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Final Thesis

The ESG paradigm

assessing the ESG relevance on risk premia

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Abstract

In the last twenty years, environmental footprint, social responsibility, and corporate governance (ESG) factors have played a crucial role in the financial environment, especially when it comes to selecting investments and assessing financial performance. This dissertation addresses two main questions: (i) Are ESG scores related to the stock returns, i.e., *Is it possible to do well while doing good?* (ii) *Does the method used to identify the ESG premium affect the results?* To answer those questions, the analysis is based on the method illustrated in *Chasing ESG,* by Lioui and Tarelli (2022). The reference method compares two dominant methodologies for constructing an ESG factor: the time series (ratings used to order stocks) and cross-sectional methods (ratings used to weigh stocks). The analysis is replicated in the European stock market through. The Bloomberg database provides comprehensive data on ESG and other fundamentals to carry out all the assessments. The analysis I implemented has documented significant variability in the factor-alpha across time. However, it did not provide substantial support for a relation between ESG score and stock returns. Nevertheless, it has enforced the relevance of the approach adopted in analyzing ESG premiums.

Acknowledgement

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INTRODUCTION

According to Milton Friedman, "an entity's greatest responsibility lies in the satisfaction of the shareholders. Therefore, the business should always endeavour to maximize its revenues to increase returns for the shareholders". Thus, the primary responsibility of a corporation was to maximize shareholders' profits. However, this dictate has been less pertinent in the last twenty years. Indeed, Environmental, social, and corporate (ESG) responsibilities have gained the attention of financial investors, even though those factors are not directly related to firm fundamentals and were believed to be a burden to a firm's financial performance related to cost increases.

The global sustainable investment review has reported that at the beginning of 2020, the amount invested in firms with high ESG standing reached USD 35.3 trillion in the five major markets and, a 15% increase between 2018-2020. Moreover, The quote of sustainable investment assets under management makes up 35.9% of the total assets under management. Further, according to Morningstar, flows into U.S. sustainable funds increased to more than USD 20 and USD 50 billion in 2019 and 2020, respectively.

Although Socially Responsible Investing (SRI) has existed since the 1920s, it has only recently seen a significant increase in interest. As a result, it has become a general concern rather than a niche investment practice. The literature identifies two main possible reasons that might explain this change, and one is about non-pecuniary motives. Indeed, This rising trend in ESG attention has been fuelled by modern-day events, such as climate change conducing to extreme weather events, the greenhouse effect and melting glaciers. Moreover, the constant fight for human rights and the recent covid-19 pandemic, which put under pressure the health system, causing a global health crisis, made investors realize how social factors are crucial for the well-being of the employee of a company. The other is that they might believe sustainability guarantees better risk-adjusted returns (Hartzmark and Sussman 2019). Consequently, this phenomenon has grabbed the attention of the big three rating agencies (Moody's, S&P, and Fitch), starting to include ESG evaluation in their ratings.

Thousands of academic studies have empirically investigated if this growing interest in ESG investments impacts stock returns by assessing the relation between ESG ratings and stock performances. For example, Margolis et al. (2007) consider 167 studies between 1972 and 2007. Friede et al. (2015) consider more than 2000 papers published until 2014. Atz et al. (2021) cover nearly 1400 studies published between 2015 and 2020. The broad conclusion

from meta-studies in this field is that the empirical result is mixed at best, with positive, negative, or nonsignificant relations equally plausible. One key aspect of this mixed evidence is the heterogeneity in the methods applied to compute the ESG premium contribution.

The present research is devoted primarily to assessing analytically and empirically the difference between ESG factors computed using two main approaches: the time-series method (TS) by Fama and French (2020) and the cross-sectional (CS) based on Fama and MacBeth (1973).

Firstly, Chapter 1 will be dedicated to describing the literature surrounding ESG. A historical overview will be helpful in understanding which events have led to the present attention. Additionally, we will explain the evolution of ESG ratings focusing on the European market and detail the challenges those metrics exhibit. Then in Chapter 2, we will illustrate the methodology followed for constructing ESG-based factors based on the study by Lioui and Tarelli (2022). Their methodology is grounded on the seminal contributions of Black et al. (1972) and Fama and MacBeth (1973), who developed the now-standard approach to test the cross-sectional implications of linear asset pricing models. Fama (1976) elaborates on this approach, which is extended and used by Back et al. (2013, 2015), Fama and French (2020), and Bolton and Kacperczyk (2021a,b), among others.

Moreover, Chapter 3 will present the data used to perform the analysis, describing the database consulted to collect all the required data. Finally, in Chapter 4 will describe the main results, starting with the empirical comparison between the TS and CS ESG factors and then analyzing the impact of ESG factors on the stock returns.

CHAPTER 1
ESG LITERATURE REVIEW

This first chapter provides an helpful summary of the environment in which ESG investment trends developed. Section 1 illustrates the historical evolution of socially responsible investment starting with a brief discussion on the economic theory and following with the historical facts. Section 2 answers the question of why sustainable investment is so relevant and how the financial system can play a relevant role in supporting this purpose. Section 3 is dedicated on explaining the ESG rating system starting from its early beginning and ending with questioning their reliance and providing some future development.

1.1 Historical Overview

Over the past two decades, environmental footprint, social responsibility and corporate governance (ESG) factors have played a crucial role in the financial industry, becoming determining factors in assessing investment choices. This change is not the result of an abrupt change of direction on the part of industry players but is the result of an evolution observed through the ages. Indeed, even though has been recently proven the theoretical importance of non-economic factors in the investment decision of individuals, religious communities have preached sustainable investment to their adherents since the dawn of time, and with the passing of time, this insight reached increasingly more people even beyond the religious sphere.

1.1.1 The Evolution of Economic Theory

Historically, financial returns and risk have been always considered by economists and investors as the two only factors that guided investment decisions. This notion derives from the neoclassical school of economic thought, in which the key concept is defining an individual as *homo oeconomicus*. The term refers to economic agents who have rational preferences regarding purposes, maximize their utility, or if firms, maximize their profits, and act independently based on complete and relevant information (Roy Weintraub (2002), Marinescu (2016)). However, the *homo oeconomicus* assumption is an unsatisfactory model if we incorporate psychology within the economic analysis. Indeed, since the 90s the behavioural economic theory attracted increasing interests, by showing how the concept *homo oeconomicus* has limitations in describing the choices of individuals and how psychology plays a relevant role in decision-making.

Kahnemann and Tversky (1989) tested the relationship between rational choice and the unpredictable nature of human psychology involved in decision-making and highlighted the effect of human nature in the economic sphere. In other words, this theory provided evidences on at least two things: either a person has no primary rational interest, or he considers self-interest to be a wider sphere than his person. In both cases, these features have publicly and academically proven that the neoclassic assumptions are deceitful since they do not consider the major role played by human irrational nature.

Realising that economic decisions are not based solely on returns and risks, but are instead based on the desire to integrate a set of values into the choice that transcends financial return as an end in itself, is the first step in introducing socially responsible investing, SRI.

1.1.2 Socially responsible investment's evolution

The Forum for Sustainable and Responsible Investment, USSIF, defines SRI as an investment discipline that considers environmental, social, and corporate governance (ESG) criteria to generate long-term competitive financial returns and positive societal impact. Although the definition is a recent coinage, this kind of investing has an ancient origin, rooted in the religious dimension. Religious scriptures have influenced investments for thousands of years based on qualitative criteria. From biblical times to the present day, Jewish directives found in the Mosaic Law specifically describe methods for ethical investing. More recently, in the Christian era, Methodists, Protestant Quakers and other religious denominations have consciously avoided investing in stocks labelled *sin stocks*.

Sin stocks define a series of stocks belonging to certain industries or sectors. These include alcohol, gambling, tobacco and the production of weapons and war devices. Islamic investment, otherwise referred to as Shariah-compliant investment, follows basic rules laid down in the Quran, including the screening of investments by companies involved in specific undesirable industries. The framework provided a basis for considering other objectives such as environmental, social and governance dimensions in investments.

While these religious groups had specific guidelines in excluding undesirable investments, the concept of social responsibility also started to develop in business. Especially, the role of private companies in the public area. Towards the end of the 19th century, there was an increased awareness among investors of the role of companies in society and how this is relevant to portfolio construction and capital allocation. Small (1895) stated that it was the fundamental responsibility of all companies to be public servants. The 20th century brought

a growing interest in business ethics and corporate social responsibility on financial performance. Berle and Means (1969) further supported Small's argument by stating that corporations were more than just legal devices, but a true corporate system. For instance, large, listed companies had the foundation towards a direct public interest, such as the construction of bridges and canals, infrastructure, banks, and insurance companies. Indeed, they argue that corporations, having been founded with an interest in the public as their primary objective, have a philanthropic duty in addition to having "conscientious" day-to-day business practices. Similarly, Andrew Carnegie in his 1899 book *The Gospel of Wealth* argued that wealthy individuals and corporations had a similar obligation to their community as a steward.

These studies began to influence the roles of leaders towards civil society, e.g. J.D. Rockefeller and Henry Ford. The Great Depression and World War II made the consideration of non-financial factors in corporate policy even more popular. Especially during the Great Depression, some saw a risk of excessive economic and political power on the part of large corporate organisations. Consequently, there were numerous initiatives to make large corporations accountable to the public authority, mainly through control mechanisms. This led to a diffusion of investment selection through not only financial screening but by including elements of social responsibility in traditional portfolio theory (Hill (2006), Epstein (1987)).

The strong cultural development in the period 1950-1990 increased the importance of individual social responsibility (Schueth, 2003). Several historical events in the period 1950-1980 contributed to the development of sensitivity towards SRI investments (protest movements against the Vietnam War, civil movements for women's rights and against the Cold War). Socially responsible investing has moved from the question of the necessity of such an opportunity to the question of the methods to be used to integrate non-financial information into investment theory, Schueth (2003). Starting from a niche market strategy, SRI has become a common investment philosophy (Revelli (2016), Epstein (1987)).

At the end of the 20th century, positive events such as the Affordable Housing Act or negative events such as the Chernobyl disaster in 1986 and the Exxon oil spill in 1989 made investors more sensitive to the integration of SRI factors into traditional trading strategies. The concept of exclusion (negative screening) became popular, particularly among those religious or socially conscious investors who wanted to avoid investing in certain sectors or companies that they perceived as antithetical to their values. This led to the creation of the Domini 400

Social Index, today known as the MSCI KLD 400 Social Index, which allowed entering into the modern era of socially responsible investing. Founded in 1991, This index is composed of 400 large-cap listed firms selected for their "positive social and environmental impact records" (Gilbert, 2010; Sauer, 1997; Harjoto, 2011). The index became the backbone of a financial movement, which has shown the equal importance of the socially responsible investing dimension in providing returns equal or even superior to traditional investment strategies. (Gilbert, 2010; Duuren et al. 2015; Revelli and Viviani, 2014).

After the creation of the Domini 400 Social Index, in 1992 Michael Jantzi designed the *Seven Pillars of Corporate Social Performance and Responsibility* (CSP/CSR). These seven pillars include community issues, diverse workplace, employee relations, environmental performance, international, product and business practice, and others (e.i compensation, proxy voting, ownership in other companies, etc.). In the model, each firm was rated on a scale of -2 to +2, where -2 denotes the presence of a serious issue in that pillar and + 2 indicates a successful implementation in that specific pillar, Fauzi (2009). In the following years, these pillars constitute the foundation for the qualitative assessment of sustainability practices within firms, as well as the development of quantitative metrics useful in portfolio construction.

This model was the forerunner of the ESG rating system, which unlike the previous provides simultaneous cross-sectional data for predicting the distribution of stock returns in a wide range of asset classes. Thus, the rating system provides to firms and private investors the opportunity to incorporate environmental, social and governance risks into their investment policy. The first dimension E – environmental considers how a company performs as a steward of nature (e.g., Climate change, energy emission, water management, and resource depletion). The second dimension S – social examines how a company manages its relationships with employees, suppliers, customers, and the community (e.g., health and wellbeing, building safety, employee relations, diversity, and impact on communities). The third and last dimension G – governance deals with how a company is governed (e.g., executive pay, shareholder rights, board diversity and structure audits).

At the same time, Eugene Fama and Kenneth French published *The Cross-Section of Expected Stock Returns*, an asset pricing model to explain stock returns across a range of factors. Fama and French show that cross-sectional data on 3 identified factors (MKT, SMB, HML) explain asset returns more accurately than the single index model. These same cross-sectional data were developing in the ESG space at the time when Fama and French first published their

asset pricing model. Until then, they were simply laying the foundation for a cautious acceptance of the possibility that ESG integration could offer investors more return opportunities in a saturated market.

The development of this global cross-sectional data has been supported by extensive legislation. Specifically, European legislation has required firms to disclose environmental and social practices. However, the most significant document to date in the area of responsible investment is the 2004 report on the Financial Initiative for the Environment Programme, published by the United Nations, known also as *Who cares win*. The phrase "*Environmental, Social, Corporate Governance analysis*" was coined to describe the categories of analysis for socially responsible investing. This phrase was later shortened to ESG investing (Gilbert, 2010). The United Nations subsequently established the Principles for Responsible Investment (PRI), published in 2006. These principles aim to set standards through which firms can design their policies and have been accepted by 1,600 signatories, globally and industry-wide.

The Principles for Responsible Investment (PRI) states the following principles:

1. We will incorporate ESG issues into investment analysis and decision-making processes

2. We will be active owners and incorporate ESG issues into our ownership policies and practices

3. We will seek appropriate disclosure on ESG issues by the entities in which we invest

4. We will promote acceptance and implementation of the principles within the investment industry

5. We will work together to enhance our effectiveness in implementing the principles

6. We will each report on our activities and progress towards implementing the principles (United Nations)

Soon after, the first thematic portfolio has been designed by Deutsche Asset Management, their fund focused on climate change (Gilbert, 2010). Quickly this portfolio strategy has been widely adopted and became known as "impact investing". (Gilbert, 2010; Domanska Szaruga and Wysokinska-Senkus, 2013; Combs, 2014). The most common model used to implement investing strategy is Green Investing, based on constructing a portfolio that aims at reducing environmental risk (Domanska-Szaruga and Wysokinska-Senkus, 2013; Lesser, Lobe, and

Walkshausl, 2014). In 2015, during the United Nations Climate Change Conference (also referred to as COP21) has been clear that also multiple countries were starting to take action against unsustainable practices by making public commitments. In 2016 this demonstration of intent was then ratified in what is known as the Paris Climate Agreement or Paris Agreement. In the agreement, several countries have publicly committed to reducing greenhouse gas emissions through a series of targets, The goal of the agreement is to limit global warming to below 2°C, specifically below 1.5°C, compared to pre-industrial levels.

1.1.3 The present situation of socially responsible investment

Since the 1990s, many academics have tried to quantify the value of research-based ESG integration by measuring different economic dimensions, as well as measuring the extent to which ESG-based investment strategies have been integrated into institutional investment portfolios. Many governments, from The United Nations to the European Commission, have promoted investment initiatives to integrate ESG strategies into investment portfolios. These government initiatives pursued large financial intermediaries to change their general attitude to ESG research-based strategies within portfolio construction. Thanks to those regulatory bodies, the ESG-based investing strategies wave reached not only the developed nations such as the United States and Western Europe but also the emerging market nations such as parts of Asia and Latin America (Odell and Ali, 2016; Passant et al. 2016).

Figure 1 reports the percentage of each region in socially responsible investments (as of the end of the year 2020)

Table 1 represents the proportion of sustainable investing assets relative to total managed assets during the period starting in 2014 and ending in 2020, showing the significance of weighting towards the responsible investing strategies for each region.

It is worth highlighting that even though the United States represents the 48% of the global SRI assets, the SRI assets relative to the total managed is only 33.2%. Conversely, although Canada represents only 7% of global SRI assets, the proportion of SRI assets is 61.8% of Canadian total managed assets. These data suggest that regions as the United States have so far failed to incorporate SRI assets into their investment strategies compared to Canada and parts of Europe, thus indicating that there might be an interesting development in the coming years to show whether incorporating ESG strategies such as positive or negative screening, ESG integration and ESG engagement will lead to higher returns than investments without the incorporation of such information.

Figure 1 Proportion of global sustainable investing assets by region 2020

Source Global Sustainable Investment review 2020
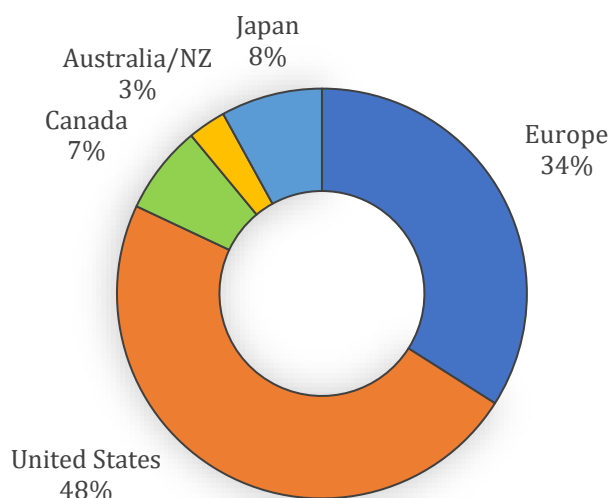
Table 1 Proportion of sustainable investing assets relative to total managed assets 2014-2020

Source Global Sustainable Investment review 2020

Region	2014	2016	2018	2020
Europe	58.8%	52.6%	48.8%	41.6%
United States	17.9%	21.6%	25.7%	33.2%
Canada	31.3%	37.8%	50.6%	61.8%
Australasia	16.6%	50.6%	63.2%	37.9%
Japan	-	3.4%	18.3%	24.3%

Moving to Europe and Australasia[1] regions, it is quite surprising to note such a negative trend in their percentages of sustainable assets managed in their market. For instance, in the Europe region is visible a constant decay through all the interval, whereas in Australasia region there has been a steep drop-down between 2018 and 2020. This indicates a major change in how sustainable investments are defined and shows an evolution of the sustainable market in these regions. In Europe, the evolution was steered by intense legislative activity,

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[1] Australasia is a region which comprises Australia, New Zealand, and some near islands in the Pacific Ocean.

which lead to the definition of sustainable standards for sustainable financial products. In Australasia, two factors led to this result, the first is the change in the sustainable investment standards for inclusion in the regional survey data conducted by the RIAA, and the second is the change in the data source used to define the total market size, based on the national central bank's definition.

Figure 2 depicts the difference in allocation of sustainable investment between retail and institutional investors in the period 2014-2020, data provided by the Global Sustainable Investment review 2020[2].

Figure 2 Global shares of institutional and retail sustainable investing assets 2014-2020

Source Global Sustainable Investment revie 2020
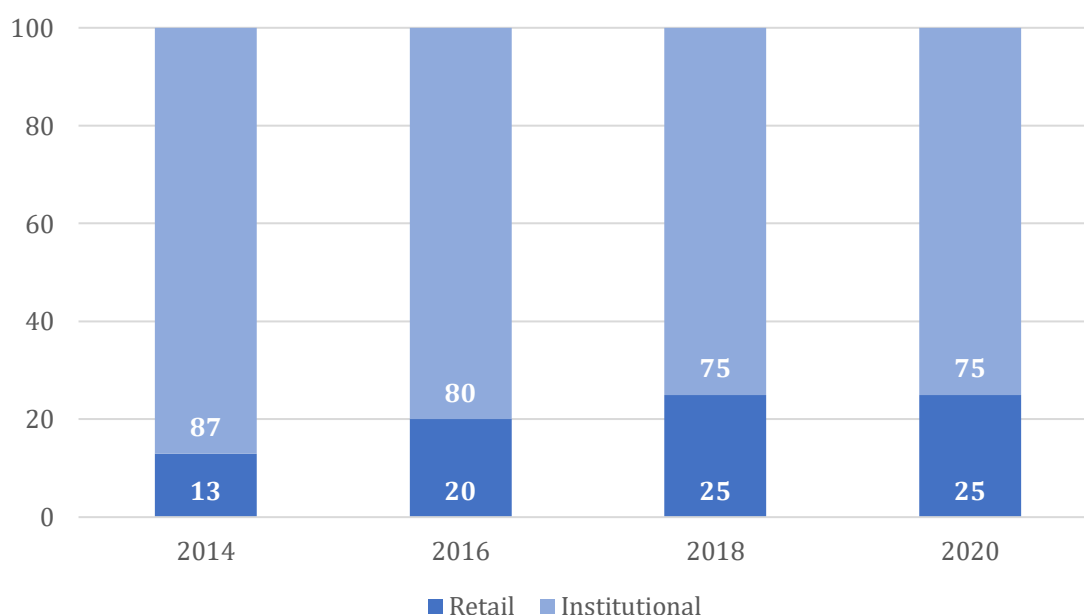
The distinction between these two categories concerns the subject who decides to invest. Retail investments are made by individuals that purchase a share in professionally managed funds through a bank or an investment platform with a low initial capital requirement. While Institutional assets concern investments made by a wide range of 'institutional' entities (e.g., universities, pension funds, foundations, and insurances) with higher capital requirements.

Although institutional investors tend to dominate the financial market, the data provided by the GSIA 2020 Annual Report demonstrates the rapid growth of interest by retail investors in sustainable investment since the classification has been made in 2012. At the time, institutional investors held 89% of assets compared with 11% held by retail investors.

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[2] This data was not collected in Australasia or Europe for 2020.

Nowadays, investors can rely on a wide range of indices that consider the aggregate performance of ESG-rated firms, like the Dow Jones Sustainability Index, the Sustainalytics STOXX ESG Leaders indices, and the MSCI Inc. ESG indices.

1.2 The relevance of sustainable investment

The economic model on which we rely has been developed considering only two scarce economic factors, labour, and capital. In the 19th century, during the industrial revolution, when this model has been developed, natural resources were plentiful and there was no concern about the environmental impact of human activities (Daly and Farley, 2011). Therefore, relying on this kind of model could be dangerous since we no longer live in an empty world and each year, we reach the earth overshoot day[3] earlier and earlier. Although many firms are in denial, we have started a sustainable transaction into a low-carbon and more circular economy.

However, considering only the environmental impact of our activities it's only half of the problem. Mass production has led to mass consumption, generating negative effects on the labour sphere. Longer working hours, underpayment, and child labour, have affected previously the developed world and later have been relocated to the developing world. To guide the transition toward a sustainable and inclusive economy, social regulations have been increasingly introduced to counter these practices and promote decent work, access to education, and health care. A major milestone has been the development of the 2030 United Nations Agenda for Sustainable Development.

The concept of sustainable development is the integration result of three aspects: environmental, social and economic, that allows current and future generations to have the resources needed without pressuring the biosphere. On the environmental side, climate change, land-use change, biodiversity loss, and depletion of natural resources are destabilizing the Earth system. In the social aspect, the levels of poverty, hunger and lack of health care show that many people live below minimum social standards.

1.2.1 Environmental challenges

No environmental issues were taken into account in the economic models we still use nowadays and labour and capital are the standard variables considered while building economic models. Similarly, the financial theory does not consider the value of natural

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[3] Earth Overshoot Day is the calculated illustrative calendar date on which humanity's resource consumption for the year exceeds Earth's capacity to regenerate those resources that year, Wikipedia.

resources but considers mainly short-term cash flows. The exploitation and potential depletion of resources are ignored. The environmental challenge is to keep the planet liveable for current and future generations. There is growing evidence that human activities are affecting the Earth system, threatening the future livability of the planet. The '*planetary boundaries*' framework of Steffen et al. (2015), Figure 3, defines a safe space for humanity by considering the limits/boundaries of nine productive ecological capacities of the planet. Applying the precautionary principle, the planetary boundary itself lies at the intersection of the medium dark and light grey zones.

Figure 3 The planetary boundaries. **Source** Steffen et al. (2015)
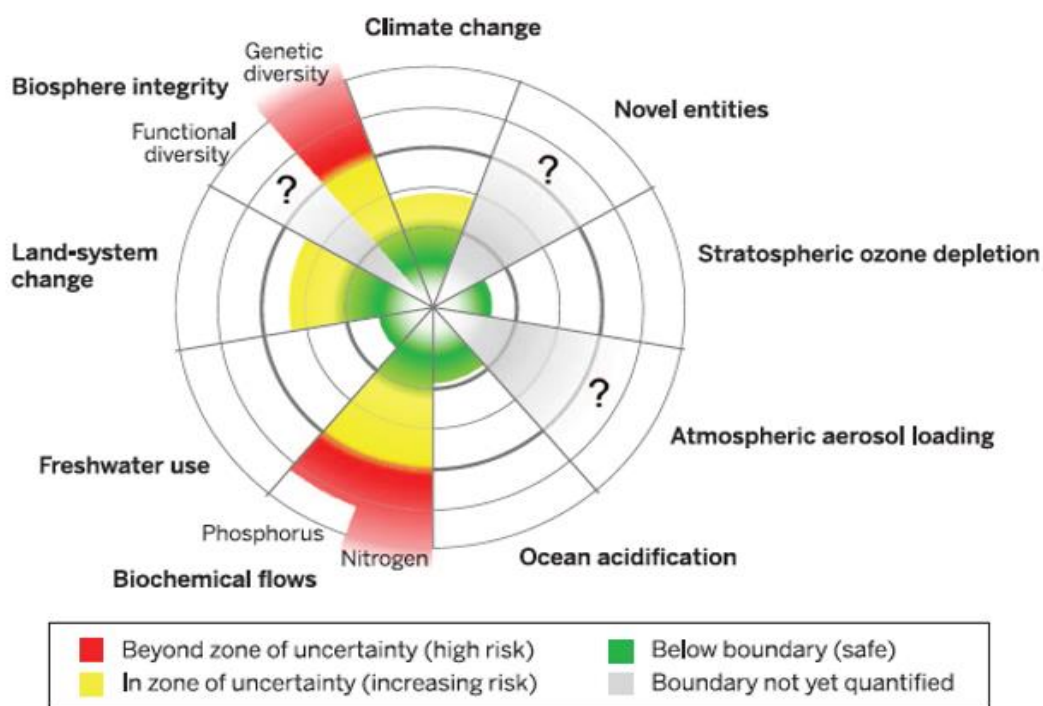
To illustrate how the framework works, we look at the control variable for climate change, which is assessed through the concentration of greenhouse gases, GHGs, in the atmosphere, measured in parts per million (ppm). For this risk, the planet boundary is set at 350 ppm, a threshold that we reached and crossed in 1995. In 2015 we reached 339 ppm and is increasing by 3 ppm per year. To contrast this trend an upper limit of 450 ppm has been set, this will limit global warming to 2°C above the pre-industrial level and lies at the intersection of the light grey and dark cycle.

Moreover, the linear production and consumption systems rely on extraction of raw materials (take), processing into products (make), consumption (use), and disposal (waste). The ongoing availability assumption of unlimited and cheap natural resources is increasingly risky

since it put under pressure non-renewable resources and potentially renewable resources are declining in their extent and regenerative capacity. In addition, the addiction to fossil fuels energy overburdens the Earth system's natural sink (absorbing pollution).

As Figure 3 shows, with the current linear production and consumption system is going beyond planetary boundaries where human activities destabilize the Earth system. To discourage that, a transition to a more circular economy based on sustainable production and consumption, including the use of renewable energy, reuse of materials, and land restoration, can mitigate these risks.

1.2.2 Social foundations

The competitive economic system derived from mass production has also a negative side. The constant growth regime, the aim for a more efficient service and the pressure to bit the competition has led to long working hours, exploitation and child labour, first in the *developed* world and then, with the delocalization phenomenon, in the *developing* countries. In order to contrast this trend, essential human rights (e.g., food, water, health care, freedom of expression, political participation, and personal security) must be guaranteed for all people, leading them to live a life of equal opportunities and dignity. To this aim, Raworth (2017) delineates 12 top social priorities that define social foundations, grouped in three clusters:

i.   *welfare*: through food security, adequate income (not less than $3.10 per day), improved water and sanitation, housing, and healthcare.

ii.   *productivity*: through education, decent work, and modern energy services.

iii.   *potential*: through networks, gender equality, social equity, having a political voice, peace, and justice.

Although these social foundations establish the minimum principles that should be guaranteed to all world populations, sustainable development aims to let people and communities prosper further beyond these minimum levels, leading lives of creativity and fulfilment. To this aim, Sustainable development merges the concept of planetary boundaries with the complementary concept of social foundations. This allows current and future generations to have the resources needed such as food, water, health care, and energy, without pressuring the biosphere (Raworth, 2017). The combination of social foundation and the biological ceiling has been summarized by Kate Raworth (2017) as the Doughnut Economy (see Figure 4) which shows that the safe and just space for humanity lies between

these two boundaries, in other cases if the human activity will outboard these boundaries it will incur in an overshoot of natural resource or a shortfall of social conditions.

Figure 4 The doughnut: the safe and just space for humanity. **Source** Raworth (2017).
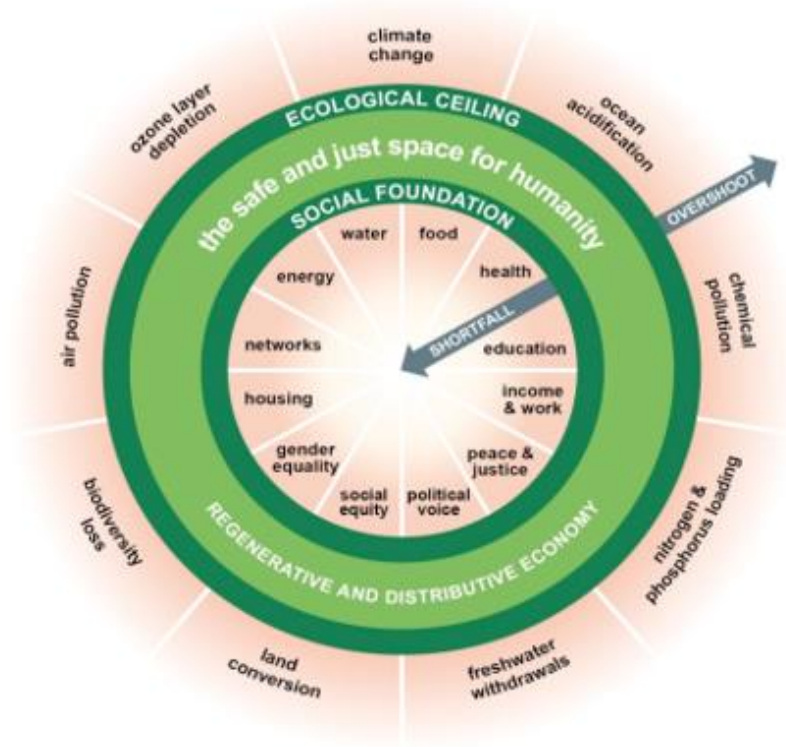
1.2.3 Sustainable development: the global strategy

To guarantee a sound transition towards a sustainable and inclusive economy, the Union Nations has developed the 2030 Agenda for Sustainable Development (UN, 2015). Inside the document has delineated 17 sustainable development goals, SDGs, which will stimulate a cohesive action on main critical areas, that should be reached over the period 2015-2030. Following Rockström and Sukhdev (2016), the SDGs can be classified into three levels: the economy level, the society, and the environment. Nevertheless, it must be highlighted that the SDGs are interrelated. In Table 2 are listed the 17 United Nations SDGs.

