3 | 54.1 | 47.4 | 51.7 | 35.4 | 54.0 | 37.9 |
| 2017-12-31 | 49.2 | 54.3 | 50.1 | 52.7 | 37.6 | 59.1 | 39.7 |
| 2018-12-31 | 49.4 | 52.8 | 52.7 | 60.7 | 41.9 | 59.7 | 42.2 |
| 2019-12-31 | 57.7 | 51.4 | 51.4 | 60.3 | 42.7 | 59.9 | 44.4 |
| 2020-12-31 | 57.0 | 56.0 | 50.3 | 63.5 | 43.4 | 59.9 | 53.1 |
| 2021-12-31 | 56.2 | 53.7 | 51.0 | 55.7 | 43.4 | 63.9 | 53.5 |

Figure 21: ESG scores for the first few stocks of the DJTSEC market index across the seven years under study. Python reports on the left the relevant disclosure date. We note that ratings strictly increase through the years and downgrades are barely relevant.

Aim of hypothesis 3 was to demonstrate whether investors value downgrades more than upgrades, integrating ESG announcements as "bad news" or "good news", respectively. However, the study of ESG ratings provided substantial insight, exemplified by figure 13 of chapter 3. ESG scores increased consistently and clearly through the years under scrutiny. Observed downgrades are not statistically relevant, both in number and value, to be considered for the analysis. A further boost has been evident in the last two years and will be discussed in the final part of the chapter devoted to study the impact of Covid19. So, for the regression analysis, we assume that investors have integrated as "bad news", not downgrades but scores that they considered a negative performance of companies in the ESG framework. This is the reason, according to the regression with dummy variables, the highest step of the "magenta scale" (figure 15) denotes the shift from laggard to average scores. Investors usually blame laggard companies and look forward to better ones, as happens for credit risk ratings.

**The Impact of Covid19 on Cumulative Abnormal Returns and ESG Ratings**

At the beginning of this thesis, the origins and development of ESG investing have been discussed. It was pointed out how concerns about environmental and social issues are leading to a restructuring of the financial market. Moreover, the interest in ESG investment strategies raised in the last decade and the Covid19 pandemic even stimulated investors' attraction to sustainable finance. Someway, Covid19 highlighted how businesses operate or what is called firm purpose. It emphasised the necessities of shareholders, strengthening the concept of company threats and opportunities. The pandemic has done much more: it negatively affected some sectors, favouring others considerably.

In the first chapter, the behaviour of ESG and non-ESG funds during the Covid crisis and later times has been examined. The behaviour of funds is related to the performance of companies belonging to them. In particular, in the two years period 2020-2021, technology and services companies went strong, whereas the energy sector was strongly weakened. The chemical, pharmaceutical and healthcare sectors received an unexpected boost. The global pandemic stressed a disconnection between the financial market and daily life. While the volatility in the stock market peaked, investors were choosing ESG investment approaches. The first interest of investors has been and continues to be the environmental aspect, above all, climate change problems. However, the pandemic has pushed interest in the social component, social matters such as work conditions, the protection of employees, and the supply chain.

Cumulative abnormal returns have been used as an indicator to analyse how Covid19 impacted companies in the sample. During the years between 2015 and 2019, only a few companies showed statistically significant CARs, either positive or negative. However, for years 2020 and 2021, the number of stocks with a CAR significantly different from zero increased remarkably. As said above, businesses operating in specific market sectors registered different reactions to the pandemic.

Tech companies like NVIDIA Corporation (NVDA), ASML Holding (ASML), Adobe Systems Incorporated (ADBE), Qualcomm Incorporated (QCOM), and Intuit (INTU) reached well-above-average cumulative abnormal returns. The services and financial sectors with firms such as Mastercard (MA), Amazon (AMZN), Morgan Stanley (MS), United Parcel Service (UPS), BlackRock (BLK), and Netflix (NFLX) recorded substantial CARs improvements. Conversely, energy, oil and gas sectors experienced well-below-average CARs, as exemplified by Exxon Mobil Corporation (XOM), ConocoPhillips (COP), TotalEnergies (TTE), Schlumberger (SLB), Occidental Petroleum Corporation (OXY), and Valero Energy Corporation (VLO).

These businesses across different market sectors registered the most significant impact during the Covid crisis. However, about half of the 150 companies presented meaningful positive or negative cumulative abnormal returns between 2020 and 2021. Moreover, the analysis of average abnormal returns has confirmed investors positively integrated ESG scores in both years. The AAR on the disclosure date is positive. Moreover, in 2021, the mean of AARs over the event window was about 0.03, but AARs after day 0, i.e. 2021-12-31, were above average with a value of approximately 0.05. This may flag investors have regarded the evident growth of scores as "good news".

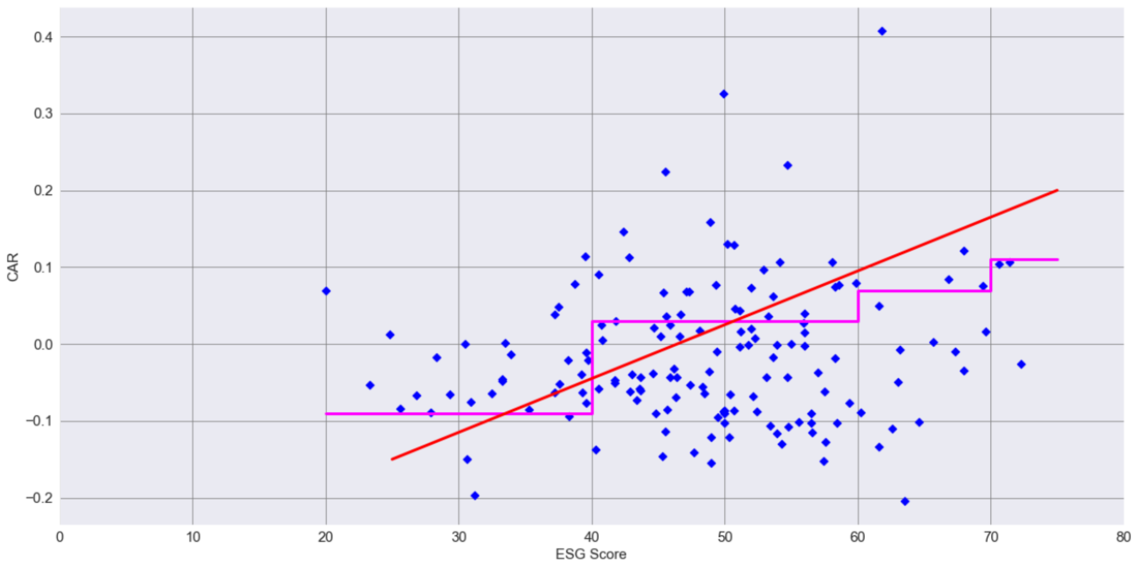

Figure 22: the output of the regressions of CARs on ESG scores over the event window (2020). The red line represents the linear regression. The magenta "scale" shows the outcome of the regression with the four dummy variables.

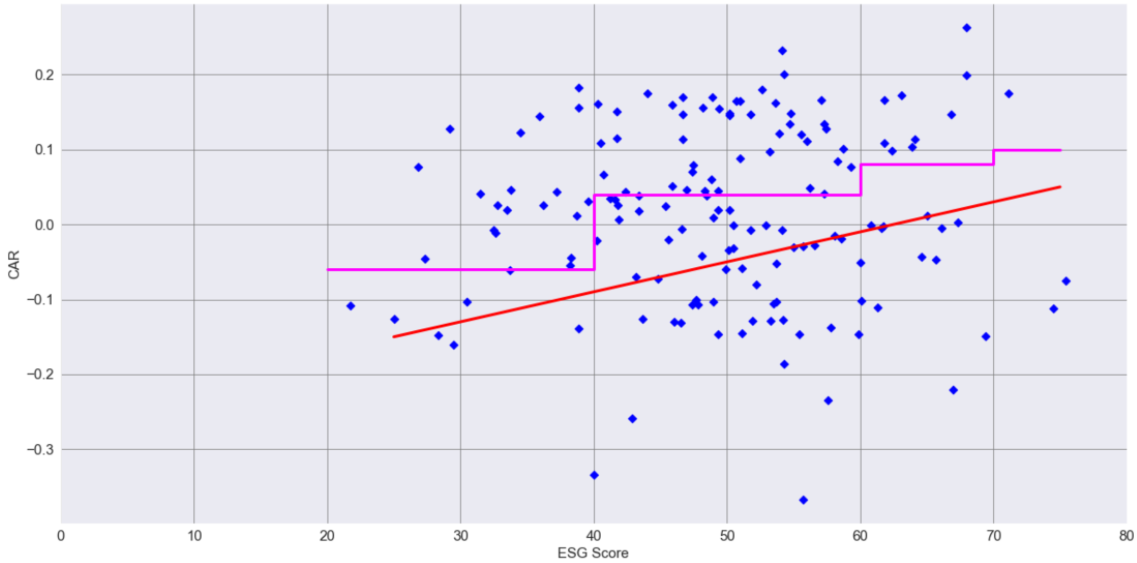


Figure 23: the output of the regressions of CARs on ESG scores over the event window (2021). The red line represents the linear regression. The magenta "scale" shows the outcome of the regression with the four dummy variables.

Concerning the years affected by the pandemic, the linear regression fits data better than the previous years. Several CARs follow an increasing trend caught by the "red line". The number of outliers is lower than in the other years under scrutiny, especially on the left side of the graph involving laggard scores. Most cumulative abnormal returns are paired with average ratings. The regression with dummy variables still grasps that investors give more weight to upgrades from B to BB, i.e. from laggard to average scores. Moreover, the "magenta scale" points out that investors significantly value the ratings over the BBB interval.

The final part of the data analysis suggests that the Covid19 may have had a relevant impact on the development of ESG ratings. Figure 13 of chapter 3 highlights how ESG scores progressively increased over the years under study. In particular, during the last two years, just a few companies received a laggard rating, most firms obtained upgrades, and some were to the high-levels BBB or A.

Observing the increasing trend of ESG scores, it seems that the pandemic has prompted companies to integrate environmental, social and governance responsibilities into their corporate purpose. On the other side, the rating activity of MSCI and Bloomberg has been fostering the effort of firms to improve their ESG standards with higher scores.

## Conclusion

This thesis has demonstrated how businesses that understand and integrate ESG factors, not for greenwashing but promptly incorporating, in the long-run, tend to be better-performing businesses. Primarily those that grasp ESG opportunities and enhance risk estimation strategies within their market sector. Moreover, agencies such as MSCI and Bloomberg provide information to investors and stakeholders in the stock market. In particular, the increasing interest in ESG issues strengthened and improved the rating activity of MSCI towards ESG practices of companies. The reshaping of investing through more sustainable finance began several years ago and accelerated in the last few years. Analysts believe that the Covid pandemic even fostered the attraction for ESG investments, and more firms adapted their corporate structure to integrate ESG concerns responding to investors' requirements.

The short-term event study has been performed through the Python routine, employing the libraries pandas and statsmodels. Empirical evidence verified the statistically significant presence of abnormal returns over the event window. In particular, the abnormal return on the event date, or better, the average abnormal return across stocks, may signal a positive or negative investors' reaction while integrating ESG news as "good" or "bad", respectively. Moreover, average abnormal returns persist after day 0, violating the semi-strong form of the Efficient Market Hypothesis and showing a delay of either market participants or the stock market in incorporating ESG news. The methodology proved the anticipation of the ESG disclosure because abnormal returns appear a few days before the event date. Such insight contradicts the semi-strong form of EMH again and conveys the infringement of insider trading rules.

The aggregate measure of abnormal returns stock-by-stock over the event period exhibits a quite-strong relationship with ESG scores. Cumulative abnormal returns regressed on ESG ratings provide a graphical representation of two models. First, the linear relationship offers a fair picture of the evolution of CARs when ESG scores increase. It may be inaccurate for some years under scrutiny, and conversely, it may grasp the growing trend during the years hit by Covid19. However, the model shows a substantial presence of outliers. So, the regression with four dummy, or categorical, variables is the best representation of the relationship between CAR and ESG score. It captures the impact of ESG news on investors' behaviour. The "scale" resulting from the regression highlights how investors value the upgrades in ESG scores. They give more weight to improvements from a laggard rating to an average one. And investors appreciate most the ratings in the category BBB, i.e. from 60 to 70, according to the Bloomberg rating system.

Empirical findings proved how ESG scores progressively increased across the years under study. We treated such a trend as a series of upgrades, and downgrades are not statistically relevant to be analysed. In particular, during the last two years, impacted by the pandemic, just a few companies received laggard ratings and most obtained upgrades to the BBB rank. Some firms enhanced to the high-quality grade A, getting a score in the interval from 70 to 80. It seems that the interest in ESG issues is not just advertising or greenwashing but current and effective. The evidence collected in the final part of this thesis may confirm the latest research, according to which Covid19 has prompted investors and businesses to operate differently to protect the planet. The rating activity of agencies such as MSCI and Bloomberg is essential to support the effort of market participants to choose sustainable investments. Moreover, these agencies provide analysts with the necessary tools to develop insights as those addressed in this thesis.

While performing the event study methodology, we mentioned event-induced volatility but did not deepen the topic. A further investigation may expand this case and the behaviour of the volatility of abnormal returns in pre-event time. Moreover, it may be interesting to conduct an ad hoc event study about the impact of Covid19 pandemic on investors' and companies' ESG choices, also thanks to the instruments of MSCI and Bloomberg databases.

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# Appendix

The Python Routine.

```
#!/usr/bin/env python
# coding: utf-8

# In[1]:
import pandas as pd
import numpy as np
import scipy
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn
import datetime as dt
# In[2]:
Returns=pd.read_excel('DJTSEC Returns.xlsx', index_col=0)
Returns
# In[3]:
RiskFree=Returns['TYield10Y']
ExcessReturns=Returns.sub(RiskFree, axis=0)
ExcessReturns
# In[4]:
ExcessReturns=ExcessReturns.drop(['TYield10Y'], axis=1)
ExcessReturns
# #### Excess Returns of 150 DJTSEC Stocks and DJTSEC Market Index
# In[5]:
seaborn.set_style('darkgrid')
plt.rc('figure', figsize=(20, 10))
plt.rc('savefig', dpi=90)
plt.rc('font', family='sans-serif')
plt.rc('font', size=15)
plt.plot(ExcessReturns)
plt.title('Excess Returns 7 Years Window')
plt.xlim((pd.to_datetime('2014-12-02'),pd.to_datetime('2022-02-
01')))
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()

# #### Year 2015
# In[6]:
estSize=253
idx=ExcessReturns[ExcessReturns.index < '2015-12-31'].iloc[-20]
print(idx)
est_window_stop=idx.name
endEstWindow=ExcessReturns.index.get_loc(est_window_stop)
print(f'{est_window_stop} is in the position {endEstWindow} of the
dataframe')
# We estimate the market model for each excess return computed
above.
# The abnormal returns, defined by $\hat{\epsilon}_{i,t}$, are
obtained with a single factor model:
# \begin{equation}
# R_{i,t}= \alpha_i + \beta_i R_{DJTSEC,t} + \epsilon_{i,t}
# \end{equation}
# In[7]:
n=ExcessReturns.shape[1]-1
```

```
alphas=np.zeros((n, 1))
betas=np.zeros((n, 1))
sigma2=np.zeros((n, 1))
n
# In[8]:
x=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, n]
x=sm.add_constant(x)
x
# In[9]:
for i in range(n):

    y=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, i]
    model=sm.OLS(y,x)
    results=model.fit()

    print(results.summary())
    alphas[i]=results.params[0]
    betas[i]=results.params[1]
    sigma2[i]=results.scale
# In[10]:
IndexER=ExcessReturns['DJTSEC'].iloc[endEstWindow:endEstWindow+41]
IndexER
# In[11]:
PT=pd.DataFrame(index=IndexER.index)
columns=['AAPL', 'MSFT', 'V', 'NVDA', 'UNH', 'JNJ', 'GOOGL', 'MA',
'HD', 'WMT', 'COST', 'ASML', 'LLY', 'CSCO', 'AVGO', 'AMZN', 'ACN',
'JPM', 'CVX', 'XOM', 'BAC', 'PFE', 'MRK', 'CRM', 'ROG', 'ADBE',
'QCOM', 'TMO', 'NOVN', 'PG', 'IBM', 'LOW', 'COP', 'INTU', 'WFC',
'MC', 'NOVOB', 'ABT', 'INTC', 'DHR', 'SAP', 'BMY', 'KO', 'NESN',
'TTE', 'PM', 'ADP', 'AMGN', 'SCHW', 'GS', 'RTX', 'RY', 'SPGI',
'MS', 'ELV', 'TJX', 'NKE', 'TSLA', 'UNP', 'CVS', 'UPS', 'TD',
'BLK', 'CBA', 'RIGD', 'TGT', 'AMAT', 'MDT', 'CAT', 'GM', 'LMT',
'DE', 'AXP', 'PLD', 'NEE', 'F', 'NFLX', 'SAN', 'T', 'LIN', 'CI',
'MCD', 'C', 'ENB', 'EOG', 'MBG', 'SBUX', 'GILD', 'MU', 'MO', 'HDB',
'CB', 'DG', 'BKNG', 'CSL', 'OR', 'GE', 'SLB', 'SIE', 'LRCX', 'VZ',
'BX', 'DTE', 'BA', 'NOC', 'ORLY', 'MMC', 'SYK', 'AMT', 'BHP',
'CNQ', 'CME', 'AZO', 'DUK', 'PGR', 'ALV', 'SO', 'CNR', 'ADM', 'AI',
'PXD', 'SU', 'DIS', 'CMCSA', 'PNC', 'HUM', 'NAB', 'MMM', 'CHTR',
'ABI', 'BDX', 'CL', 'BMO', 'GIS', 'ICE', 'AIR', 'ZURN', 'IBE',
'TFC', 'OXY', 'IBN', 'BNS', 'USB', 'AON', 'D', 'UBSG', 'APD',
'SYY', 'ITW', 'VLO']
tcolumns=['SAR(AAPL)', 'SAR(MSFT)', 'SAR(V)', 'SAR(NVDA)',
'SAR(UNH)', 'SAR(JNJ)', 'SAR(GOOGL)', 'SAR(MA)', 'SAR(HD)',
'SAR(WMT)', 'SAR(COST)', 'SAR(ASML)', 'SAR(LLY)', 'SAR(CSCO)',
'SAR(AVGO)', 'SAR(AMZN)', 'SAR(ACN)', 'SAR(JPM)', 'SAR(CVX)',
'SAR(XOM)', 'SAR(BAC)', 'SAR(PFE)', 'SAR(MRK)', 'SAR(CRM)',
'SAR(ROG)', 'SAR(ADBE)', 'SAR(QCOM)', 'SAR(TMO)', 'SAR(NOVN)',
'SAR(PG)', 'SAR(IBM)', 'SAR(LOW)', 'SAR(COP)', 'SAR(INTU)',
'SAR(WFC)', 'SAR(MC)', 'SAR(NOVOB)', 'SAR(ABT)', 'SAR(INTC)',
'SAR(DHR)', 'SAR(SAP)', 'SAR(BMY)', 'SAR(KO)', 'SAR(NESN)',
'SAR(TTE)', 'SAR(PM)', 'SAR(ADP)', 'SAR(AMGN)', 'SAR(SCHW)',
'SAR(GS)', 'SAR(RTX)', 'SAR(RY)', 'SAR(SPGI)', 'SAR(MS)',
'SAR(ELV)', 'SAR(TJX)', 'SAR(NKE)', 'SAR(TSLA)', 'SAR(UNP)',
'SAR(CVS)', 'SAR(UPS)', 'SAR(TD)', 'SAR(BLK)', 'SAR(CBA)',
'SAR(RIGD)', 'SAR(TGT)', 'SAR(AMAT)', 'SAR(MDT)', 'SAR(CAT)',
'SAR(GM)', 'SAR(LMT)', 'SAR(DE)', 'SAR(AXP)', 'SAR(PLD)',
'SAR(NEE)', 'SAR(F)', 'SAR(NFLX)', 'SAR(SAN)', 'SAR(T)',
'SAR(LIN)', 'SAR(CI)', 'SAR(MCD)', 'SAR(C)', 'SAR(ENB)',
```

```
'SAR(EOG)', 'SAR(MBG)', 'SAR(SBUX)', 'SAR(GILD)', 'SAR(MU)',
'SAR(MO)', 'SAR(HDB)', 'SAR(CB)', 'SAR(DG)', 'SAR(BKNG)',
'SAR(CSL)', 'SAR(OR)', 'SAR(GE)', 'SAR(SLB)', 'SAR(SIE)',
'SAR(LRCX)', 'SAR(VZ)', 'SAR(BX)', 'SAR(DTE)', 'SAR(BA)',
'SAR(NOC)', 'SAR(ORLY)', 'SAR(MMC)', 'SAR(SYK)', 'SAR(AMT)',
'SAR(BHP)', 'SAR(CNQ)', 'SAR(CME)', 'SAR(AZO)', 'SAR(DUK)',
'SAR(PGR)', 'SAR(ALV)', 'SAR(SO)', 'SAR(CNR)', 'SAR(ADM)',
'SAR(AI)', 'SAR(PXD)', 'SAR(SU)', 'SAR(DIS)', 'SAR(CMCSA)',
'SAR(PNC)', 'SAR(HUM)', 'SAR(NAB)', 'SAR(MMM)', 'SAR(CHTR)',
'SAR(ABI)', 'SAR(BDX)', 'SAR(CL)', 'SAR(BMO)', 'SAR(GIS)',
'SAR(ICE)', 'SAR(AIR)', 'SAR(ZURN)', 'SAR(IBE)', 'SAR(TFC)',
'SAR(OXY)', 'SAR(IBN)', 'SAR(BNS)', 'SAR(USB)', 'SAR(AON)',
'SAR(D)', 'SAR(UBSG)', 'SAR(APD)', 'SAR(SYY)', 'SAR(ITW)',
'SAR(VLO)']
pcolumns=['p-SAR(AAPL)', 'p-SAR(MSFT)', 'p-SAR(V)', 'p-SAR(NVDA)',
'p-SAR(UNH)', 'p-SAR(JNJ)', 'p-SAR(GOOGL)', 'p-SAR(MA)', 'p-
SAR(HD)', 'p-SAR(WMT)', 'p-SAR(COST)', 'p-SAR(ASML)', 'p-SAR(LLY)',
'p-SAR(CSCO)', 'p-SAR(AVGO)', 'p-SAR(AMZN)', 'p-SAR(ACN)', 'p-
SAR(JPM)', 'p-SAR(CVX)', 'p-SAR(XOM)', 'p-SAR(BAC)', 'p-SAR(PFE)',
'p-SAR(MRK)', 'p-SAR(CRM)', 'p-SAR(ROG)', 'p-SAR(ADBE)', 'p-
SAR(QCOM)', 'p-SAR(TMO)', 'p-SAR(NOVN)', 'p-SAR(PG)', 'p-SAR(IBM)',
'p-SAR(LOW)', 'p-SAR(COP)', 'p-SAR(INTU)', 'p-SAR(WFC)', 'p-
SAR(MC)', 'p-SAR(NOVOB)', 'p-SAR(ABT)', 'p-SAR(INTC)', 'p-
SAR(DHR)', 'p-SAR(SAP)', 'p-SAR(BMY)', 'p-SAR(KO)', 'p-SAR(NESN)',
'p-SAR(TTE)', 'p-SAR(PM)', 'p-SAR(ADP)', 'p-SAR(AMGN)', 'p-
SAR(SCHW)', 'p-SAR(GS)', 'p-SAR(RTX)', 'p-SAR(RY)', 'p-SAR(SPGI)',
'p-SAR(MS)', 'p-SAR(ELV)', 'p-SAR(TJX)', 'p-SAR(NKE)', 'p-
SAR(TSLA)', 'p-SAR(UNP)', 'p-SAR(CVS)', 'p-SAR(UPS)', 'p-SAR(TD)',
'p-SAR(BLK)', 'p-SAR(CBA)', 'p-SAR(RIGD)', 'p-SAR(TGT)', 'p-
SAR(AMAT)', 'p-SAR(MDT)', 'p-SAR(CAT)', 'p-SAR(GM)', 'p-SAR(LMT)',
'p-SAR(DE)', 'p-SAR(AXP)', 'p-SAR(PLD)', 'p-SAR(NEE)', 'p-SAR(F)',
'p-SAR(NFLX)', 'p-SAR(SAN)', 'p-SAR(T)', 'p-SAR(LIN)', 'p-SAR(CI)',
'p-SAR(MCD)', 'p-SAR(C)', 'p-SAR(ENB)', 'p-SAR(EOG)', 'p-SAR(MBG)',
'p-SAR(SBUX)', 'p-SAR(GILD)', 'p-SAR(MU)', 'p-SAR(MO)', 'p-
SAR(HDB)', 'p-SAR(CB)', 'p-SAR(DG)', 'p-SAR(BKNG)', 'p-SAR(CSL)',
'p-SAR(OR)', 'p-SAR(GE)', 'p-SAR(SLB)', 'p-SAR(SIE)', 'p-
SAR(LRCX)', 'p-SAR(VZ)', 'p-SAR(BX)', 'p-SAR(DTE)', 'p-SAR(BA)',
'p-SAR(NOC)', 'p-SAR(ORLY)', 'p-SAR(MMC)', 'p-SAR(SYK)', 'p-
SAR(AMT)', 'p-SAR(BHP)', 'p-SAR(CNQ)', 'p-SAR(CME)', 'p-SAR(AZO)',
'p-SAR(DUK)', 'p-SAR(PGR)', 'p-SAR(ALV)', 'p-SAR(SO)', 'p-
SAR(CNR)', 'p-SAR(ADM)', 'p-SAR(AI)', 'p-SAR(PXD)', 'p-SAR(SU)',
'p-SAR(DIS)', 'p-SAR(CMCSA)', 'p-SAR(PNC)', 'p-SAR(HUM)', 'p-
SAR(NAB)', 'p-SAR(MMM)', 'p-SAR(CHTR)', 'p-SAR(ABI)', 'p-SAR(BDX)',
'p-SAR(CL)', 'p-SAR(BMO)', 'p-SAR(GIS)', 'p-SAR(ICE)', 'p-
SAR(AIR)', 'p-SAR(ZURN)', 'p-SAR(IBE)', 'p-SAR(TFC)', 'p-SAR(OXY)',
'p-SAR(IBN)', 'p-SAR(BNS)', 'p-SAR(USB)', 'p-SAR(AON)', 'p-SAR(D)',
'p-SAR(UBSG)', 'p-SAR(APD)', 'p-SAR(SYY)', 'p-SAR(ITW)', 'p-
SAR(VLO)']
ObsRet=ExcessReturns.loc[IndexER.index]
print(ObsRet)
PT
# In[12]:
for i in range(n):
    print(i)
    PT[columns[i]]=ObsRet.iloc[:, i]-alphas[i]-betas[i]*IndexER
    PT[tcolumns[i]]=PT[columns[i]]/np.sqrt(sigma2[i])
    PT[pcolumns[i]]=2*scipy.stats.norm.cdf(-
np.absolute(PT[tcolumns[i]]), loc=0, scale=1)
```

```
print(PT)
# #### Average Abnormal Returns
# In[13]:
PT['AvgAR']=PT[tcolumns].mean(axis=1)
PT['SAvgAR']=PT['AvgAR']/np.sqrt(np.sum(sigma2/n**2))
PT['p-SAvgAR']=2*scipy.stats.norm.cdf(-np.absolute(PT['SAvgAR']),
loc=0, scale=1)
print(PT['AvgAR'])
print(PT['SAvgAR'])
print(PT['p-SAvgAR'])
# In[14]:
x=list(range(-20, 21))
y=PT['AvgAR']
x1=(-20, 21)
y1=(0, 0)
plt.plot(x, y, color='green', marker='v')
plt.plot(x1, y1, color='blue', linewidth=3)
plt.xlim(-20, 21)
plt.xlabel('Event Window')
plt.ylabel('AAR')
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[15]:
print(np.mean(PT['AvgAR']))
# #### Cumulative Abnormal Returns
# In[16]:
CumulativeAbnormalReturns=pd.DataFrame(columns=columns,
index=['CAR', 'SCAR', 'p-value'])
CumulativeAbnormalReturns
# In[17]:
CumulativeAbnormalReturns.loc['CAR']=PT[columns].sum(axis=0)
CumulativeAbnormalReturns
# In[18]:
win=PT.shape[0]
CumulativeAbnormalReturns.loc['SCAR']=CumulativeAbnormalReturns.loc
['CAR']/(np.sqrt(win*sigma2[0,:]))
CumulativeAbnormalReturns
# In[19]:
CumulativeAbnormalReturns.loc['p-
value']=CumulativeAbnormalReturns.loc['SCAR'].apply(lambda
x:(2*scipy.stats.norm.cdf(-np.absolute(x), loc=0, scale=1)))
print(CumulativeAbnormalReturns)
# In[20]:
print(CumulativeAbnormalReturns.loc['p-value']>0.05)
# In[21]:
x=list(range(150))
y=CumulativeAbnormalReturns.loc['p-value']
x1=(-1, 150)
y1=(0.05, 0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.scatter(x, y, color='red', marker='o')
plt.plot(x1, y1, color='black', linewidth=3)
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
```

```
# In[22]:
x=list(range(150))
y=(CumulativeAbnormalReturns.loc['p-value']>0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.title('Significance of p-value')
plt.scatter(x, y, color='red', marker='x')
plt.minorticks_on()
plt.grid(color='black', which='both')
plt.show()
# In[23]:
Scores=pd.read_excel('ESG Scores.xlsx', index_col=0)
print(Scores)
# In[24]:
print(Scores.loc['2015-12-31'])
# In[25]:
x=Scores.loc['2015-12-31']
y=CumulativeAbnormalReturns.loc['CAR']
plt.xlim(0, 70)
plt.xlabel('ESG Score')
plt.ylabel('CAR')
plt.scatter(x, y, color='blue', marker='D')
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()

# #### Study of Correlation
# In[26]:
Returns=Returns.drop(['TYield10Y', 'DJTSEC'], axis=1)
CorrMatrix=Returns.corr()
CorrMatrix
# In[27]:
seaborn.heatmap(data=CorrMatrix, xticklabels=False,
yticklabels=False)

# #### Study of Variance and Volatility
# In[28]:
VarCov=ExcessReturns.cov()
VarCov
# In[29]:
plt.plot(VarCov)
plt.xlabel('Stock')
plt.xticks(color='w')
plt.xlim(-1, 151)
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()
# In[30]:
plt.scatter(VarCov, VarCov, color='orange')
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()

# #### Year 2016
# In[5]:
estSize=253
idx=ExcessReturns[ExcessReturns.index < '2016-12-31'].iloc[-20]
```

```
print(idx)
est_window_stop=idx.name
endEstWindow=ExcessReturns.index.get_loc(est_window_stop)
print(f'{est_window_stop} is in the position {endEstWindow} of the
dataframe')
# In[6]:
n=ExcessReturns.shape[1]-1
alphas=np.zeros((n, 1))
betas=np.zeros((n, 1))
sigma2=np.zeros((n, 1))
n
# In[7]:
x=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, n]
x=sm.add_constant(x)
x
# In[8]:
for i in range(n):

    y=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, i]
    model=sm.OLS(y,x)
    results=model.fit()

    print(results.summary())
    alphas[i]=results.params[0]
    betas[i]=results.params[1]
    sigma2[i]=results.scale
# In[9]:
IndexER=ExcessReturns['DJTSEC'].iloc[endEstWindow:endEstWindow+41]
IndexER
# In[10]:
PT=pd.DataFrame(index=IndexER.index)
columns=['AAPL', 'MSFT', 'V', 'NVDA', 'UNH', 'JNJ', 'GOOGL', 'MA',
'HD', 'WMT', 'COST', 'ASML', 'LLY', 'CSCO', 'AVGO', 'AMZN', 'ACN',
'JPM', 'CVX', 'XOM', 'BAC', 'PFE', 'MRK', 'CRM', 'ROG', 'ADBE',
'QCOM', 'TMO', 'NOVN', 'PG', 'IBM', 'LOW', 'COP', 'INTU', 'WFC',
'MC', 'NOVOB', 'ABT', 'INTC', 'DHR', 'SAP', 'BMY', 'KO', 'NESN',
'TTE', 'PM', 'ADP', 'AMGN', 'SCHW', 'GS', 'RTX', 'RY', 'SPGI',
'MS', 'ELV', 'TJX', 'NKE', 'TSLA', 'UNP', 'CVS', 'UPS', 'TD',
'BLK', 'CBA', 'RIGD', 'TGT', 'AMAT', 'MDT', 'CAT', 'GM', 'LMT',
'DE', 'AXP', 'PLD', 'NEE', 'F', 'NFLX', 'SAN', 'T', 'LIN', 'CI',
'MCD', 'C', 'ENB', 'EOG', 'MBG', 'SBUX', 'GILD', 'MU', 'MO', 'HDB',
'CB', 'DG', 'BKNG', 'CSL', 'OR', 'GE', 'SLB', 'SIE', 'LRCX', 'VZ',
'BX', 'DTE', 'BA', 'NOC', 'ORLY', 'MMC', 'SYK', 'AMT', 'BHP',
'CNQ', 'CME', 'AZO', 'DUK', 'PGR', 'ALV', 'SO', 'CNR', 'ADM', 'AI',
'PXD', 'SU', 'DIS', 'CMCSA', 'PNC', 'HUM', 'NAB', 'MMM', 'CHTR',
'ABI', 'BDX', 'CL', 'BMO', 'GIS', 'ICE', 'AIR', 'ZURN', 'IBE',
'TFC', 'OXY', 'IBN', 'BNS', 'USB', 'AON', 'D', 'UBSG', 'APD',
'SYY', 'ITW', 'VLO']
tcolumns=['SAR(AAPL)', 'SAR(MSFT)', 'SAR(V)', 'SAR(NVDA)',
'SAR(UNH)', 'SAR(JNJ)', 'SAR(GOOGL)', 'SAR(MA)', 'SAR(HD)',
'SAR(WMT)', 'SAR(COST)', 'SAR(ASML)', 'SAR(LLY)', 'SAR(CSCO)',
'SAR(AVGO)', 'SAR(AMZN)', 'SAR(ACN)', 'SAR(JPM)', 'SAR(CVX)',
'SAR(XOM)', 'SAR(BAC)', 'SAR(PFE)', 'SAR(MRK)', 'SAR(CRM)',
'SAR(ROG)', 'SAR(ADBE)', 'SAR(QCOM)', 'SAR(TMO)', 'SAR(NOVN)',
'SAR(PG)', 'SAR(IBM)', 'SAR(LOW)', 'SAR(COP)', 'SAR(INTU)',
'SAR(WFC)', 'SAR(MC)', 'SAR(NOVOB)', 'SAR(ABT)', 'SAR(INTC)',
'SAR(DHR)', 'SAR(SAP)', 'SAR(BMY)', 'SAR(KO)', 'SAR(NESN)',
'SAR(TTE)', 'SAR(PM)', 'SAR(ADP)', 'SAR(AMGN)', 'SAR(SCHW)',
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'SAR(GS)', 'SAR(RTX)', 'SAR(RY)', 'SAR(SPGI)', 'SAR(MS)',
'SAR(ELV)', 'SAR(TJX)', 'SAR(NKE)', 'SAR(TSLA)', 'SAR(UNP)',
'SAR(CVS)', 'SAR(UPS)', 'SAR(TD)', 'SAR(BLK)', 'SAR(CBA)',
'SAR(RIGD)', 'SAR(TGT)', 'SAR(AMAT)', 'SAR(MDT)', 'SAR(CAT)',
'SAR(GM)', 'SAR(LMT)', 'SAR(DE)', 'SAR(AXP)', 'SAR(PLD)',
'SAR(NEE)', 'SAR(F)', 'SAR(NFLX)', 'SAR(SAN)', 'SAR(T)',
'SAR(LIN)', 'SAR(CI)', 'SAR(MCD)', 'SAR(C)', 'SAR(ENB)',
'SAR(EOG)', 'SAR(MBG)', 'SAR(SBUX)', 'SAR(GILD)', 'SAR(MU)',
'SAR(MO)', 'SAR(HDB)', 'SAR(CB)', 'SAR(DG)', 'SAR(BKNG)',
'SAR(CSL)', 'SAR(OR)', 'SAR(GE)', 'SAR(SLB)', 'SAR(SIE)',
'SAR(LRCX)', 'SAR(VZ)', 'SAR(BX)', 'SAR(DTE)', 'SAR(BA)',
'SAR(NOC)', 'SAR(ORLY)', 'SAR(MMC)', 'SAR(SYK)', 'SAR(AMT)',
'SAR(BHP)', 'SAR(CNQ)', 'SAR(CME)', 'SAR(AZO)', 'SAR(DUK)',
'SAR(PGR)', 'SAR(ALV)', 'SAR(SO)', 'SAR(CNR)', 'SAR(ADM)',
'SAR(AI)', 'SAR(PXD)', 'SAR(SU)', 'SAR(DIS)', 'SAR(CMCSA)',
'SAR(PNC)', 'SAR(HUM)', 'SAR(NAB)', 'SAR(MMM)', 'SAR(CHTR)',
'SAR(ABI)', 'SAR(BDX)', 'SAR(CL)', 'SAR(BMO)', 'SAR(GIS)',
'SAR(ICE)', 'SAR(AIR)', 'SAR(ZURN)', 'SAR(IBE)', 'SAR(TFC)',
'SAR(OXY)', 'SAR(IBN)', 'SAR(BNS)', 'SAR(USB)', 'SAR(AON)',
'SAR(D)', 'SAR(UBSG)', 'SAR(APD)', 'SAR(SYY)', 'SAR(ITW)',
'SAR(VLO)']
pcolumns=['p-SAR(AAPL)', 'p-SAR(MSFT)', 'p-SAR(V)', 'p-SAR(NVDA)',
'p-SAR(UNH)', 'p-SAR(JNJ)', 'p-SAR(GOOGL)', 'p-SAR(MA)', 'p-
SAR(HD)', 'p-SAR(WMT)', 'p-SAR(COST)', 'p-SAR(ASML)', 'p-SAR(LLY)',
'p-SAR(CSCO)', 'p-SAR(AVGO)', 'p-SAR(AMZN)', 'p-SAR(ACN)', 'p-
SAR(JPM)', 'p-SAR(CVX)', 'p-SAR(XOM)', 'p-SAR(BAC)', 'p-SAR(PFE)',
'p-SAR(MRK)', 'p-SAR(CRM)', 'p-SAR(ROG)', 'p-SAR(ADBE)', 'p-
SAR(QCOM)', 'p-SAR(TMO)', 'p-SAR(NOVN)', 'p-SAR(PG)', 'p-SAR(IBM)',
'p-SAR(LOW)', 'p-SAR(COP)', 'p-SAR(INTU)', 'p-SAR(WFC)', 'p-
SAR(MC)', 'p-SAR(NOVOB)', 'p-SAR(ABT)', 'p-SAR(INTC)', 'p-
SAR(DHR)', 'p-SAR(SAP)', 'p-SAR(BMY)', 'p-SAR(KO)', 'p-SAR(NESN)',
'p-SAR(TTE)', 'p-SAR(PM)', 'p-SAR(ADP)', 'p-SAR(AMGN)', 'p-
SAR(SCHW)', 'p-SAR(GS)', 'p-SAR(RTX)', 'p-SAR(RY)', 'p-SAR(SPGI)',
'p-SAR(MS)', 'p-SAR(ELV)', 'p-SAR(TJX)', 'p-SAR(NKE)', 'p-
SAR(TSLA)', 'p-SAR(UNP)', 'p-SAR(CVS)', 'p-SAR(UPS)', 'p-SAR(TD)',
'p-SAR(BLK)', 'p-SAR(CBA)', 'p-SAR(RIGD)', 'p-SAR(TGT)', 'p-
SAR(AMAT)', 'p-SAR(MDT)', 'p-SAR(CAT)', 'p-SAR(GM)', 'p-SAR(LMT)',
'p-SAR(DE)', 'p-SAR(AXP)', 'p-SAR(PLD)', 'p-SAR(NEE)', 'p-SAR(F)',
'p-SAR(NFLX)', 'p-SAR(SAN)', 'p-SAR(T)', 'p-SAR(LIN)', 'p-SAR(CI)',
'p-SAR(MCD)', 'p-SAR(C)', 'p-SAR(ENB)', 'p-SAR(EOG)', 'p-SAR(MBG)',
'p-SAR(SBUX)', 'p-SAR(GILD)', 'p-SAR(MU)', 'p-SAR(MO)', 'p-
SAR(HDB)', 'p-SAR(CB)', 'p-SAR(DG)', 'p-SAR(BKNG)', 'p-SAR(CSL)',
'p-SAR(OR)', 'p-SAR(GE)', 'p-SAR(SLB)', 'p-SAR(SIE)', 'p-
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'p-SAR(DUK)', 'p-SAR(PGR)', 'p-SAR(ALV)', 'p-SAR(SO)', 'p-
SAR(CNR)', 'p-SAR(ADM)', 'p-SAR(AI)', 'p-SAR(PXD)', 'p-SAR(SU)',
'p-SAR(DIS)', 'p-SAR(CMCSA)', 'p-SAR(PNC)', 'p-SAR(HUM)', 'p-