Table 2 Sustainable Development goals divided for each level. **Source** UN 2015.

Societal goals

Goal 1	End poverty in all its forms everywhere.
Goal 2	End hunger, achieve food security and improved nutrition, and promote sustainable agriculture.
Goal 3	Ensure healthy lives and promote well-being for all at all ages.
Goal 4	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all
Goal 5	Achieve gender equality and empower all women and girls.
Goal 7	Ensure access to affordable, reliable, sustainable, and modern energy for all.
Goal 11	Make cities and human settlements inclusive, safe, resilient, and sustainable.
Goal 16	Promote peaceful and inclusive societies for sustainable development, provide access to justice for all, and build effective, accountable, and inclusive institutions at all levels.

Environmental goals

Goal 6	Ensure availability and sustainable management of water and sanitation for all.
Goal 13	Take urgent action to combat climate change and its impacts.
Goal 15	Conserve and sustainably use the oceans, seas, and marine resources for sustainable development.
Goal 16	Protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, halt and reverse land degradation, and halt biodiversity loss.

Overall goals

Goal 17	Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development.

With the definitions of these goals, the UN hopes to provide a new direction for future government policies, like regulation and taxation of environmental and social challenges, and to help the formation of a cohesive global strategy. Technology innovations can play a crucial role in boosting sustainable changes (e.g., the development of solar and wind energy and electric cars at decreasing cost) and supplement policies (e.g. carbon pricing). Although the public sector has a leading role in the transaction also companies must be part of the transaction, preparing for this transition (future makers) and even being part of the solution (Mercer, 2015). On the other hand, however other companies are waiting for the transition to unfold before acting (future takers), continuing business as usual, and becoming part of the problem. Although the path and speed of the transition are uncertain and may even be

rough, with failures along the way, the sustainable development agenda provides a direction for thinking ahead.

1.2.4 The role of financial system

As we have seen above, the IT sector can play a crucial role in boosting sustainable advancement and, more widely, companies can be divided into future makers and future takers regarding how they are reacting to sustainable challenges. In the same shape, the financial sector can have a role centrally similar to that of the IT sector and financial intermediaries can be future makers or future takers. Levine (2005) lists the functions of the financial system as follows:

I.   Produce information ex-ante about possible investments and allocate capital.

II. Monitor investments and exert corporate governance after providing finance.

III. Facilitate the trading, diversification, and management of risk.

IV. Mobilize and pool savings.

V.   Ease the exchange of goods and services.

From the sustainable finance (from now on SF) perspective, the first three activities are the main relevant. The efficient allocation of funds in the system is the core activity in finance. Finance therefore can lead organizations to a more sustainable approach to their business by facilitating the orientation of capital towards more sustainable investments, leading, and accelerating the transaction to a sustainable economy.

In terms of monitoring investments, finance can price the risk of future cash flows for valuation purposes. This capability is useful for managing the risk inherent in environmental uncertainty. In addition, scenario analysis is becoming a fundamental tool to assess the risk and evaluate its different outcomes.

Since the definition of SF in the 1990s, the concept has evolved into a broad notion of corporate sustainability. Table 3 shows the roadmap for SF dived into three stages, and for each of them defines four aspects: (i) the value created; (ii) the ranking of the three factors; (iii) the optimization method; and (iv) the horizon. The roadmap highlights the need to move from shareholder value to stakeholder value or the triple bottom line: people, planet, and profit.

Table 3 Framework for Sustainable Finance. **Source:** Schoenmaker (2017).

Sustainable Financie Typology	Value created	Ranking of factors	Optimisation	Horizon
Finance as usual	Shareholder value	F	Max F	Short term
Sustainable Finance 1.0	Refined shareholder value	F>> S and E	Max F Subject to S and E	Short term
Sustainable Finance 2.0	Shareholder value (triple bottom line)	I = F+S+E	Optimise I	Medium term
Sustainable Finance 3.0	Common good value	S and E > F	Optimise S and E subject to F	Long term

Note: F = financial value; S = social impact; E = environmental impact; I = integrated value

Sustainable Finance 1.0 - The first step to reaching SF is the application of negative screening to all those stocks that can be categorised as sin stock, a concept defined in Section 1.1. Unfortunately, the initial effects of exclusion and divestment are limited (Skancke, 2016). From a financial point of view, fewer investors holding the excluded companies leads to lower share prices and a higher cost of capital. Heinkel, Kraus, and Zechner (2001) showed that to pressure polluting companies to reform it is necessary for over 20% of green investors. However, has been empirically verified that at most 10 per cent of funds are invested by green investors. In addition, disinvestment may stigmatize a sector or company to the extent of losing its license to operate or lead to less investment in the sector. Although this process has quite negative implications, it will result in setting a norm for acceptable standards.

A slightly more positive variant of the negative screening is the sustainable management approach. Implementing sustainable practices to reduce business risk. Even though these sustainable implementations will have benefits over social and environmental issues, the focus of these activities remains economic. Corporate success is still assessed from a purely

economic point of view and is still focused on serving the company itself and its economic goals (Dyllick and Muff, 2016).

Sustainable Finance 2.0 - In the second stage of the process, the time period will be the medium long-term, and financial intermediaries' decision-making process will explicitly consider the negative social and environmental externalities. This attention will be requested since these externalities will be priced (e.g. a carbon tax) and/or might affect the company's reputation. Thus, incorporating these externalities reduces the risk of financial investments becoming unprofitable. However, internalising them could lead to a perverse outcome, given that social and environmental impacts manifest over a longer horizon and are also more uncertain than financial impacts.

These externalities can result in a negative impact that can be offset by large gains. To contrast this possibility the SF must be equipped with a system capable of avoiding it, the value will be worsened compared to its initial value. In addition, the inherent uncertainty makes them difficult to price (e.g. underlying climate scenarios). A final caveat is participation (Coulson, 2016). This issue requires the integration of stakeholders to form an inclusive and pluralistic approach to assessing the social and environmental impacts.

Sustainable Finance 3.0 – In the final phase, the focus moves from risk to opportunity. Instead of avoiding investment opportunities related to reputation risk by negative screening, as in the first phase, in this phase, intermediaries will include investment projects with a positive impact on the social and environmental spheres. Thus, the central idea is that finance's role turns from primacy, profit maximization, to serving as a means to optimize sustainable development.

To summarize, the three stages of SF lead to a progressive increase in the level of realised socio-environmental value. Firstly, SF 1.0 defines a minimum level below which investors cannot go. Corporate or investment projects which do not reach this threshold are excluded. Next, in SF 2.0 the privately discounted financial, social, and environmental values are balanced with a comprehensive approach to optimize the integrated value. Finally, in SF 3.0 the socio-environmental value is optimized. Firms and investment projects with a high impact on socio-environmental value are eligible for investment or lending and are on an inclusion list. The first two phases are focused on avoiding reputation risk (the minimum level of CSR where externalities are expected to be priced at some point), while the third aims to catch all the opportunities to realise socio-environmental impact through investments and loans.

The majority of businesses currently operate at the SF 1.0 level, prioritising financial value. About 30–40% of financial institutions and 20–30% of businesses base their investment and operational decisions on sustainable principles. These businesses are between SF 1.0 and 2.0 and are only partially maximising the integrated value. We are just over yet still very near SF 2.0. Making the transition from SF 1.0 to SF 2.0 is a true challenge. Last but not least, less than 1% of financial institutions are part of the small group embracing SF 3.0. The structure is flexible. NGOs use an increase in exclusions to encourage investors to increase the minimum standard. The social-environmental component in the integrated value calculation may move upward as a result of the introduction of government regulation or taxation on social and environmental externalities.

1.3 The ESG rating system

The PRI's Report (2020) defines ESG rating agencies as firms that "assess a securities issuer (bonds or equities) according to their exposure and performance related to ESG criteria and compared to their peers". These pieces of information are quantifiable but are not freely available to investors. The simple disclosure of SRI in all its aspects, with increased influence on ESG screening, is one of the main objectives of ESG rating agencies. The objective of ESG rating agencies can also be considered a mission (Schäfer, 2005). Firstly, the rating assists the company, senior management, and the board of directors in determining whether important long-term assets and connections are being developed (Chatterji & Levine, 2006). These non-financial performance measures are fundamental to a thorough examination of the company. The second, related to the first, is to help the opposite side of the spectrum, represented by consumers, regulators or future employees, to better understand the social performance of the company. Pressures from external stakeholders are undoubtedly relevant for firms and will lead them to modify their practices and activities. It not only helps to know the company better but also to identify business risks (Schäfer, 2005). Moreover, rating agencies provide a wide range of services such as sector-specific reports, benchmarking, assistance with corporate engagement initiatives, screening of portfolios and training courses (Escrig-Olmedo et. Al., 2010). In addition, dispute alerts and engagement services are said to be included in the spectrum of services offered (Novethic Research, 2013).

1.3.1 ESG rating and its beginning

The more important has become prudent policy in corporate governance the greater has been the popularity of ESG rating agencies (Escrig-Olmedo et. Al. 2010). Furthermore, the ESG market is becoming increasingly relevant for investors, who are eager for more

information. Based on Schuler and Cording's (2006) work, the growth of ESG rating agencies could be related to the reliance on their sources of information about the company's results. Indeed, investors are more prone to base their investment decision on information provided by an external agent instead on rely solely on a firm's disclosure, giving ESG rating agencies an important role in sustainable investments.

Major asset management and investment companies, such as Vanguard, BlackRock or Berkshire Hathaway, consider now ESG information in their decision-making process. Also, the before-mentioned Principles for Responsible Investment developed by the United Nations (PRI) are a significant part of this adoption. These principles, other than representing an important United Nations programme on responsible investment, enable fund managers to integrate ESG activities into their investment decision-making process. However, gathering and computing ESG analysis is expensive in terms of capital and time. Thus, fund managers externalize these commitments to external ESG rating agencies (ACCF, 2018). A key role of ESG scores is that they assist institutional and retail investors to acknowledge new issues and compare the sustainability performance of their peers (Sustainability, 2018).

1.3.2 Sustainability vs financial performance

The valuation of ESG's scores impact on the financial sector has become a major topic in the academic world. Great attention has been given to assess the economic and financial performance of ESG stocks and portfolios. Specifically, academics concentrate their efforts on assessing the ESG portfolio profitability, the impact of ESG on companies' financial performance, and the effect of ESG scores on credit ratings. Most studies, covering both industrialised countries and emerging economies, emphasise the positive impact of ESG efforts and disclosure on corporate financial performance (Billio et al. 2020).

In addressing the first issue, the impact of ESG on companies' financial performance, academics provided a wide range of studies, concerning both industrialized and emerging countries, emphasising the positive impact of this relation. Indeed, Zhao et al. (2018) looking at Chinese listed power generation companies find that the larger the ESG scores are the better will be the financial performance of that firm. Moving to the US market, Brogi and Lagasio (2019) provided the same conclusion as Zhao et al., especially for the banking sector, but in this case, they used MSCI ESG KLD STATS data from 2000 to 2016 and measured profitability through ROA. Still, Ortas et al. (2015) assess the hypothesis on Spain, France and Japan markets by collecting data from the ASSET4 Database including MSCI data and

obtained similar results to the previous studies for firms that adopted the United Nations Global Compact (UNGC). Yet, there exist studies that have landed on different conclusions. For instance, Landi and Sciarelli (2019), focusing on Italian listed companies and focusing on Italian listed companies and using the FTSE MIB, find no statistical impact of ESG on company performance. Still, Miralles-Quiròs et al. (2019) assessed the issue on OECD members and runs their analysis based on the ESG data provided by Thomson Reuters Eikon, finding very weak effects of only some of the ESG pillars. Thus, it must be highlighted that it is not possible to define a solid conclusion on the issue, since rating agencies use different methodologies, countries have their specific peculiarities, and the ESG materiality is blurred. To smooth this situation, it is needed to standardise ESG accounting procedures, enabling investors, politicians and scientists to better assess the effects of ESG performance.

The second topic on which academics focussed on is the study of the performance of ESG portfolios. Kempf and Osthoff (2007), Statman and Glushkov (2009), Nofsinger and Varma (2014), and Henke (2016) amongst others, reached a positive conclusion, highlighting that investing in ESG-firms-based portfolios provides improved portfolio performance. Building their analysis on data from KLD Research & Analytics, Kempf and Osthoff (2007) find that by applying a long strategy to green stocks (stocks with high ESG ratings) and shorting brown ones (stocks with low ESG ratings), the portfolio will result in high abnormal returns. Using the same database, Statman and Glushkov (2009) observed that green investors have a yield advantage over conventional ones. Yet, the authors also observed that systematic negative screening of sin stock can penalize the performance of the portfolio. Going further, Nofsinger and Varma (2014) focused their analysis on socially responsible mutual funds and assess an outperformance trend of these funds during periods of market turbulence. Based on the study, this effect is remarkable for sustainable funds that use positive screening strategies. Finally, in his work, Henke (2016) used data provided by US SIF and Euro SIF to evaluate funds in these areas. His evidence shows ESG portfolios' outperformance also during crisis periods and even after robust checks. As before, even in this stand exist studies that arrive at different conclusions. Regarding the work, by Henke (2016) a similar analysis has been performed on Asian stock markets, revealing that SRI portfolios have better returns only in Japan, whereas in the rest of Asian stock markets there are no rewards (Yen et al. 2019). Still, Auer and Schuhmacher (2016) reached the same conclusion for the Asia-Pacific region and the US, while in Europe the portfolio's performance can be even negative. However, Friede et al. (2015) provided a meta-analysis that combines over 2200 studies and concluded that about 90% of them show a non-negative relationship between ESG and

corporate financial performance with an explicit positive relationship in the large majority. Additionally, Halbritter and Dorfleitner (2015) observed that the size and direction of the overperformance of ESG portfolios are highly dependent on the rating agencies, highlighting considerable discrepancies between ESG ratings and the need for more harmonisation.

The last strand of literature regards the impact of credit ratings related to the ESG factors. Attig et al. (2013) have proved that credit agencies provide a higher credit rating to those firms with good social performance. In the same way, Devalle et al. (2017) and Weber et al. (2010) have shown that even companies with high performance in environmental and sustainability benefit from relatively high ratings. Also, Kiesel and Lucke (2019) establish a slight but still clear impact of ESG performance on rating decisions, especially regarding the corporate G - governance pillar. As previously, there exist other studies that demonstrated opposite results. Based on the result by Jang et al. (2020) which focuses their attention on South Korea and used ESG data from Korea Corporate Governance Service (KCGS), the ESG scores are complementary to the credit rating and help firms to reach a lower cost for debt financing, in particular for small firms. In the same conclusion is the work by Bhattacharya and Sharma (2019), who performed a similar analysis to the Indian market, and obtained that ESG affects positively the credit rating of small and middle-level firms. Even in this case, the ESG impact is blurred and harmonization of ESG data should be considered to clear away the fog, given also the relevant role played by the financial sector.

1.3.3 Challenges for ESG ratings

From its introduction, the ESG data have undeniably changed, but there is still a long journey ahead and many hurdles to face. Trusting solely on ESG scores provided by rating agencies for investment decisions is not a recommendable choice, given the large range of mistakes that rating agencies can make (Mooij 2017). Additionally, ESG-related information can also be contradictory and have different values, meaning that gathering all of them in a single number will lead to other specific issues (BlackRock 2018).

In 2018, BlackRock in its Sustainable Report highlighted four major issues while considering ESG. The first is reliability: each ESG metric is weighted by applying different methodologies. Since each ESG rating agency uses its own method, the ratings might have a poor correlation. To make ESG widely accessible, a standardization of the method applied at the industry level is required (Escrig-Olmedo, Muoz-Torres, & Fernandez-Izquierdo, 2010) and given the absence of the best strategy, the space for comparison between the different methods is narrow, leading to a lack of comparability of ESG scores (Hawley, 2017).

However, arguments in favour of the differences between agencies have been raised, arguing that they may be helpful (Chatterji & Levine, 2006). It is also argued that the 'normalisation' of ratings can over- or underweight a company or even a sector because the company- and the sector-specific risks are not considered in the analysis, making it repetitive (ACCF, 2018). It is worth remarking that the reliability issue is due to the absence of communication in the ESG rating sectors (Wigglesworth, 2018). Rating agencies like MSCI and Sustainalytics, which dominate the industry, have a score association of 0.32, provided by CSRHub. In comparison, S&P and Moody's Agencies Rating have a correlation rate equal to 0.9.

The second flaw is Coverage. Given that the majority of ESG data is recent and that only large corporations disclose in-depth their sustainability challenges, it is understandable why. Obtaining an ESG rating requires a lot of work from businesses as well as significant fees from stakeholders and customers (Chatterji & Levine, 2006). This involves filling a huge amount of documentation, having compliance inspectors visit, establishing safety procedures, and completing hundreds of pages worth of surveys about their socioeconomic, financial, governance, and ethical strategies each year, said the same study. Given the abundance of rules and principles, it can be challenging for stakeholders to identify which ones are reliable measures of social accountability. In addition, the authors claim that because there are so many surveys and questionnaires, it is impractical for organisations to react to each one, and occasionally they don't respond as extensively as they should. Consumers and stakeholders will become irritated by the abundance of rating institutions, claim Chatterji and Levine (2006) because they won't know what to search for or what is correct or wrong.

The third significant flaw in the EGS has been discovered to be the poor quality of the data. Since data are typically self-reported, there is a risk of errors and unreliability. An increased transparency by companies and the availability of standard reporting methods are both necessary. The first step in improving ESG reporting should be standardisation, which might take the shape of a set of industry-specific standards with enough detail to permit fair comparisons between businesses. Nearly 80% of investors, according to a Deloitte study from 2016, are dissatisfied with the poor level of comparability in sustainability reporting for businesses in the same industry. Investors believe that in the future, comparability and accuracy will be the most crucial features of ESG ratings (SustainAbility, 2019).

Recently, Khan, Serafeim, and Yoon (2015) showed the value of distinguishing between significant environmental issues and those that are not. It was discovered that businesses that did better on material sustainability issues outperformed those that performed worse. The

Sustainability Accounting Standards Board, which establishes accounting standards, was responsible for the classification. According to Chatterji and Levine (2006), these measurements are also argued to be imprecise, inaccurate, and incomparable, endangering both general welfare and corporate social success. The authors define accuracy as a test that accurately portrays the correct dimension of social obligation, which is frequently congruent with materiality, and reliability as a test that can yield the same result. Regarding transparency and disclosure, Jim Hawley (2017) identifies three biases: geographical bias, factorial bias and investor or stakeholder bias.

Geographical bias regards the tendency to adopt European standards since in this area the ESG regulation is more developed and binding than in other areas (ACCF, 2018). The weighting given to each ESG group is typically kept a secret. This is why one of the main misconceptions about transparency is a factor bias. In terms of investor prejudice, large companies are more likely to receive high scores when they report on more ESG variables, nearly leading to a "check the box" bias. As stated by Gese, Lee, Melas, Nagy, and Nishikawa (2017), this may also be attributable to increased financial control, which encourages more acquisitions and investments to improve their ESG profile. This analysis also reveals that there has been no research into the types of data sources used and how they are used. Indeed, many ESG Rating Agencies are attempting to protect their intellectual property and databases, which may explain how they operate. Then, according to a 2016 BlackRock study, businesses with compliance challenges and corporate ethics issues were more likely to have a higher level of ESG-friendly policy transparency. Furthermore, ACCF supports this in their 2018 Report, stating that businesses with poor ESG policies can still achieve a good ESG Rating by being transparent.

The final major flaw in ESG rating is recurrence. Most ESG metrics are only updated once a year, making it difficult for investors to trust the data required to mitigate risk and maximise returns. There are also evidences of reporting delays, making it difficult for economic agents to collect data on time (Hawley, 2017). Is all of the information relevant, given all of the challenges and various implications that characterise ESG data? During the research, I decided to look at multiple indicators for E, S, and G to see if they all provided unique and useful information or if they all contributed to the overall scoring. Is the information provided by each indicator thus truly relevant and meaningful?

1.3.4 Future of ESG rating

The industry now has a large number of ESG Rating Agencies, each of which employs its methodology, implying a potential integration phase (Escrig-Olmedo, Muoz-Torres, and Fernandez-Izquierdo, 2010). According to the authors, the most powerful agencies in the industry will lead this process, and their overall goal is to remain in business. There is no literature on the future of the ESG Rating Agencies industry, implying that it is a difficult subject to be concerned about and forecast. One widely held belief is that once rating systems are well-developed and streamlined, they will have a significant impact on organisational behaviour (Dillenburg, Greene, & Erekson, 2003).

According to Schäfer (2005), providing mechanisms similar to those found in the international credit rating market may emerge in the ESG rating market. In his view, these credit rating companies may also be vertically integrated. On the subject of CRAs, the PRI makes some pertinent observations in its 2017 ESG, Credit Risk, and Rating Report (Part 1). The growing demand from investors for more advice and supervision from CRAs, particularly in terms of ESG, as well as additional scenario analysis to determine potential patterns and risks, is forcing CRAs to pay more attention to ESG.

CHAPTER 2
METHODOLOGY

This Chapter will describe the approach adopted to construct the ESG-based factors model. First, Section 1 will illustrate factor models and their use in finance. In particular, it will be defined the three main categories, their significant advantages, and the main differences between their use in the time-series setup compared to the cross-sectional regression framework. Then, section 2 will review the well-known approach of Fama and Macbeth, known as the two-stage regression. This regression method will be the building block for the model used to investigate the relevance of ESG. Finally, section 3 will be devoted to explaining the method empirically used to control the ESG factor, to compare the time series and cross-sectional factors, and finally will briefly discuss the multivariate implementation of the method. All the relevant proofs and derivations are reported in Appendix A.

The relevant literature used in this Chapter relies firstly on Connor (1995), who gives an overview of three types of factor models for asset returns and compares their explanatory power; to Campbell, Lo and MacKinlay (1997) and Grinold and Kahn (2000) who survey the econometric specification of these models. Zivot and Wang (2003) and the textbook by Ruppert (2010) have also been consulted on this topic. Finally, Fama and Macbeth (1973), Fama and French (2020), Lioui and Tarelli (2022), and Pàstor et al. (2021) are the primary resources on which we rely to cover the last two sections.

2.1 Factor Models

The investigation of high-dimensional data can be complex, as in the large portfolios analysis. They are challenging to visualize, demand heavy computing power, and frequently require specialized statistical methods to be handled. However, it is possible to implement dimension reduction techniques on those data types: since most of their variation can be represented in lower-dimensional spaces. Specifically, factor analysis can summarize the behaviour of portfolio returns as a function of a limited number of fundamental variables, identified as factors or risk factors. By defining a factor model, we decompose stock returns as functions of factors common to all stocks and of stock-specific shocks. The three main categories of factor variables used in these models are macroeconomic, fundamental, and statistical. The first explains the returns with economic time series like interest rates, inflation rates, or gross domestic product, GDP. The second uses firm-specific characteristics, such as firm size,

dividend yield or, in our case, firm sustainability scores. Finally, the third treats the common factors as unobservable or latent factors that must be estimated from the asset returns.

When it comes to addressing the explanatory power among the three types of factors of stock returns, it has been proved by Connor (1995) that the macroeconomic approach seems to be the one with the lowest explanatory power. In contrast, statistical and fundamental factor models have a better capacity and timing in addressing the behaviour of stock returns.

2.1.1 Factor model generalization

Although each of the three-factor models defines the factor variable differently, the formula of returns is familiar to everyone:

$$R_{it} = \alpha_i + \beta_{1i}f_{1t} + \beta_{2i}f_{2t} + \cdots + \beta_{Ki}f_{Kt} + \epsilon_{it} \tag{1}$$

where R_{it} is the return on asset i ($i = 1, \ldots, N$) in time period t ($t = 1, \ldots, T$) expressed as real or in excess of the risk-free rate, α_i is the intercept, f_{kt} is the kth common factor ($k = 1, \ldots, K$) at time t, β_{ki} is the factor loading or exposure to the risk factor for asset i on the kth factor, and ϵ_{it} is the specific error term, called unique risk. In the model, we assume that the factor realizations f_t are independent of asset i, with unconditional moments, and that the asset specific risk is uncorrelated with the common factors. Finally, we assume that ϵ_{it} is serially uncorrelated and contemporaneously uncorrelated shock across assets.

2.1.2 Cross-sectional vs. time-series factor regressions

Equation (1) can be rewritten as a cross-sectional regression model at time t by stacking the equations for each stock to give

$$\boldsymbol{R_t} = \boldsymbol{\alpha} + \boldsymbol{B}\boldsymbol{f_t} + \boldsymbol{\epsilon_t}, \qquad t = 1, \ldots, T \tag{2}$$

where $\boldsymbol{R_t}$ is the $N \times 1$ vector of stock returns at time t, $\boldsymbol{B}$ is the matrix $N \times K$ that contains all the factor betas, $\boldsymbol{f_t}$ is the $K \times 1$ vector of factors, and $\boldsymbol{\epsilon_t}$ is the $N \times 1$ vector of error terms.

Equation (1) can also be seen as a time-series regression model for asset i by stacking observations for a given stock resulting in

$$\boldsymbol{R_i} = \boldsymbol{1}_T \alpha_i + \boldsymbol{F}\boldsymbol{\beta_i} + \boldsymbol{\epsilon_i}, \qquad i = 1, \ldots, N \tag{3}$$

Still $\boldsymbol{R_i}$ is the $T \times 1$ vectors of i asset return in the time interval, $\boldsymbol{1}_T$ is a $T \times 1$ vector of ones, $\boldsymbol{F}$ is a $T \times K$ matrix of factors realizations, $\boldsymbol{\beta_i}$ is a $K \times 1$ vector of factor loadings, and as before $\boldsymbol{\epsilon_i}$ is the $T \times 1$ vector of stock specific risks.

Factor models that rely on macroeconomic and fundamental variables to compute the regression parameters usually are analyzed through time-series regressions. When it is required, fundamental factor models also use the cross-sectional approach. There are two main differences between the time-series and the cross-sectional methods. First, with time-series regression, we estimate the parameters of one asset at a time on a multiperiod interval. In contrast, in cross-sectional regression, we jointly estimate the parameters for all the stocks at different times. The second difference regards the different parameters to be estimated. Indeed, in a time-series regression, the parameters are the factor loadings, and the factor realizations are directly measured. In contrast, in a cross-sectional regression, the opposite is true since the loadings are known, and the risk premiums are inferred.

2.1.3 Factor models highlight

Entrusting the assessment of asset returns to a close number of selected factors guarantees some advantages. Estimating the covariance matrix of many assets using a factor model instead of computing the simple covariance allows for a more accurate estimation. Indeed, each simple variance-covariance matrix contains $n(n + 1)/2$ parameters, that must be estimated with errors and the larger the number of stocks *n*, and the lower will be the accuracy resulting due to the accumulation of estimation errors. Conversely, with factor models, a better bias-variance trade-off can be achieved, since this method needs to estimate $n \times p$ parameters in β, k^2 parameters in the factors' covariance matrix and n parameters in the residuals diagonal covariance matrix, totalling $nk + n + k^2$ parameters. In practical applications, the number of asset returns is larger than the number of factors, thus $nk + n + k^2$ is much smaller than $n(n + 1)/2$. Another advantage of using a factor model is expediency. Having fewer parameters to estimate is convenient. Suppose we want to enlarge our returns sample with additional asset returns. If we are relying on simple covariance, this will require us to run the covariance calculation among all the old and new assets and have access to the updated data of the old assets. Instead, in a factor model we need only to regress the new stocks with the k factors and only this last data set must be updated.

After defining the risk factors and their ability in explaining the stock or portfolio returns, the next investigation will be to define an approach able to find the premium from factors

exposures'. To this end, we present the well-known contribution provided by the Fama-Macbeth (1973) two-step regression.

2.2 Fama Macbeth two-stage regression

The contribution by Fama and Macbeth (1973) presents a particular way of testing how risk factors describe portfolio returns. In the first step, they perform a time series regression where the portfolio's returns are regressed against one or more factors to define how much the portfolio is exposed to that or those factors.

2.2.1 The two-stage regression

In equation form, N time-series regression on K factors need to be estimated to find the loadings $\beta_{i,t}$.

$$R_{1,t} = \alpha_1 + \beta_{1,F_1}f_{1,t} + \beta_{1,F_2}f_{2,t} + \cdots + \beta_{1,F_K}f_{K,t} + \epsilon_{1,t}$$
$$R_{2,t} = \alpha_2 + \beta_{2,F_1}f_{1,t} + \beta_{2,F_2}f_{2,t} + \cdots + \beta_{2,F_K}f_{K,t} + \epsilon_{2,t}.$$
$$\vdots \quad \vdots \qquad\qquad\qquad \vdots$$
$$R_{N,t} = \alpha_N + \beta_{N,F_1}f_{1,t} + \beta_{N,F_2}f_{2,t} + \cdots + \beta_{N,F_K}f_{K,t} + \epsilon_{N,t}$$

$$(4)$$

The following step allows to compute a cross-sectional regression between the portfolio's returns and each time factor's exposure estimated previously. This allows us to find the time series risk premia coefficients for each factor.

In equation form, the cross-sectional regression is performed T times the returns on the K estimated

$$R_{i,1} = \lambda_0 + \lambda_{1,1}\hat{\beta}_{i,F_1} + \lambda_{1,2}\hat{\beta}_{i,F_2} + \cdots + \lambda_{1,K}\hat{\beta}_{i,F_K} + \epsilon_{i,1}$$
$$R_{i,2} = \lambda_0 + \lambda_{2,1}\hat{\beta}_{i,F_1} + \lambda_{2,2}\hat{\beta}_{i,F_2} + \cdots + \lambda_{2,K}\hat{\beta}_{i,F_K} + \epsilon_{i,2}$$
$$\vdots \quad \vdots \qquad\qquad\qquad \vdots$$
$$R_{i,T} = \lambda_0 + \lambda_{T,1}\hat{\beta}_{i,F_1} + \lambda_{T,2}\hat{\beta}_{i,F_2} + \cdots + \lambda_{T,K}\hat{\beta}_{i,F_K} + \epsilon_{i,T}$$

$$(5)$$

where $\hat{\beta}_{i,t}$ are the estimated factor exposures computed in the first step, and $\lambda_{k,t}$ are the risk premiums given the factor exposures on each time instant, including the constant λ_0.