SAR(NAB)', 'p-SAR(MMM)', 'p-SAR(CHTR)', 'p-SAR(ABI)', 'p-SAR(BDX)',
'p-SAR(CL)', 'p-SAR(BMO)', 'p-SAR(GIS)', 'p-SAR(ICE)', 'p-
SAR(AIR)', 'p-SAR(ZURN)', 'p-SAR(IBE)', 'p-SAR(TFC)', 'p-SAR(OXY)',
'p-SAR(IBN)', 'p-SAR(BNS)', 'p-SAR(USB)', 'p-SAR(AON)', 'p-SAR(D)',
'p-SAR(UBSG)', 'p-SAR(APD)', 'p-SAR(SYY)', 'p-SAR(ITW)', 'p-
SAR(VLO)']
ObsRet=ExcessReturns.loc[IndexER.index]
print(ObsRet)
PT
```

```
# In[11]:
for i in range(n):
    print(i)
    PT[columns[i]]=ObsRet.iloc[:, i]-alphas[i]-betas[i]*IndexER
    PT[tcolumns[i]]=PT[columns[i]]/np.sqrt(sigma2[i])
    PT[pcolumns[i]]=2*scipy.stats.norm.cdf(-
np.absolute(PT[tcolumns[i]]), loc=0, scale=1)
PT
# #### Average Abnormal Returns
# In[12]:
PT['AvgAR']=PT[tcolumns].mean(axis=1)
PT['SAvgAR']=PT['AvgAR']/np.sqrt(np.sum(sigma2/n**2))
PT['p-SAvgAR']=2*scipy.stats.norm.cdf(-np.absolute(PT['SAvgAR']),
loc=0, scale=1)
print(PT['AvgAR'])
print(PT['SAvgAR'])
print(PT['p-SAvgAR'])
# In[13]:
seaborn.set_style('darkgrid')
plt.rc('figure', figsize=(20, 10))
plt.rc('savefig', dpi=90)
plt.rc('font', family='sans-serif')
plt.rc('font', size=15)
# In[14]:
x=list(range(-20, 21))
y=PT['AvgAR']
x1=(-20, 21)
y1=(0, 0)
plt.plot(x, y, color='green', marker='v')
plt.plot(x1, y1, color='blue', linewidth=3)
plt.xlim(-20, 21)
plt.xlabel('Event Window')
plt.ylabel('AAR')
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[15]:
print(np.mean(PT['AvgAR']))
# #### Cumulative Abnormal Returns
# In[16]:
CumulativeAbnormalReturns=pd.DataFrame(columns=columns,
index=['CAR', 'SCAR', 'p-value'])
CumulativeAbnormalReturns
# In[17]:
CumulativeAbnormalReturns.loc['CAR']=PT[columns].sum(axis=0)
CumulativeAbnormalReturns
# In[18]:
win=PT.shape[0]
CumulativeAbnormalReturns.loc['SCAR']=CumulativeAbnormalReturns.loc
['CAR']/(np.sqrt(win*sigma2[0,:]))
CumulativeAbnormalReturns
# In[19]:
CumulativeAbnormalReturns.loc['p-
value']=CumulativeAbnormalReturns.loc['SCAR'].apply(lambda
x:(2*scipy.stats.norm.cdf(-np.absolute(x), loc=0, scale=1)))
CumulativeAbnormalReturns
# In[20]:
print(CumulativeAbnormalReturns.loc['p-value']>0.05)
```

```
# In[21]:
x=list(range(150))
y=CumulativeAbnormalReturns.loc['p-value']
x1=(-1, 150)
y1=(0.05, 0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.scatter(x, y, color='red', marker='o')
plt.plot(x1, y1, color='black', linewidth=3)
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[22]:
x=list(range(150))
y=(CumulativeAbnormalReturns.loc['p-value']>0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.title('Significance of p-value')
plt.scatter(x, y, color='red', marker='x')
plt.minorticks_on()
plt.grid(color='black', which='both')
plt.show()
# In[23]:
Scores=pd.read_excel('ESG Scores.xlsx', index_col=0)
print(Scores)
# In[24]:
print(Scores.loc['2016-12-31'])
# In[25]:
x=Scores.loc['2016-12-31']
y=CumulativeAbnormalReturns.loc['CAR']
plt.xlim(0, 70)
plt.xlabel('ESG Score')
plt.ylabel('CAR')
plt.scatter(x, y, color='blue', marker='D')
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()

# #### Year 2017
# In[5]:
estSize=253
idx=ExcessReturns[ExcessReturns.index < '2017-12-31'].iloc[-20]
print(idx)
est_window_stop=idx.name
endEstWindow=ExcessReturns.index.get_loc(est_window_stop)
print(f'{est_window_stop} is in the position {endEstWindow} of the
dataframe')
# In[6]:
n=ExcessReturns.shape[1]-1
alphas=np.zeros((n, 1))
betas=np.zeros((n, 1))
sigma2=np.zeros((n, 1))
n
# In[7]:
x=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, n]
x=sm.add_constant(x)
```

```
x
# In[8]:
for i in range(n):

    y=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, i]
    model=sm.OLS(y,x)
    results=model.fit()

    print(results.summary())
    alphas[i]=results.params[0]
    betas[i]=results.params[1]
    sigma2[i]=results.scale
# In[9]:
IndexER=ExcessReturns['DJTSEC'].iloc[endEstWindow:endEstWindow+41]
IndexER
# In[10]:
PT=pd.DataFrame(index=IndexER.index)
columns=['AAPL', 'MSFT', 'V', 'NVDA', 'UNH', 'JNJ', 'GOOGL', 'MA',
'HD', 'WMT', 'COST', 'ASML', 'LLY', 'CSCO', 'AVGO', 'AMZN', 'ACN',
'JPM', 'CVX', 'XOM', 'BAC', 'PFE', 'MRK', 'CRM', 'ROG', 'ADBE',
'QCOM', 'TMO', 'NOVN', 'PG', 'IBM', 'LOW', 'COP', 'INTU', 'WFC',
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'TTE', 'PM', 'ADP', 'AMGN', 'SCHW', 'GS', 'RTX', 'RY', 'SPGI',
'MS', 'ELV', 'TJX', 'NKE', 'TSLA', 'UNP', 'CVS', 'UPS', 'TD',
'BLK', 'CBA', 'RIGD', 'TGT', 'AMAT', 'MDT', 'CAT', 'GM', 'LMT',
'DE', 'AXP', 'PLD', 'NEE', 'F', 'NFLX', 'SAN', 'T', 'LIN', 'CI',
'MCD', 'C', 'ENB', 'EOG', 'MBG', 'SBUX', 'GILD', 'MU', 'MO', 'HDB',
'CB', 'DG', 'BKNG', 'CSL', 'OR', 'GE', 'SLB', 'SIE', 'LRCX', 'VZ',
'BX', 'DTE', 'BA', 'NOC', 'ORLY', 'MMC', 'SYK', 'AMT', 'BHP',
'CNQ', 'CME', 'AZO', 'DUK', 'PGR', 'ALV', 'SO', 'CNR', 'ADM', 'AI',
'PXD', 'SU', 'DIS', 'CMCSA', 'PNC', 'HUM', 'NAB', 'MMM', 'CHTR',
'ABI', 'BDX', 'CL', 'BMO', 'GIS', 'ICE', 'AIR', 'ZURN', 'IBE',
'TFC', 'OXY', 'IBN', 'BNS', 'USB', 'AON', 'D', 'UBSG', 'APD',
'SYY', 'ITW', 'VLO']
tcolumns=['SAR(AAPL)', 'SAR(MSFT)', 'SAR(V)', 'SAR(NVDA)',
'SAR(UNH)', 'SAR(JNJ)', 'SAR(GOOGL)', 'SAR(MA)', 'SAR(HD)',
'SAR(WMT)', 'SAR(COST)', 'SAR(ASML)', 'SAR(LLY)', 'SAR(CSCO)',
'SAR(AVGO)', 'SAR(AMZN)', 'SAR(ACN)', 'SAR(JPM)', 'SAR(CVX)',
'SAR(XOM)', 'SAR(BAC)', 'SAR(PFE)', 'SAR(MRK)', 'SAR(CRM)',
'SAR(ROG)', 'SAR(ADBE)', 'SAR(QCOM)', 'SAR(TMO)', 'SAR(NOVN)',
'SAR(PG)', 'SAR(IBM)', 'SAR(LOW)', 'SAR(COP)', 'SAR(INTU)',
'SAR(WFC)', 'SAR(MC)', 'SAR(NOVOB)', 'SAR(ABT)', 'SAR(INTC)',
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'SAR(GS)', 'SAR(RTX)', 'SAR(RY)', 'SAR(SPGI)', 'SAR(MS)',
'SAR(ELV)', 'SAR(TJX)', 'SAR(NKE)', 'SAR(TSLA)', 'SAR(UNP)',
'SAR(CVS)', 'SAR(UPS)', 'SAR(TD)', 'SAR(BLK)', 'SAR(CBA)',
'SAR(RIGD)', 'SAR(TGT)', 'SAR(AMAT)', 'SAR(MDT)', 'SAR(CAT)',
'SAR(GM)', 'SAR(LMT)', 'SAR(DE)', 'SAR(AXP)', 'SAR(PLD)',
'SAR(NEE)', 'SAR(F)', 'SAR(NFLX)', 'SAR(SAN)', 'SAR(T)',
'SAR(LIN)', 'SAR(CI)', 'SAR(MCD)', 'SAR(C)', 'SAR(ENB)',
'SAR(EOG)', 'SAR(MBG)', 'SAR(SBUX)', 'SAR(GILD)', 'SAR(MU)',
'SAR(MO)', 'SAR(HDB)', 'SAR(CB)', 'SAR(DG)', 'SAR(BKNG)',
'SAR(CSL)', 'SAR(OR)', 'SAR(GE)', 'SAR(SLB)', 'SAR(SIE)',
'SAR(LRCX)', 'SAR(VZ)', 'SAR(BX)', 'SAR(DTE)', 'SAR(BA)',
'SAR(NOC)', 'SAR(ORLY)', 'SAR(MMC)', 'SAR(SYK)', 'SAR(AMT)',
'SAR(BHP)', 'SAR(CNQ)', 'SAR(CME)', 'SAR(AZO)', 'SAR(DUK)',
'SAR(PGR)', 'SAR(ALV)', 'SAR(SO)', 'SAR(CNR)', 'SAR(ADM)',
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'SAR(AI)', 'SAR(PXD)', 'SAR(SU)', 'SAR(DIS)', 'SAR(CMCSA)',
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'SAR(ABI)', 'SAR(BDX)', 'SAR(CL)', 'SAR(BMO)', 'SAR(GIS)',
'SAR(ICE)', 'SAR(AIR)', 'SAR(ZURN)', 'SAR(IBE)', 'SAR(TFC)',
'SAR(OXY)', 'SAR(IBN)', 'SAR(BNS)', 'SAR(USB)', 'SAR(AON)',
'SAR(D)', 'SAR(UBSG)', 'SAR(APD)', 'SAR(SYY)', 'SAR(ITW)',
'SAR(VLO)']
pcolumns=['p-SAR(AAPL)', 'p-SAR(MSFT)', 'p-SAR(V)', 'p-SAR(NVDA)',
'p-SAR(UNH)', 'p-SAR(JNJ)', 'p-SAR(GOOGL)', 'p-SAR(MA)', 'p-
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'p-SAR(CSCO)', 'p-SAR(AVGO)', 'p-SAR(AMZN)', 'p-SAR(ACN)', 'p-
SAR(JPM)', 'p-SAR(CVX)', 'p-SAR(XOM)', 'p-SAR(BAC)', 'p-SAR(PFE)',
'p-SAR(MRK)', 'p-SAR(CRM)', 'p-SAR(ROG)', 'p-SAR(ADBE)', 'p-
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'p-SAR(LOW)', 'p-SAR(COP)', 'p-SAR(INTU)', 'p-SAR(WFC)', 'p-
SAR(MC)', 'p-SAR(NOVOB)', 'p-SAR(ABT)', 'p-SAR(INTC)', 'p-
SAR(DHR)', 'p-SAR(SAP)', 'p-SAR(BMY)', 'p-SAR(KO)', 'p-SAR(NESN)',
'p-SAR(TTE)', 'p-SAR(PM)', 'p-SAR(ADP)', 'p-SAR(AMGN)', 'p-
SAR(SCHW)', 'p-SAR(GS)', 'p-SAR(RTX)', 'p-SAR(RY)', 'p-SAR(SPGI)',
'p-SAR(MS)', 'p-SAR(ELV)', 'p-SAR(TJX)', 'p-SAR(NKE)', 'p-
SAR(TSLA)', 'p-SAR(UNP)', 'p-SAR(CVS)', 'p-SAR(UPS)', 'p-SAR(TD)',
'p-SAR(BLK)', 'p-SAR(CBA)', 'p-SAR(RIGD)', 'p-SAR(TGT)', 'p-
SAR(AMAT)', 'p-SAR(MDT)', 'p-SAR(CAT)', 'p-SAR(GM)', 'p-SAR(LMT)',
'p-SAR(DE)', 'p-SAR(AXP)', 'p-SAR(PLD)', 'p-SAR(NEE)', 'p-SAR(F)',
'p-SAR(NFLX)', 'p-SAR(SAN)', 'p-SAR(T)', 'p-SAR(LIN)', 'p-SAR(CI)',
'p-SAR(MCD)', 'p-SAR(C)', 'p-SAR(ENB)', 'p-SAR(EOG)', 'p-SAR(MBG)',
'p-SAR(SBUX)', 'p-SAR(GILD)', 'p-SAR(MU)', 'p-SAR(MO)', 'p-
SAR(HDB)', 'p-SAR(CB)', 'p-SAR(DG)', 'p-SAR(BKNG)', 'p-SAR(CSL)',
'p-SAR(OR)', 'p-SAR(GE)', 'p-SAR(SLB)', 'p-SAR(SIE)', 'p-
SAR(LRCX)', 'p-SAR(VZ)', 'p-SAR(BX)', 'p-SAR(DTE)', 'p-SAR(BA)',
'p-SAR(NOC)', 'p-SAR(ORLY)', 'p-SAR(MMC)', 'p-SAR(SYK)', 'p-
SAR(AMT)', 'p-SAR(BHP)', 'p-SAR(CNQ)', 'p-SAR(CME)', 'p-SAR(AZO)',
'p-SAR(DUK)', 'p-SAR(PGR)', 'p-SAR(ALV)', 'p-SAR(SO)', 'p-
SAR(CNR)', 'p-SAR(ADM)', 'p-SAR(AI)', 'p-SAR(PXD)', 'p-SAR(SU)',
'p-SAR(DIS)', 'p-SAR(CMCSA)', 'p-SAR(PNC)', 'p-SAR(HUM)', 'p-
SAR(NAB)', 'p-SAR(MMM)', 'p-SAR(CHTR)', 'p-SAR(ABI)', 'p-SAR(BDX)',
'p-SAR(CL)', 'p-SAR(BMO)', 'p-SAR(GIS)', 'p-SAR(ICE)', 'p-
SAR(AIR)', 'p-SAR(ZURN)', 'p-SAR(IBE)', 'p-SAR(TFC)', 'p-SAR(OXY)',
'p-SAR(IBN)', 'p-SAR(BNS)', 'p-SAR(USB)', 'p-SAR(AON)', 'p-SAR(D)',
'p-SAR(UBSG)', 'p-SAR(APD)', 'p-SAR(SYY)', 'p-SAR(ITW)', 'p-
SAR(VLO)']
ObsRet=ExcessReturns.loc[IndexER.index]
print(ObsRet)
PT
# In[11]:
for i in range(n):
    print(i)
    PT[columns[i]]=ObsRet.iloc[:, i]-alphas[i]-betas[i]*IndexER
    PT[tcolumns[i]]=PT[columns[i]]/np.sqrt(sigma2[i])
    PT[pcolumns[i]]=2*scipy.stats.norm.cdf(-
np.absolute(PT[tcolumns[i]]), loc=0, scale=1)
PT
# #### Average Abnormal Returns
# In[12]:
PT['AvgAR']=PT[tcolumns].mean(axis=1)
PT['SAvgAR']=PT['AvgAR']/np.sqrt(np.sum(sigma2/n**2))
PT['p-SAvgAR']=2*scipy.stats.norm.cdf(-np.absolute(PT['SAvgAR']),
loc=0, scale=1)
```

```
print(PT['AvgAR'])
print(PT['SAvgAR'])
print(PT['p-SAvgAR'])
# In[13]:
seaborn.set_style('darkgrid')
plt.rc('figure', figsize=(20, 10))
plt.rc('savefig', dpi=90)
plt.rc('font', family='sans-serif')
plt.rc('font', size=15)
# In[14]:
x=list(range(-20, 21))
y=PT['AvgAR']
x1=(-20, 21)
y1=(0, 0)
plt.plot(x, y, color='green', marker='v')
plt.plot(x1, y1, color='blue', linewidth=3)
plt.xlim(-20, 21)
plt.xlabel('Event Window')
plt.ylabel('AAR')
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[15]:
print(np.mean(PT['AvgAR']))
# #### Cumulative Abnormal Returns
# In[16]:
CumulativeAbnormalReturns=pd.DataFrame(columns=columns,
index=['CAR', 'SCAR', 'p-value'])
CumulativeAbnormalReturns
# In[17]:
CumulativeAbnormalReturns.loc['CAR']=PT[columns].sum(axis=0)
CumulativeAbnormalReturns
# In[18]:
win=PT.shape[0]
CumulativeAbnormalReturns.loc['SCAR']=CumulativeAbnormalReturns.loc
['CAR']/(np.sqrt(win*sigma2[0,:]))
CumulativeAbnormalReturns
# In[19]:
CumulativeAbnormalReturns.loc['p-
value']=CumulativeAbnormalReturns.loc['SCAR'].apply(lambda
x:(2*scipy.stats.norm.cdf(-np.absolute(x), loc=0, scale=1)))
CumulativeAbnormalReturns
# In[20]:
print(CumulativeAbnormalReturns.loc['p-value']>0.05)
# In[21]:
x=list(range(150))
y=CumulativeAbnormalReturns.loc['p-value']
x1=(-1, 150)
y1=(0.05, 0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.scatter(x, y, color='red', marker='o')
plt.plot(x1, y1, color='black', linewidth=3)
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[22]:
```

```
x=list(range(150))
y=(CumulativeAbnormalReturns.loc['p-value']>0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.title('Significance of p-value')
plt.scatter(x, y, color='red', marker='x')
plt.minorticks_on()
plt.grid(color='black', which='both')
plt.show()
# In[23]:
Scores=pd.read_excel('ESG Scores.xlsx', index_col=0)
print(Scores)
# In[24]:
print(Scores.loc['2017-12-31'])
# In[25]:
x=Scores.loc['2017-12-31']
y=CumulativeAbnormalReturns.loc['CAR']
plt.xlim(0, 70)
plt.xlabel('ESG Score')
plt.ylabel('CAR')
plt.scatter(x, y, color='blue', marker='D')
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()

# #### Year 2018
# In[5]:
estSize=253
idx=ExcessReturns[ExcessReturns.index < '2018-12-31'].iloc[-20]
print(idx)
est_window_stop=idx.name
endEstWindow=ExcessReturns.index.get_loc(est_window_stop)
print(f'{est_window_stop} is in the position {endEstWindow} of the
dataframe')
# In[6]:
n=ExcessReturns.shape[1]-1
alphas=np.zeros((n, 1))
betas=np.zeros((n, 1))
sigma2=np.zeros((n, 1))
n
# In[7]:
x=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, n]
x=sm.add_constant(x)
x
# In[8]:
for i in range(n):

    y=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, i]
    model=sm.OLS(y,x)
    results=model.fit()

    print(results.summary())
    alphas[i]=results.params[0]
    betas[i]=results.params[1]
    sigma2[i]=results.scale
# In[9]:
IndexER=ExcessReturns['DJTSEC'].iloc[endEstWindow:endEstWindow+41]
```

```
IndexER
# In[10]:
PT=pd.DataFrame(index=IndexER.index)
columns=['AAPL', 'MSFT', 'V', 'NVDA', 'UNH', 'JNJ', 'GOOGL', 'MA',
'HD', 'WMT', 'COST', 'ASML', 'LLY', 'CSCO', 'AVGO', 'AMZN', 'ACN',
'JPM', 'CVX', 'XOM', 'BAC', 'PFE', 'MRK', 'CRM', 'ROG', 'ADBE',
'QCOM', 'TMO', 'NOVN', 'PG', 'IBM', 'LOW', 'COP', 'INTU', 'WFC',
'MC', 'NOVOB', 'ABT', 'INTC', 'DHR', 'SAP', 'BMY', 'KO', 'NESN',
'TTE', 'PM', 'ADP', 'AMGN', 'SCHW', 'GS', 'RTX', 'RY', 'SPGI',
'MS', 'ELV', 'TJX', 'NKE', 'TSLA', 'UNP', 'CVS', 'UPS', 'TD',
'BLK', 'CBA', 'RIGD', 'TGT', 'AMAT', 'MDT', 'CAT', 'GM', 'LMT',
'DE', 'AXP', 'PLD', 'NEE', 'F', 'NFLX', 'SAN', 'T', 'LIN', 'CI',
'MCD', 'C', 'ENB', 'EOG', 'MBG', 'SBUX', 'GILD', 'MU', 'MO', 'HDB',
'CB', 'DG', 'BKNG', 'CSL', 'OR', 'GE', 'SLB', 'SIE', 'LRCX', 'VZ',
'BX', 'DTE', 'BA', 'NOC', 'ORLY', 'MMC', 'SYK', 'AMT', 'BHP',
'CNQ', 'CME', 'AZO', 'DUK', 'PGR', 'ALV', 'SO', 'CNR', 'ADM', 'AI',
'PXD', 'SU', 'DIS', 'CMCSA', 'PNC', 'HUM', 'NAB', 'MMM', 'CHTR',
'ABI', 'BDX', 'CL', 'BMO', 'GIS', 'ICE', 'AIR', 'ZURN', 'IBE',
'TFC', 'OXY', 'IBN', 'BNS', 'USB', 'AON', 'D', 'UBSG', 'APD',
'SYY', 'ITW', 'VLO']
tcolumns=['SAR(AAPL)', 'SAR(MSFT)', 'SAR(V)', 'SAR(NVDA)',
'SAR(UNH)', 'SAR(JNJ)', 'SAR(GOOGL)', 'SAR(MA)', 'SAR(HD)',
'SAR(WMT)', 'SAR(COST)', 'SAR(ASML)', 'SAR(LLY)', 'SAR(CSCO)',
'SAR(AVGO)', 'SAR(AMZN)', 'SAR(ACN)', 'SAR(JPM)', 'SAR(CVX)',
'SAR(XOM)', 'SAR(BAC)', 'SAR(PFE)', 'SAR(MRK)', 'SAR(CRM)',
'SAR(ROG)', 'SAR(ADBE)', 'SAR(QCOM)', 'SAR(TMO)', 'SAR(NOVN)',
'SAR(PG)', 'SAR(IBM)', 'SAR(LOW)', 'SAR(COP)', 'SAR(INTU)',
'SAR(WFC)', 'SAR(MC)', 'SAR(NOVOB)', 'SAR(ABT)', 'SAR(INTC)',
'SAR(DHR)', 'SAR(SAP)', 'SAR(BMY)', 'SAR(KO)', 'SAR(NESN)',
'SAR(TTE)', 'SAR(PM)', 'SAR(ADP)', 'SAR(AMGN)', 'SAR(SCHW)',
'SAR(GS)', 'SAR(RTX)', 'SAR(RY)', 'SAR(SPGI)', 'SAR(MS)',
'SAR(ELV)', 'SAR(TJX)', 'SAR(NKE)', 'SAR(TSLA)', 'SAR(UNP)',
'SAR(CVS)', 'SAR(UPS)', 'SAR(TD)', 'SAR(BLK)', 'SAR(CBA)',
'SAR(RIGD)', 'SAR(TGT)', 'SAR(AMAT)', 'SAR(MDT)', 'SAR(CAT)',
'SAR(GM)', 'SAR(LMT)', 'SAR(DE)', 'SAR(AXP)', 'SAR(PLD)',
'SAR(NEE)', 'SAR(F)', 'SAR(NFLX)', 'SAR(SAN)', 'SAR(T)',
'SAR(LIN)', 'SAR(CI)', 'SAR(MCD)', 'SAR(C)', 'SAR(ENB)',
'SAR(EOG)', 'SAR(MBG)', 'SAR(SBUX)', 'SAR(GILD)', 'SAR(MU)',
'SAR(MO)', 'SAR(HDB)', 'SAR(CB)', 'SAR(DG)', 'SAR(BKNG)',
'SAR(CSL)', 'SAR(OR)', 'SAR(GE)', 'SAR(SLB)', 'SAR(SIE)',
'SAR(LRCX)', 'SAR(VZ)', 'SAR(BX)', 'SAR(DTE)', 'SAR(BA)',
'SAR(NOC)', 'SAR(ORLY)', 'SAR(MMC)', 'SAR(SYK)', 'SAR(AMT)',
'SAR(BHP)', 'SAR(CNQ)', 'SAR(CME)', 'SAR(AZO)', 'SAR(DUK)',
'SAR(PGR)', 'SAR(ALV)', 'SAR(SO)', 'SAR(CNR)', 'SAR(ADM)',
'SAR(AI)', 'SAR(PXD)', 'SAR(SU)', 'SAR(DIS)', 'SAR(CMCSA)',
'SAR(PNC)', 'SAR(HUM)', 'SAR(NAB)', 'SAR(MMM)', 'SAR(CHTR)',
'SAR(ABI)', 'SAR(BDX)', 'SAR(CL)', 'SAR(BMO)', 'SAR(GIS)',
'SAR(ICE)', 'SAR(AIR)', 'SAR(ZURN)', 'SAR(IBE)', 'SAR(TFC)',
'SAR(OXY)', 'SAR(IBN)', 'SAR(BNS)', 'SAR(USB)', 'SAR(AON)',
'SAR(D)', 'SAR(UBSG)', 'SAR(APD)', 'SAR(SYY)', 'SAR(ITW)',
'SAR(VLO)']
pcolumns=['p-SAR(AAPL)', 'p-SAR(MSFT)', 'p-SAR(V)', 'p-SAR(NVDA)',
'p-SAR(UNH)', 'p-SAR(JNJ)', 'p-SAR(GOOGL)', 'p-SAR(MA)', 'p-
SAR(HD)', 'p-SAR(WMT)', 'p-SAR(COST)', 'p-SAR(ASML)', 'p-SAR(LLY)',
'p-SAR(CSCO)', 'p-SAR(AVGO)', 'p-SAR(AMZN)', 'p-SAR(ACN)', 'p-
SAR(JPM)', 'p-SAR(CVX)', 'p-SAR(XOM)', 'p-SAR(BAC)', 'p-SAR(PFE)',
'p-SAR(MRK)', 'p-SAR(CRM)', 'p-SAR(ROG)', 'p-SAR(ADBE)', 'p-
SAR(QCOM)', 'p-SAR(TMO)', 'p-SAR(NOVN)', 'p-SAR(PG)', 'p-SAR(IBM)',
```

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'p-SAR(LOW)', 'p-SAR(COP)', 'p-SAR(INTU)', 'p-SAR(WFC)', 'p-
SAR(MC)', 'p-SAR(NOVOB)', 'p-SAR(ABT)', 'p-SAR(INTC)', 'p-
SAR(DHR)', 'p-SAR(SAP)', 'p-SAR(BMY)', 'p-SAR(KO)', 'p-SAR(NESN)',
'p-SAR(TTE)', 'p-SAR(PM)', 'p-SAR(ADP)', 'p-SAR(AMGN)', 'p-
SAR(SCHW)', 'p-SAR(GS)', 'p-SAR(RTX)', 'p-SAR(RY)', 'p-SAR(SPGI)',
'p-SAR(MS)', 'p-SAR(ELV)', 'p-SAR(TJX)', 'p-SAR(NKE)', 'p-
SAR(TSLA)', 'p-SAR(UNP)', 'p-SAR(CVS)', 'p-SAR(UPS)', 'p-SAR(TD)',
'p-SAR(BLK)', 'p-SAR(CBA)', 'p-SAR(RIGD)', 'p-SAR(TGT)', 'p-
SAR(AMAT)', 'p-SAR(MDT)', 'p-SAR(CAT)', 'p-SAR(GM)', 'p-SAR(LMT)',
'p-SAR(DE)', 'p-SAR(AXP)', 'p-SAR(PLD)', 'p-SAR(NEE)', 'p-SAR(F)',
'p-SAR(NFLX)', 'p-SAR(SAN)', 'p-SAR(T)', 'p-SAR(LIN)', 'p-SAR(CI)',
'p-SAR(MCD)', 'p-SAR(C)', 'p-SAR(ENB)', 'p-SAR(EOG)', 'p-SAR(MBG)',
'p-SAR(SBUX)', 'p-SAR(GILD)', 'p-SAR(MU)', 'p-SAR(MO)', 'p-
SAR(HDB)', 'p-SAR(CB)', 'p-SAR(DG)', 'p-SAR(BKNG)', 'p-SAR(CSL)',
'p-SAR(OR)', 'p-SAR(GE)', 'p-SAR(SLB)', 'p-SAR(SIE)', 'p-
SAR(LRCX)', 'p-SAR(VZ)', 'p-SAR(BX)', 'p-SAR(DTE)', 'p-SAR(BA)',
'p-SAR(NOC)', 'p-SAR(ORLY)', 'p-SAR(MMC)', 'p-SAR(SYK)', 'p-
SAR(AMT)', 'p-SAR(BHP)', 'p-SAR(CNQ)', 'p-SAR(CME)', 'p-SAR(AZO)',
'p-SAR(DUK)', 'p-SAR(PGR)', 'p-SAR(ALV)', 'p-SAR(SO)', 'p-
SAR(CNR)', 'p-SAR(ADM)', 'p-SAR(AI)', 'p-SAR(PXD)', 'p-SAR(SU)',
'p-SAR(DIS)', 'p-SAR(CMCSA)', 'p-SAR(PNC)', 'p-SAR(HUM)', 'p-
SAR(NAB)', 'p-SAR(MMM)', 'p-SAR(CHTR)', 'p-SAR(ABI)', 'p-SAR(BDX)',
'p-SAR(CL)', 'p-SAR(BMO)', 'p-SAR(GIS)', 'p-SAR(ICE)', 'p-
SAR(AIR)', 'p-SAR(ZURN)', 'p-SAR(IBE)', 'p-SAR(TFC)', 'p-SAR(OXY)',
'p-SAR(IBN)', 'p-SAR(BNS)', 'p-SAR(USB)', 'p-SAR(AON)', 'p-SAR(D)',
'p-SAR(UBSG)', 'p-SAR(APD)', 'p-SAR(SYY)', 'p-SAR(ITW)', 'p-
SAR(VLO)']
ObsRet=ExcessReturns.loc[IndexER.index]
print(ObsRet)
PT
# In[11]:
for i in range(n):
    print(i)
    PT[columns[i]]=ObsRet.iloc[:, i]-alphas[i]-betas[i]*IndexER
    PT[tcolumns[i]]=PT[columns[i]]/np.sqrt(sigma2[i])
    PT[pcolumns[i]]=2*scipy.stats.norm.cdf(-
np.absolute(PT[tcolumns[i]]), loc=0, scale=1)
PT
# #### Average Abnormal Returns
# In[12]:
PT['AvgAR']=PT[tcolumns].mean(axis=1)
PT['SAvgAR']=PT['AvgAR']/np.sqrt(np.sum(sigma2/n**2))
PT['p-SAvgAR']=2*scipy.stats.norm.cdf(-np.absolute(PT['SAvgAR']),
loc=0, scale=1)
print(PT['AvgAR'])
print(PT['SAvgAR'])
print(PT['p-SAvgAR'])
# In[13]:
seaborn.set_style('darkgrid')
plt.rc('figure', figsize=(20, 10))
plt.rc('savefig', dpi=90)
plt.rc('font', family='sans-serif')
plt.rc('font', size=15)
# In[14]:
x=list(range(-20, 21))
y=PT['AvgAR']
x1=(-20, 21)
y1=(0, 0)
```