Consequently, the insight of Fama-Macbeth (1973) is to compute the average of these coefficients ($\gamma_{k,t}$) to give the expected premium for a unit exposure to each risk factor over time. In other words, the T cross-sectional regressions are replaced by a single regression of N average portfolio's returns against K factor exposure with lengths N:

$$E[R_i] = \lambda_0 + \lambda_1 \hat{\beta}_{i,F_1} + \lambda_2 \hat{\beta}_{i,F_2} + \cdots + \lambda_K \hat{\beta}_{i,F_K} + \epsilon_i \qquad (6)$$

The two-step estimation method by Fama Macbeth (1973) has been widely used in finance and accounting, to the extent of becoming a standard practice to examine macroeconomic and fundamental factors and their pricing power in the cross-section of asset returns. Indeed, even this empirical analysis will construct the pure ESG portfolio using the second regression equation as the equation model.

2.2.2 The aftermath of the FM two-stage regression

Evidence from Fama and Macbeth's (FM 1973) cross-section regressions demonstrating that average returns are linked to asset characteristics is frequently used to motivate factors in time-series asset pricing models. For example, Fama and French's three-factor approach is based on evidence that size and book-to-market equity ratio reflect variations in average stock returns that the capital asset pricing model misses (CAPM). Moreover, Fama and Macbeth's (FM 1973) regressions are a type of factor model. Rearranging the cross-section regression as a Fama and French three-factor model on the excess average returns, where excess stock returns for month $t, R_{it}, i = 1, \dots, n$, are regressed on previously observed values of size (MC_{it-1}) and the book-to-market ratio (BM_{it-1}) portfolios returns, namely,

$$R_{it} - R_{zt} = R_{MC} MC_{it-1} + R_{BM} BM_{it-1} + e_{it} \qquad (7)$$

The slopes estimates can be seen as portfolio returns that can be interpreted as factors and R_{zt} is the month t return common to all assets and not captured by the regression explanatory variables. Fama (1976) highlighted two main results. First, the slope for each variable in an FM cross-sectional regression is the return on a portfolio of the left-hand-side (LHS) assets with weights for the assets that set the month $t - 1$ portfolio value of the variable to one and zero out other explanatory variables. Second, each FM slope portfolio requires no net investment; long positions in LHS assets are financed with short positions in other LHS assets. $R_{BM,t}$, for instance, is the month t return on a zero-investment portfolio whose weights for LHS assets set the portfolio value of BM_{it-1} to one and set the portfolio values of MC_{it-1} to zero.

Fama and French (2020) insight is that when the cross-section regression is stacked across t, it becomes an asset pricing model that can be used in time-series applications. In addition they compare the cross-sectional factor to the time-series factor.

$$R_{it} - R_{ft} = a_i + b_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + e_{it} \tag{8}$$

In three-factor model in regression equation (8), R_{ft} is the monthly risk-free rate and R_{mt} is the value-weighted (VW) monthly stock market return. The remaining two factors are differences between returns on diversified portfolios to reflect the size and book-to-market asset characteristics. The intercept a_i is the pricing error for LHS asset i in the time-series regression. Fama and French (2020) shown that there are important differences between equation 7 and 8. First, in the time series regression 8 the factors are prespecified, hence there is no attempt to optimize them. Indeed, a least squares time-series regression optimizes an asset's factor loadings on the prespecified factors, subject to the constraint the disturbances are independent and identically distributed (i.i.d) across time. In short, the time-series regression (8) optimizes loadings on factors that are not themselves optimized. Fama and French comperes this two approaches and found out that time-series models that use only cross-section factors provide better descriptions of average returns than time-series models that use time-series factors. They also found that this is true when we impose constant factor loadings and when we use time-varying loadings that are natural for timeseries factors and time-varying loadings that are natural for cross-section factors.

2.3 Construction of pure ESG factors portfolios

The previous discussion is the ground level necessary to develop a factor model in which the only factor is the ESG stock rating. This will allow investigating the ESG contribution to the stock returns.

2.3.1 The univariate cross-sectional ESG model

For our purpose, the analysis relies on Lioui and Tarelli (2022) , who built an univariate cross-sectional factor, counting only on the ESG characteristic of an individual asset. Their results are based directly on the contribution of Fama and French (2020), which describes why using cross-section factors on time-series models, with the approach by Fama Macbeth (1973) has a better explaining property on average returns than using time-series factors. This finding led Lioui and Tarelli (2022) to build the following model, which can be seen as the second step of the Fama and Macbeth (1973) regression. In this case, this second step is the starting model as described in Fama and French (2020):

$$r_{i,t} = \lambda_{0,t} + \lambda_{1,t} EGS_{i,t-1} + \epsilon_{i,t} \tag{9}$$

where $r_{i,t}$ is the monthly excess return on stock i between $t-1$ and t, while $EGS_{i,t-1}$ is the ESG rating of stock i at the begging of the period, and $\lambda_{1,t}$ will be proven to be the ESG factor's return. To generate a long-short portfolio, as described in Fama and French (2020), the ratings among stocks are de-meaned, such that $\sum_{i=1}^{N_{t-1}} EGS_{i,t-1} = 0$

The cross-sectional model (9) can then be expressed in vector form as

$$\boldsymbol{r}_t = \lambda_{0,t}\boldsymbol{1}_{N_{t-1}} + \lambda_{1,t}\boldsymbol{EGS}_{t-1} + \boldsymbol{\epsilon}_t \tag{10}$$

where $\boldsymbol{r}_t$ is the $N_{t-1} \times 1$ vector of excess returns of the stock at time t, $\boldsymbol{1}_{N_{t-1}}$ is an $N_{t-1} \times 1$ vector of ones, and $\boldsymbol{EGS}_{t-1}$ is the $N_{t-1} \times 1$ vector of lagged stock' ESG ratings.

$$\begin{bmatrix} \hat{\lambda}_{0,t} \\ \hat{\lambda}_{1,t} \end{bmatrix} = \left(\boldsymbol{X}'_{t-1}\boldsymbol{X}_{t-1}\right)^{-1}\boldsymbol{X}_{t-1}\boldsymbol{r}_t \tag{11}$$

To estimate the two time-t lambda coefficients the referenced literature uses the ordinary least square (OLS), as stated in equation (11). The vector $\boldsymbol{X}_{t-1}$ is defined as $\boldsymbol{X}_{t-1} = \begin{bmatrix} \boldsymbol{1}_{N_{t-1}} & \boldsymbol{EGS}_{t-1} \end{bmatrix}$, and the coefficients estimated can be interpreted as the portfolio excess returns. Notably, Lioui and Tarelli (2022) showed that formula (11) can be interpreted as the return of a portfolio built from two different combination of $\boldsymbol{r}_t$ and with weights respectively $\boldsymbol{w}_{t-1} = \begin{bmatrix} \frac{1}{N_{t-1}}\boldsymbol{1}_{N_{t-1}} & \frac{\boldsymbol{EGS}_{t-1}}{\boldsymbol{EGS}'_{t-1}\boldsymbol{EGS}_{t-1}} \end{bmatrix}$, where the weights of the first portfolio are equally distributed over the N_{t-1} observations and the other portfolio sort the weights of each stock on its ESG rating, $\boldsymbol{w}_{UCS,t-1} = \frac{\boldsymbol{EGS}_{t-1}}{\boldsymbol{EGS}'_{t-1}\boldsymbol{EGS}_{t-1}}$, relies exclusively on information at time t -1 providing a univariate cross-sectional (UCS) zero-investment portfolio (long high- and short low-ESG stocks) that does not suffer from look-ahead bias. Moreover, having de-meaned the independent variable in equation (10) allows the constant $\hat{\lambda}_{0,t} = \frac{\boldsymbol{1}_{N_{t-1}}\boldsymbol{r}_t}{N_{t-1}}$ to be just the cross-sectional mean excess returns and $\hat{\lambda}_{1,t} = \boldsymbol{w}_{UCS,t-1}\boldsymbol{r}_t$ is the excess returns of the zero-investment portfolio, as following Fama and French (2020), with variance $\sigma^2_{\hat{\lambda}_{1,t}} = \frac{\boldsymbol{EGS}'_{t-1}\boldsymbol{\Sigma}_{\epsilon,t}\boldsymbol{EGS}_{t-1}}{\left(\boldsymbol{EGS}'_{t-1}\boldsymbol{EGS}_{t-1}\right)^2}$ where $\boldsymbol{\Sigma}_{\epsilon,t} = \sigma^2_{\epsilon,t}\boldsymbol{I}_{N_{t-1}}$ is the homoscedastic i.i.d covariance matrix of error terms, therefore the zero-investment portfolio variance is $\frac{\sigma^2_{\epsilon,t}}{\boldsymbol{EGS}'_{t-1}\boldsymbol{EGS}_{t-1}}$ and the conditional Sharpe ratio is $S_t = \sqrt{\frac{\boldsymbol{EGS}'_{t-1}\boldsymbol{EGS}_{t-1}}{\sigma^2_{\epsilon,t}}}\hat{\lambda}_{1,t}$.

One important property highlighted in Lioui and Tarelli (2022) is that the weights depend solely on the ESG rating available at time t-1; thus, the portfolio is not affected by any look-

ahead bias. However, these weights, are not immune from the scaling of the ESG ratings. This issue regards only cross-sectional factors, indeed in time-series factors, the ESG scores are used to sort stocks living the factors unaffected.

To overcome this problem when creating characteristic based UCS factors Fama and French (2020) propose to standardize the ESG rating to have a unit variance. This implies setting $ESG'_{t-1}ESG_{t-1} = N_{t-1} - 1$. In another contribution by Pástor et. al (2021), rescaling of the ratings is made in order to have a univariate cross-sectional ESG factor with the same variance as the time-series factor over the period in analysis, even though this latter method it does not guarantee the absence of look-ahead bias.

In the asset pricing literature these techniques are common tools for controlling estimation risk and improving diversification, particularly when dealing with numerous stocks. Yet, they are arbitrary choices that rescale the high- and low-ESG stock positions undermining the UCS factors' weight, the assessment of the ESG factor return, and the comparison between TS and CS comparison.

2.3.2 ESG rating target

To address this issue, Lioui and Tarelli (2022) require that the UCS factor matches an ESG rating target by rescaling the portfolio as follows:

$$w_{UCS,t-1} = \frac{\rho_{t-1}}{ESG'_{t-1}ESG_{t-1}} ESG_{t-1} \tag{12}$$

Where, $\rho_{t-1} \neq 0$ is a suitable scaling constant. This parameter ρ_{t-1} guarantees the achievement of many desirable UCS factor features in particular, the parameter solves the scale problem of ESG rating without imposing any conditions, such as unite variance, and making irrelevant the choice of the scale, since the parameter can be set equal to a stated percentile of the distribution of stock ESG ratings. In addition, ρ_{t-1} is the new ESG rating of the long-short portfolio underlying the standard UCS factor: with an excess return, $\theta_{1,t} = \rho_{t-1}\hat{\lambda}_{1,t}$, proportional to the standard one. The return variance is equal to $\frac{\rho_{t-1}\sigma^2_{\epsilon,t}}{ESG'_{t-1}ESG_{t-1}}$ and, therefore, guarantees the independence of the conditional Sharpe ratio from the scaling parameter. Thus, Lioui and Tarelli (2022) method guarantees control over the ESG values of the long-short portfolio without compromising the minimum-variance feature of the UCS factor. Moreover, it guarantees diversification. Indeed the assemblage of a long-short portfolio that matches the target ESG rating, ρ_{t-1}, does not require any sort of screening activity on stocks. The factor is easily derived by rescaling all of the positions (long and short)

by the same scalar, which is the chosen ESG rating target. Finally, the portfolio does not experience any look-ahead bias, because the weights still depend solely on the information available at time $t - 1$.

The suggested new factor would obtain if the Fama and Macbeth (1973) cross-sectional regression is adjusted as follow:

$$r_t = \theta_{0,t} \mathbf{1}_{N_{t-1}} + \theta_{1,t} \frac{ESG_{t-1}}{\rho_{t-1}} + \epsilon_t \tag{13}$$

$$w_{t-1} = \left[\frac{1}{N_{t-1}} \mathbf{1}_{N_{t-1}} \quad \frac{\rho_{t-1}}{ESG'_{t-1} ESG_{t-1}} ESG_{t-1} \right] \tag{14}$$

where equation (13) is the predictive regression and equation (14) is the weights in the two new portfolios. As mentioned above, bringing the adjustment of the weights introduced in equation (12) is equivalent to considering ESG ratings relative to the target $\frac{ESG_{t-1}}{\rho_{t-1}}$, rather than in absolute terms ESG_{t-1}.

This outcome demonstrates the flexibility of the cross-sectional approach and its real-time predictive ability regarding the ESG rating. Relative to Fama and Macbeth (1973) seminal contribution, Lioui and Tarelli (2022) have proven the necessity of rescaling the independent variable by a target rating since, in this kind of analysis, the stock's rating plays a crucial role concerning the target. This observation is the starting point to balance and compare meaningfully the ratings of time-series and univariate cross-sectional factors.

2.3.3 Comparison between the two approaches

The excess return of time-series and cross-sectional factors are denoted by $r_{TS,t}$ and $r_{UCS,t}$, respectively. Thus, we can derive the following expressions:

$$r_{UCS,t} = \frac{\rho_{t-1}}{ESG'_{t-1} ESG_{t-1}} ESG_{t-1} r_t \tag{15}$$

$$r_{TS,t} = MC'_{t-1} W_{t-1} r_t \tag{16}$$

Where MC'_{t-1} is an $N_{t-1} \times 1$ vector collecting the market capitalizations of the stocks in the cross-section at time $t - 1$, and W_{t-1} is the weights diagonal matrix defined as

$$W_{t-1} = \frac{1}{\mathbf{1}'_{N_{t-1}} I_{N_{L,t-1}} MC_{t-1}} I_{N_{L,t-1}} - \frac{1}{\mathbf{1}'_{N_{t-1}} I_{N_{S,t-1}} MC_{t-1}} I_{N_{S,t-1}} \tag{17}$$

Where $I_{N_{L,t-1}}$, and $I_{N_{S,t-1}}$ are two diagonal matrices with $N_{L,t-1}$, and $N_{S,t-1}$ diagonal elements equal to one, distinguishing stocks belonging to the long/short portfolio leg, and

the other matrix element are equal to zero. The criteria to sort stocks in the two portfolio legs is the ESG ratings, e.g., we include in the long (short) leg stock above the 70th percentile (below the 30th percentile). The return spread between the two portfolios is:

$$r_{UCS,t} - r_{TS,t} = \left(\frac{\rho_{t-1}}{ESG'_{t-1}ESG_{t-1}} ESG_{t-1} - MC'_{t-1}W_{t-1} \right) r_t \tag{18}$$

From this, counting for the predictive relation expressed in equation (13) we can compute the expectation of the spread:

$$E_{t-1}[r_{UCS,t} - r_{TS,t}] = \theta_{1,t} \left(1 - \frac{MC'_{t-1}W_{t-1}ESG_{t-1}}{\rho_{t-1}} \right) \tag{19}$$

The ESG rating of the time-series factor is expressed by $MC'_{t-1}W_{t-1}ESG_{t-1}$. If we establish the ESG rating of cross-sectional factor equal to the time-series one, e.i, $\rho_{t-1} = MC'_{t-1}W_{t-1}ESG_{t-1}$, the return spread between the two portfolios will be zero. To further investigate the additional sources that the spread between the two factors may generate, we consider the conditional variance of the return spread, assuming that the standard OLS assumptions hold.

$$
\begin{aligned}
Var_{t-1}&[r_{UCS,t} - r_{TS,t}] \\
&= \frac{\sigma_{\epsilon,t}^2 \rho_{t-1}}{ESG'_{t-1}ESG_{t-1}} (\rho_{t-1} - MC_{t-1}W_{t-1}ESG_{t-1}) \\
&- \frac{\sigma_{\epsilon,t}^2 \rho_{t-1}}{ESG'_{t-1}ESG_{t-1}} W'_{t-1}ESG'_{t-1}MC_{t-1} + \sigma_{\epsilon,t}^2 MC'_{t-1}W_{t-1}W'_{t-1}MC_{t-1}
\end{aligned}
\tag{20}
$$

If the target rating is set equal for both portfolios, the conditional variance will be simplified as:

$$
\begin{aligned}
Var_{t-1}&[r_{UCS,t} - r_{TS,t}] \\
&= \sigma_{\epsilon,t}^2 \left(MC'_{t-1}W_{t-1}W'_{t-1}MC_{t-1} - \frac{\rho_{t-1}}{ESG'_{t-1}ESG_{t-1}} \right)
\end{aligned}
\tag{21}
$$

Even if the method allows setting the expected spread difference equal to zero, by equalizing the TS and UCS factors, the same can't be stated for the variance (21). Indeed, even if the two portfolios have the same expected return thanks to the parameter ρ_{t-1}, it does not provide that the two portfolios have the same variance. In other words, the norm transformation of the two portfolios differs and this can matter in ex-post analysis. Overall, comparing TS and UCS standard factor is challenging, since they have different ESG scores. However, if we assume that the ESG ratings are the only relevant factors, as in equation 11,

and we consider true the hypothesis expressed in equation 13, we can reduce the spread difference between the two portfolios factor to merely noise.

2.3.4 Brief discussion of multivariate ESG model

The discussion will not be complete without a brief description on how the previous methodology can be applied in a multivariate setup . Indeed, in the asset pricing models literature, there is an extensive evidence regarding the relationship between excess returns and stock characteristics including size, book-to-market ratio, and profitability (e.g., see Kelly et al., 2019 and the references therein). A significant correlation between ESG ratings and other stock features has also been demonstrated by a number of studies (e.g., Brammer et al., 2006; Lioui and Sharma, 2012). To investigate this relationship, we cannot rely on the time-series approach, since is not flexible enough to control these multiple characteristics. In fact, the approach reaches its limit very quickly when more characteristics are considered since the expected return is spread over those factors and it is not possible to isolate each factor's contribution. Whereas the cross-sectional approach allows us to neutralize the ex-ante exposure on the other characteristics, which is our focus in the analysis but has an ex-post limit in controlling the exposure (Fama and French (2020)).

The inclusion of other factor characteristics in the model is straightforward. The multivariate cross-sectional model, deriving from regression 13, can be expressed as:

$$r_t = \gamma_{0,t} \mathbf{1}_{N_{t-1}} + \gamma_{1,t} \frac{\boldsymbol{ESG}_{t-1}}{\rho_{t-1}} + \gamma_{2,t} \boldsymbol{C}_{t-1} + \epsilon_t \tag{22}$$

Where $\boldsymbol{C}_{t-1}$ represent an $N_{t-1} \times 1$ vector counting for the characteristic added to the analysis, and as for the vector $\boldsymbol{ESG}_{t-1}$, vector $\boldsymbol{C}_{t-1}$ has been de-meaned. The three excess returns coefficients for the three portfolios are defined by setting the weights of each portfolio as $\boldsymbol{X}_{t-1}(\boldsymbol{X}'_{t-1}\boldsymbol{X}_{t-1})^{-1}$, where $\boldsymbol{X}_{t-1} = \left[\mathbf{1}_{N_{t-1}} \quad \frac{\boldsymbol{ESG}_{t-1}}{\rho_{t-1}} \quad \boldsymbol{C}_{t-1}\right]$. The portfolio regarding the ESG factor is

$$\boldsymbol{w}_{MCS,t-1} = \rho_{t-1} \frac{(\boldsymbol{C}'_{t-1}\boldsymbol{C}_{t-1})\boldsymbol{ESG}_{t-1} - (\boldsymbol{ESG}'_{t-1}\boldsymbol{C}_{t-1})\boldsymbol{C}_{t-1}}{(\boldsymbol{ESG}'_{t-1}\boldsymbol{ESG}_{t-1})(\boldsymbol{C}'_{t-1}\boldsymbol{C}_{t-1}) - (\boldsymbol{ESG}'_{t-1}\boldsymbol{C}_{t-1})^2} \tag{23}$$

Although we have expanded our model to another characteristic besides ESG, the resulting portfolio has the same desired property as before: it is still a long-short portfolio, and ρ_{t-1} is still the ESG rating of the portfolio, which can be chosen regardless of the characteristic long-short portfolio. Indeed, the characteristic of the long-short portfolio $\boldsymbol{w}_{MCS,t-1}\boldsymbol{C}_{t-1}$, is

zero and so there is not any return spread between MCS factors and ESG ratings. Thus, the portfolio $w_{MCS,t-1}$ is a pure ESG portfolio factor and can still be compared with other ESG portfolios.

CHAPTER 3
DATA

This chapter provides information on the data used to perform the analysis. Section 1 illustrates the database used to collect the ESG data and the type of manipulation performed on the raw data. Section 2 is dedicated to the equity part and explains the database used, the data collected, and the screening activity carried out. The last section, Section 3, shows some descriptive statistics on portfolio weights and equity excess returns, followed by a fundamental analysis of ESG predictability on equity returns.

3.1 ESG data

The ESG data required for the analyses have been collected from Bloomberg's Environmental, Social and Governance (Bloomberg ESG) database. The data vendor provided data regarding the Environment, Social and Government pillars, as well as for ESG cumulative pillar. For the analysis, has been retained data covering a time interval starting in 2004 and ending in 2021, which is a sufficiently long time series to provide relevance to the empirical analyses.

Looking deeper at the data vendor, the Bloomberg ESG database covers ESG metrics and ESG disclosure sources for more than 14,000 companies in more than 100 countries. The sustainability scores are divided into over 2,000 fields covering a wide range of key sustainability topics annually. For example, the Environmental score includes valuations such as water consumption, energy consumption and carbon emissions. In contrast, the Social score assesses topics like the women employed, diversity and inclusion, and in the Government, the score is possible to find values on the board independence, the shareholder's rights and CSR strategy. While the topics and data fields included in the score were chosen primarily based on industry-agnostic frameworks, specific topics may not apply to all industries. The final score ranges from 0 to 100, where 0 is assigned to companies that do not disclose any data points included in the score. Each topic within a pillar is equally weighted, and topic weights are distributed across fields related to the issue, with quantitative fields receiving a higher weighting than binary fields.

$$NPR(\boldsymbol{X}) = \frac{\left(TR(\boldsymbol{X}) - \frac{1}{2}\mathbf{1}_N\right)}{N} \tag{24}$$

The purpose of the analysis is to use ESG ratings as weight factors for the composition of each portfolio. Therefore, the percentile ranks of the monthly scores were calculated to normalize the rating distribution and rescale them between 0 and 1, achieving monthly stock weights for E, S, and G, as well as ESG scores. The monthly score has been computed starting from the last annual observation available and repeating until the new one is disclosed. The normalized percentile ranks have been performed following equation 24, where $TR(X)$ are the tied ranks of the values in the rating X, and the tied ranks are obtained by sorting the set of values from smallest (1) to largest (N).

3.2 Stock data

The analyses used monthly stock returns and market capitalizations observed from the Bloomberg database between December 2001 and December 2021 to replicate the study of Liuoi and Tarelli (2022) in the European market. Like in the two professors' study, Since the data vendor provides ESG metrics starting from 2004, this replication, has considered only returns beginning in December 2004 for the principal analysis. To guarantee the absence of main market anomalies, Firms with a market capitalization below the 25th percentile, those with monthly returns greater than 200 per cent, and observations with stock prices less than 1 euro were excluded from the analysis. To compute the stock excess returns has been considered the 30-day European Treasury Bill returns as the risk-free returns, as have been used the returns on the six Fama-French-Carhart factors (FFC6), which include the market (MKT), size (SMB), book-to-market (HML), profitability (CMA), and momentum (MOM) factors (Carhart, 1997; Fama and French, 2018)[4] , to study the time variation of the ESG factor abnormal returns (CAPM and multifactor alphas).

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[4] Kenneth French is to be thanked for making the 30-day European Treasury Bill and common factor returns available on his website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Figure 5 STOXX 600 breakdown of components divided by country of origin

STOXX 600 components by countries
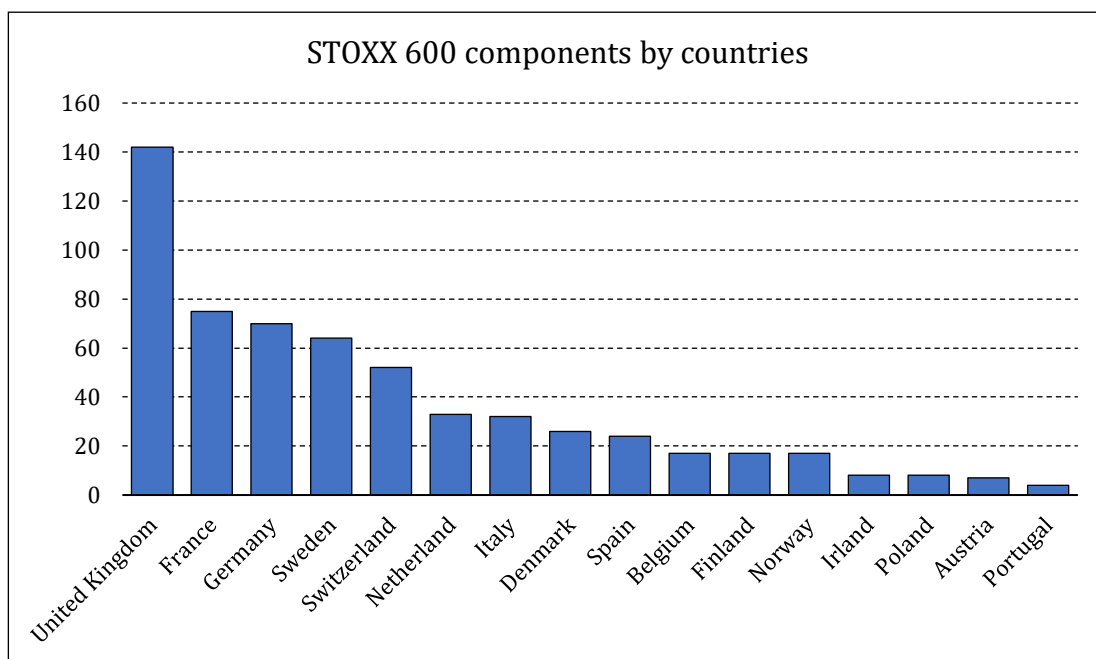
Source STOXX 600 guideline

In the referred study, the professors focus their attention on the U.S. stock market and create an ESG pure market portfolio. To replicate the same portfolio on the European Stock markets, the securities selection fell on the components of the STOXX Europe 600 index. The index, conceived by STOXX Ltd[5], contains a set number of 600 companies representing large, mid, and small capitalization firms from 17 European nations, accounting for about 90% of the European stock market's free-float market capitalization without limiting the assortment to the Eurozone. As reported in Figure 5, the majority of firms that compose the index are from United Kindom (142 companies) at a distance followed by France (75 companies), Germany (70 companies) and Sweden (64 companies). In the tail, we have Poland (8 companies), Austria (8 companies) and Portugal (4 companies). Looking at the percentage of sectors represented in the index, shown in Figure 6, most companies operate in the Industrial sector (122 companies), followed by the Financial sector (100 companies) and the Consumer Discretionary sector (64 companies). The least represented are the Energy (14 companies), the Utilities (34 companies), and the Real Estate sector (35 companies)[6].

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[5] STOXX Ltd. is a Swiss worldwide integrated index provider that covers all asset classes and marketplaces throughout the world by developing, maintaining, distributing, and marketing a comprehensive global family of rigorously rules-based and transparent indexes. STOXX is a component of Qontigo, which was formed in 2019 by the merger of STOXX, DAX, and Axioma. Qontigo is a subsidiary of the Deutsche Börse Group, which is headquartered in Eschborn and has offices in New York, Zug, and London. STOXX calculates over 10,000 indices and also serves as the DAX index administrator. Reference: *www.qontigo.com*
[6] Index guide, STOXX, Retrieved 2017-02-03.

Figure 6 STOXX 600 breakdown of components divided by operating sector.