```
plt.plot(x, y, color='green', marker='v')
plt.plot(x1, y1, color='blue', linewidth=3)
plt.xlim(-20, 21)
plt.xlabel('Event Window')
plt.ylabel('AAR')
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[15]:
print(np.mean(PT['AvgAR']))
# #### Cumulative Abnormal Returns
# In[16]:
CumulativeAbnormalReturns=pd.DataFrame(columns=columns,
index=['CAR', 'SCAR', 'p-value'])
CumulativeAbnormalReturns
# In[17]:
CumulativeAbnormalReturns.loc['CAR']=PT[columns].sum(axis=0)
CumulativeAbnormalReturns
# In[18]:
win=PT.shape[0]
CumulativeAbnormalReturns.loc['SCAR']=CumulativeAbnormalReturns.loc
['CAR']/(np.sqrt(win*sigma2[0,:]))
CumulativeAbnormalReturns
# In[19]:
CumulativeAbnormalReturns.loc['p-
value']=CumulativeAbnormalReturns.loc['SCAR'].apply(lambda
x:(2*scipy.stats.norm.cdf(-np.absolute(x), loc=0, scale=1)))
CumulativeAbnormalReturns
# In[20]:
print(CumulativeAbnormalReturns.loc['p-value']>0.05)
# In[21]:
x=list(range(150))
y=CumulativeAbnormalReturns.loc['p-value']
x1=(-1, 150)
y1=(0.05, 0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.scatter(x, y, color='red', marker='o')
plt.plot(x1, y1, color='black', linewidth=3)
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[22]:
x=list(range(150))
y=(CumulativeAbnormalReturns.loc['p-value']>0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.title('Significance of p-value')
plt.scatter(x, y, color='red', marker='x')
plt.minorticks_on()
plt.grid(color='black', which='both')
plt.show()
# In[23]:
Scores=pd.read_excel('ESG Scores.xlsx', index_col=0)
print(Scores)
# In[24]:
```

```
print(Scores.loc['2018-12-31'])
# In[25]:
x=Scores.loc['2018-12-31']
y=CumulativeAbnormalReturns.loc['CAR']
plt.xlim(0, 70)
plt.xlabel('ESG Score')
plt.ylabel('CAR')
plt.scatter(x, y, color='blue', marker='D')
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()

# #### Year 2019
# In[5]:
estSize=253
idx=ExcessReturns[ExcessReturns.index < '2019-12-31'].iloc[-20]
print(idx)
est_window_stop=idx.name
endEstWindow=ExcessReturns.index.get_loc(est_window_stop)
print(f'{est_window_stop} is in the position {endEstWindow} of the
dataframe')
# In[6]:
n=ExcessReturns.shape[1]-1
alphas=np.zeros((n, 1))
betas=np.zeros((n, 1))
sigma2=np.zeros((n, 1))
n
# In[7]:
x=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, n]
x=sm.add_constant(x)
x
# In[8]:
for i in range(n):

    y=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, i]
    model=sm.OLS(y,x)
    results=model.fit()

    print(results.summary())
    alphas[i]=results.params[0]
    betas[i]=results.params[1]
    sigma2[i]=results.scale
# In[9]:
IndexER=ExcessReturns['DJTSEC'].iloc[endEstWindow:endEstWindow+41]
IndexER
# In[10]:
PT=pd.DataFrame(index=IndexER.index)
columns=['AAPL', 'MSFT', 'V', 'NVDA', 'UNH', 'JNJ', 'GOOGL', 'MA',
'HD', 'WMT', 'COST', 'ASML', 'LLY', 'CSCO', 'AVGO', 'AMZN', 'ACN',
'JPM', 'CVX', 'XOM', 'BAC', 'PFE', 'MRK', 'CRM', 'ROG', 'ADBE',
'QCOM', 'TMO', 'NOVN', 'PG', 'IBM', 'LOW', 'COP', 'INTU', 'WFC',
'MC', 'NOVOB', 'ABT', 'INTC', 'DHR', 'SAP', 'BMY', 'KO', 'NESN',
'TTE', 'PM', 'ADP', 'AMGN', 'SCHW', 'GS', 'RTX', 'RY', 'SPGI',
'MS', 'ELV', 'TJX', 'NKE', 'TSLA', 'UNP', 'CVS', 'UPS', 'TD',
'BLK', 'CBA', 'RIGD', 'TGT', 'AMAT', 'MDT', 'CAT', 'GM', 'LMT',
'DE', 'AXP', 'PLD', 'NEE', 'F', 'NFLX', 'SAN', 'T', 'LIN', 'CI',
'MCD', 'C', 'ENB', 'EOG', 'MBG', 'SBUX', 'GILD', 'MU', 'MO', 'HDB',
'CB', 'DG', 'BKNG', 'CSL', 'OR', 'GE', 'SLB', 'SIE', 'LRCX', 'VZ',
```

```
'BX', 'DTE', 'BA', 'NOC', 'ORLY', 'MMC', 'SYK', 'AMT', 'BHP',
'CNQ', 'CME', 'AZO', 'DUK', 'PGR', 'ALV', 'SO', 'CNR', 'ADM', 'AI',
'PXD', 'SU', 'DIS', 'CMCSA', 'PNC', 'HUM', 'NAB', 'MMM', 'CHTR',
'ABI', 'BDX', 'CL', 'BMO', 'GIS', 'ICE', 'AIR', 'ZURN', 'IBE',
'TFC', 'OXY', 'IBN', 'BNS', 'USB', 'AON', 'D', 'UBSG', 'APD',
'SYY', 'ITW', 'VLO']
tcolumns=['SAR(AAPL)', 'SAR(MSFT)', 'SAR(V)', 'SAR(NVDA)',
'SAR(UNH)', 'SAR(JNJ)', 'SAR(GOOGL)', 'SAR(MA)', 'SAR(HD)',
'SAR(WMT)', 'SAR(COST)', 'SAR(ASML)', 'SAR(LLY)', 'SAR(CSCO)',
'SAR(AVGO)', 'SAR(AMZN)', 'SAR(ACN)', 'SAR(JPM)', 'SAR(CVX)',
'SAR(XOM)', 'SAR(BAC)', 'SAR(PFE)', 'SAR(MRK)', 'SAR(CRM)',
'SAR(ROG)', 'SAR(ADBE)', 'SAR(QCOM)', 'SAR(TMO)', 'SAR(NOVN)',
'SAR(PG)', 'SAR(IBM)', 'SAR(LOW)', 'SAR(COP)', 'SAR(INTU)',
'SAR(WFC)', 'SAR(MC)', 'SAR(NOVOB)', 'SAR(ABT)', 'SAR(INTC)',
'SAR(DHR)', 'SAR(SAP)', 'SAR(BMY)', 'SAR(KO)', 'SAR(NESN)',
'SAR(TTE)', 'SAR(PM)', 'SAR(ADP)', 'SAR(AMGN)', 'SAR(SCHW)',
'SAR(GS)', 'SAR(RTX)', 'SAR(RY)', 'SAR(SPGI)', 'SAR(MS)',
'SAR(ELV)', 'SAR(TJX)', 'SAR(NKE)', 'SAR(TSLA)', 'SAR(UNP)',
'SAR(CVS)', 'SAR(UPS)', 'SAR(TD)', 'SAR(BLK)', 'SAR(CBA)',
'SAR(RIGD)', 'SAR(TGT)', 'SAR(AMAT)', 'SAR(MDT)', 'SAR(CAT)',
'SAR(GM)', 'SAR(LMT)', 'SAR(DE)', 'SAR(AXP)', 'SAR(PLD)',
'SAR(NEE)', 'SAR(F)', 'SAR(NFLX)', 'SAR(SAN)', 'SAR(T)',
'SAR(LIN)', 'SAR(CI)', 'SAR(MCD)', 'SAR(C)', 'SAR(ENB)',
'SAR(EOG)', 'SAR(MBG)', 'SAR(SBUX)', 'SAR(GILD)', 'SAR(MU)',
'SAR(MO)', 'SAR(HDB)', 'SAR(CB)', 'SAR(DG)', 'SAR(BKNG)',
'SAR(CSL)', 'SAR(OR)', 'SAR(GE)', 'SAR(SLB)', 'SAR(SIE)',
'SAR(LRCX)', 'SAR(VZ)', 'SAR(BX)', 'SAR(DTE)', 'SAR(BA)',
'SAR(NOC)', 'SAR(ORLY)', 'SAR(MMC)', 'SAR(SYK)', 'SAR(AMT)',
'SAR(BHP)', 'SAR(CNQ)', 'SAR(CME)', 'SAR(AZO)', 'SAR(DUK)',
'SAR(PGR)', 'SAR(ALV)', 'SAR(SO)', 'SAR(CNR)', 'SAR(ADM)',
'SAR(AI)', 'SAR(PXD)', 'SAR(SU)', 'SAR(DIS)', 'SAR(CMCSA)',
'SAR(PNC)', 'SAR(HUM)', 'SAR(NAB)', 'SAR(MMM)', 'SAR(CHTR)',
'SAR(ABI)', 'SAR(BDX)', 'SAR(CL)', 'SAR(BMO)', 'SAR(GIS)',
'SAR(ICE)', 'SAR(AIR)', 'SAR(ZURN)', 'SAR(IBE)', 'SAR(TFC)',
'SAR(OXY)', 'SAR(IBN)', 'SAR(BNS)', 'SAR(USB)', 'SAR(AON)',
'SAR(D)', 'SAR(UBSG)', 'SAR(APD)', 'SAR(SYY)', 'SAR(ITW)',
'SAR(VLO)']
pcolumns=['p-SAR(AAPL)', 'p-SAR(MSFT)', 'p-SAR(V)', 'p-SAR(NVDA)',
'p-SAR(UNH)', 'p-SAR(JNJ)', 'p-SAR(GOOGL)', 'p-SAR(MA)', 'p-
SAR(HD)', 'p-SAR(WMT)', 'p-SAR(COST)', 'p-SAR(ASML)', 'p-SAR(LLY)',
'p-SAR(CSCO)', 'p-SAR(AVGO)', 'p-SAR(AMZN)', 'p-SAR(ACN)', 'p-
SAR(JPM)', 'p-SAR(CVX)', 'p-SAR(XOM)', 'p-SAR(BAC)', 'p-SAR(PFE)',
'p-SAR(MRK)', 'p-SAR(CRM)', 'p-SAR(ROG)', 'p-SAR(ADBE)', 'p-
SAR(QCOM)', 'p-SAR(TMO)', 'p-SAR(NOVN)', 'p-SAR(PG)', 'p-SAR(IBM)',
'p-SAR(LOW)', 'p-SAR(COP)', 'p-SAR(INTU)', 'p-SAR(WFC)', 'p-
SAR(MC)', 'p-SAR(NOVOB)', 'p-SAR(ABT)', 'p-SAR(INTC)', 'p-
SAR(DHR)', 'p-SAR(SAP)', 'p-SAR(BMY)', 'p-SAR(KO)', 'p-SAR(NESN)',
'p-SAR(TTE)', 'p-SAR(PM)', 'p-SAR(ADP)', 'p-SAR(AMGN)', 'p-
SAR(SCHW)', 'p-SAR(GS)', 'p-SAR(RTX)', 'p-SAR(RY)', 'p-SAR(SPGI)',
'p-SAR(MS)', 'p-SAR(ELV)', 'p-SAR(TJX)', 'p-SAR(NKE)', 'p-
SAR(TSLA)', 'p-SAR(UNP)', 'p-SAR(CVS)', 'p-SAR(UPS)', 'p-SAR(TD)',
'p-SAR(BLK)', 'p-SAR(CBA)', 'p-SAR(RIGD)', 'p-SAR(TGT)', 'p-
SAR(AMAT)', 'p-SAR(MDT)', 'p-SAR(CAT)', 'p-SAR(GM)', 'p-SAR(LMT)',
'p-SAR(DE)', 'p-SAR(AXP)', 'p-SAR(PLD)', 'p-SAR(NEE)', 'p-SAR(F)',
'p-SAR(NFLX)', 'p-SAR(SAN)', 'p-SAR(T)', 'p-SAR(LIN)', 'p-SAR(CI)',
'p-SAR(MCD)', 'p-SAR(C)', 'p-SAR(ENB)', 'p-SAR(EOG)', 'p-SAR(MBG)',
'p-SAR(SBUX)', 'p-SAR(GILD)', 'p-SAR(MU)', 'p-SAR(MO)', 'p-
SAR(HDB)', 'p-SAR(CB)', 'p-SAR(DG)', 'p-SAR(BKNG)', 'p-SAR(CSL)',
```

```
'p-SAR(OR)', 'p-SAR(GE)', 'p-SAR(SLB)', 'p-SAR(SIE)', 'p-
SAR(LRCX)', 'p-SAR(VZ)', 'p-SAR(BX)', 'p-SAR(DTE)', 'p-SAR(BA)',
'p-SAR(NOC)', 'p-SAR(ORLY)', 'p-SAR(MMC)', 'p-SAR(SYK)', 'p-
SAR(AMT)', 'p-SAR(BHP)', 'p-SAR(CNQ)', 'p-SAR(CME)', 'p-SAR(AZO)',
'p-SAR(DUK)', 'p-SAR(PGR)', 'p-SAR(ALV)', 'p-SAR(SO)', 'p-
SAR(CNR)', 'p-SAR(ADM)', 'p-SAR(AI)', 'p-SAR(PXD)', 'p-SAR(SU)',
'p-SAR(DIS)', 'p-SAR(CMCSA)', 'p-SAR(PNC)', 'p-SAR(HUM)', 'p-
SAR(NAB)', 'p-SAR(MMM)', 'p-SAR(CHTR)', 'p-SAR(ABI)', 'p-SAR(BDX)',
'p-SAR(CL)', 'p-SAR(BMO)', 'p-SAR(GIS)', 'p-SAR(ICE)', 'p-
SAR(AIR)', 'p-SAR(ZURN)', 'p-SAR(IBE)', 'p-SAR(TFC)', 'p-SAR(OXY)',
'p-SAR(IBN)', 'p-SAR(BNS)', 'p-SAR(USB)', 'p-SAR(AON)', 'p-SAR(D)',
'p-SAR(UBSG)', 'p-SAR(APD)', 'p-SAR(SYY)', 'p-SAR(ITW)', 'p-
SAR(VLO)']
ObsRet=ExcessReturns.loc[IndexER.index]
print(ObsRet)
PT
# In[11]:
for i in range(n):
    print(i)
    PT[columns[i]]=ObsRet.iloc[:, i]-alphas[i]-betas[i]*IndexER
    PT[tcolumns[i]]=PT[columns[i]]/np.sqrt(sigma2[i])
    PT[pcolumns[i]]=2*scipy.stats.norm.cdf(-
np.absolute(PT[tcolumns[i]]), loc=0, scale=1)
PT
# #### Average Abnormal Returns
# In[12]:
PT['AvgAR']=PT[tcolumns].mean(axis=1)
PT['SAvgAR']=PT['AvgAR']/np.sqrt(np.sum(sigma2/n**2))
PT['p-SAvgAR']=2*scipy.stats.norm.cdf(-np.absolute(PT['SAvgAR']),
loc=0, scale=1)
print(PT['AvgAR'])
print(PT['SAvgAR'])
print(PT['p-SAvgAR'])
# In[13]:
seaborn.set_style('darkgrid')
plt.rc('figure', figsize=(20, 10))
plt.rc('savefig', dpi=90)
plt.rc('font', family='sans-serif')
plt.rc('font', size=15)
# In[14]:
x=list(range(-20, 21))
y=PT['AvgAR']
x1=(-20, 21)
y1=(0, 0)
plt.plot(x, y, color='green', marker='v')
plt.plot(x1, y1, color='blue', linewidth=3)
plt.xlim(-20, 21)
plt.xlabel('Event Window')
plt.ylabel('AAR')
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[15]:
print(np.mean(PT['AvgAR']))
# #### Cumulative Abnormal Returns
# In[16]:
CumulativeAbnormalReturns=pd.DataFrame(columns=columns,
index=['CAR', 'SCAR', 'p-value'])
```

```
CumulativeAbnormalReturns
# In[17]:
CumulativeAbnormalReturns.loc['CAR']=PT[columns].sum(axis=0)
CumulativeAbnormalReturns
# In[18]:
win=PT.shape[0]
CumulativeAbnormalReturns.loc['SCAR']=CumulativeAbnormalReturns.loc
['CAR']/(np.sqrt(win*sigma2[0,:]))
CumulativeAbnormalReturns
# In[19]:
CumulativeAbnormalReturns.loc['p-
value']=CumulativeAbnormalReturns.loc['SCAR'].apply(lambda
x:(2*scipy.stats.norm.cdf(-np.absolute(x), loc=0, scale=1)))
CumulativeAbnormalReturns
# In[20]:
print(CumulativeAbnormalReturns.loc['p-value']>0.05)
# In[21]:
x=list(range(150))
y=CumulativeAbnormalReturns.loc['p-value']
x1=(-1, 150)
y1=(0.05, 0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.scatter(x, y, color='red', marker='o')
plt.plot(x1, y1, color='black', linewidth=3)
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[22]:
x=list(range(150))
y=(CumulativeAbnormalReturns.loc['p-value']>0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.title('Significance of p-value')
plt.scatter(x, y, color='red', marker='x')
plt.minorticks_on()
plt.grid(color='black', which='both')
plt.show()
# In[23]:
Scores=pd.read_excel('ESG Scores.xlsx', index_col=0)
print(Scores)
# In[24]:
print(Scores.loc['2019-12-31'])
# In[25]:
x=Scores.loc['2019-12-31']
y=CumulativeAbnormalReturns.loc['CAR']
plt.xlim(0, 80)
plt.xlabel('ESG Score')
plt.ylabel('CAR')
plt.scatter(x, y, color='blue', marker='D')
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()