Source: STOXX 600 guideline

STOXX 600 components by sectors

- Communication Services
- Consumer Discretionary
- Consumer Staples
- Energy
- Financials
- Health Care
- Industrials
- Information Technology
- Materials
- Real Estate
- Utilities
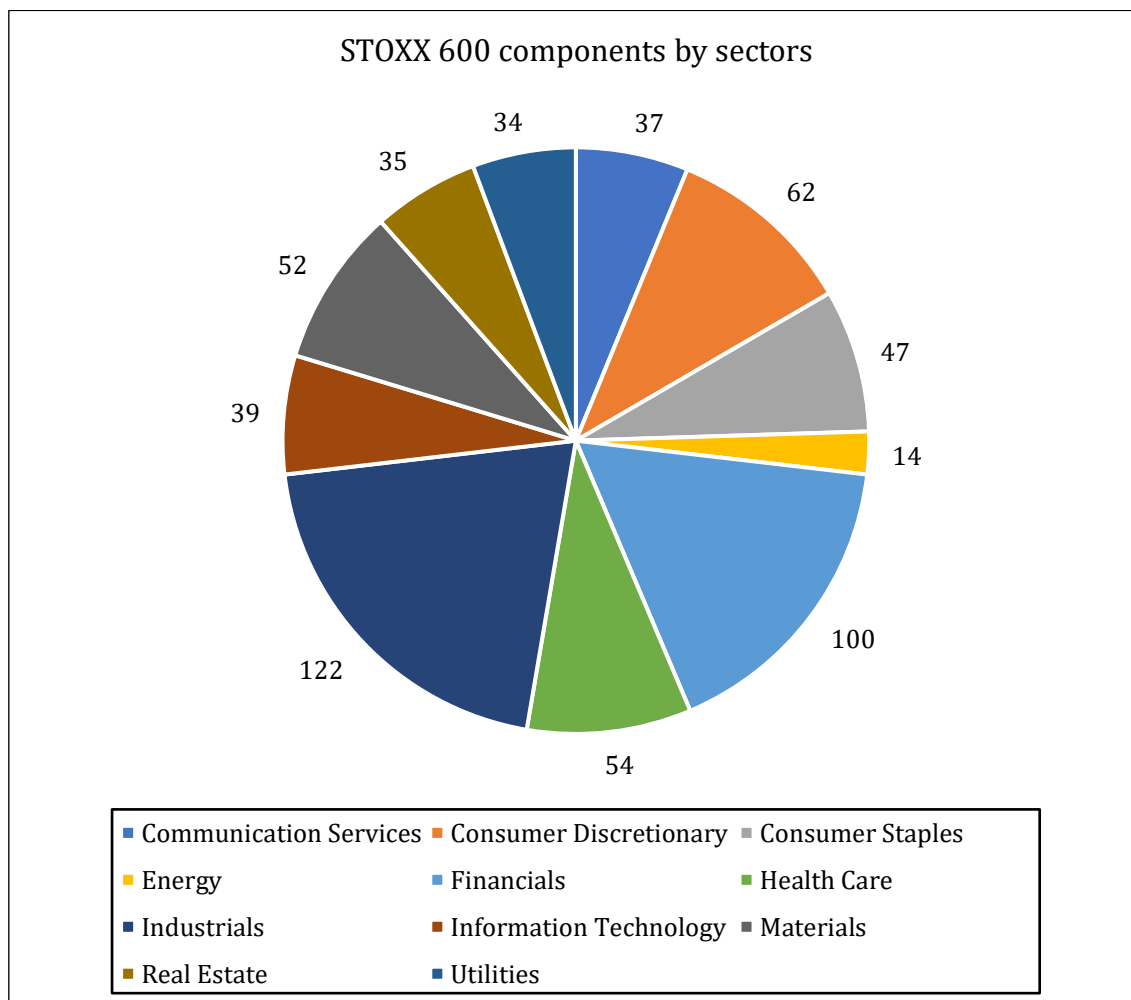
3.3 Primary results

Table 4 shows the data summary statistics based on the Bloomberg ESG ratings. The table displays summary information for the Bloomberg ESG STOXX600 stock universe, including ratings and monthly excess returns (expressed as percentages). There are four ESG ratings available: an overall rating (ESG), as well as pillar ratings for environmental (E), social (S), and governance (G). Ratings are provided as percentile ratings ranging from 0 to 1. Large or small market capitalization stocks have a market capitalization that is greater than or less than the 25th percentile. The cross-sectional statistic is calculated for each date, and the time-series averages are shown in the table. The sampling period runs from December 2004 until December 2021.

Monthly, the mean excess return for the whole universe, which includes around 600 stocks, is − 8.49%, while the standard deviation is 7.58%. Companies with monthly market

capitalizations less than the 25th percentile have a similar average return (-8.26%) and a slightly higher standard deviation (9.13%), whereas excess stock returns with monthly market capitalizations above the 25th percentile still have a similar average return but a lower volatility (-8.72% and 6.08%, respectively).

Many well-known market anomalies vanish when minor stocks are removed from the test assets. However, because microcaps are illiquid, extracting the ESG premium from them would be challenging for a real-time investor (e.g., Chordia et al., 2014; Hou et al., 2020). In addition, Brammer et al. (2006) discovered a favourable relationship between ESG ratings and market capitalization. As a result and as anticipated in the previous section, microcaps stocks with market capitalizations below the 25th percentile, have been excluded from the study.

Table 4 ESG statistics in summary **Source:** Bloomberg

	Mean	Std	5%	25%	50%	75%	95%
All Stocks							
ESG	0.50	0.29	0.06	0.26	0.50	0.75	0.95
E	0.51	0.29	0.06	0.26	0.51	0.75	0.95
S	0.50	0.29	0.06	0.26	0.50	0.75	0.95
G	0.50	0.29	0.07	0.26	0.50	0.76	0.94
Excess Returns	-8.49	7.58	-19.56	-12.88	-8.73	-4.43	3.26
Large Market Capitalization							
ESG	0.63	0.28	0.09	0.46	0.69	0.86	0.98
E	0.62	0.26	0.13	0.45	0.66	0.83	0.97
S	0.59	0.29	0.08	0.37	0.63	0.85	0.97
G	0.58	0.30	0.09	0.32	0.62	0.86	0.97
Excess Returns	-8.72	6.08	-18.06	-12.50	-8.84	-5.12	1.02
Small Market Capitalization							
ESG	0.39	0.24	0.05	0.21	0.38	0.54	0.81
E	0.34	0.25	0.04	0.14	0.29	0.47	0.80
S	0.44	0.24	0.08	0.26	0.42	0.61	0.83
G	0.43	0.26	0.06	0.19	0.44	0.64	0.81
Excess Returns	-8.26	9.13	-20.93	-13.28	-8.66	-3.77	5.37

The starting point of the Fama Macbeth methodology (1973) is to run a predictive regression, hence exploiting the predictive capacity of ESG ratings is a fundamental component of the analysis. We repeat the predictive regression, discussed in the previous chapter (Equation 10), for each cross-section, utilizing past ESG scores as well as each pillar score. The scores

are normalized percentile ranks computed in the method specified in Section 1. To achieve the objective it has been run the Fama Macbeth cross-sectional regression between the monthly stock returns and their monthly ESG scores. Figure 7 shows the time series and average adjusted-R^2 from the predictive regressions. The time series of the cross-sectional adjusted-R^2 from univariate predictive regressions of excess stock returns on lagged aggregate ESG ratings (ESG) and individual pillar scores are shown in this figure (E, S, and G). Bloomberg ESG provides the ESG ratings. The asset universe is limited to companies having market capitalizations greater than the 25th percentile. The sample mean of the adjusted-R^2 is indicated by the red horizontal line. The sample spans the years December 2004 to December 2021.

R^2 measures the proportion of the total variation in the exogenous variable that can be linearly predicted by the endogenous variable, in our case the capacity of sustainable scores to predict stock returns, while adjusted-R^2 provides a better analysis because it takes into account the number of independent variables present in the model[7].

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[7] David Ruppert (2011) Statistics and Data Analysis for Financial Engineering,1st ed., Springer, New York.

Figure 7 Adjusted-R^2 of ESG ratings. **Source:** Bloomberg
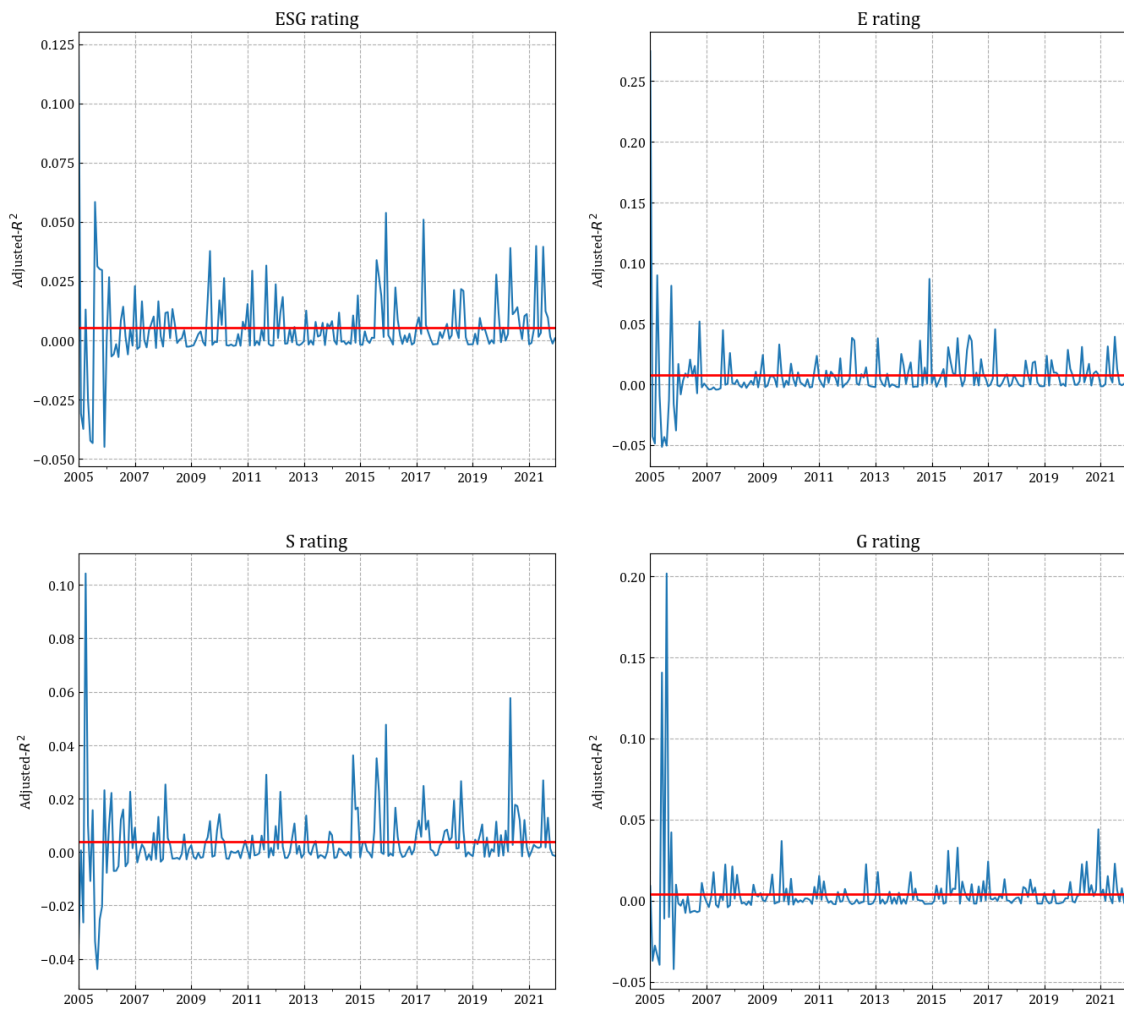
The predictive capacity of ESG ratings varies significantly. Between 2005 and 2007, due to a lack of diversification deriving from the low number of ESG information by companies. Indeed the adjusted-R^2 assumes rather high values on all pillars, whereas after 2007 the range assumed by the adjusted-R^2 decreased for all. Focusing on the latter range, the E-dimension has the highest predictive power, on average 0.72%, and the highest peak at 8.69%. On the other hand, the governance pillar has a more stationary behaviour, while the peaks of the S dimension have an increasing trend over the interval considered. Looking at the events of the main period, such as the 2008 financial crisis, the sovereign debt crisis, the 2016 Paris Agreement and the covid-19 epidemic, the predictive ability of the ESG dimensions reached a peak or many local maxima, which could be attributed to the fact that investing in socially responsible companies pays off in periods when trust in companies is low or when there is an increasing focus on the sustainability topic (Lins et al., 2017). Although after the year 2007, these levels of adjusted-R^2 appear modest, but still economically significant. As will be illustrated in the following chapter, the main difference between the approaches is the

heaviness given to the predictability of the ESG characteristics. Indeed, the time series factor approach uses the ESG characteristics in an ordinal manner and will give too much importance to the predictability values taken by the predictive regression, whereas the cross-sectional approach will not, thanks also to the implementation of the target rating.

CHAPTER 4
ANALYSIS RESULTS

This chapter shows the empirical results from assessing the thesis hypothesis. Section 1 presents the empirical comparison between TS and CS ESG portfolio factors, beginning with the presentation of descriptive statistics of the factor returns through assessing factor returns performance measures, followed by the investigation of the time variation of the factor anomalous returns in CAPM and multifactor alphas. Section 2 focuses on expanding on the UCS method by presenting actual data on the relationship between a factor's ESG rating and its performance. Finally, Section 3 completes the assessment by including the multivariate frameworks. In the first part, two multivariate cross-sectional portfolios, MCS(1) and MCS(TS), are built to neutralize the exposure to additional firm characteristics. Then the implications of the multivariate approach are assessed in the relationship between factors' ESG rating and risk premium. The analysis has been done through the use of python. All the source materials are available in Appendix B.

4.1 Comparison of approaches

The first objective of the analysis is to assess how the methodology applied for the construction of the portfolio factors impacts the resulting ESG risk premiums; in other words, how much the risk premium calculated with the time-series approach differs from the one computed with the cross-sectional method.

To achieve this goal, three different portfolios are constructed and will be compared. The first portfolio is based on the TS method. This approach is quite typical since it involves value-weighting securities rated above the 70th percentile (below the 30th percentile) to generate the portfolio's long (short) leg. Consistent with Fama and French (2020), the second and third portfolios are based on the univariate cross-section (UCS) method. The first UCS factor, UCS(1), is built with the ESG ratings adjusted to have a unit variance in each cross-section. Hence, the normalized score of the factor, rather than the original rating scale score, has a variance equal to one. The second portfolio, UCS(TS), is constructed using equation 12 of chapter 2; using the target rating coefficient ρ_{t-1} to set the rating equal to that of the TS factor allowing comparison between the two methods.

4.1.1 Excess returns of TS and CS factors

Table 5 summarises the excess return statistics for the TS, UCS(1), and UCS(TS) factors. On a monthly basis, excess returns are stated as a percentage. The mean, median, standard deviation (Std), minimum and maximum (Min and Max) of excess returns, CAPM alpha (α_{CAPM}) and beta (β_{CAPM}), FFC6 alpha (α_{FF6}), the difference in CAPM alpha relative to the TS factor ($\Delta\alpha_{CAPM,TS}$), the difference in FFC6 alpha relative to the TS factor ($\Delta\alpha_{FF6,TS}$), with their Newey-West t-statistics reported for each method. At the 5% level, the data in bold are statistically significant. Sharpe ratio is abbreviated as SR. Bloomberg ESG provides the ESG data, and the sample period begins in December 2004 to December 2021.

Starting by assessing the TS factors, the monthly average excess returns for all four dimensions, CAPM and FFC6 alphas are mainly negative and, in some pillars, not significant; this is true for the E dimension. In ESG and G dimensions, when controlling for the multifactor model, the alpha drops. This behaviour suggests that exposure to FFC6 factors can partially explain the CAPM alpha of the TS factors. Although in S-based and E-based portfolios, the multifactor alphas are more significant than the CAPM alpha, blurring the previous conclusion. Overall, in the entire sample based on the TS approach, there is some indication of statistically significant alphas. Although the performances of these portfolios are somewhat unsatisfactory, all portfolios lost about 7.5% of the total value with a poor risk-reward (Sharpe ratios are -0.284, -1.148, -0.237 and -0.257, respectively), also justified by massive volatility over the period. These findings reject the existence of an economically positive ESG premium when using a value-weighted portfolio.

Moving to the UCS approach, the performance of the portfolios is still unsatisfactory but less adverse than in the TS approach, and the comparison of performances between the two portfolios diverges significantly. Concerning the ESG portfolios, the average monthly total returns approach zero in both UCS(1) and UCS(TS) portfolios. In contrast, volatility in the UCS(TS) is more than double, 1.67%, compared to that of the UCS(1) portfolio, 0.07%, and the Sharpe ratio is also worse (-0.268 and -0.411, respectively). The UCS(TS) volatility evidence leads to the assumption that the cross-sectional approach is more conservative than the TS approach. Although the mean factor returns and variance are lower in the UCS(TS) portfolio than in the TS, the risk remuneration is better in the TS, leading to a preference for the value-weighted portfolio rather than the cross-sectional.

Table 5 ESG factor returns summary statistics for time-series or cross-sectional.

	TS	UCS(1)	UCS(TS)	TS	UCS(1)	UCS(TS)
		ESG			**E**	
Mean	**-9.137**	**-0.018**	**-0.685**	-5.576	**-0.016**	**-0.177**
t stat	-4.054	-3.829	-5.872	-2.110	-2.496	-3.438
p-value	0.044	0.000	0.002	0.052	0.000	0.001
Median	-8.084	-0.014	-0.650	-3.927	-0.010	-0.158
Std	32.189	0.069	1.666	37.744	0.090	0.734
Min	-131.569	-0.553	-6.337	-142.694	-0.912	-3.629
Max	81.767	0.273	4.260	190.968	0.494	2.412
α_{CAPM}	**-8.134**	**-0.018**	**-0.664**	**-4.769**	**-0.016**	**-0.176**
t stat	-4.024	-3.566	-7.244	-1.642	-2.432	-2.979
p-value	0.000	0.000	0.000	0.101	0.015	0.003
β_{CAPM}	**-1.701**	-0.001	-0.035	**-1.367**	0.000	0.000
t stat	-4.266	-1.180	-0.959	-2.840	-0.108	-0.027
p-value	0.000	0.238	0.338	0.005	0.914	0.978
α_{FF6}	**-7.911**	**-0.017**	**-0.610**	**-5.526**	**-0.013**	**-0.161**
t stat	-3.731	-3.371	-6.090	-2.527	-2.548	-4.011
p-value	0.000	0.001	0.000	0.012	0.011	0.000
SR	-0.284	-0.268	-0.411	-0.148	-0.175	-0.241
		S			**G**	
Mean	**-7.474**	**-0.013**	**-0.185**	-9.921	**-0.013**	**-0.207**
t stat	-3.383	-2.669	-4.763	-3.675	-2.778	-4.453
p-value	0.044	0.000	0.001	0.053	0.000	0.001
Median	-5.276	-0.011	-0.173	-7.879	-0.011	-0.197
Std	31.560	0.067	0.554	38.555	0.065	0.662
Min	-141.546	-0.312	-2.327	-126.017	-0.428	-3.105
Max	103.088	0.544	1.708	92.643	0.420	2.729
α_{CAPM}	**-6.232**	**-0.012**	**-0.181**	**-8.703**	**-0.012**	**-0.202**
t stat	-3.540	-3.830	-4.890	-3.238	-3.649	-4.838
p-value	0.000	0.000	0.000	0.001	0.000	0.000
β_{CAPM}	**-2.105**	-0.001	-0.006	**-2.066**	-0.001	-0.007
t stat	-3.062	-1.338	-0.562	-2.719	-1.341	-0.704
p-value	0.002	0.181	0.575	0.007	0.180	0.482
α_{FF6}	**-7.265**	**-0.012**	**-0.177**	**-8.066**	**-0.010**	**-0.166**
t stat	-3.828	-3.861	-6.454	-3.485	-3.739	-4.613
p-value	0.000	0.000	0.000	0.001	0.000	0.000
SR	-0.237	-0.187	-0.334	-0.257	-0.195	-0.312

Going forward and evaluating the monthly alphas, on the ESG rating, the UCS(1) portfolio's CAPM alpha is equal to the average monthly returns, -0.018. In contrast, the UCS(TS) portfolio's CAPM alpha is slightly lower than the average monthly returns,-0.685 and -0.664, respectively. In the remaining portfolios, the trend remains similar: the CAPM alphas of the UCS(1) portfolio is equal to or close to the average monthly returns and exceeds the CAPM

alphas of the UCS(TS) portfolio. Estimates for β_{CAPM} show that the difference in returns implies that the TS factors are more (negatively) exposed to the market than the CS(TS) factors. Indeed, CS market betas are always significantly lower than the alphas and are always not significant, with a 5% significance level. In contrast, the TS market betas are always significant, with greater values than CS betas. Hence, the CS approach can create pure ESG portfolios whose returns are explained in significant part only by the ESG factor weights. In contrast, the TS factor returns lack this ability and is more sensitive to market oscillations.

Even when the assessment focus is the multifactor alphas, the UCS alphas are lower than the average returns and the CAPM alphas. In the UCS(TS) alphas, the reduction is more significant than in the UCS(1), where the loss is 0.001% in ESG, 0.003% in E, 0.000% in S, and 0.001% in G. Those reductions highlight that when considering other characteristics besides the market returns, they better explain the factor returns and do not undermine the capacity of the UCS factor in creating pure ESG portfolio returns.

Figure 8 L^2-norm for time series and cross-sectional variables.
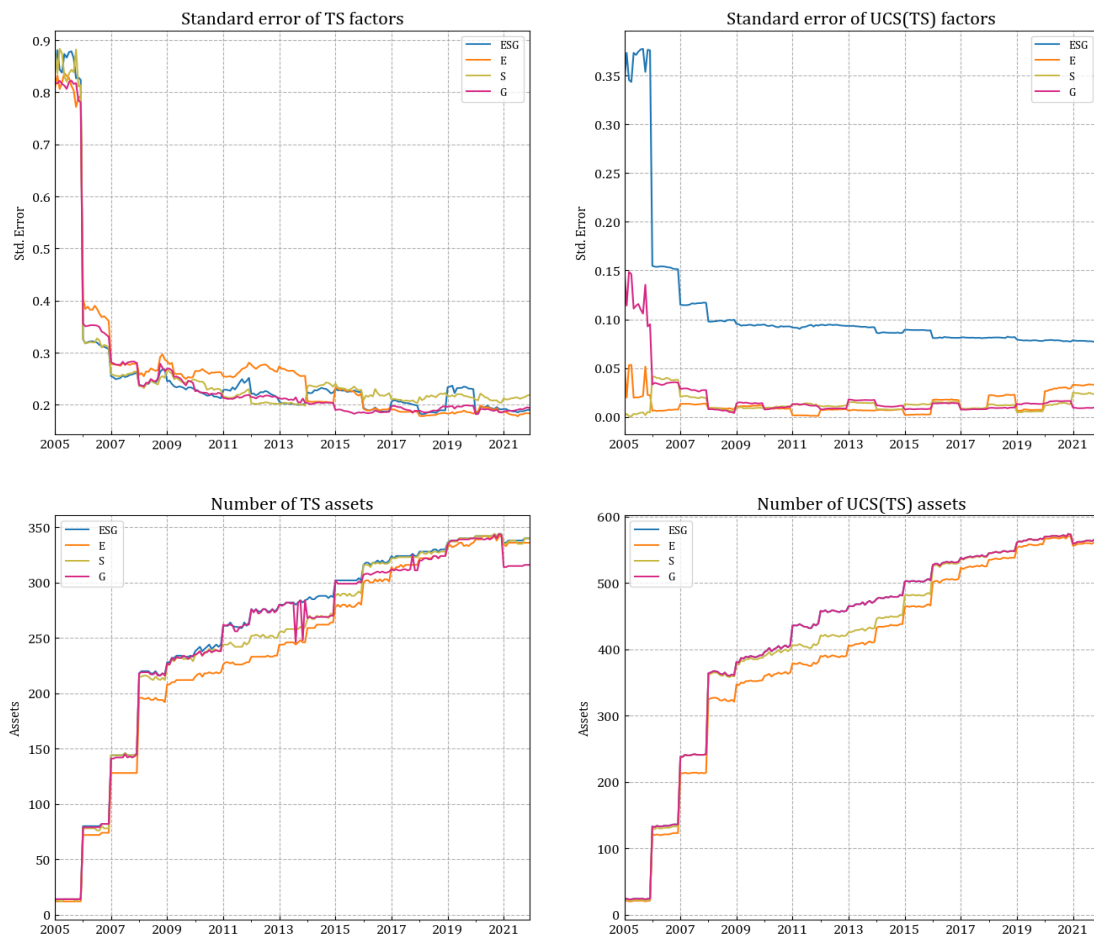
The difference in portfolio regularisation between the factor weights can be analyzed by visualizing the L2-norm of the TS and UCS(TS) factors. Figure 8 shows the L^2-norm of the TS and UCS(TS) factor weights derived for each rating and cross-section and the total number of assets across the period. The criteria are constructed using ESG ratings from the Bloomberg database.

Over the sample period, the component norms decrease, indicating an increase in the number of firms in the dataset. The weights of a uniformly weighted portfolio of N stocks have an L^2-norm of $1/N$, which is decreasing with the number of securities. A similar case occurs in a highly diversified portfolio. The portfolio norms of the TS factors are more than twice as high as those of the UCS(TS) factors. This is because TS factors are value-weighted, whereas CS factors are minimum L^2-norm portfolios. The fact that the TS excludes equities between the 30th and 70th percentile further damages the diversity of the TS components. Differences in portfolio norms are likely to contribute to TS factors' lower performance than CS factors.

An additional observation from Table 5 emerges on the G pillar. Indeed, a heated argument over whether the G characteristic should be included in ESG ratings and the predictive power of G ratings to forecast stock returns has always animated academic discussions. According to Lioui et al. (2016) and Pedersen et al. (2021), no ESG premium is associated with governance ratings. However, according to the present analysis, an ESG premium is associated with governance ratings, thus stressing the idea this issue requires further research.

4.1.2 A time-varying perspective

The robustness of factor excess returns is a well known issue in the literature on factor investing (e.g., Hou et al., 2020; Jacobs and Müller, 2020; Jensen et al., 2021; McLean and Pontiff, 2016). The recent reversal of the value-growth stock hierarchy has most likely contributed to widespread mistrust (e.g., Cornell and Damodaran, 2021). The classical spanning test, which involves regressing a candidate factor's returns onto the returns of other factors, ignores any potential temporal fluctuation of the alpha. This is a problem for an ESG-based factor since the interaction between negative (caused by positive ESG preferences) and positive (induced by an unexpected rise in ESG preferences) contributions to the factor's alpha necessitates a dynamic viewpoint, Lioui and Tarelli (2022). The assumption that the alphas and/or loadings depend on observable stock characteristics is a systematic approach.

On the other hand, UCS factors are not exposed to exogenous variables other than ESG by design. As a result, it is impossible to assume that alpha time variation drivers are factor features. Instead, the time-series regression has been recast into a state-space model where the parameter alphas are time varying. It is thus possible to represent this regression through a local level model which estimates are based on the Kalman filter to extract the time series of the non-observable alphas.

State-space models often depict the link between certain hidden (unobservable) variables and their measured values, representing them in equation system where the observable process is defined in the measurement equation, and the unobservable stochastic process is defined in the state equation. The state components can be estimated based on all past observations, known as the predicted state method. The state estimates are considered for given values of hyperparameters (i.e. the variance of unobserved and state errors) and for given initial values of the state components[8]. The estimations of the state elements are performed by the previously mentioned Kalman filter, Kalman(1960). The filter is a recursive algorithm that provides all the estimates relevant to the predicted state by optimizing the maximum likelihood function.

To be more precise, the time varying alpha model is described in equation (25) where $r_{i,t}$ refers to the observable equation, or measurement equation, of the factor-i excess returns, and α_t is the time-varying unobservable alpha process or state equation.

$$\begin{cases} \alpha_t = \alpha_{t-1} + \epsilon_{\alpha,t}, & \epsilon_{\alpha,t} \sim N(0, \sigma_\alpha^2) \\ r_{i,t} = \alpha_t + \beta r_{M,t} + \epsilon_{i,t}, & \epsilon_{i,t} \sim N(0, \sigma_i^2) \end{cases} \qquad (25)$$

The alpha state equation behaves as a random walk process with volatility σ_α, which has the benefit of not enforcing an ex-ante mean-reverting or trending behaviour of the factor's aberrant return. This model choice is in line with the current literature (e.g., Racicot and Théoret, 2016) and, unlike an AR(1) specification, does not need an estimate of the long-run mean and alpha persistence. To simplify the analysis, it has been assumed that a constant CAPM beta and homoscedastic returns with volatility σ_i, Liuoi and Tarelli (2022).

The time series of the filtered CAPM alphas of the TS, UCS(1), and UCS(TS) factors, as well as the corresponding cumulative alphas across the sample period, are displayed in Figure 9. Stock ESG ratings in UCS(1) are standardized to have unit variance. The UCS(TS) factor

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[8] Commandeur, J.J. and Koopman, S.J., 2007. An introduction to state space time series analysis. Oxford University Press.

must have the same ratings as the TS factor. The criteria are constructed using ratings from the Bloomberg database.

All the UCS alphas are steady and close or equal to zero across the time interval. Instead, the TS components vary with time and follow a deep declining trend at the end of the sample period. Consistently with the findings of Table 5, the graphs depict a general lack of significant premium returns from the pure ESG portfolios with both methods, with the E-based TS being the only exception.

As discussed in Chapter 3, the TS approach is highly sensitive to the prediction capacity of the ESG metrics, allowing for significant premium returns in the boom period and considerable losses in the next burst. The E-based portfolio is a perfect example of this result. Indeed, the alphas were significantly positive between 2007 and 2010, when the subprime bubble burst, and then again around 2014 and 2016. At the end of the sample period, the alphas follow a decreasing trend, deeper in the year of the Covid-19 pandemic, and then seem to start an increasing trend leaving some hope for a future ESG factor premium.

On the UCS approach, the two portfolios present the same flat behaviour, whit the UCS(1) being constantly zero and the UCS(TS) portfolio slightly less than zero. However, as shown in Table 5, the risk-return ratio of UCS(TS) was strongly influenced by equating the rating with that of the TS series, justifying significant spread differences between the two, most notable in the ESG- and E-based portfolios.

To perform an exhaustive assessment, the potential exposure to other pricing factors has been performed through applying the Kalman filter to the Fama-French-Carhart six-factor alphas. To do so, the measurement equation has been enlarged to account for the five additional price components using the state-space model from Equation 25, and the results have been reported in Figure 10. As in the previous figure, the filtered FFC6 alphas for the TS and two UCS factors are shown in this picture. Stock ESG ratings in UCS(1) are standardized to have unit variance. Therefore, the UCS(TS) factor must have the same ratings as the TS factor. The criteria are constructed using ratings from the Bloomberg database.

The FFC6 alphas of the UCS factors in Fig 10 are always near zero and non-significant in terms of premium returns, comparable in amount and patterns to the CAPM alphas in Fig 9. The only notable difference is the spread between the two UCS portfolios which is wider in the ESG- and E-based portfolios when other characteristics are considered. In the TS alphas, the FFC6 alphas show some differences from the previous CAPM alphas. Most

notably, all pillars show some ESG premium at the beginning of the sample period. The E-dimension's previous performance has been reduced, and from 2011, it presents a flat trend ranging between -0.025 and -0.075.