# #### Year 2020
# In[5]:
```

```
estSize=253
idx=ExcessReturns[ExcessReturns.index < '2020-12-31'].iloc[-20]
print(idx)
est_window_stop=idx.name
endEstWindow=ExcessReturns.index.get_loc(est_window_stop)
print(f'{est_window_stop} is in the position {endEstWindow} of the
dataframe')
# In[6]:
n=ExcessReturns.shape[1]-1
alphas=np.zeros((n, 1))
betas=np.zeros((n, 1))
sigma2=np.zeros((n, 1))
n
# In[7]:
x=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, n]
x=sm.add_constant(x)
x
# In[8]:
for i in range(n):

    y=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, i]
    model=sm.OLS(y,x)
    results=model.fit()

    print(results.summary())
    alphas[i]=results.params[0]
    betas[i]=results.params[1]
    sigma2[i]=results.scale
# In[9]:
IndexER=ExcessReturns['DJTSEC'].iloc[endEstWindow:endEstWindow+41]
IndexER
# In[10]:
PT=pd.DataFrame(index=IndexER.index)
columns=['AAPL', 'MSFT', 'V', 'NVDA', 'UNH', 'JNJ', 'GOOGL', 'MA',
'HD', 'WMT', 'COST', 'ASML', 'LLY', 'CSCO', 'AVGO', 'AMZN', 'ACN',
'JPM', 'CVX', 'XOM', 'BAC', 'PFE', 'MRK', 'CRM', 'ROG', 'ADBE',
'QCOM', 'TMO', 'NOVN', 'PG', 'IBM', 'LOW', 'COP', 'INTU', 'WFC',
'MC', 'NOVOB', 'ABT', 'INTC', 'DHR', 'SAP', 'BMY', 'KO', 'NESN',
'TTE', 'PM', 'ADP', 'AMGN', 'SCHW', 'GS', 'RTX', 'RY', 'SPGI',
'MS', 'ELV', 'TJX', 'NKE', 'TSLA', 'UNP', 'CVS', 'UPS', 'TD',
'BLK', 'CBA', 'RIGD', 'TGT', 'AMAT', 'MDT', 'CAT', 'GM', 'LMT',
'DE', 'AXP', 'PLD', 'NEE', 'F', 'NFLX', 'SAN', 'T', 'LIN', 'CI',
'MCD', 'C', 'ENB', 'EOG', 'MBG', 'SBUX', 'GILD', 'MU', 'MO', 'HDB',
'CB', 'DG', 'BKNG', 'CSL', 'OR', 'GE', 'SLB', 'SIE', 'LRCX', 'VZ',
'BX', 'DTE', 'BA', 'NOC', 'ORLY', 'MMC', 'SYK', 'AMT', 'BHP',
'CNQ', 'CME', 'AZO', 'DUK', 'PGR', 'ALV', 'SO', 'CNR', 'ADM', 'AI',
'PXD', 'SU', 'DIS', 'CMCSA', 'PNC', 'HUM', 'NAB', 'MMM', 'CHTR',
'ABI', 'BDX', 'CL', 'BMO', 'GIS', 'ICE', 'AIR', 'ZURN', 'IBE',
'TFC', 'OXY', 'IBN', 'BNS', 'USB', 'AON', 'D', 'UBSG', 'APD',
'SYY', 'ITW', 'VLO']
tcolumns=['SAR(AAPL)', 'SAR(MSFT)', 'SAR(V)', 'SAR(NVDA)',
'SAR(UNH)', 'SAR(JNJ)', 'SAR(GOOGL)', 'SAR(MA)', 'SAR(HD)',
'SAR(WMT)', 'SAR(COST)', 'SAR(ASML)', 'SAR(LLY)', 'SAR(CSCO)',
'SAR(AVGO)', 'SAR(AMZN)', 'SAR(ACN)', 'SAR(JPM)', 'SAR(CVX)',
'SAR(XOM)', 'SAR(BAC)', 'SAR(PFE)', 'SAR(MRK)', 'SAR(CRM)',
'SAR(ROG)', 'SAR(ADBE)', 'SAR(QCOM)', 'SAR(TMO)', 'SAR(NOVN)',
'SAR(PG)', 'SAR(IBM)', 'SAR(LOW)', 'SAR(COP)', 'SAR(INTU)',
'SAR(WFC)', 'SAR(MC)', 'SAR(NOVOB)', 'SAR(ABT)', 'SAR(INTC)',
```

```
'SAR(DHR)', 'SAR(SAP)', 'SAR(BMY)', 'SAR(KO)', 'SAR(NESN)',
'SAR(TTE)', 'SAR(PM)', 'SAR(ADP)', 'SAR(AMGN)', 'SAR(SCHW)',
'SAR(GS)', 'SAR(RTX)', 'SAR(RY)', 'SAR(SPGI)', 'SAR(MS)',
'SAR(ELV)', 'SAR(TJX)', 'SAR(NKE)', 'SAR(TSLA)', 'SAR(UNP)',
'SAR(CVS)', 'SAR(UPS)', 'SAR(TD)', 'SAR(BLK)', 'SAR(CBA)',
'SAR(RIGD)', 'SAR(TGT)', 'SAR(AMAT)', 'SAR(MDT)', 'SAR(CAT)',
'SAR(GM)', 'SAR(LMT)', 'SAR(DE)', 'SAR(AXP)', 'SAR(PLD)',
'SAR(NEE)', 'SAR(F)', 'SAR(NFLX)', 'SAR(SAN)', 'SAR(T)',
'SAR(LIN)', 'SAR(CI)', 'SAR(MCD)', 'SAR(C)', 'SAR(ENB)',
'SAR(EOG)', 'SAR(MBG)', 'SAR(SBUX)', 'SAR(GILD)', 'SAR(MU)',
'SAR(MO)', 'SAR(HDB)', 'SAR(CB)', 'SAR(DG)', 'SAR(BKNG)',
'SAR(CSL)', 'SAR(OR)', 'SAR(GE)', 'SAR(SLB)', 'SAR(SIE)',
'SAR(LRCX)', 'SAR(VZ)', 'SAR(BX)', 'SAR(DTE)', 'SAR(BA)',
'SAR(NOC)', 'SAR(ORLY)', 'SAR(MMC)', 'SAR(SYK)', 'SAR(AMT)',
'SAR(BHP)', 'SAR(CNQ)', 'SAR(CME)', 'SAR(AZO)', 'SAR(DUK)',
'SAR(PGR)', 'SAR(ALV)', 'SAR(SO)', 'SAR(CNR)', 'SAR(ADM)',
'SAR(AI)', 'SAR(PXD)', 'SAR(SU)', 'SAR(DIS)', 'SAR(CMCSA)',
'SAR(PNC)', 'SAR(HUM)', 'SAR(NAB)', 'SAR(MMM)', 'SAR(CHTR)',
'SAR(ABI)', 'SAR(BDX)', 'SAR(CL)', 'SAR(BMO)', 'SAR(GIS)',
'SAR(ICE)', 'SAR(AIR)', 'SAR(ZURN)', 'SAR(IBE)', 'SAR(TFC)',
'SAR(OXY)', 'SAR(IBN)', 'SAR(BNS)', 'SAR(USB)', 'SAR(AON)',
'SAR(D)', 'SAR(UBSG)', 'SAR(APD)', 'SAR(SYY)', 'SAR(ITW)',
'SAR(VLO)']
pcolumns=['p-SAR(AAPL)', 'p-SAR(MSFT)', 'p-SAR(V)', 'p-SAR(NVDA)',
'p-SAR(UNH)', 'p-SAR(JNJ)', 'p-SAR(GOOGL)', 'p-SAR(MA)', 'p-
SAR(HD)', 'p-SAR(WMT)', 'p-SAR(COST)', 'p-SAR(ASML)', 'p-SAR(LLY)',
'p-SAR(CSCO)', 'p-SAR(AVGO)', 'p-SAR(AMZN)', 'p-SAR(ACN)', 'p-
SAR(JPM)', 'p-SAR(CVX)', 'p-SAR(XOM)', 'p-SAR(BAC)', 'p-SAR(PFE)',
'p-SAR(MRK)', 'p-SAR(CRM)', 'p-SAR(ROG)', 'p-SAR(ADBE)', 'p-
SAR(QCOM)', 'p-SAR(TMO)', 'p-SAR(NOVN)', 'p-SAR(PG)', 'p-SAR(IBM)',
'p-SAR(LOW)', 'p-SAR(COP)', 'p-SAR(INTU)', 'p-SAR(WFC)', 'p-
SAR(MC)', 'p-SAR(NOVOB)', 'p-SAR(ABT)', 'p-SAR(INTC)', 'p-
SAR(DHR)', 'p-SAR(SAP)', 'p-SAR(BMY)', 'p-SAR(KO)', 'p-SAR(NESN)',
'p-SAR(TTE)', 'p-SAR(PM)', 'p-SAR(ADP)', 'p-SAR(AMGN)', 'p-
SAR(SCHW)', 'p-SAR(GS)', 'p-SAR(RTX)', 'p-SAR(RY)', 'p-SAR(SPGI)',
'p-SAR(MS)', 'p-SAR(ELV)', 'p-SAR(TJX)', 'p-SAR(NKE)', 'p-
SAR(TSLA)', 'p-SAR(UNP)', 'p-SAR(CVS)', 'p-SAR(UPS)', 'p-SAR(TD)',
'p-SAR(BLK)', 'p-SAR(CBA)', 'p-SAR(RIGD)', 'p-SAR(TGT)', 'p-
SAR(AMAT)', 'p-SAR(MDT)', 'p-SAR(CAT)', 'p-SAR(GM)', 'p-SAR(LMT)',
'p-SAR(DE)', 'p-SAR(AXP)', 'p-SAR(PLD)', 'p-SAR(NEE)', 'p-SAR(F)',
'p-SAR(NFLX)', 'p-SAR(SAN)', 'p-SAR(T)', 'p-SAR(LIN)', 'p-SAR(CI)',
'p-SAR(MCD)', 'p-SAR(C)', 'p-SAR(ENB)', 'p-SAR(EOG)', 'p-SAR(MBG)',
'p-SAR(SBUX)', 'p-SAR(GILD)', 'p-SAR(MU)', 'p-SAR(MO)', 'p-
SAR(HDB)', 'p-SAR(CB)', 'p-SAR(DG)', 'p-SAR(BKNG)', 'p-SAR(CSL)',
'p-SAR(OR)', 'p-SAR(GE)', 'p-SAR(SLB)', 'p-SAR(SIE)', 'p-
SAR(LRCX)', 'p-SAR(VZ)', 'p-SAR(BX)', 'p-SAR(DTE)', 'p-SAR(BA)',
'p-SAR(NOC)', 'p-SAR(ORLY)', 'p-SAR(MMC)', 'p-SAR(SYK)', 'p-
SAR(AMT)', 'p-SAR(BHP)', 'p-SAR(CNQ)', 'p-SAR(CME)', 'p-SAR(AZO)',
'p-SAR(DUK)', 'p-SAR(PGR)', 'p-SAR(ALV)', 'p-SAR(SO)', 'p-
SAR(CNR)', 'p-SAR(ADM)', 'p-SAR(AI)', 'p-SAR(PXD)', 'p-SAR(SU)',
'p-SAR(DIS)', 'p-SAR(CMCSA)', 'p-SAR(PNC)', 'p-SAR(HUM)', 'p-
SAR(NAB)', 'p-SAR(MMM)', 'p-SAR(CHTR)', 'p-SAR(ABI)', 'p-SAR(BDX)',
'p-SAR(CL)', 'p-SAR(BMO)', 'p-SAR(GIS)', 'p-SAR(ICE)', 'p-
SAR(AIR)', 'p-SAR(ZURN)', 'p-SAR(IBE)', 'p-SAR(TFC)', 'p-SAR(OXY)',
'p-SAR(IBN)', 'p-SAR(BNS)', 'p-SAR(USB)', 'p-SAR(AON)', 'p-SAR(D)',
'p-SAR(UBSG)', 'p-SAR(APD)', 'p-SAR(SYY)', 'p-SAR(ITW)', 'p-
SAR(VLO)']
ObsRet=ExcessReturns.loc[IndexER.index]
```

```
print(ObsRet)
PT
# In[11]:
for i in range(n):
    print(i)
    PT[columns[i]]=ObsRet.iloc[:, i]-alphas[i]-betas[i]*IndexER
    PT[tcolumns[i]]=PT[columns[i]]/np.sqrt(sigma2[i])
    PT[pcolumns[i]]=2*scipy.stats.norm.cdf(-
np.absolute(PT[tcolumns[i]]), loc=0, scale=1)
PT
# #### Average Abnormal Returns
# In[12]:
PT['AvgAR']=PT[tcolumns].mean(axis=1)
PT['SAvgAR']=PT['AvgAR']/np.sqrt(np.sum(sigma2/n**2))
PT['p-SAvgAR']=2*scipy.stats.norm.cdf(-np.absolute(PT['SAvgAR']),
loc=0, scale=1)
print(PT['AvgAR'])
print(PT['SAvgAR'])
print(PT['p-SAvgAR'])
# In[13]:
seaborn.set_style('darkgrid')
plt.rc('figure', figsize=(20, 10))
plt.rc('savefig', dpi=90)
plt.rc('font', family='sans-serif')
plt.rc('font', size=15)
# In[14]:
x=list(range(-20, 21))
y=PT['AvgAR']
x1=(-20, 21)
y1=(0, 0)
plt.plot(x, y, color='green', marker='v')
plt.plot(x1, y1, color='blue', linewidth=3)
plt.xlim(-20, 21)
plt.xlabel('Event Window')
plt.ylabel('AAR')
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[15]:
print(np.mean(PT['AvgAR']))
# #### Cumulative Abnormal Returns
# In[16]:
CumulativeAbnormalReturns=pd.DataFrame(columns=columns,
index=['CAR', 'SCAR', 'p-value'])
CumulativeAbnormalReturns
# In[17]:
CumulativeAbnormalReturns.loc['CAR']=PT[columns].sum(axis=0)
CumulativeAbnormalReturns
# In[18]:
win=PT.shape[0]
CumulativeAbnormalReturns.loc['SCAR']=CumulativeAbnormalReturns.loc
['CAR']/(np.sqrt(win*sigma2[0,:]))
CumulativeAbnormalReturns
# In[19]:
CumulativeAbnormalReturns.loc['p-
value']=CumulativeAbnormalReturns.loc['SCAR'].apply(lambda
x:(2*scipy.stats.norm.cdf(-np.absolute(x), loc=0, scale=1)))
CumulativeAbnormalReturns
```

```
# In[20]:
print(CumulativeAbnormalReturns.loc['p-value']>0.05)
# In[21]:
x=list(range(150))
y=CumulativeAbnormalReturns.loc['p-value']
x1=(-1, 150)
y1=(0.05, 0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.scatter(x, y, color='red', marker='o')
plt.plot(x1, y1, color='black', linewidth=3)
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[22]:
x=list(range(150))
y=(CumulativeAbnormalReturns.loc['p-value']>0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.title('Significance of p-value')
plt.scatter(x, y, color='red', marker='x')
plt.minorticks_on()
plt.grid(color='black', which='both')
plt.show()
# In[23]:
Scores=pd.read_excel('ESG Scores.xlsx', index_col=0)
print(Scores)
# In[24]:
print(Scores.loc['2020-12-31'])
# In[25]:
x=Scores.loc['2020-12-31']
y=CumulativeAbnormalReturns.loc['CAR']
plt.xlim(0, 80)
plt.xlabel('ESG Score')
plt.ylabel('CAR')
plt.scatter(x, y, color='blue', marker='D')
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()

# #### Year 2021
# In[5]:
estSize=253
idx=ExcessReturns[ExcessReturns.index < '2021-12-31'].iloc[-20]
print(idx)
est_window_stop=idx.name
endEstWindow=ExcessReturns.index.get_loc(est_window_stop)
print(f'{est_window_stop} is in the position {endEstWindow} of the
dataframe')
# In[6]:
n=ExcessReturns.shape[1]-1
alphas=np.zeros((n, 1))
betas=np.zeros((n, 1))
sigma2=np.zeros((n, 1))
n
# In[7]:
```