Figure 9 Conditional CAPM alpha of time series and univariate cross-sectional components based on firm characteristics.
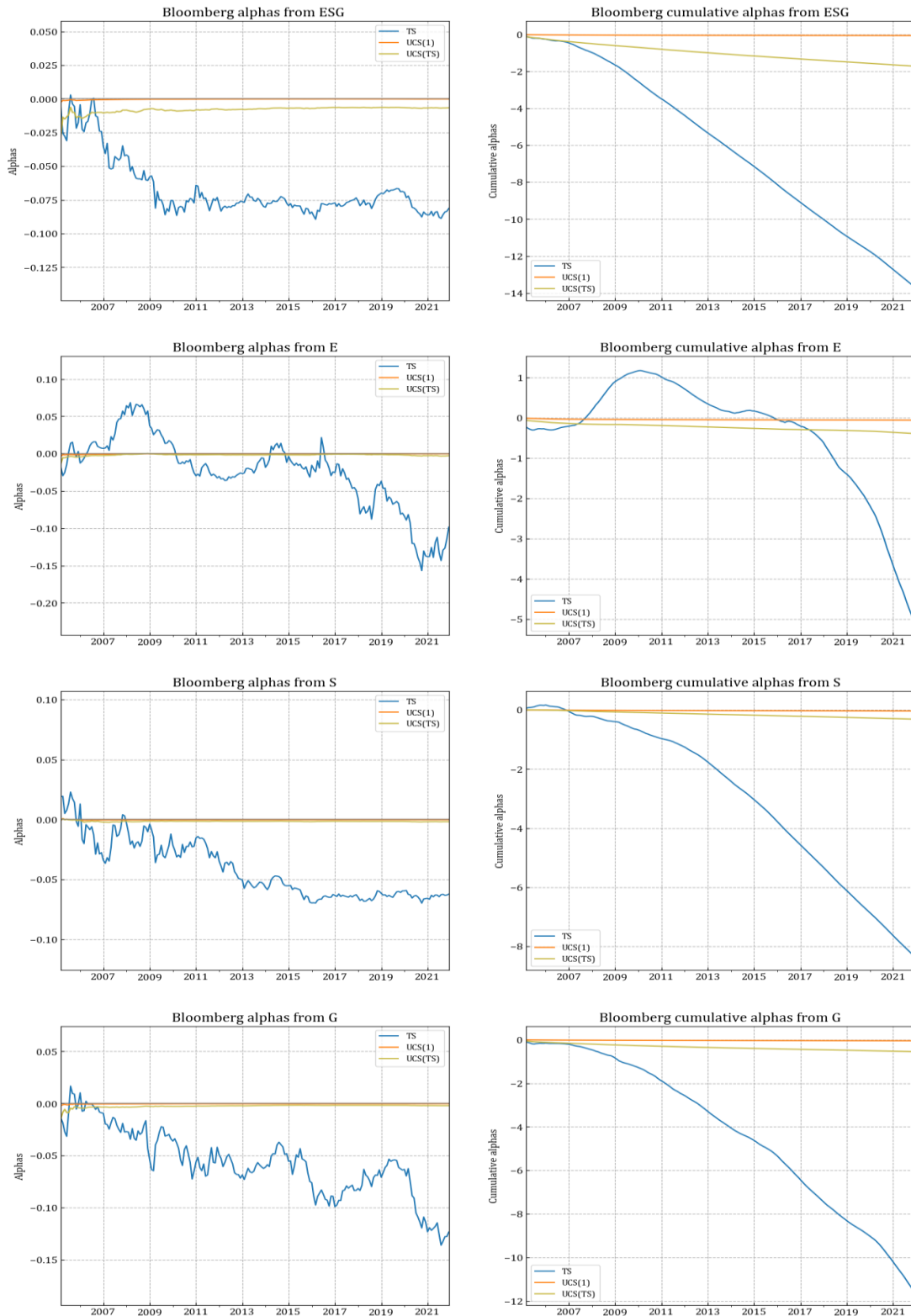
Figure 10 Conditional Fama-French-Carhart six factors alpha of time series and univariate cross-sectional components based on business characteristics.
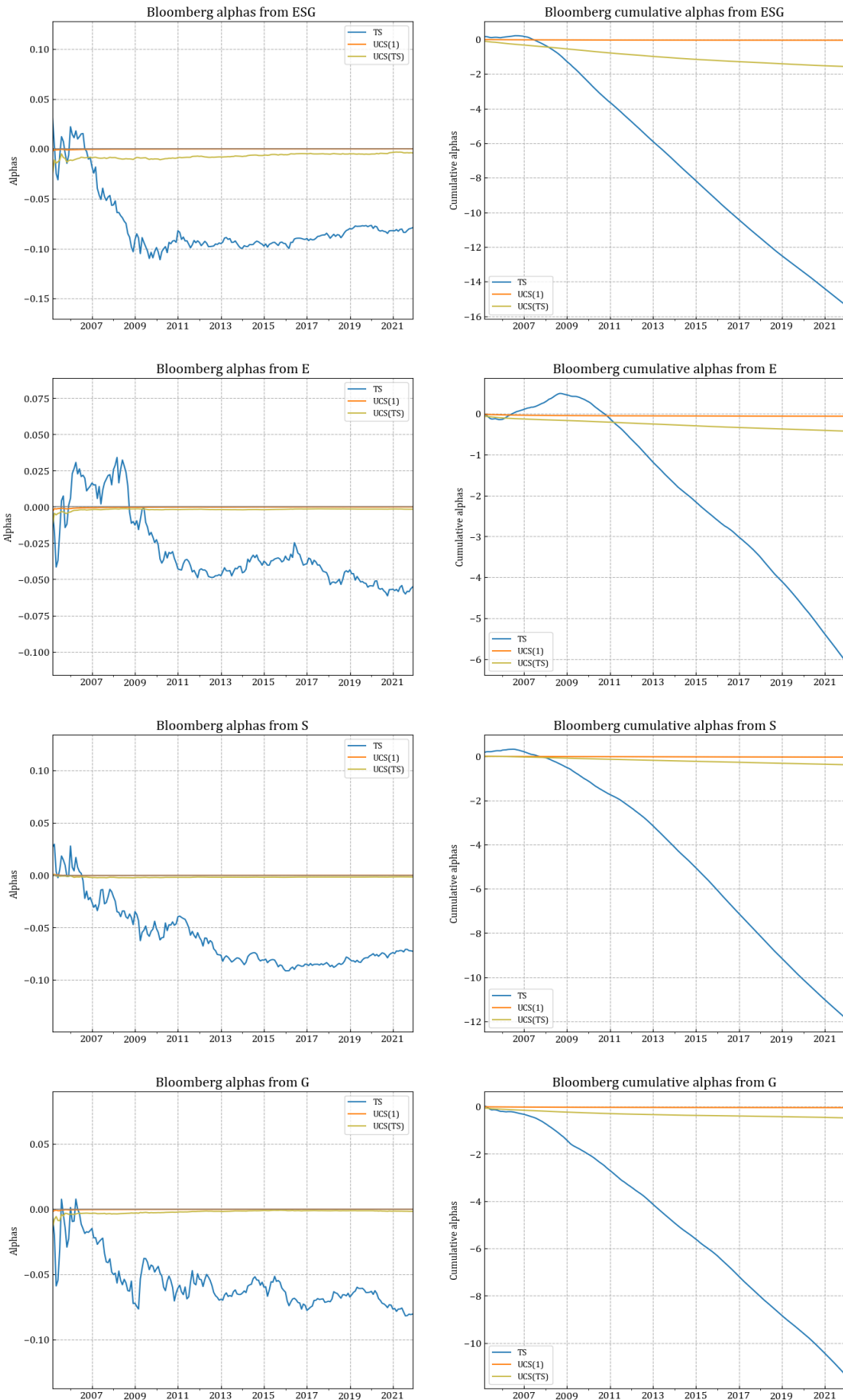
4.1.3 Relevant findings

The analysis compares two methodologies for creating pure ESG factor portfolios to assess discrepancies in the risk premium associated with the two-factor approaches by equalizing UCS factors to TS factors. All portfolios are meant to replicate a European stock market portfolio by considering listed firms that compose the Stoxx 600 index.

Following the empirical results, the data suggests that it is not possible to accept the hypothesis about the existence of a positive risk premium associated with ESG factors. In both approaches, unconditional and conditional alphas of the pure ESG portfolios as proven to be always negative and enormously significant, suggesting that taking long positions on green stocks and shorting brown stocks is unrewarding. The only discrepancy in the ESG risk premium has been recorded between the great recession on the E-based TS portfolios: even when FFC6 is considered, the conditional alpha remains positive. In the end, the following values realign with the one observed in the unconditional one.

The UCS approach recorded lower negative alphas than the TS approach indicating a potential superiority of cross-sectional over the time series factors. Indeed, the mean excess returns are near zero in all four rating portfolios, whereas time-series portfolios present deep negative means and higher volatilities. It also presents more negative variability in the conditional alphas over the CS approach. Even though the CS method is more parsimonious when constructed to track the ESG premium, in the opposite strategy investment, shorting green stocks and going long on brown stocks, the value-weighted approach dominates the CS method generating huge returns, rejecting the mistrust of the value-weighted approach described by Cornell and Damodaran (2021).

4.2 Tracking sustainability performance

The analysis now focuses on further evaluation of the CS approach. To this purpose, the target rating previously presented allows the creation of target portfolios. In particular, three UCS portfolios have been created with three different target ratings. The three targets are equal to the 25th, the 75th and the 90th percentile of ESG rating distributions, respectively UCS(25), UCS(75) and UCS(90). Targeting the 25th percentile entails constructing a portfolio with a sustainability profile significantly lower than the median, namely a brown factor, as opposed to a green factor aimed at the 75th percentile, and hence a sustainability profile significantly higher than the median. In contrast, the ESG factor targeting the 90th percentile can provide insight into the nature of socially responsible investing's returns to

scale. As done above, the factors' conditional and unconditional time-varying performance has been performed.

4.2.1 The characteristics of univariate cross-sectional ESG factors

As explained in chapter 2, factor weights are proportional to stock ESG ratings. All equities with positive (negative) de-meaned ratings are represented by the long (short) leg. However, because a UCS factor's portfolio weights are all proportionate to the rating objective ρ_{t-1}, the weighted features of the long and short legs scale accordingly to ρ_{t-1}, meaning that the ratio of the two legs' features is independent of the goal rating.

Figure 11 depicts the ratings of the rating based on the data providers. The graph depicts the ratings of the CS factors based on the ratings (ESG, E, S, and G) from Bloomberg ESG data providers. The factor rating objectives correspond to the 25th (CS(25), 75th (CS(75), and 90th (CS(90)) percentiles of the cross section's current values. Notably, because factor rating goals are determined by the distribution of scores in the cross-section, UCS factors with the same percentile target have the same rating. The ESG, E, and S ratings of the CS variables remain consistent during the sample period. The ratings are close to -0.25, 0.25, and 0.40, with the 25th, 75th, and 90th percentiles of a uniform distribution between -0.5 and 0.5, respectively. The G score varies significantly during the sample period, mainly on the 75th, and 90th percentiles, which might be attributable to the insufficient granularity of the government pillar evaluations in this Bloomberg ESG database.

Figure 11 Cross-sectioal ESG factor ratings.
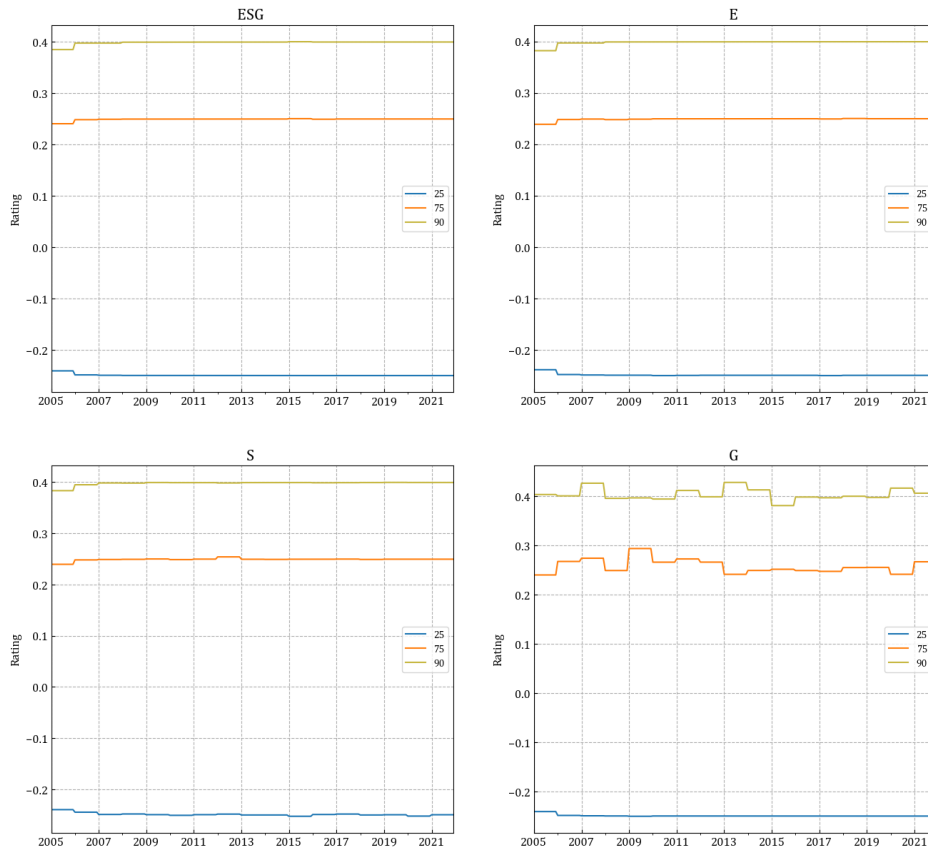
Table 6 shows the full-sample summary statistics for the returns of UCS factors. This table presents the summary statistics of excess returns for the UCS ESG factors corresponding to the 25th (UCS(25), 75th (UCS(75), and 90th (UCS(90)) percentiles of the rating scale every month. For each portfolio has been reported the mean, median, standard deviation (Std), minimum and maximum (Min and Max) of excess returns, CAPM alpha (αCAPM) and FFC6 alpha (αFFC6), and the Sharpe Ratio (SR), together with their Newey-West t-statistics in parentheses. The numbers in bold are statistically significant at the 5% level. Bloomberg ESG provides the ESG data, and the sample period begins in December 2004 to December 2021.

Factor returns present the same differences across all the different pillars, with brown portfolios, UCS(25), overperforming green and scale portfolios, UCS(75) and UCS(90), respectively. For example, considering the UCS(25) portfolios, the mean excess returns are always positive for all the pillars (0.247% in ESG, 0.201% in E, 0.183% in S, and 0.180% in G). In addition, the CAPM and multifactor alphas are all significant and positive as well as the Sharpe ratio.

Unfortunately, the same results are not founded in the UCS(75) and UCS(90) portfolios, where all the parameters take negative values, and in some cases, the UCS(90) values are even

worst. In the green portfolios, the mean returns are equal to brown mean returns but with the opposite sign. In contrast, scale portfolios mean returns are lower than the other two target portfolios. The UCS(90) mean returns are equal to -0.395% in ESG, -0.322% in E, -0.291 in S, and -0.293 in G. In contrast with the brown alphas, the CAPM and multifactor alphas for the green and scale portfolios are always significant and negative. Besides the G-based portfolios, where the alpha of UCS(75) has a different value from the UCS(25) alpha, in the other score-based portfolios, the UCS(75) has alphas always equal to the UCS(25)' alphas.

Table 6 Univariate cross-sectional ESG factors.

	ESG			E		
	25	**75**	**90**	**25**	**75**	**90**
Mean	0.247	-0.247	-0.395	0.201	-0.201	-0.322
t stat	6.055	-6.056	-6.055	4.235	-4.238	-4.236
p-value	0.080	0.080	0.128	0.093	0.093	0.149
Median	0.229	-0.229	-0.367	0.205	-0.205	-0.328
Std	0.582	0.582	0.932	0.678	0.678	1.085
Min	-1.349	-2.929	-4.686	-1.830	-3.715	-5.944
Max	2.929	1.349	2.159	3.715	1.830	2.928
α_{CAPM}	**0.241**	**-0.241**	**-0.385**	**0.202**	**-0.202**	**-0.324**
t stat	7.205	-7.207	-7.204	3.831	-3.835	-3.832
p-value	0.000	0.000	0.000	0.000	0.000	0.000
α_{FF6}	**0.221**	**-0.221**	**-0.353**	**0.179**	**-0.179**	**-0.286**
t stat	6.225	-6.229	-6.226	4.239	-4.244	-4.241
p-value	0.000	0.000	0.000	0.000	0.000	0.000
SR	0.424	-0.424	-0.424	0.297	-0.297	-0.297
	S			G		
	25	**75**	**90**	**25**	**75**	**90**
Mean	0.183	-0.182	-0.291	0.180	-0.189	-0.293
t stat	4.829	-4.831	-4.827	4.921	-4.943	-4.898
p-value	0.074	0.074	0.118	0.072	0.075	0.117
Median	0.208	-0.210	-0.335	0.210	-0.219	-0.343
Std	0.540	0.539	0.862	0.524	0.546	0.854
Min	-2.063	-1.940	-3.105	-1.646	-1.738	-2.671
Max	1.961	2.063	3.301	1.590	1.719	2.765
α_{CAPM}	**0.177**	**-0.177**	**-0.282**	**0.175**	**-0.183**	**-0.284**
t stat	5.090	-5.120	-5.109	5.335	-5.553	-5.284
p-value	0.000	0.000	0.000	0.000	0.000	0.000
β_{CAPM}	0.010	-0.010	-0.015	0.010	-0.010	-0.016
t stat	0.825	-0.841	-0.838	0.939	-1.004	-0.940
p-value	0.410	0.400	0.402	0.348	0.315	0.347
α_{FF6}	**0.177**	**-0.176**	**-0.282**	**0.147**	**-0.152**	**-0.238**
t stat	6.933	-6.906	-6.895	5.476	-5.469	-5.315
p-value	0.000	0.000	0.000	0.000	0.000	0.000
SR	0.338	-0.338	-0.338	0.344	-0.346	-0.343

In contrast, UCS(90)' alphas are always lower than UCS(75)' alphas. Finally, for ESG-, E- and S- based portfolios, the Sharpe ratios are in absolute terms equal for all three target rating portfolios (0.424 in ESG, 0.297 in E, and 0.338 in S). At the same time, there is a discrepancy between values in the G dimension. The most relevant information that can be taken from the risk remuneration parameter is that even if the UCS(90) recorded the worst performance in terms of returns and volatility, it was able to maintain a risk remuneration equal to the green portfolio, thanks to the scale-invariant characteristic of the CS approach.

Overall, from the evidence in Table 6, brown firms overperformed green and scale firms, with green portfolios having the same performances but with opposite signs compared to brown portfolios and scale portfolios having the worst performances. Hence, is not possible to reject the neutral argument on the ESG factor returns since portfolios targeting green firms have underperformed portfolios targeting brown firms, disproving the thesis of *doing well while doing good* for the considered firms and sample period. In addition, it is not possible to reject the equilibrium model from Pàstor et al. (2021) without previously performing the time-varying analysis of the portfolio alphas.

4.2.2 Time-varying evolution

In the equilibrium model of Pàstor et al. (2021), agents' preferences for green holdings influence asset pricing. Agents are ready to pay extra money for greener enterprises, cutting the firms' capital expenses. As a result, CAPM alphas are negative for green assets and favourable for brown assets. Furthermore, agents with higher ESG preferences, whose portfolios are more skewed toward green assets and less skewed toward brown assets, receive lower projected returns. However, such agents are not sad because their possessions provide them utility. Hence, by computing the conditional alphas is possible to evaluate if the equilibrium model condition holds for all the sample periods.

Figure 12 and 13 show the filtered alphas of the CAPM and FFC6 factor models obtained through the Bloomberg ESG database. Figure 11 depicts the time series of filtered CAPM alphas for the UCS factors corresponding to three separate ratings—the 25th (UCS(25)), 75th (UCS(75), and 90th (UCS(90)) percentiles of the present cross-section. The factors are built using ratings from Bloomberg data providers (E SG, E, S, or G). While Figure 13 depicts the time series of filtered FFC6 alphas for the UCS factors corresponding to three separate ratings—the 25th (UCS(25)), 75th (UCS(75), and 90th (UCS(90)) percentiles of the present cross-section. The factors are built using ratings from Bloomberg data providers (E SG, E, S, or G).

Before proceeding further with the analyiss, it is worth noting that the choice of the selected target ρ affects the resulting unconditional alphas. For all the portfolios created, the time-varying alphas exhibit the same stochastic behaviour as found in the previous comparison analysis. Even when comparing the different pillars, the behaviour of the alphas does not change, reinforcing the findings provided in Table 6 regarding unconditional alphas. Between the CAPM and FFC6 approaches, the usual reduction of alphas values ranges with more significant CAPM alphas than FFC6 alphas.

Focusing on CAPM alphas, UCS(25) dominates the other two portfolios in terms of performance. In the ESG and G dimensions, UCS(75) and UCS(90) started with estimates around -1% and followed a slightly positive trend that however did not turn positive but approached zero afterward. The same behaviour with opposite direction is observed in UCS(25). The same trends are observed in the alphas of FFC6, with a pronounced approach to the end of the sample size that gives hope for a possible future performance to overcome the green and scale portfolio and, thus, the risk premium of ESG factors. The S-pillar is the only one with an ESG risk premium at the beginning of the sampling period. However, this situation occurs for only a few initial observations, which leads to the conclusion that this is not due to the excellent performance of green stocks but instead to the optimization process of the Kalman filter, whereby incorrect observations may be incurred when considering initial estimates. This is even more evident in the S-based FFC6 alphas, where after the change of tendency in all three portfolios, it followed a steady behaviour, where UCS(25) takes only positive values and the other two portfolios only negative ones. Also, in the E pillar is observed a positive trend between 2005 to the end of 2008 for the green portfolios. However, even in this case, the trend stopped before taking positive values and was followed by constant negative values until the end of the sample period. Moreover, in E-based alpha FFC6, this observation is less relevant, suggesting that when other price factors are considered, alpha ESG returns diminish in importance.

Figure 12 Conditional CAPM alpha of univariate cross-sectional ESG components for different ESG ratings and company characteristics.
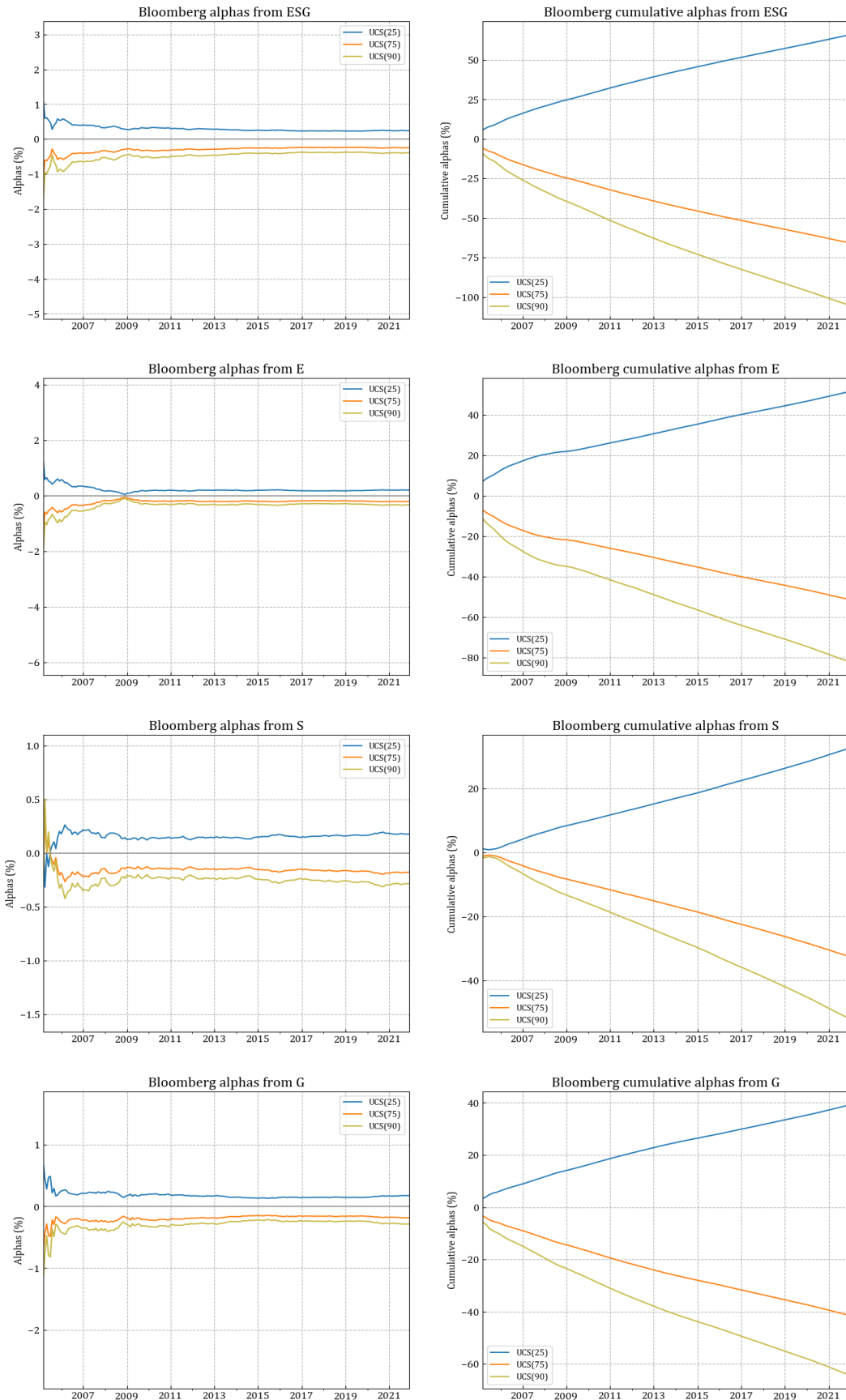
Figure 13 Conditional FFC6 alpha of univariate cross-sectional ESG components for different ESG ratings and company characteristics.
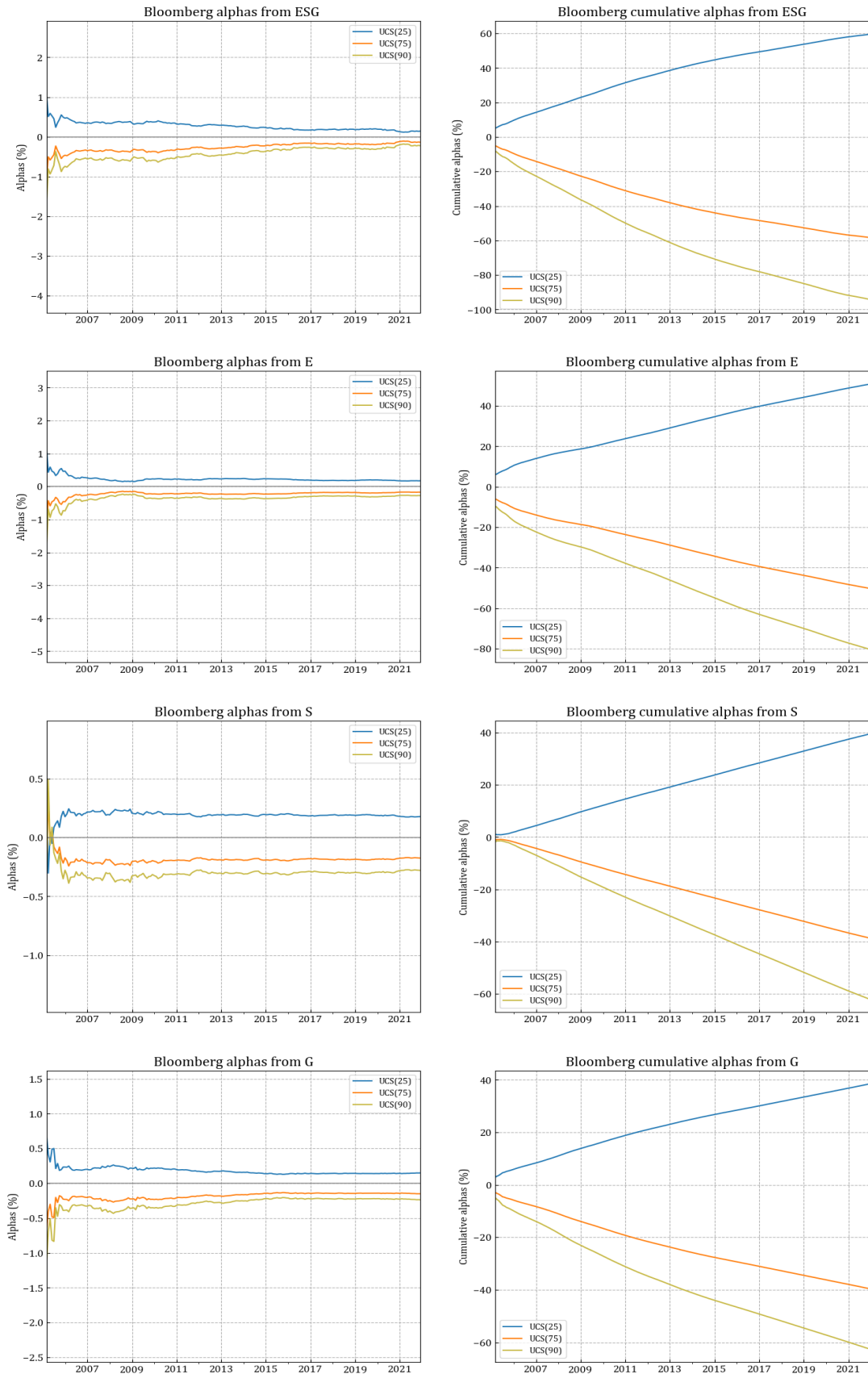
This further analysis on different target rating portfolios has not changed the main conclusions from the previous analysis. In all scenarios, the brown firms overperformed the green firms. This result provide evidence against the rejectiof of the equilibrium model hypothesis by Pàstor et. al (2020), that green stocks generate lower returns than brown stocks since investors prefer to hold sustainable firms to ensure themself against climate risk. Although, further evaluation of the agents' preferences must provide a complete evaluation of the model. Moreover, the most dynamic behaviour was observed at the beginning of the sample period in the E dimension. Green stocks followed an increasing trend in this pillar until equalizing brown stocks in 2009. On the other hand, brown stocks followed the opposite trend, steadily decreasing until 2009 and then rising again to stay still until the end of the sample period.

4.3 Multivariate Framework

To provide a comprehensive analysis of ESG factors, the focus is now on the multivariate factor model. Considering a broad set of risky factors allows for cleaning out the exposure to ESG from other stock's characteristics. In Chapter 2 it has been stressed this analysis is not feasible through the TS approach, where portfolio weights are sorted according to specific criteria that require several complex sorting steps in the multivariate framework. On the other hand, the CS approach easily allows the analysis to be extended to other factors through the ex-ante characteristic exposure neutralization of ESG CS factors.

The starting point for constructing the additional characteristic was the collection of FFC6 factor returns for the European market from the Kenneth French website. These returns were used as exogenous variables in the two-stage regression of Fama and MacBeth (1973), where the endogenous variables were stock returns. To obtain monthly time-varying factor exposures, rolling Ordinary Least Squares regressions were run with a 12-months window. Once these aditional characteristics are considered, the creation of the pure ESG portfolios follows the straightforward methodology used for the univariate approach and described in Section 3 of Chapter 2.

4.3.1 TS vs MCS

To pursue the comparison between the two approaches on the multivariate framework, the multivariate cross-sectional factor portfolios, MCS(1) and MCS(TS), substituted the UCS(1) and UCS(TS) portfolios. In contrast, the same TS portfolios have been considered. To allow

comparison between the two methods, the MCS(TS) have a monthly target rating equal to the monthly ESG TS factor.

Table 7 provides the summary statistics of the factor returns. This table summarises the excess return statistics for the TS, MCS(1), and MCS(TS) factors. On a monthly basis, excess returns are stated as a percentage. The mean, median, standard deviation (Std), minimum and maximum (Min and Max) of excess returns, CAPM alpha (α_{CAPM}) and beta (β_{CAPM}), FFC6 alpha (α_{FF6}), with their Newey-West t-statistics reported for each method. At the 5% level, the data in bold are statistically significant. Sharpe ratio is abbreviated as SR. Bloomberg ESG provides the ESG data, and the sample period begins in December 2004 to December 2021.

Since nothing has changed in the composition of the TS portfolios, the same observation made in the univariate framework still holds in the multivariate one. For each pillar, the TS portfolios present larger volatility and excess returns than multivariate portfolios with a better Sharpe ratio than the MCS approach. The TS Sharpe ratios are −0.284% (ESG), −-0.148% (E), −0.237% (S), and −0.257% (G). In the MCS(TS) factors are -0.782%, -0.539%, -0.557%, and -0.291%. The CAPM alphas are for most significant and negative. Also, the market betas are significant and negative. Unfortunately, the same mixture results are encountered when the difference between the CAPM alphas and the FF6 are evaluated.

In the multivariate cross-sectional approach, a relevant observation can be made regarding the discrepancies in the factor returns between the UCS and MCS approaches. Indeed, If firm characteristics other than ESG were not determining factors for stock returns, as expected in the univariate analysis, the TS, UCS(TS), and MCS(TS) variables should yield comparable returns because the conditional spread in expected returns is zero. However, significant variances between these parameters may be seen in the data. The average returns for the TS factors are −9.137% (ESG), −5.576% (E), −4.747% (S), and −9.921% (G). In the UCS(TS) factors are 0.685%, −0.207%, 0.194%, and −0.207%, respectively. And finally, in the MCS(TS) factors are -0.591%,-0.170%,-0.145%, and -0.127%, respectively.

The MCS alphas are always significant and less than the TS approach. The market betas are virtually zero and not significant, as in the UCS approach, confirming the absence of dependency between factor returns and market returns and the superiority of the CS approach to the TS approach in creating portfolios whose returns can be explained entirely by the ESG weights. The G- based MCS alphas are the lowest leading to the hypothesis that

among all ESG metrics, the G score has the lowest explanatory power (e.g., Lioui et al., 2016; Pedersen et al., 2021).

Table 7 ESG factors are classified as time-series or cross-sectional.

	TS	MCS(1)	MCS(TS)	TS	MCS(1)	MCS(TS)
		ESG			E	
Mean	**-9.137**	**-0.015**	-0.613	-5.576	**-0.012**	-0.164
t stat	-4.054	-4.852	-9.226	-2.110	-4.285	-6.226
p-value	0.044	0.006	0.131	0.052	0.005	0.052
Median	-8.084	-0.011	-0.594	-3.927	-0.009	-0.110
Std	32.189	0.045	0.948	37.744	0.040	0.376
Min	-131.569	-0.314	-3.741	-142.694	-0.321	-1.644
Max	81.767	0.186	2.275	190.968	0.114	1.039
α_{CAPM}	**-8.134**	**-0.016**	**-0.619**	**-4.769**	**-0.012**	**-0.163**
t stat	-4.024	-3.965	-9.232	-1.642	-2.858	-3.810
p-value	0.000	0.000	0.000	0.101	0.004	0.000
β_{CAPM}	**-1.701**	0.000	0.011	**-1.367**	0.000	-0.002
t stat	-4.266	0.762	0.731	-2.840	0.028	-0.251
p-value	0.000	0.446	0.465	0.005	0.978	0.802
α_{FF6}	**-7.911**	**-0.016**	**-0.588**	**-5.526**	**-0.011**	**-0.144**
t stat	-3.731	-3.248	-8.614	-2.527	-2.652	-4.309
p-value	0.000	0.001	0.000	0.012	0.008	0.000
SR	-0.284	-0.341	-0.646	-0.148	-0.300	-0.436
		S			G	
Mean	**-7.474**	**-0.007**	**-0.140**	-9.921	**-0.002**	-0.117
t stat	-3.383	-2.205	-6.379	-3.675	-0.527	-3.262
p-value	0.044	0.006	0.043	0.053	0.009	0.071
Median	-5.276	-0.007	-0.128	-7.879	-0.008	-0.149
Std	31.560	0.042	0.314	38.555	0.064	0.514
Min	-141.546	-0.225	-1.197	-126.017	-0.385	-2.320
Max	103.088	0.421	0.780	92.643	0.469	2.791
α_{CAPM}	**-6.232**	**-0.007**	**-0.142**	**-8.703**	**-0.002**	**-0.113**
t stat	-3.540	-3.948	-5.372	-3.238	-0.330	-2.253
p-value	0.000	0.000	0.000	0.001	0.742	0.024
β_{CAPM}	**-2.105**	0.000	0.004	**-2.066**	-0.001	-0.008
t stat	-3.062	0.902	0.746	-2.719	-1.485	-1.103
p-value	0.002	0.367	0.456	0.007	0.138	0.270
α_{FF6}	**-7.265**	**-0.007**	**-0.132**	**-8.066**	**-0.001**	**-0.109**
t stat	-3.828	-5.333	-5.894	-3.485	-0.262	-2.252
p-value	0.000	0.000	0.000	0.001	0.793	0.024
SR	-0.237	-0.153	-0.447	-0.257	-0.038	-0.228

When considering the time-varying alphas estimated through the Kalman filter on both CAPM and FFC6 regression models, the results are similar compared to the previous univariate analysis. Figure 14 and Figure 15 display the time-varying alpha on the CAPM and FFC6 regression models, respectively.

Overall, the TS alphas display significant fluctuations compared to the MCS approach, with worst cumulative sums computed for all pillars. However, even in the multivariate framework, there is no evidence of a substantial ESG risk premium. Only in the E pillar the TS alphas recorded a significant risk premium during the sub-prime crisis, leading to the hypothesis that among all the sustainable pillars, only the Environmental one has manifested some countercyclical behaviour and hence can perform well during resection periods.

Figure 14 Conditional CAPM alpha of time series and multivariate cross-sectional components based on business characteristics
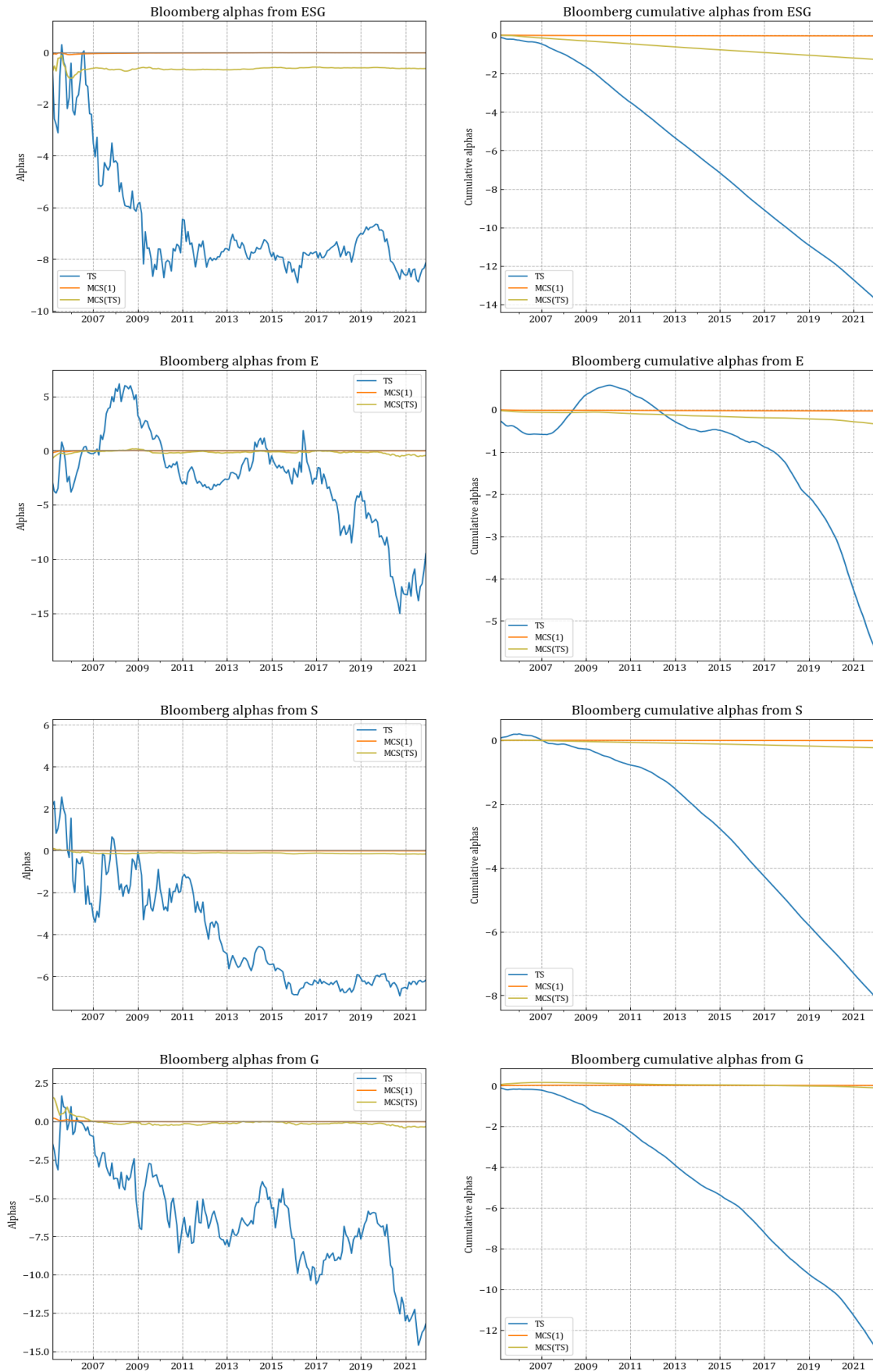
Figure 15 Conditional Fama-French-Carhart six factors alpha of time series and univariate cross-sectional components based on business characteristics.
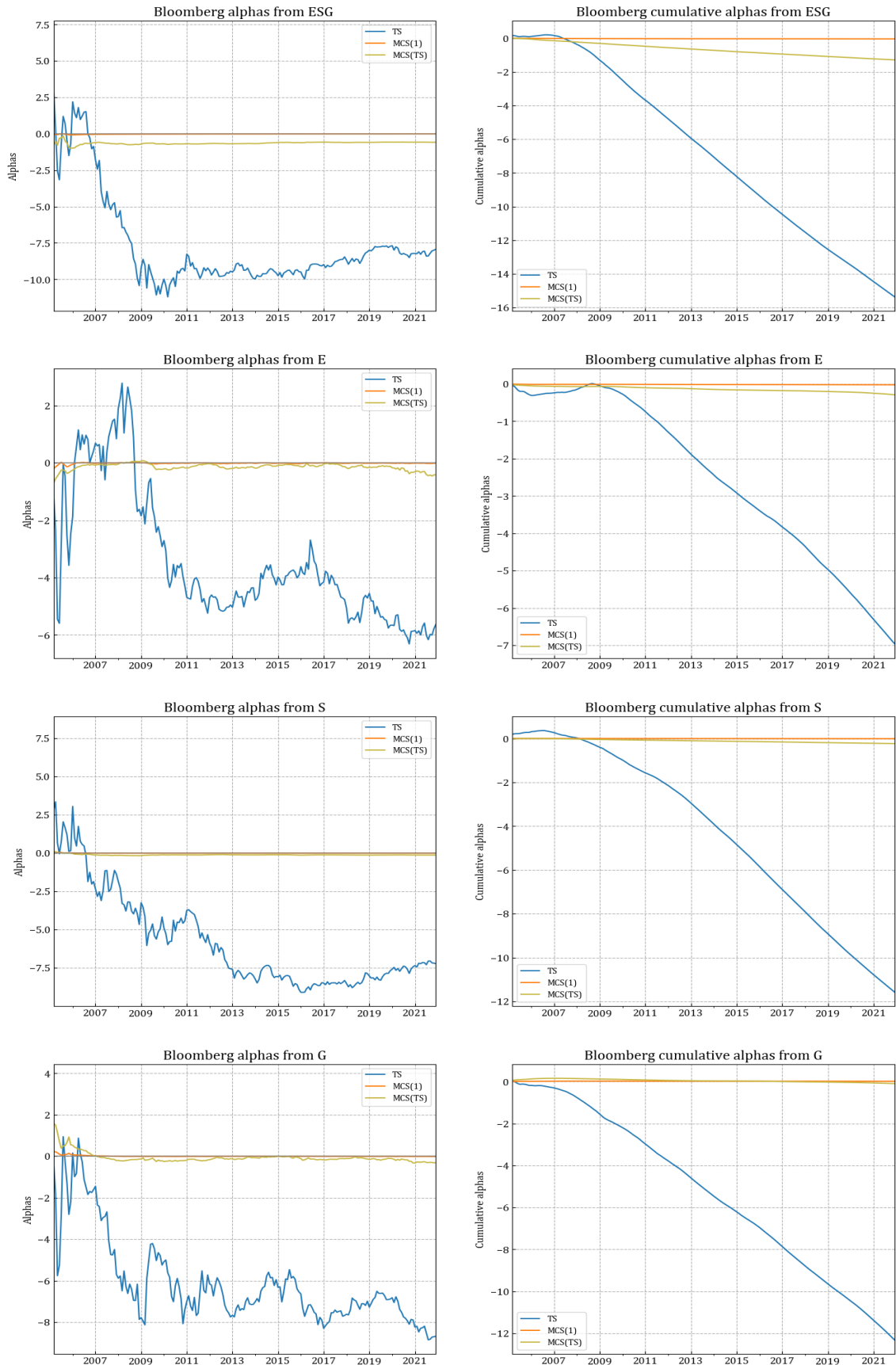
In the univariate framework, controlling for other firm characteristics exposure was not possible. Therefore, the analysis of the target rating portfolio regularisation has been provided to demonstrate the relevance of adopting multivariate techniques. Even in this cae, the same target portfolios have been constructed to allow comparisons between the two frameworks. The three rating targets are the 25th, the 75th and the 90th percentile of ESG distributions, which is the same used before and reported in Figure 11. The resulting target rating portfolios are identified as MCS(25), MCS(75), and MCS(90).

Table 8 shows the full-sample summary statistics for the returns of MCS factors. This table presents the summary statistics of excess returns for the MCS ESG factors corresponding to the 25th (MCS(25), 75th (MCS(75), and 90th (MCS(90)) percentiles of the rating scale every month. For each portfolio has been reported the mean, median, standard deviation (Std), minimum and maximum (Min and Max) of excess returns, CAPM alpha (αCAPM) and FFC6 alpha (αFFC6), and the Sharpe Ratio (SR), together with their Newey-West t-statistics in parentheses. The figures in bold are statistically significant at the 5% level. Bloomberg ESG provides the ESG data, and the sample period begins in December 2004 to December 2021.

Again, factor returns present the same differences across all the different pillars, with brown portfolios, MCS(25), overperforming green and scale portfolios, MCS(75) and MCS(90), respectively. Moreover, the values of the different parameters are lower than the ones recorded in the univariate analysis. However, the risk remuneration is in absolute value larger than the Sharpe ratio of the univariate approach. This primary observation highlights the importance of considering additional firm characteristics to understand the factor returns' behaviour better.

Table 8 Multivariate cross-sectional ESG factors.

	ESG			E		
	25	**75**	**90**	**25**	**75**	**90**
Mean	**0.213**	**-0.213**	-0.341	**0.160**	**-0.160**	-0.255
t stat	9.379	-9.380	-9.378	6.996	-7.002	-6.995
p-value	0.045	0.045	0.072	0.045	0.045	0.072
Median	0.203	-0.203	-0.325	0.141	-0.142	-0.226
Std	0.325	0.325	0.520	0.326	0.326	0.521
Min	-0.766	-1.297	-2.076	-0.648	-1.088	-1.740
Max	1.297	0.766	1.226	1.088	0.648	1.036
α_{CAPM}	**0.216**	**-0.216**	**-0.345**	**0.158**	**-0.158**	**-0.253**
t stat	9.451	-9.451	-9.450	4.316	-4.323	-4.315
p-value	0.000	0.000	0.000	0.000	0.000	0.000
α_{FF6}	**0.205**	**-0.205**	**-0.327**	**0.133**	**-0.133**	**-0.212**
t stat	8.769	-8.774	-8.773	4.686	-4.695	-4.684
p-value	0.000	0.000	0.000	0.000	0.000	0.000
SR	0.657	-0.657	-0.657	0.490	-0.490	-0.490
	S			G		
Mean	**0.124**	**-0.124**	-0.198	0.123	-0.130	-0.197
t stat	5.573	-5.565	-5.568	4.589	-4.712	-4.490
p-value	0.044	0.044	0.070	0.053	0.054	0.087
Median	0.123	-0.124	-0.197	0.144	-0.144	-0.234
Std	0.318	0.318	0.508	0.382	0.394	0.628
Min	-1.667	-0.956	-1.529	-1.835	-1.507	-2.531
Max	0.966	1.667	2.668	1.507	1.835	3.082
α_{CAPM}	**0.126**	**-0.126**	**-0.202**	**0.119**	**-0.125**	**-0.191**
t stat	5.223	-5.247	-5.242	3.185	-3.285	-3.109
p-value	0.000	0.000	0.000	0.001	0.001	0.002
α_{FF6}	**0.119**	**-0.119**	**-0.190**	**0.115**	**-0.122**	**-0.185**
t stat	5.970	-5.962	-5.960	3.271	-3.366	-3.176
p-value	0.000	0.000	0.000	0.001	0.001	0.002
SR	0.390	-0.390	-0.390	0.321	-0.330	-0.314

The MCS(25) have mean returns equal to 0.205%in ESG, 0.160% in E, 0.124% in S, and 0.123% in G. The MCS(75) have the same mean factor returns of the MCS(25) but with opposite sign. While the mean factor returns are -0.304% in ESG, -0.255% in E, -0.198% in S, and -0.197% in G, all not significant at alpha equal to 0.05%. ESG-based portfolios reported the highest mean factor returns and the highest Sharpe ratio., followed by E pillar portfolios. Besides the other pillar, in the G dimension, the mean factor returns are all not significant at the 0.05 per cent significance level. In addition, the MCS(25) mean and MCS(75) do not take the same absolute value with opposite signs. The observation on the G pillar can again derive from the time-series behaviour of the target value. Indeed, as shown in Figure 11, the 75th percentile presents some swinging behaviour and is not stable at the 0.25 value.

Moving to the evaluation of the unconditional alphas, the brown portfolio is the only one recording a return premium. In contrast, the other two registered only negative alpha on both CAPM and multifactor assessment. In all pillars, the CAPM and FFC6 alphas are significant at the 0.05% significance level, and the highest alphas are recorded in the ESG dimension, followed by the E alphas. As for the descriptive statistics, the G pillar alphas differs in values and patterns from the other pillars, but they are all significant at a 0.05% significance level. Once more, The multivariate target portfolios recorded values that behave as in the univariate approach. However, still, the inclusion of other firm characteristics reduces their values. The evidence rejects the existence of any ESG risk premium when the factor returns are cleaned out from exposure to other firm characteristics.

To perform a time-sensitive analysis, it has been computed also the time-varying alphas for the MCS(25), MCS(75), and MCS(90) portfolios. The method implied is again the Kalman Filter with the same state equation assumed for the previous analysis. The time-varying alphas for the multifactor framework provide some unexpected pattern behaviour that differs from the patterns experienced in the univariate framework. Further discussion will be based on the graph shown in Figure 16 and Figure 17, which respectively present the resulting time-varying CAPM alphas and FFC6 alphas.

Figure 16 shows the time series of filtered CAPM alphas for the UCS factors corresponding to three separate ratings—the 25th (MCS(25)), 75th (MCS(75), and 90th (MCS(90)) percentiles of the present cross-section. The factors are built using ratings from Bloomberg data providers (ESG, E, S, or G). While Figure 17 depicts the time series of filtered FFC6 alphas for the UCS factors corresponding to three separate ratings—the 25th (UCS(25)), 75th (UCS(75), and 90th (UCS(90)) percentiles of the present cross-section. The factors are built using ratings from Bloomberg data providers (ESG, E, S, or G).

Figure 16 Conditional CAPM alphas of multivariate cross-sectional ESG components for different ESG ratings and company characteristics.
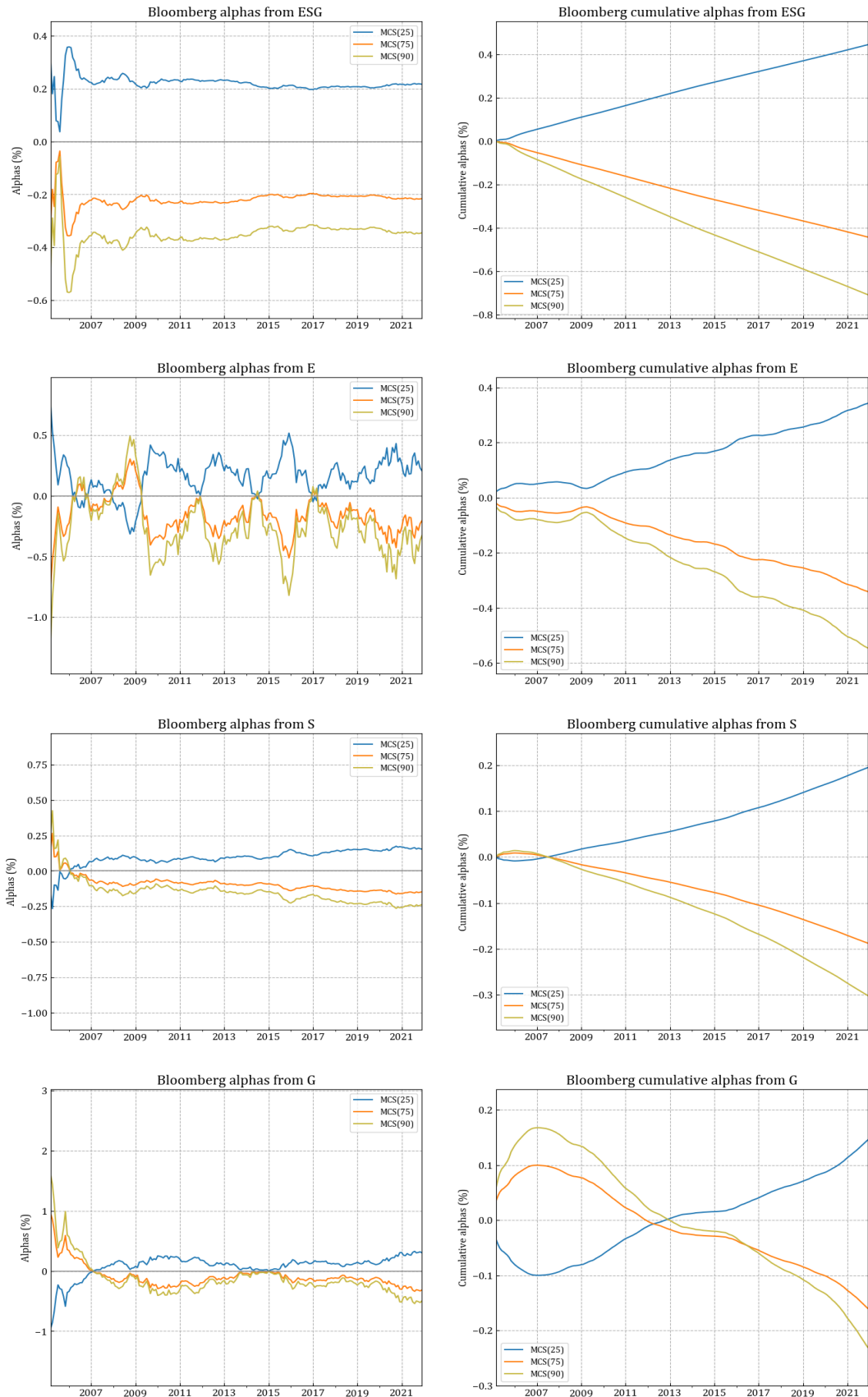
Figure 17 Conditional FF6C alphas of multivariate cross-sectional ESG components for different ESG ratings and company characteristics.
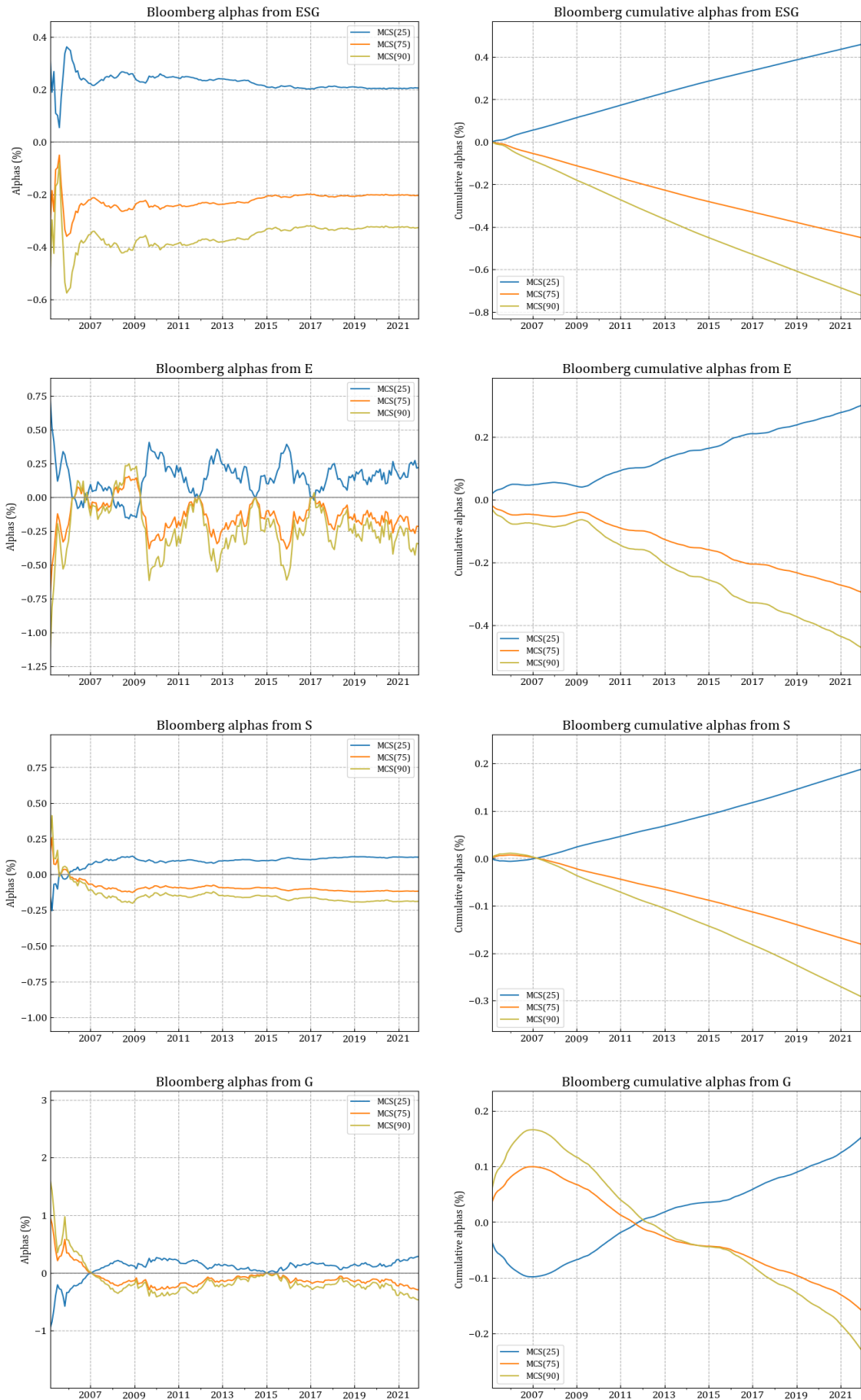
Starting with analyzing the CAPM, there is a clear difference in the behaviour of E and G alphas from the univariate case seen in the previous chapters. At the same time, the ESG and S conditional alphas present similar trends. E-based unconditional alphas present much noise during all sample periods. In some time instances, there are even trend inversions, with the MCS(75) and MCS(90) recording positive alphas and MCS(25) alphas dropping under zero. The most relevant inversion is between the end of 2007 and the end of 2009, a time interval characterized by the explosion of the subprime crisis. The same trend, but with less amplitude, has been observed in 2006, in the middle of 2014, and between the end of 2016 and the beginning of 2017. The possibility of an E return premium was made when comparing the TS, and MCS approaches. Now that the analysis focus is exclusively on the cross-sectional approach is possible to confirm the presence of a risk-return related to the E pillar and for most limited to the period of the subprime crisis. Again, the E pillar seems the only sustainable metric capable of generating risk premium.

Although the E pillar presents evidences of some premium, the E premium vanishes when considering cumulative alphas. This observation is not valid for the S- and G-based alphas. Both pillars experienced an ESG premium at the beginning of the sample periods, which is more persistent in the G pillar, and both present a cumulative ESG premium, which still is more evident in the G dimension. The S-based alphas recorded positive alphas for MCS(75) and MSC(90) during the first year of analysis. On the cumulative side, the MCS(75) and MCS(90) alphas outperformed the MCS(25) until the end of 2008. The story behind G-based alphas is interesting. The green portfolios only recorded positive alphas until 2007, and for the remaining time, they remained negative. However, on the cumulative side, the MCS(75) and MCS(90) portfolio alphas reached zero in 2012 and 2013, respectively. This cumulative behaviour can be justified by the narrow spread of the brown alpha with the green alphas, which was almost zero between 2014 and half past 2015, and then began to diverge significantly.