```
x=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, n]
x=sm.add_constant(x)
x
# In[8]:
for i in range(n):

    y=ExcessReturns.iloc[endEstWindow-estSize:endEstWindow, i]
    model=sm.OLS(y,x)
    results=model.fit()

    print(results.summary())
    alphas[i]=results.params[0]
    betas[i]=results.params[1]
    sigma2[i]=results.scale
# In[9]:
IndexER=ExcessReturns['DJTSEC'].iloc[endEstWindow:endEstWindow+41]
IndexER
# In[10]:
PT=pd.DataFrame(index=IndexER.index)
columns=['AAPL', 'MSFT', 'V', 'NVDA', 'UNH', 'JNJ', 'GOOGL', 'MA',
'HD', 'WMT', 'COST', 'ASML', 'LLY', 'CSCO', 'AVGO', 'AMZN', 'ACN',
'JPM', 'CVX', 'XOM', 'BAC', 'PFE', 'MRK', 'CRM', 'ROG', 'ADBE',
'QCOM', 'TMO', 'NOVN', 'PG', 'IBM', 'LOW', 'COP', 'INTU', 'WFC',
'MC', 'NOVOB', 'ABT', 'INTC', 'DHR', 'SAP', 'BMY', 'KO', 'NESN',
'TTE', 'PM', 'ADP', 'AMGN', 'SCHW', 'GS', 'RTX', 'RY', 'SPGI',
'MS', 'ELV', 'TJX', 'NKE', 'TSLA', 'UNP', 'CVS', 'UPS', 'TD',
'BLK', 'CBA', 'RIGD', 'TGT', 'AMAT', 'MDT', 'CAT', 'GM', 'LMT',
'DE', 'AXP', 'PLD', 'NEE', 'F', 'NFLX', 'SAN', 'T', 'LIN', 'CI',
'MCD', 'C', 'ENB', 'EOG', 'MBG', 'SBUX', 'GILD', 'MU', 'MO', 'HDB',
'CB', 'DG', 'BKNG', 'CSL', 'OR', 'GE', 'SLB', 'SIE', 'LRCX', 'VZ',
'BX', 'DTE', 'BA', 'NOC', 'ORLY', 'MMC', 'SYK', 'AMT', 'BHP',
'CNQ', 'CME', 'AZO', 'DUK', 'PGR', 'ALV', 'SO', 'CNR', 'ADM', 'AI',
'PXD', 'SU', 'DIS', 'CMCSA', 'PNC', 'HUM', 'NAB', 'MMM', 'CHTR',
'ABI', 'BDX', 'CL', 'BMO', 'GIS', 'ICE', 'AIR', 'ZURN', 'IBE',
'TFC', 'OXY', 'IBN', 'BNS', 'USB', 'AON', 'D', 'UBSG', 'APD',
'SYY', 'ITW', 'VLO']
tcolumns=['SAR(AAPL)', 'SAR(MSFT)', 'SAR(V)', 'SAR(NVDA)',
'SAR(UNH)', 'SAR(JNJ)', 'SAR(GOOGL)', 'SAR(MA)', 'SAR(HD)',
'SAR(WMT)', 'SAR(COST)', 'SAR(ASML)', 'SAR(LLY)', 'SAR(CSCO)',
'SAR(AVGO)', 'SAR(AMZN)', 'SAR(ACN)', 'SAR(JPM)', 'SAR(CVX)',
'SAR(XOM)', 'SAR(BAC)', 'SAR(PFE)', 'SAR(MRK)', 'SAR(CRM)',
'SAR(ROG)', 'SAR(ADBE)', 'SAR(QCOM)', 'SAR(TMO)', 'SAR(NOVN)',
'SAR(PG)', 'SAR(IBM)', 'SAR(LOW)', 'SAR(COP)', 'SAR(INTU)',
'SAR(WFC)', 'SAR(MC)', 'SAR(NOVOB)', 'SAR(ABT)', 'SAR(INTC)',
'SAR(DHR)', 'SAR(SAP)', 'SAR(BMY)', 'SAR(KO)', 'SAR(NESN)',
'SAR(TTE)', 'SAR(PM)', 'SAR(ADP)', 'SAR(AMGN)', 'SAR(SCHW)',
'SAR(GS)', 'SAR(RTX)', 'SAR(RY)', 'SAR(SPGI)', 'SAR(MS)',
'SAR(ELV)', 'SAR(TJX)', 'SAR(NKE)', 'SAR(TSLA)', 'SAR(UNP)',
'SAR(CVS)', 'SAR(UPS)', 'SAR(TD)', 'SAR(BLK)', 'SAR(CBA)',
'SAR(RIGD)', 'SAR(TGT)', 'SAR(AMAT)', 'SAR(MDT)', 'SAR(CAT)',
'SAR(GM)', 'SAR(LMT)', 'SAR(DE)', 'SAR(AXP)', 'SAR(PLD)',
'SAR(NEE)', 'SAR(F)', 'SAR(NFLX)', 'SAR(SAN)', 'SAR(T)',
'SAR(LIN)', 'SAR(CI)', 'SAR(MCD)', 'SAR(C)', 'SAR(ENB)',
'SAR(EOG)', 'SAR(MBG)', 'SAR(SBUX)', 'SAR(GILD)', 'SAR(MU)',
'SAR(MO)', 'SAR(HDB)', 'SAR(CB)', 'SAR(DG)', 'SAR(BKNG)',
'SAR(CSL)', 'SAR(OR)', 'SAR(GE)', 'SAR(SLB)', 'SAR(SIE)',
'SAR(LRCX)', 'SAR(VZ)', 'SAR(BX)', 'SAR(DTE)', 'SAR(BA)',
'SAR(NOC)', 'SAR(ORLY)', 'SAR(MMC)', 'SAR(SYK)', 'SAR(AMT)',
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'SAR(BHP)', 'SAR(CNQ)', 'SAR(CME)', 'SAR(AZO)', 'SAR(DUK)',
'SAR(PGR)', 'SAR(ALV)', 'SAR(SO)', 'SAR(CNR)', 'SAR(ADM)',
'SAR(AI)', 'SAR(PXD)', 'SAR(SU)', 'SAR(DIS)', 'SAR(CMCSA)',
'SAR(PNC)', 'SAR(HUM)', 'SAR(NAB)', 'SAR(MMM)', 'SAR(CHTR)',
'SAR(ABI)', 'SAR(BDX)', 'SAR(CL)', 'SAR(BMO)', 'SAR(GIS)',
'SAR(ICE)', 'SAR(AIR)', 'SAR(ZURN)', 'SAR(IBE)', 'SAR(TFC)',
'SAR(OXY)', 'SAR(IBN)', 'SAR(BNS)', 'SAR(USB)', 'SAR(AON)',
'SAR(D)', 'SAR(UBSG)', 'SAR(APD)', 'SAR(SYY)', 'SAR(ITW)',
'SAR(VLO)']
pcolumns=['p-SAR(AAPL)', 'p-SAR(MSFT)', 'p-SAR(V)', 'p-SAR(NVDA)',
'p-SAR(UNH)', 'p-SAR(JNJ)', 'p-SAR(GOOGL)', 'p-SAR(MA)', 'p-
SAR(HD)', 'p-SAR(WMT)', 'p-SAR(COST)', 'p-SAR(ASML)', 'p-SAR(LLY)',
'p-SAR(CSCO)', 'p-SAR(AVGO)', 'p-SAR(AMZN)', 'p-SAR(ACN)', 'p-
SAR(JPM)', 'p-SAR(CVX)', 'p-SAR(XOM)', 'p-SAR(BAC)', 'p-SAR(PFE)',
'p-SAR(MRK)', 'p-SAR(CRM)', 'p-SAR(ROG)', 'p-SAR(ADBE)', 'p-
SAR(QCOM)', 'p-SAR(TMO)', 'p-SAR(NOVN)', 'p-SAR(PG)', 'p-SAR(IBM)',
'p-SAR(LOW)', 'p-SAR(COP)', 'p-SAR(INTU)', 'p-SAR(WFC)', 'p-
SAR(MC)', 'p-SAR(NOVOB)', 'p-SAR(ABT)', 'p-SAR(INTC)', 'p-
SAR(DHR)', 'p-SAR(SAP)', 'p-SAR(BMY)', 'p-SAR(KO)', 'p-SAR(NESN)',
'p-SAR(TTE)', 'p-SAR(PM)', 'p-SAR(ADP)', 'p-SAR(AMGN)', 'p-
SAR(SCHW)', 'p-SAR(GS)', 'p-SAR(RTX)', 'p-SAR(RY)', 'p-SAR(SPGI)',
'p-SAR(MS)', 'p-SAR(ELV)', 'p-SAR(TJX)', 'p-SAR(NKE)', 'p-
SAR(TSLA)', 'p-SAR(UNP)', 'p-SAR(CVS)', 'p-SAR(UPS)', 'p-SAR(TD)',
'p-SAR(BLK)', 'p-SAR(CBA)', 'p-SAR(RIGD)', 'p-SAR(TGT)', 'p-
SAR(AMAT)', 'p-SAR(MDT)', 'p-SAR(CAT)', 'p-SAR(GM)', 'p-SAR(LMT)',
'p-SAR(DE)', 'p-SAR(AXP)', 'p-SAR(PLD)', 'p-SAR(NEE)', 'p-SAR(F)',
'p-SAR(NFLX)', 'p-SAR(SAN)', 'p-SAR(T)', 'p-SAR(LIN)', 'p-SAR(CI)',
'p-SAR(MCD)', 'p-SAR(C)', 'p-SAR(ENB)', 'p-SAR(EOG)', 'p-SAR(MBG)',
'p-SAR(SBUX)', 'p-SAR(GILD)', 'p-SAR(MU)', 'p-SAR(MO)', 'p-
SAR(HDB)', 'p-SAR(CB)', 'p-SAR(DG)', 'p-SAR(BKNG)', 'p-SAR(CSL)',
'p-SAR(OR)', 'p-SAR(GE)', 'p-SAR(SLB)', 'p-SAR(SIE)', 'p-
SAR(LRCX)', 'p-SAR(VZ)', 'p-SAR(BX)', 'p-SAR(DTE)', 'p-SAR(BA)',
'p-SAR(NOC)', 'p-SAR(ORLY)', 'p-SAR(MMC)', 'p-SAR(SYK)', 'p-
SAR(AMT)', 'p-SAR(BHP)', 'p-SAR(CNQ)', 'p-SAR(CME)', 'p-SAR(AZO)',
'p-SAR(DUK)', 'p-SAR(PGR)', 'p-SAR(ALV)', 'p-SAR(SO)', 'p-
SAR(CNR)', 'p-SAR(ADM)', 'p-SAR(AI)', 'p-SAR(PXD)', 'p-SAR(SU)',
'p-SAR(DIS)', 'p-SAR(CMCSA)', 'p-SAR(PNC)', 'p-SAR(HUM)', 'p-
SAR(NAB)', 'p-SAR(MMM)', 'p-SAR(CHTR)', 'p-SAR(ABI)', 'p-SAR(BDX)',
'p-SAR(CL)', 'p-SAR(BMO)', 'p-SAR(GIS)', 'p-SAR(ICE)', 'p-
SAR(AIR)', 'p-SAR(ZURN)', 'p-SAR(IBE)', 'p-SAR(TFC)', 'p-SAR(OXY)',
'p-SAR(IBN)', 'p-SAR(BNS)', 'p-SAR(USB)', 'p-SAR(AON)', 'p-SAR(D)',
'p-SAR(UBSG)', 'p-SAR(APD)', 'p-SAR(SYY)', 'p-SAR(ITW)', 'p-
SAR(VLO)']
ObsRet=ExcessReturns.loc[IndexER.index]
print(ObsRet)
PT
# In[11]:
for i in range(n):
    print(i)
    PT[columns[i]]=ObsRet.iloc[:, i]-alphas[i]-betas[i]*IndexER
    PT[tcolumns[i]]=PT[columns[i]]/np.sqrt(sigma2[i])
    PT[pcolumns[i]]=2*scipy.stats.norm.cdf(-
np.absolute(PT[tcolumns[i]]), loc=0, scale=1)
PT
# #### Average Abnormal Returns
# In[12]:
PT['AvgAR']=PT[tcolumns].mean(axis=1)
PT['SAvgAR']=PT['AvgAR']/np.sqrt(np.sum(sigma2/n**2))
```

```
PT['p-SAvgAR']=2*scipy.stats.norm.cdf(-np.absolute(PT['SAvgAR']),
loc=0, scale=1)
print(PT['AvgAR'])
print(PT['SAvgAR'])
print(PT['p-SAvgAR'])
# In[13]:
seaborn.set_style('darkgrid')
plt.rc('figure', figsize=(20, 10))
plt.rc('savefig', dpi=90)
plt.rc('font', family='sans-serif')
plt.rc('font', size=15)
# In[14]:
x=list(range(-20, 21))
y=PT['AvgAR']
x1=(-20, 21)
y1=(0, 0)
plt.plot(x, y, color='green', marker='v')
plt.plot(x1, y1, color='blue', linewidth=3)
plt.xlim(-20, 21)
plt.xlabel('Event Window')
plt.ylabel('AAR')
plt.minorticks_on()
plt.grid(color='grey', which='both')
plt.show()
# In[15]:
print(np.mean(PT['AvgAR']))
# #### Cumulative Abnormal Returns
# In[16]:
CumulativeAbnormalReturns=pd.DataFrame(columns=columns,
index=['CAR', 'SCAR', 'p-value'])
CumulativeAbnormalReturns
# In[17]:
CumulativeAbnormalReturns.loc['CAR']=PT[columns].sum(axis=0)
CumulativeAbnormalReturns
# In[18]:
win=PT.shape[0]
CumulativeAbnormalReturns.loc['SCAR']=CumulativeAbnormalReturns.loc
['CAR']/(np.sqrt(win*sigma2[0,:]))
CumulativeAbnormalReturns
# In[19]:
CumulativeAbnormalReturns.loc['p-
value']=CumulativeAbnormalReturns.loc['SCAR'].apply(lambda
x:(2*scipy.stats.norm.cdf(-np.absolute(x), loc=0, scale=1)))
CumulativeAbnormalReturns
# In[20]:
print(CumulativeAbnormalReturns.loc['p-value']>0.05)
# In[21]:
x=list(range(150))
y=CumulativeAbnormalReturns.loc['p-value']
x1=(-1, 150)
y1=(0.05, 0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.scatter(x, y, color='red', marker='o')
plt.plot(x1, y1, color='black', linewidth=3)
plt.minorticks_on()
plt.grid(color='grey', which='both')
```

```
plt.show()
# In[22]:
x=list(range(150))
y=(CumulativeAbnormalReturns.loc['p-value']>0.05)
plt.xlim(-1, 150)
plt.xlabel('Stock')
plt.ylabel('p-value')
plt.title('Significance of p-value')
plt.scatter(x, y, color='red', marker='x')
plt.minorticks_on()
plt.grid(color='black', which='both')
plt.show()
# In[23]:
Scores=pd.read_excel('ESG Scores.xlsx', index_col=0)
print(Scores)
# In[24]:
print(Scores.loc['2021-12-31'])
# In[25]:
x=Scores.loc['2021-12-31']
y=CumulativeAbnormalReturns.loc['CAR']
plt.xlim(0, 80)
plt.xlabel('ESG Score')
plt.ylabel('CAR')
plt.scatter(x, y, color='blue', marker='D')
plt.minorticks_on()
plt.grid(color='grey', which='major')
plt.show()
```