In the FFC6 conditional alphas, the MCS are similar in levels and patterns to the CAPM alphas, implying again that controlling ex-ante for additional stock characteristics reduces the ex-post exposure to other pricing factors. The ESG, S, and G pillars present the same values and trends recorded for the CAPM alphas. In the E pillar, the same noise trends are present; the local ESG premiums are still there, but they take lower values this time.

CONCLUSION

Sustainable investment considers financial performance and environmental, social and governance requirements. This investment strategy was initially established by imposing negative screens under the banner of socially responsible investing (SRI). However, in recent years its scope has grown considerably. Assets managed with a focus on sustainability have collected tens of billions of dollars and this appear to be the beginning of a trend appear to be growing. Given this rapid expansion, this analysis aims to provide evidence of premiums associated with ESG factors. Several approaches can be considered for determining the ESG premium, and the fundamental differences between methods are relevant.

Under this prerequisite, the analysis looks at the Liuoi and Tarelli's (2022) methodology, but applied to the European stock market. The methodology used focus on ESG ratings and other company characteristics. This methodology makes it possible to construct pure ESG factors that are directly comparable between the different pillars of ESG ratings (ESG, E, S and G).

The assessment of the difference in factor premiums between the TS and the CS approach provides the following results.

First, both methods suggests a negative performance over the sample periods, with highly-rated firms underperforming low-rated firms at least for the last two decades. In addition, the negative time-varying alphas computed from both methods lead to the rejection of positive premiums associated with the ESG metrics. However, the TS approach over the E pillar seems more supportive regarding the existence of some risk premiums, especially during some economic crisis, even though this evidence is not enough to reject the neutrality hypothesis suggested in the literature on ESG factor premiums (e.g. Ferriani et. Al 2021, Maiti 2021, and Naffa et. Al. 2022).

Second, the TS-filtered alphas feature a substantial time variation compared to the CS-filtered alphas and delivers a better Sharpe ratio, even though the CS approach is built on a minimum variance portfolio idea. Thus, it is possible to reject the superiority of the CS factor over the TS factors in the European market. In addition, if the opposite investment strategy were chosen, the TS alphas would have reached higher positive alpha than the CS alphas, reinforcing the preference for a value-weighted strategy for a European stock portfolio.

Third, the previous conclusions are still valid even when the analysis is computed considering more firm characteristics, in a multivariate setup. In this framework, both methods reject the existence of ESG factor premiums and the preference for a TS approach is still valid. In addition, cleaning the effect of other characteristics in the CS approach leads to alphas that are more volatile compared to the previous cases. This evidence is mostly visible for E, confirming it is the most relevant pillar for the factor premium analysis.

Then the analysis evaluated the performance of UCS and MCS target portfolios through the method by Lioui and Tarelli (2022). The MCS target portfolios present lower values than the UCS target portfolios, and conditional multifactor models delivers even more time variation. Thus the multifactor approach has better explanatory power than the univariate approach. However, even in this analysis, it is not possible to confirm the presence of an ESG risk premium since the low-rated firms overperformed the high-rated firms. Although, as before, it must be stressed that the E pillar supports the risk premium hypothesis, albeit modestly. In addition, the evidence leads to the assumption that the European stock market has always been in a condition similar to that described in the equilibrium model, Pàstor et al.(2021).

Overall the conclusions provided by the study of Liuoi and Tarelli (2022) are not supported by this analysis. Hence, the European stock market presents no ESG factor premium over the sample period. Although, as proven by Billio et. al (2021) and confirmed by Lioui and Tarelli (2022), empirical evidences based on different data sources provide different results. This might imply that disagreement among data providers has a significant impact on the performance of ESG factors analysis. In addition, differences in the economic sectors included in the portfolio analysis could also explain the discrepancy between the EU ESG performance compared to the US ESG performance. For example, many European firms operate in the manufactural sector, whereas the US portfolio consists of more tech firms which collect higher ESG values than industrial firms. In light of this evidence, it would be interesting to extend this thesis' analysis by considering different ESG data (with particular focus on the dynamic on the E pillar) to explore how these different conclusions might be further justified.

APPENDIX

A Proofs and derivations

A.1 Derivation of the vector of portfolio weights w_{t-1}, *from Lioui and Tarelli (2022) Appendix:*

$$w_{t-1} = \left[\mathbf{1}_{N_{t-1}} \, ESG_{t-1}\right] \left(\left[\mathbf{1}_{N_{t-1}} \, ESG_{t-1}\right]'\left[\mathbf{1}_{N_{t-1}} \, ESG_{t-1}\right]\right)^{-1}$$

$$= \left[\mathbf{1}_{N_{t-1}} \, ESG_{t-1}\right] \begin{bmatrix} \mathbf{1}'_{N_{t-1}}\mathbf{1}_{N_{t-1}} & \mathbf{1}'_{N_{t-1}}ESG_{t-1} \\ \mathbf{1}_{N_{t-1}}ESG'_{t-1} & ESG'_{t-1}ESG_{t-1} \end{bmatrix}^{-1}$$

$$= \left[\frac{1}{N_{t-1}}\mathbf{1}_{N_{t-1}} \quad \frac{EGS_{t-1}}{EGS'_{t-1}EGS_{t-1}}\right]$$

Since ESG_{t-1} are de-meaned $ESG'_{t-1}\mathbf{1}_{N_{t-1}} = 0$ and $\mathbf{1}'_{N_{t-1}}\mathbf{1}_{N_{t-1}} = N_{t-1}$

A.2 Derivation of equation 14 consider regression 11, from Lioui and Tarelli (2022) Appendix:

$$w_{t-1} = \left[\mathbf{1}_{N_{t-1}} \, \frac{ESG_{t-1}}{\rho_{t-1}}\right]\left(\left[\mathbf{1}_{N_{t-1}} \, \frac{ESG_{t-1}}{\rho_{t-1}}\right]'\left[\mathbf{1}_{N_{t-1}} \, \frac{ESG_{t-1}}{\rho_{t-1}}\right]\right)^{-1}$$

$$= \left[\mathbf{1}_{N_{t-1}} \, \frac{ESG_{t-1}}{\rho_{t-1}}\right]\begin{bmatrix} \mathbf{1}'_{N_{t-1}}\mathbf{1}_{N_{t-1}} & \mathbf{1}'_{N_{t-1}}\frac{ESG_{t-1}}{\rho_{t-1}} \\ \mathbf{1}_{N_{t-1}}\frac{ESG'_{t-1}}{\rho_{t-1}} & \frac{ESG'_{t-1}}{\rho_{t-1}}\frac{ESG_{t-1}}{\rho_{t-1}} \end{bmatrix}^{-1}$$

$$= \left[\frac{1}{N_{t-1}}\mathbf{1}_{N_{t-1}} \quad \frac{\rho_{t-1}}{EGS'_{t-1}EGS_{t-1}}EGS_{t-1}\right]$$

Since ESG_{t-1} are de-meaned $ESG'_{t-1}\mathbf{1}_{N_{t-1}} = 0$ and $\mathbf{1}'_{N_{t-1}}\mathbf{1}_{N_{t-1}} = N_{t-1}$

A.3 Derivation of equation 18, based on Lioui and Tarelli (2022) Appendix:

$$E_{t-1}\left[r_{UCS,t} - r_{TS,t}\right] = \left(\frac{\rho_{t-1}}{ESG'_{t-1}ESG_{t-1}}ESG'_{t-1} - MC'_{t-1}W_{t-1}\right)E_{t-1}[r_t]$$

$$= \left(\frac{\rho_{t-1}}{ESG'_{t-1}ESG_{t-1}}ESG'_{t-1} - MC'_{t-1}W_{t-1}\right)\left(\theta_{0,t}\mathbf{1}_{N_{t-1}} + \theta_{1,t}\frac{ESG_{t-1}}{\rho_{t-1}}\right)$$

$$= \theta_{0,t}\left(\frac{\rho_{t-1}}{ESG'_{t-1}ESG_{t-1}}ESG'_{t-1} - MC'_{t-1}W_{t-1}\right)\mathbf{1}_{N_{t-1}}$$

$$+\theta_{1,t}\left(\frac{\rho_{t-1}}{ESG'_{t-1}ESG_{t-1}}ESG'_{t-1} - MC'_{t-1}W_{t-1}\right)\frac{ESG_{t-1}}{\rho_{t-1}}$$

The two portfolios have zero net exposure, it follows that $\frac{\rho_{t-1}}{ESG'_{t-1}ESG_{t-1}}ESG'_{t-1}\mathbf{1}_{N_{t-1}} = 0$,

and $MC'_{t-1}W_{t-1}\mathbf{1}_{N_{t-1}} = 0$. As a consequence, the term $\theta_{0,t}$ becomes zero.

A.4 Derivation of equation 20 and proof that MCS factors are not exposure to additional characteristics, based on Liuoi and Tarelli (2022) Appendix.

$$w_{t-1} = \left[\mathbf{1}_{N_{t-1}} \quad \frac{ESG_{t-1}}{\rho_{t-1}} \quad C_{t-1}\right]\left(\left[\mathbf{1}_{N_{t-1}} \quad \frac{ESG_{t-1}}{\rho_{t-1}} \quad C_{t-1}\right]'\left[\mathbf{1}_{N_{t-1}} \quad \frac{ESG_{t-1}}{\rho_{t-1}} \quad C_{t-1}\right]\right)^{-1}$$

$$= \left[\mathbf{1}_{N_{t-1}} \quad \frac{ESG_{t-1}}{\rho_{t-1}} \quad C_{t-1}\right]\begin{bmatrix} \mathbf{1}_{N_{t-1}}\mathbf{1}_{N_{t-1}} & 0 & 0 \\ 0 & \dfrac{ESG'_{t-1}ESG_{t-1}}{\rho^2_{t-1}} & \dfrac{ESG'_{t-1}C_{t-1}}{\rho_{t-1}} \\ 0 & \dfrac{ESG'_{t-1}C_{t-1}}{\rho_{t-1}} & C'_{t-1}C_{t-1} \end{bmatrix}$$

$$= \left[\frac{1}{N_{t-1}}\mathbf{1}_{N_{t-1}} \quad w_{MCS,t-1} \quad w_{C,t-1}\right]$$

$$w_{MCS,t-1} = \rho_{t-1}\frac{(C'_{t-1}C_{t-1})ESG_{t-1} - (ESG'_{t-1}C_{t-1})C'_{t-1}}{(ESG'_{t-1}ESG_{t-1})(C'_{t-1}C_{t-1}) - (ESG'_{t-1}C_{t-1})^2}$$

$$w_{C,t-1} = \frac{(ESG'_{t-1}ESG_{t-1})C_{t-1} - (ESG'_{t-1}C_{t-1})ESG'_{t-1}}{(ESG'_{t-1}ESG_{t-1})(C'_{t-1}C_{t-1}) - (ESG'_{t-1}C_{t-1})^2}$$

Then, the exposure of ESG factor to the carateristic is

$$w_{MCS,t-1}C_{t-1} = \rho_{t-1}\frac{(C'_{t-1}C_{t-1})ESG_{t-1}C_{t-1} - (ESG'_{t-1}C_{t-1})C'_{t-1}C_{t-1}}{(ESG'_{t-1}ESG_{t-1})(C'_{t-1}C_{t-1}) - (ESG'_{t-1}C_{t-1})^2} = 0$$

B Python syntax

B.1 Cleaning datasets

```python
1.  import pandas as pd
2.  import numpy as np
3.
4.  def rating_NPR(rating):
5.      """rating_NPR function compute percentile ranks of row annual scores to
    normalize the rating
6.      distribution and rescale them between 0 and 1 and computing the rating
    monthly values"""
7.      for t in rating.columns:
8.          # applicazione della trasformazione (NPR(X))
9.          rating[t].loc[rating[t].notna()]= (rating[t].
10.                                     rank(numeric_only=True).dropna()-
11.                                     np.dot(-
    .5,np.ones(rating[t].count())))/rating[t].count()
12.     # standardizazione range temporale
13.     cols = pd.date_range(start = rating.columns[0],end =rating.columns[-1]
    ,freq = 'M', name = 'Date').drop(rating.columns[0])
14.     rating_m = pd.DataFrame(index = rating.index, columns = cols) #dataframe
15.     for t in rating_m.columns:
16.         rating_m[t] = rating.loc[:,rating.columns.year ==
    rating_m[t].name.year-1] #riempimento database mensile
17.     return rating_m
18.
19. def screening(Ratings,Prices,Mkt_cap,Returns):
20.     """Compute the list of stocks that satisfy the following requirements:
21.             (a) the sustainable score exist;
22.             (b) has a market cap highet than first perentile
23.             (c) price higher of €1
24.             (d) returns below 200% of the mean
25.     the first requirement is mandatory but the other three are mutualt
    excludable"""
26.     stocklist = []
27.     for t in Ratings.columns:
28.         stocks =
    Ratings[t].loc[(Ratings[t].notna())&((Mkt_cap[t]>Mkt_cap[t].quantile(0.25))|
29.                                     (Prices[t]>1)|
30.                                     (Returns[t]<
    (Returns[t].mean()+Returns[t].mean()*200)/100))
31.                             ].index
32.         stocklist.append(stocks)
33.     return stockist
34.
35. ################### DOWNLODAD DATASETS####################################
36. ratings =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOXX
    600.xlsx',
37.                 sheet_name = 1, header = (0,1), index_col = 0, parse_dates
    = True)
38.
39. stockPrices =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOXX
    600.xlsx',
40.                 sheet_name = 3, index_col = 0, parse_dates = True)
41.
42. stockMkt_cap =
    (pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOX
    X600.xlsx',
43.                 sheet_name = 4, index_col = 0, parse_dates = True))
44.
45. ############################### CLEANING DATASETS#######################
46. stockPrices.interpolate(method = 'linear',inplace = True)
```

```python
47.
48. stockReturns = stockPrices.pct_change(1)
49. # trasformazione cross-sectional dei datasets
50. stockReturns = stockReturns.loc[stockReturns.index.year >
    ratings.index[0].year].T
51. stockMkt_cap = stockMkt_cap.loc[stockMkt_cap.index.year >
    ratings.index[0].year].T
52. stockPrices = stockPrices.loc[stockPrices.index.year >
    ratings.index[0].year].T
53.
54. #standardizazione range temporale
55. stockReturns.columns = pd.date_range(start = stockReturns.columns[0],
56.                                       end = stockReturns.columns[-1], freq =
    'M')
57. stockMkt_cap.columns = pd.date_range(start = stockMkt_cap.columns[0],
58.                                       end = stockMkt_cap.columns[-1], freq =
    'M')
59. stockPrices.columns = pd.date_range(start = stockPrices.columns[0],
60.                                       end = stockPrices.columns[-1],freq='M')
61.
62. ##################################### ESG MANIPULATION#####################
63. # OPERAZIONE:
64. # (1) DIVISIONE del dataset di partenza in 4 specifici dataset per ogni valore
    si sostenibilità;
65. # (2) RIDEFINIZIONE INDICI dassando da un multi-index (Stock + rating) a un
    indice solo (Stock)
66. #      -- ex: indice di partenza ['A2A MI Equity']['ESG','E','S','G'] indice
    finale ['A2A MI Equity']
67. # (3) TRASFORMAZIONE applicazione della normalizazione tramite funzione
    rating_NPR(X)
68.
69. ESG = (ratings.iloc[:,0:ratings.shape[1]:4]).T
70. ESG.index = ESG.index.unique(0)
71. ESG = rating_NPR(ESG)
72.
73. E = (ratings.iloc[:,1:ratings.shape[1]:4]).T
74. E.index = E.index.unique(0)
75. E = rating_NPR(E)
76.
77. S = (ratings.iloc[:,2:ratings.shape[1]:4]).T
78. S.index = S.index.unique(0)
79. S = rating_NPR(S)
80.
81. G = (ratings.iloc[:,3:ratings.shape[1]:4]).T
82. G.index = G.index.unique(0)
83. G = rating_NPR(G)
84.
85. ############################## EXCESS RETURNS############################
86.
87. RF = pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
    F_6_Factors.csv',
88.                  index_col =0,parse_dates=True,
    infer_datetime_format=True)['RF'] #caricamento rf
89.
90. stockExcess = stockReturns.T.copy()
91.
92. for stock in stockExcess.columns:
93.     stockExcess[stock] = stockExcess[stock] - RF
94. stockExcess = stockExcess.T
95.
96. ################################### SAVE FILES#######################
97.
98. writer =
    pd.ExcelWriter('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOX
    X600_clean.xlsx',
99.                   engine='xlsxwriter')
```

```
100.
101.        stockPrices.to_excel(writer, sheet_name='Prices')
102.        stockReturns.to_excel(writer, sheet_name='Returns')
103.        stockMkt_cap.to_excel(writer, sheet_name='Capitalization')
104.        stockExcess.to_excel(writer, sheet_name='Excess')
105.        writer.save()
106.
107.        writer =
     pd.ExcelWriter('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Rati
     ngs.xlsx',
108.                                        engine='xlsxwriter')
109.
110.        ESG.to_excel(writer, sheet_name='ESG')
111.        E.to_excel(writer, sheet_name='E')
112.        S.to_excel(writer, sheet_name='S')
113.        G.to_excel(writer, sheet_name='G')
114.        writer.save()
```

B.2 ESG weights definition

```
1.  import pandas as pd
2.  import numpy as np
3.
4.  stocksPrices =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOXX
    600_clean.xlsx',
5.                      sheet_name = 'Prices', index_col = 0)
6.
7.  stocksMkt_cap =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOXX
    600_clean.xlsx',
8.                      sheet_name = 'Capitalization', index_col = 0)
9.
10. stocksReturns =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOXX
    600_clean.xlsx',
11.                     sheet_name = 'Returns', index_col = 0)
12.
13. stocksExcess
    = pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/ST
    OXX600_clean.xlsx',
14.                     sheet_name = 'Excess', index_col = 0)
15.
16. ESG =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
17.                     sheet_name = 'ESG', index_col = 0)
18.
19. E =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
20.                     sheet_name = 'E', index_col = 0)
21.
22. S =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
23.                     sheet_name = 'S', index_col = 0)
24.
25. G =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
26.                     sheet_name = 'G', index_col = 0)
27.
28. def screening(Ratings,Prices,Mkt_cap,Returns):
29.     """Compute the list of stocks that satisfy the following requirements:
```

```python
30.             (a) the sustainable score exist;
31.          --- AND(
32.             (b) has a market cap highet than first perentile
33.          -- OR
34.             (c) price higher of €1
35.          -- OR
36.             (d) returns below 200% of the mean)
37.     the first requirement is mandatory but the other three are mutualy
    excludable"""
38.     stocklist =
    Ratings.loc[(Ratings.notna())&((Mkt_cap>Mkt_cap.quantile(0.25))|
39.                                   (Prices>1)|
40.                                   (Returns<
    (Returns.mean()+Returns.mean()*200)/100))]
41.     return stockist
42.
43. def TS_weights(Ratings,Prices,Mkt_cap,Returns):
44.     rating_TS = pd.DataFrame(index = Ratings.index,columns = Ratings.columns)
45.     for t in Ratings.columns:
46.         scores = screening(Ratings[t],Prices[t],Mkt_cap[t],Returns[t])
47.         MC = (Mkt_cap[t][scores.index])
48.         l = scores >= scores.quantile(.7)
49.         s = scores <= scores.quantile(.3)
50.         I = np.identity(len(MC))
51.         I_L = I*l.values
52.         I_S = I*s.values
53.         ones = np.ones(len(MC))
54.         W = ((1/(ones.T@I_L@MC))*I_L) - ((1/(ones.T@I_S@MC))*I_S)
55.         rating_TS[t][scores.index] = MC.T@W
56.     return rating_TS
57.
58. def UCS_weights(Ratings,Prices,Mkt_cap,Returns):
59.     rating_CS = pd.DataFrame(index = Ratings.index,columns = Ratings.columns)
60.     for t in Ratings.columns:
61.         scores = screening(Ratings[t],Prices[t],Mkt_cap[t],Returns[t])
62.         scores = scores - scores.mean()
63.         scores = scores/scores.sem()
64.         rating_CS[t][scores.index] = scores
65.     return rating_CS
66.
67. def target_rho(TS_ratings,ratings):
68. #     MW = TS_ratings[TS_ratings.notna()]
69. #     esg = ratings[TS_ratings[TS_ratings.notna()].index]
70.     rho = TS_ratings.T@ratings
71.     return rho
72.
73. def UCSts_weights(Ratings,Prices,Mkt_cap,Returns,TS_rating):
74.     rating_UCSts = pd.DataFrame(index = Ratings.index,columns =
    Ratings.columns)
75.     rhos = []
76.     for t in Ratings.columns:
77.         scores = screening(Ratings[t],Prices[t],Mkt_cap[t],Returns[t])
78.         scores = scores - scores.mean()
79.         rho = target_rho(TS_rating[t][scores.index],scores)
80.         rating_UCSts[t][scores.index] = scores/rho
81.         rhos.append(rho)
82.     rhos = pd.Series(rhos,index=Ratings.columns)
83.     return rating_UCSts,rhos
84.
85. ESG_TS=TS_weights(ESG,stocksPrices,stocksMkt_cap,stocksReturns)
86. E_TS=TS_weights(E,stocksPrices,stocksMkt_cap,stocksReturns)
87. S_TS=TS_weights(S,stocksPrices,stocksMkt_cap,stocksReturns)
88. G_TS=TS_weights(G,stocksPrices,stocksMkt_cap,stocksReturns)
89.
```

```python
90. writer =
    pd.ExcelWriter('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weig
    hts_TS.xlsx',
91.                                engine='xlsxwriter')
92.
93. ESG_TS.to_excel(writer, sheet_name='ESG')
94. E_TS.to_excel(writer, sheet_name='E')
95. S_TS.to_excel(writer, sheet_name='S')
96. G_TS.to_excel(writer, sheet_name='G')
97. writer.save()
98.
99. ESG_CS = UCS_weights(ESG,stocksPrices,stocksMkt_cap,stocksReturns)
100.        E_CS = UCS_weights(E,stocksPrices,stocksMkt_cap,stocksReturns)
101.        S_CS = UCS_weights(S,stocksPrices,stocksMkt_cap,stocksReturns)
102.        G_CS = UCS_weights(G,stocksPrices,stocksMkt_cap,stocksReturns)
103.
104.        writer =
    pd.ExcelWriter('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weig
    hts_CS.xlsx',
105.                                engine='xlsxwriter')
106.
107.        ESG_CS.to_excel(writer, sheet_name='ESG')
108.        E_CS.to_excel(writer, sheet_name='E')
109.        S_CS.to_excel(writer, sheet_name='S')
110.        G_CS.to_excel(writer, sheet_name='G')
111.        writer.save()
112.
113.        ESG_CSts,ESG_rhos =
    UCSts_weights(ESG,stocksPrices,stocksMkt_cap,stocksReturns,ESG_TS)
114.        E_CSts, E_rhos =
    UCSts_weights(E,stocksPrices,stocksMkt_cap,stocksReturns,ESG_TS)
115.        S_CSts,S_rhos =
    UCSts_weights(S,stocksPrices,stocksMkt_cap,stocksReturns,ESG_TS)
116.        G_CSts,G_rhos =
    UCSts_weights(G,stocksPrices,stocksMkt_cap,stocksReturns,ESG_TS)
117.
118.        writer =
    pd.ExcelWriter('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weig
    hts_CSts.xlsx',
119.                                engine='xlsxwriter')
120.
121.        ESG_CSts.to_excel(writer, sheet_name='ESG')
122.        E_CSts.to_excel(writer, sheet_name='E')
123.        S_CSts.to_excel(writer, sheet_name='S')
124.        G_CSts.to_excel(writer, sheet_name='G')
125.        writer.save()
126.
127.        def l2normTS(TS):
128.            l2norm =[]
129.            for t in TS.columns:
130.                l2norm.append(np.sqrt(np.dot(TS[t].loc[TS[t].notna()],TS[t].loc
    [TS[t].notna()].T)))
131.            l2norm = pd.Series(l2norm,index=TS.columns)
132.            return l2norm
133.
134.        def l2normCS(ratings,rho):
135.            l2norm=[]
136.            for t in ratings.columns:
137.                l2norm.append(abs(rho[t])/np.sqrt(np.dot(ratings[t].loc[ratings
    [t].notna()].T,
138.                                               ratings[t].loc[ratings
    [t].notna()])))
139.            l2norm = pd.Series(l2norm,index=ratings.columns)
140.            return l2norm
141.
142.        l2_norm_TS = pd.DataFrame({'ESG': l2normTS(ESG_TS),'E': l2normTS(E_TS),
```

```
143.                                          'S': l2normTS(S_TS), 'G':l2normTS(G_TS)})
144.       l2_norm_CSts = pd.DataFrame({'ESG': l2normCS(ESG_CSts,ESG_rhos), 'E':
    l2normCS(E_CSts,E_rhos),
145.                                          'S':
    l2normCS(S_CSts,S_rhos),'G':l2normCS(G_CSts,G_rhos)})
146.       l2_norm_TS.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis
    /Results/l2_norm_TS.csv')
147.       l2_norm_CSts.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analys
    is/Results/l2_norm_CSts.csv')
148.
149.       Assets_TS = pd.DataFrame(index=ESG_TS.columns, columns =
    ['ESG','E','S','G'])
150.       for t in ESG_TS.columns:
151.          Assets_TS['ESG'][t] =
    (ESG_TS[t].loc[(ESG_TS[t].notna())&(ESG_TS[t]!=0)]).count()
152.          Assets_TS['E'][t] =
    (E_TS[t].loc[(E_TS[t].notna())&(E_TS[t]!=0)]).count()
153.          Assets_TS['S'][t] =
    (S_TS[t].loc[(S_TS[t].notna())&(S_TS[t]!=0)]).count()
154.          Assets_TS['G'][t] =
    (G_TS[t].loc[(G_TS[t].notna())&(G_TS[t]!=0)]).count()
155.       Assets_CSts = pd.DataFrame({'ESG': ESG_CSts.count(),'E':
    E_CSts.count(),'S': S_CSts.count(),'G':G_CSts.count()})
156.       Assets_TS.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/
    Results/Assets_TS.csv')
157.       Assets_CSts.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysi
    s/Results/Assets_CSts.csv')
```

B.3 Time-series vs cross-sectional analysis

```
1.  import pandas as pd
2.  import numpy as np
3.  import statsmodels.api as sm
4.  import yfinance as yf
5.
6.  ####################################             LOAD             DATASETS
    ####################################################
7.  #EXCESS RETURNS
8.  r                                                                         =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOXX
    600_clean.xlsx',
9.                   sheet_name ='Excess', index_col = 0)
10. # Ratings
11. ESG                                                                       =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
12.                   sheet_name = 0, index_col = 0)
13. E                                                                         =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
14.                   sheet_name = 1, index_col = 0)
15. S                                                                         =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
16.                   sheet_name = 2, index_col = 0)
17. G                                                                         =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
18.                   sheet_name = 3, index_col = 0)
19. # TIME SERIES WEIGHTS
20. ESG_TS                                                                    =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
    ts_TS.xlsx',
21.                   sheet_name ='ESG', index_col = 0)
```

```python
22.  E_TS                                                                          =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_TS.xlsx',
23.                           sheet_name ='E', index_col = 0)
24.  S_TS                                                                          =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_TS.xlsx',
25.                           sheet_name ='S', index_col = 0)
26.  G_TS                                                                          =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_TS.xlsx',
27.                           sheet_name ='G', index_col = 0)
28.  # UNIVARATE CROSS SECTIONAL weights
29.  ESG_CS                                                                        =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_CS.xlsx',
30.                           sheet_name ='ESG', index_col = 0)
31.  E_CS                                                                          =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_CS.xlsx',
32.                           sheet_name ='E', index_col = 0)
33.  S_CS                                                                          =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_CS.xlsx',
34.                           sheet_name ='S', index_col = 0)
35.  G_CS                                                                          =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_CS.xlsx',
36.                           sheet_name ='G', index_col = 0)
37.  #UNIVARIATE CROSS SECTIONAL WITH TARGET TIME SERIES UCS(T.S.) weights
38.  ESG_CSts                                                                      =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_CSts.xlsx',
39.                           sheet_name ='ESG', index_col = 0)
40.  E_CSts                                                                        =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_CSts.xlsx',
41.                           sheet_name ='E', index_col = 0)
42.  S_CSts                                                                        =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_CSts.xlsx',
43.                           sheet_name ='S', index_col = 0)
44.  G_CSts                                                                        =
     pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
     ts_CSts.xlsx',
45.                           sheet_name ='G', index_col = 0)
46.
47.  ############################COMPUTING LAMDBAS ############################
48.  def OLS_reg (returns,ratings):
49.      """Given the excees stock returns and ESG score weights, the function
     perform the
50.      monthly OLS regression :
51.      r_t = Lambda_{0,t} * 1_{N,t-1} + Lambda_{1,t} * ESG_{t-1} + e_{t}"""
52.      results = []
53.      for t in returns.columns:
54.          stocks = ratings[t].loc[ratings[t].notna()].index
55.          X = ratings[t]
56.          X = sm.add_constant(X)
57.          Y = returns[t]
58.          model = sm.OLS(Y,X,missing='drop')
59.          res = model.fit(cov_type='HAC',cov_kwds={'maxlags':12})
60.          results.append(res)
61.      return results
62.
63.  def lambdas(returns,ratings,p=1):
64.      """Given the excess returns and the  ESG weights, compute the OLS regression
```

```python
65.     to define the ESG factor returns"""
66.     coef = []
67.     reg = OLS_reg(returns,ratings)
68.     for i in range(len(reg)):
69.         coef.append(reg[i].params[p])
70.     lambdas = pd.Series(coef,index = ratings.columns)
71.     #risolvo il warning sul tipo di frequenza
72.     lambdas.index                                                          =
    pd.DatetimeIndex(lambdas.index.values,freq=lambdas.index.inferred_freq)
73.     return lambdas
74.
75. def rsquared_adj(returns,ratings):
76.     """Given the excess returns and the  ESG weights, compute the OLS regression
77.     to define the ESG rsquared adjusted"""
78.     coef = []
79.     reg = OLS_reg (returns,ratings)
80.     for i in range(len(reg)):
81.         coef.append(reg[i].rsquared_adj)
82.     rsquared_adj = pd.Series(coef,index = ratings.columns)
83.     #risolvo il warning sul tipo di frequenza
84.     rsquared_adj.index                                                     =
    pd.DatetimeIndex(rsquared_adj.index.values,freq=rsquared_adj.index.inferred_fr
    eq)
85.     return rsquared_adj
86.
87. def model_tests(Y):
88.     """compute CAPM and FF6 regression on factor returns and gives as output
    the coef estimated and
89.     their p-values
90.     MODIFED: output results objects with all informations"""
91.     FF6                                                                    =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
    F_6_Factors.csv'
92.                           , index_col = 0 )
93.     FF6.index = Y.index
94.     RM = FF6[FF6.columns[0]]
95.     FF6.drop(columns = [FF6.columns[-1]], inplace = True)
96.     res_obj1 = []
97.     res_obj2 = []
98.     for col in Y.columns:
99.         y = Y[col]
100.         capm        =        sm.OLS(y,sm.add_constant(RM),missing        =
    'drop').fit(cov_type='HAC',cov_kwds={'maxlags':12})
101.        ff6         =        sm.OLS(y,sm.add_constant(FF6),missing        =
    'drop').fit(cov_type='HAC',cov_kwds={'maxlags':12})
102.            res_obj1.append(capm)
103.            res_obj2.append(ff6)
104.        return res_obj1,res_obj2
105.
106.    def long_short(rating):
107.        long=[]
108.        short=[]
109.        for t in rating.columns:
110.            long.append(rating[t].loc[rating[t]>0].mean())
111.            short.append(rating[t].loc[rating[t]<0].mean())
112.        long = pd.Series(long,index = rating.columns,name='Long')
113.        short = pd.Series(short,index = rating.columns,name='Short')
114.        long_short = pd.concat([long,short],axis = 1)
115.        return long_short
116.
117.    def KalmanFilter(Y,capm = True ):
118.        """Compute the Kalman filtering for alpha as a local trend
119.        output the regression fitted object
120.        """
121.        Y.index                                                            =
    pd.DatetimeIndex(Y.index.values,freq=Y.index.inferred_freq)
```

```python
122.            results = pd.DataFrame(index = Y.index,columns = Y.columns)
123.            if capm == True:
124.                RM                                                                              =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
    F_6_Factors.csv',
125.                                        index_col = 0 )['Mkt-RF']
126.                RM.index=Y.index
127.                for col in Y.columns:
128.                    mod = sm.tsa.UnobservedComponents(Y[col], 'llevel',exog=RM)
129.                    res = mod.fit(cov_type='approx')
130.                    results[col] = res.level.filtered
131.            else:
132.                ff6                                                                             =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
    F_6_Factors.csv',
133.                                        index_col = 0 )
134.                ff6.drop(columns = 'RF', inplace = True)
135.                ff6.index = Y.index
136.                for col in Y.columns:
137.                    mod = sm.tsa.UnobservedComponents(Y[col], 'llevel',exog=
    ff6 )
138.                    res = mod.fit(cov_type='approx')
139.                    results[col] = res.level.filtered
140.            return results
141.
142.        # FACTOR RETURNS
143.        lambdas_TS = pd.DataFrame({'ESG':lambdas(r,ESG_TS),
144.                                   'E':lambdas(r,E_TS),
145.                                   'S':lambdas(r,S_TS),
146.                                   'G':lambdas(r,G_TS)})
147.
148.        lambdas_CS = pd.DataFrame({'ESG':lambdas(r,ESG_CS),
149.                                   'E':lambdas(r,E_CS),
150.                                   'S':lambdas(r,S_CS),
151.                                   'G':lambdas(r,G_CS)})
152.
153.        lambdas_CSts = pd.DataFrame({'ESG':lambdas(r,ESG_CSts),
154.                                     'E':lambdas(r,E_CSts),
155.                                     'S':lambdas(r,S_CSts),
156.                                     'G':lambdas(r,G_CSts)})
157.
158.        # CAPM and FF6 test
159.        APT_TScapm,APT_TSff6 = model_tests(lambdas_TS)
160.        APT_CScapm, APT_CSff6 = model_tests(lambdas_CS)
161.        APT_CStscapm,APT_CStsff6 = model_tests(lambdas_CSts)
162.
163.        ################################## SAVE #######################
164.        # Saving Lambdas
165.        writer                                                                              =
    pd.ExcelWriter('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Results/F
    actor_Returns.xlsx',
166.                                 engine='xlsxwriter')
167.
168.        lambdas_TS.to_excel(writer, sheet_name='TimeSerie')
169.        lambdas_CS.to_excel(writer, sheet_name='UCS(1)')
170.        lambdas_CSts.to_excel(writer, sheet_name='UCS(TS)')
171.
172.        writer.save()
173.
174.        KLcapm_TS = KalmanFilter(lambdas_TS)
175.        KLcapm_CS = KalmanFilter(lambdas_CS)
176.        KLcapm_CSts = KalmanFilter(lambdas_CSts)
177.
178.        KLff6_TS = KalmanFilter(lambdas_TS, False)
179.        KLff6_CS = KalmanFilter(lambdas_CS, False)
180.        KLff6_CSts = KalmanFilter(lambdas_CSts, False)
```

```python
181.
182.         ################################# SAVE SOME DATA TO PLOTS ########
183.         T = pd.date_range(start='2005-01-01',periods = 204,freq='M')
184.         mux                                                            =
     pd.MultiIndex.from_product([['ESG','ESG_c','E','E_c','S','S_c','G','G_c'],
185.                                 ['TS', 'UCS(1)', 'UCS(TS)']])
186.
187.         ESG_capm_alphas = pd.DataFrame({'TS':KLcapm_TS.ESG,
188.                                 'UCS(1)':KLcapm_CS.ESG,
189.                                 'UCS(TS)':KLcapm_CSts.ESG},index = T)
190.         E_capm_alphas = pd.DataFrame({'TS':KLcapm_TS.E,
191.                                 'UCS(1)':KLcapm_CS.E,
192.                                 'UCS(TS)':KLcapm_CSts.E}, index = T)
193.         S_capm_alphas = pd.DataFrame({'TS':KLcapm_TS.S,
194.                                 'UCS(1)':KLcapm_CS.S,
195.                                 'UCS(TS)':KLcapm_CSts.S},index = T)
196.         G_capm_alphas = pd.DataFrame({'TS':KLcapm_TS.G,
197.                                 'UCS(1)':KLcapm_CS.G,
198.                                 'UCS(TS)':KLcapm_CSts.G}, index = T)
199.         Alphas_capm = pd.concat([ESG_capm_alphas,ESG_capm_alphas.cumsum(),
200.                                 E_capm_alphas,E_capm_alphas.cumsum(),
201.                                 S_capm_alphas,S_capm_alphas.cumsum(),
202.                                 G_capm_alphas,G_capm_alphas.cumsum()],axis    =
     1)
203.         Alphas_capm.columns = mux
204.         Alphas_capm.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysi
     s/Results/Alphas_capm.csv')
205.
206.         ESG_ff6_alphas = pd.DataFrame({'TS':KLff6_TS.ESG,
207.                                 'UCS(1)':KLff6_CS.ESG,
208.                                 'UCS(TS)':KLff6_CSts.ESG}, index = T)
209.         E_ff6_alphas = pd.DataFrame({'TS':KLff6_TS.E,
210.                                 'UCS(1)':KLff6_CS.E,
211.                                 'UCS(TS)':KLff6_CSts.E}, index = T)
212.         S_ff6_alphas = pd.DataFrame({'TS':KLff6_TS.S,
213.                                 'UCS(1)':KLff6_CS.S,
214.                                 'UCS(TS)':KLff6_CSts.S}, index = T)
215.         G_ff6_alphas = pd.DataFrame({'TS':KLff6_TS.G,
216.                                 'UCS(1)':KLff6_CS.G,
217.                                 'UCS(TS)':KLff6_CSts.G}, index = T)
218.         Alphas_ff6 = pd.concat([ESG_ff6_alphas,ESG_ff6_alphas.cumsum(),
219.                                 E_ff6_alphas,E_ff6_alphas.cumsum(),
220.                                 S_ff6_alphas,S_ff6_alphas.cumsum(),
221.                                 G_ff6_alphas,G_ff6_alphas.cumsum()],axis = 1)
222.         Alphas_ff6.columns = mux
223.         Alphas_ff6.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis
     /Results/Alphas_ff6.csv')
224.
225.         r2adj                                                          =
     pd.concat([rsquared_adj(r,ESG),rsquared_adj(r,E),rsquared_adj(r,S),rsquared_ad
     j(r,G)],axis = 1)
226.
227.         r2adj.columns = ['ESG','E','S','G']
228.         r2adj.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Resu
     lts/r2adj_rawESG.csv')
229.
230.         def lambdas_series(lambdas,capm,ff6):
231.             mean = lambdas.mean()
232.             median = lambdas.quantile(.5)
233.             std = lambdas.std()
234.             minm = lambdas.min()
235.             maxx = lambdas.max()
236.             a_capm = capm.params[0]
237.             b_capm = capm.params[1]
238.             a_ff6 = ff6.params[0]
```

```python
239.            return
     pd.Series({'mean':mean*100,'t_mean':np.sqrt(len(lambdas))*mean/std,
240.                               'median':median*100,'std':std*100,'min':minm*100,
     'max':maxx*100,
241.                               'a_capm':a_capm*100,'t_ac':capm.tvalues[0],'p_ac':
     capm.pvalues[0],
242.                               'b_capm':b_capm*100,'t_bc':capm.tvalues[1],'p_bc'
     :capm.pvalues[1],
243.                               'a_ff6':a_ff6*100,'t_af':ff6.tvalues[0],'p_af':ff
     6.pvalues[0],})
244.
245.        ESG_summary=pd.concat([lambdas_series(lambdas_TS.ESG,APT_TScapm[0],APT_
     TSff6[0]).round(4),
246.                              lambdas_series(lambdas_CS.ESG,APT_CScapm[0],APT_
     CSff6[0]).round(4),
247.                              lambdas_series(lambdas_CSts.ESG,APT_CStscapm[0],
     APT_CStsff6[0]).round(4)],
248.                              axis=1)
249.        E_summary=pd.concat([lambdas_series(lambdas_TS.E,APT_TScapm[1],APT_TSff
     6[1]).round(4),
250.                              lambdas_series(lambdas_CS.E,APT_CScapm[1],APT_CS
     ff6[1]).round(4),
251.                              lambdas_series(lambdas_CSts.E,APT_CStscapm[1],AP
     T_CStsff6[1]).round(4)],
252.                              axis=1)
253.        S_summary=pd.concat([lambdas_series(lambdas_TS.S,APT_TScapm[2],APT_TSff
     6[2]).round(4),
254.                              lambdas_series(lambdas_CS.S,APT_CScapm[2],APT_CS
     ff6[2]).round(4),
255.                              lambdas_series(lambdas_CSts.S,APT_CStscapm[2],AP
     T_CStsff6[2]).round(4)],
256.                              axis=1)
257.        G_summary=pd.concat([lambdas_series(lambdas_TS.G,APT_TScapm[3],APT_TSff
     6[3]).round(4),
258.                              lambdas_series(lambdas_CS.G,APT_CScapm[3],APT_CS
     ff6[3]).round(4),
259.                              lambdas_series(lambdas_CSts.G,APT_CStscapm[3],AP
     T_CStsff6[3]).round(4)],
260.                              axis=1)
261.        summary = pd.concat([ESG_summary,E_summary,S_summary,G_summary],axis=1)
262.        summary.columns                                                       =
     pd.MultiIndex.from_product([['ESG','E','S','G'],['T.S.', 'UCS','UCS(T.S.)']])
263.        summary.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Ta
     bles/TSvsCS_sum.csv')
```

B.4 UCS portfolios analysis

```python
1.  import pandas as pd
2.  import numpy as np
3.  import statsmodels.api as sm
4.
5.  def OLS_reg (returns,ratings):
6.      """Given the excees stock returns and ESG score weights, the function
    perform the
7.      monthly OLS regression :
8.      r_t = Lambda_{0,t} * 1_{N,t-1} + Lambda_{1,t} * ESG_{t-1} + e_{t}"""
9.      results = []
10.     for t in returns.columns:
11.         stocks = ratings[t].loc[ratings[t].notna()].index
12.         X = ratings[t]
13.         X = sm.add_constant(X)
14.         Y = returns[t]
15.         model = sm.OLS(Y,X, missing='drop')
16.         res = model.fit(cov_type='HAC',cov_kwds={'maxlags':12})
17.         results.append(res)
```

```python
18.      return results
19. def lambdas(returns,ratings):
20.      """Given the excess returns and the  ESG weights, compute the OLS regression
21.      to define the ESG factor returns"""
22.      coef = []
23.      reg = OLS_reg (returns,ratings)
24.      for i in range(len(reg)):
25.          coef.append(reg[i].params[1])
26.      lambdas = pd.Series(coef,index = ratings.columns)
27.      #risolvo il warning sul tipo di frequenza
28.      lambdas.index                                                          =
    pd.DatetimeIndex(lambdas.index.values,freq=lambdas.index.inferred_freq)
29.      return lambdas
30. def model_tests(Y):
31.      """compute CAPM and FF6 regression on factor returns and gives as output
    the coef estimated and
32.      their p-values
33.      MODIFED: output results objects with all informations"""
34.      FF6                                                                    =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
    F_6_Factors.csv'
35.                          , index_col = 0 )
36.      FF6.index = Y.index
37.      RM = FF6[FF6.columns[0]]
38.      FF6.drop(columns = [FF6.columns[-1]], inplace = True)
39.      res_obj1 = []
40.      res_obj2 = []
41.      for col in Y.columns:
42.          y = Y[col]
43.          capm                                                               =
    sm.OLS(y,sm.add_constant(RM)).fit(cov_type='HAC',cov_kwds={'maxlags':12})
44.          ff6                                                                =
    sm.OLS(y,sm.add_constant(FF6)).fit(cov_type='HAC',cov_kwds={'maxlags':12})
45.          res_obj1.append(capm)
46.          res_obj2.append(ff6)
47.      return res_obj1,res_obj2
48. def Kalman_Filter_CAPM(Y,starter = None ):
49.      """Compute the Kalman filtering for alpha as a local trend
50.      output the regression fitted object
51.      """
52.      FF6                                                                    =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
    F_6_Factors.csv'
53.                          , index_col = 0 )
54.      FF6.index = Y.index
55.      RM = FF6[FF6.columns[0]]
56.      results = pd.DataFrame(index = Y.index,columns = Y.columns)
57.      obj_res = []
58.      for col in Y.columns:
59.          mod = sm.tsa.UnobservedComponents(Y[col], 'llevel',exog= RM )
60.          res = mod.fit(start_params = starter )
61.          results[col] = res.level.filtered
62.          obj_res.append(res)
63.      return obj_res
64.
65. def Kalman_Filter_FF6(Y):
66.      """Compute the Kalman filtering for alpha as a local trend
67.      output the regression fitted object
68.      """
69.      FF6                                                                    =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
    F_6_Factors.csv'
70.                          , index_col = 0 )
71.      FF6.drop(columns = 'RF', inplace = True)
72.      FF6.index = Y.index
73.      results = pd.DataFrame(index = Y.index,columns = Y.columns)
```

```python
74.      obj_res = []
75.      for col in Y.columns:
76.          mod = sm.tsa.UnobservedComponents(Y[col], 'llevel',exog= FF6)
77.          res = mod.fit()
78.          results[col] = res.level.filtered
79.          obj_res.append(res)
80.      return obj_res
81. def long_short(rating):
82.      long=[]
83.      short=[]
84.      for t in rating.columns:
85.          long.append(rating[t].loc[rating[t]>0].mean())
86.          short.append(rating[t].loc[rating[t]<0].mean())
87.      long = pd.Series(long,index = rating.columns,name='Long')
88.      short = pd.Series(short,index = rating.columns,name='Short')
89.      long_short = pd.concat([long,short],axis = 1)
90.      return long_short
91.
92. ESG                                                                =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
93.                  sheet_name = 'ESG', index_col = 0)
94.
95. E                                                                  =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
96.                  sheet_name = 'E', index_col = 0)
97.
98. S                                                                  =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
99.                  sheet_name = 'S', index_col = 0)
100.
101.      G                                                            =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
102.                  sheet_name = 'G', index_col = 0)
103.
104.      r
    =    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/ST
    OXX600_clean.xlsx',
105.                  sheet_name = 'Excess', index_col = 0)
106.
107.      ESG = ESG -ESG.mean()
108.      E = E - E.mean()
109.      S = S - S.mean()
110.      G = G - G.mean()
111.
112.      ESG_brown =  ESG/ESG.quantile(.25)
113.      E_brown =  E/E.quantile(.25)
114.      S_brown =  S/S.quantile(.25)
115.      G_brown =  G/G.quantile(.25)
116.
117.      ESG_green =  ESG/ESG.quantile(.75)
118.      E_green =  E/E.quantile(.75)
119.      S_green =  S/S.quantile(.75)
120.      G_green =  G/G.quantile(.75)
121.
122.      ESG_h =  ESG/ESG.quantile(.9)
123.      E_h =  E/E.quantile(.9)
124.      S_h =  S/S.quantile(.9)
125.      G_h =  G/G.quantile(.9)
126.
127.      mux       =       pd.MultiIndex.from_product([['ESG','E','S','G'],['25',
    '75','90']])
```

```python
128.    Ratings_rhos=
        pd.concat([ESG.quantile(.25),ESG.quantile(.75),ESG.quantile(.9),
129.                    E.quantile(.25),E.quantile(.75),E.quantile(.9),
130.                    S.quantile(.25),S.quantile(.75),S.quantile(.9),
131.                    G.quantile(.25),G.quantile(.75),G.quantile(.9)],axis=1)
132.    Ratings_rhos.columns = mux
133.    Ratings_rhos.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analys
        is/Results/Ratings_rhos.csv')
134.
135.    lambdas_brown = pd.DataFrame({'ESG':lambdas(r,ESG_brown),
136.                                   'E':lambdas(r,E_brown),
137.                                   'S':lambdas(r,S_brown),
138.                                   'G':lambdas(r,G_brown)})
139.
140.    lambdas_green = pd.DataFrame({'ESG':lambdas(r,ESG_green),
141.                                   'E':lambdas(r,E_green),
142.                                   'S':lambdas(r,S_green),
143.                                   'G':lambdas(r,G_green)})
144.
145.    lambdas_h = pd.DataFrame({'ESG':lambdas(r,ESG_h),
146.                               'E':lambdas(r,E_h),
147.                               'S':lambdas(r,S_h),
148.                               'G':lambdas(r,G_h)})
149.
150.    APT_bcapm,APT_bff6 = model_tests(lambdas_brown)
151.    APT_gcapm, APT_gff6 = model_tests(lambdas_green)
152.    APT_hcapm,APT_hff6 = model_tests(lambdas_h)
153.
154.    #Kalman Filter CAPM
155.    KLcapm_b = Kalman_Filter_CAPM(lambdas_brown)
156.    KLcapm_g = Kalman_Filter_CAPM(lambdas_green)
157.    KLcapm_h = Kalman_Filter_CAPM(lambdas_h)
158.
159.    #Kalman Filter FF6
160.    KLff6_b = Kalman_Filter_FF6(lambdas_brown)
161.    KLff6_g = Kalman_Filter_FF6(lambdas_green)
162.    KLff6_h = Kalman_Filter_FF6(lambdas_h)
163.
164.    # Saving Lambdas
165.    writer                                                                =
        pd.ExcelWriter('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Results/F
        actor_Returns_Chasing.xlsx',
166.                                    engine='xlsxwriter')
167.
168.    lambdas_brown.to_excel(writer, sheet_name='UCS(25)')
169.    lambdas_green.to_excel(writer, sheet_name='UCS(75)')
170.    lambdas_h.to_excel(writer, sheet_name='UCS(90)')
171.
172.    writer.save()
173.
174.    T = pd.date_range(start='2005-01-01',periods = 204,freq='M')
175.    mux                                                                  =
        pd.MultiIndex.from_product([['ESG','ESG_c','E','E_c','S','S_c','G','G_c'],
176.                                    ['UCS(25)', 'UCS(75)', 'UCS(90)']])
177.
178.    ESG_capm_alphas = pd.DataFrame({'TS':KLcapm_b[0].level.filtered,
179.                                     'UCS(1)':KLcapm_g[0].level.filtered,
180.                                     'UCS(TS)':KLcapm_h[0].level.filtered},
        index = T)
181.    E_capm_alphas = pd.DataFrame({'TS':KLcapm_b[1].level.filtered,
182.                                   'UCS(1)':KLcapm_g[1].level.filtered,
183.                                   'UCS(TS)':KLcapm_h[1].level.filtered},
        index = T)
184.    S_capm_alphas = pd.DataFrame({'TS':KLcapm_b[2].level.filtered,
185.                                   'UCS(1)':KLcapm_g[2].level.filtered,
```

```python
186.                                          'UCS(TS)':KLcapm_h[2].level.filtered},
     index = T)
187.        G_capm_alphas = pd.DataFrame({'TS':KLcapm_b[3].level.filtered,
188.                                       'UCS(1)':KLcapm_g[3].level.filtered,
189.                                       'UCS(TS)':KLcapm_h[3].level.filtered},
     index = T)
190.        Alphas_capm = pd.concat([ESG_capm_alphas,ESG_capm_alphas.cumsum(),
191.                                 E_capm_alphas,E_capm_alphas.cumsum(),
192.                                 S_capm_alphas,S_capm_alphas.cumsum(),
193.                                 G_capm_alphas,G_capm_alphas.cumsum()],axis    =
     1)
194.        Alphas_capm.columns = mux
195.        Alphas_capm.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysi
     s/Results/Alphas_capm_chasing.csv')
196.
197.        ESG_ff6_alphas = pd.DataFrame({'UCS(25)':KLff6_b[0].level.filtered,
198.                                       'UCS(75)':KLff6_g[0].level.filtered,
199.                                       'UCS(90)':KLff6_h[0].level.filtered},
     index = T)
200.        E_ff6_alphas = pd.DataFrame({'UCS(25)':KLff6_b[1].level.filtered,
201.                                     'UCS(75)':KLff6_g[1].level.filtered,
202.                                     'UCS(90)':KLff6_h[1].level.filtered},
     index = T)
203.        S_ff6_alphas = pd.DataFrame({'UCS(25)':KLff6_b[2].level.filtered,
204.                                     'UCS(75)':KLff6_g[2].level.filtered,
205.                                     'UCS(90)':KLff6_h[2].level.filtered},
     index = T)
206.        G_ff6_alphas = pd.DataFrame({'UCS(25)':KLff6_b[3].level.filtered,
207.                                     'UCS(75)':KLff6_g[3].level.filtered,
208.                                     'UCS(90)':KLff6_h[3].level.filtered},
     index = T)
209.        Alphas_ff6 = pd.concat([ESG_ff6_alphas,ESG_ff6_alphas.cumsum(),
210.                                E_ff6_alphas,E_ff6_alphas.cumsum(),
211.                                S_ff6_alphas,S_ff6_alphas.cumsum(),
212.                                G_ff6_alphas,G_ff6_alphas.cumsum()],axis = 1)
213.        Alphas_ff6.columns = mux
214.        Alphas_ff6.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis
     /Results/Alphas_ff6_chasing.csv')
215.
216.        # Two legs of the UCS(90)  portfolio for each rating
217.        UCS_legs                                                              =
     pd.concat([long_short(ESG_h),long_short(ESG_h),long_short(ESG_h),long_short(ES
     G_h)], axis = 1)
218.        mux     =      pd.MultiIndex.from_product([['ESG','E','S','G'],['long',
     'short']])
219.        UCS_legs.columns =mux
220.        UCS_legs.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/R
     esults/UCS90_legs.csv')
221.
222.        def lambdas_series(lambdas,capm,ff6):
223.            mean = lambdas.mean()
224.            median = lambdas.quantile(.5)
225.            std = lambdas.std()
226.            minm = lambdas.min()
227.            maxx = lambdas.max()
228.            a_capm = capm.params[0]
229.            b_capm = capm.params[1]
230.            a_ff6 = ff6.params[0]
231.            return
     pd.Series({'mean':mean*100,'t_mean':np.sqrt(len(lambdas_brown.ESG))*mean/std,
232.                       'median':median*100,'std':std*100,'min':minm*100,
     'max':maxx*100,
233.                       'a_capm':a_capm*100,'t_ac':capm.tvalues[0],'p_ac':
     capm.pvalues[0],
234.                       'b_capm':b_capm*100,'t_bc':capm.tvalues[1],'p_bc'
     :capm.pvalues[1],
```

```
235.                             'a_ff6':a_ff6*100,'t_af':ff6.tvalues[0],'p_af':ff
    6.pvalues[0],})
236.
237.       ESG_summary=pd.concat([lambdas_series(lambdas_brown.ESG,APT_bcapm[0],AP
    T_bff6[0]).round(4),
238.                          lambdas_series(lambdas_green.ESG,APT_gcapm[0],AP
    T_gff6[0]).round(4),
239.                          lambdas_series(lambdas_h.ESG,APT_hcapm[0],APT_hf
    f6[0]).round(4)],
240.                          axis=1)
241.       E_summary=pd.concat([lambdas_series(lambdas_brown.E,APT_bcapm[1],APT_bf
    f6[1]).round(4),
242.                          lambdas_series(lambdas_green.E,APT_gcapm[1],APT_
    gff6[1]).round(4),
243.                          lambdas_series(lambdas_h.E,APT_hcapm[1],APT_hff6
    [1]).round(4)],
244.                          axis=1)
245.       S_summary=pd.concat([lambdas_series(lambdas_brown.S,APT_bcapm[2],APT_bf
    f6[2]).round(4),
246.                          lambdas_series(lambdas_green.S,APT_gcapm[2],APT_
    gff6[2]).round(4),
247.                          lambdas_series(lambdas_h.S,APT_hcapm[2],APT_hff6
    [2]).round(4)],
248.                          axis=1)
249.       G_summary=pd.concat([lambdas_series(lambdas_brown.G,APT_bcapm[3],APT_bf
    f6[3]).round(4),
250.                          lambdas_series(lambdas_green.G,APT_gcapm[3],APT_
    gff6[3]).round(4),
251.                          lambdas_series(lambdas_h.G,APT_hcapm[3],APT_hff6
    [3]).round(4)],
252.                          axis=1)
253.       summary = pd.concat([ESG_summary,E_summary,S_summary,G_summary],axis=1)
254.       summary.columns                                                       =
    pd.MultiIndex.from_product([['ESG','E','S','G'],['25', '75','90']])
255.       summary.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Ta
    bles/Chasing_sum.csv')
```

B.5 Additional multivariate analysis on T.S. vas C.S. approach

```
1.  import numpy as np
2.  import pandas as pd
3.  import pandas_datareader as pdr
4.  import statsmodels.api as sm
5.
6.  FF6                                                                        =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Europe_
    6_Factors.csv',
7.                  index_col= 0, parse_dates = True,infer_datetime_format=True)
8.  FF6.index=pd.date_range(start='2004-01-01',periods =216, freq='M')
9.  FF6.index=pd.date_range(start='2004-01-01',periods =216, freq='M')
10.
11. stockPrices                                                                =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOXX
    600.xlsx',
12.                  sheet_name = 3, index_col = 0, parse_dates = True)
13.
14. stockPrices.interpolate(method = 'linear',inplace = True)
15. stockReturns = stockPrices.pct_change(1)
16. stockReturns = stockReturns.loc[stockReturns.index.year >= 2004]
17. stockExcess = stockReturns.copy()
18. stockExcess.index = pd.date_range(start='2004-01-01',periods =216, freq='M')
19. for stock in stockExcess.columns:
20.     stockExcess[stock] = stockExcess[stock] - FF6['RF']
21. stockExcess.dropna(how='all',axis=1,inplace=True)
22.
```

```python
23. from statsmodels.regression.rolling import RollingOLS
24. exog = sm.add_constant(FF6[['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA', 'WML']])
25. betas = []
26. for i in stockExcess.columns:
27.     endog = stockExcess[i]
28.     rols = RollingOLS(endog, exog, window=12,missing='drop')
29.     rres = rols.fit()
30.     params = rres.params.copy()
31.     params.index = pd.date_range(start='2004-01-01',periods =216, freq='M')
32.     betas.append(params)
33.
34. mux = pd.MultiIndex.from_product([list(stockExcess.columns),
35.                                   ['Mkt-RF', 'SMB', 'HML','RMW','CMA','WML']])
36. betas = pd.concat(betas,axis=1)
37. betas.drop(columns = 'const',inplace = True)
38. betas.columns = mux
39. betas.index.name ='Dates'
40.
41. betas.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Charat
    eristics.csv')
42.
43. def rating_NPR(rating):
44.     """rating_NPR function compute percentile ranks of row annual scores to
    normalize the rating
45.     distribution and rescale them between 0 and 1 and computing the rating
    monthly values"""
46.     for t in rating.columns:
47.         rating[t].loc[rating[t].notna()]=
    (rating[t].rank(numeric_only=True).dropna()-np.dot(-
    .5,np.ones(rating[t].count())))/rating[t].count()
48.     return rating
49.
50. betas
    =pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Charat
    eristics.csv',
51.               index_col=0,header=[0,1],            parse_dates            =
    True,infer_datetime_format=True)
52. betas.dropna(how='all',inplace=True)
53. betas.drop(index = betas.index[0],inplace=True)
54.
55. Mkt_rf = betas.iloc[:,0:betas.shape[1]:6].T
56. SMB = betas.iloc[:,1:betas.shape[1]:6].T
57. HML = betas.iloc[:,2:betas.shape[1]:6].T
58. RMW = betas.iloc[:,3:betas.shape[1]:6].T
59. CMA = betas.iloc[:,4:betas.shape[1]:6].T
60. WML = betas.iloc[:,5:betas.shape[1]:6].T
61.
62. stocks = Mkt_rf.index.unique(0)
63. Mkt_rf.index = stocks
64. SMB.index = stocks
65. HML.index = stocks
66. RMW.index = stocks
67. CMA.index = stocks
68. WML.index = stocks
69.
70. Mkt_rf = (rating_NPR(Mkt_rf) - rating_NPR(Mkt_rf).mean())
71. SMB = (rating_NPR(SMB) - rating_NPR(SMB).mean())
72. HML = (rating_NPR(HML) - rating_NPR(HML).mean())
73. RMW = (rating_NPR(RMW) - rating_NPR(RMW).mean())
74. CMA = (rating_NPR(CMA) - rating_NPR(CMA).mean())
75. WML = (rating_NPR(WML) - rating_NPR(WML).mean())
76.
77. r                                                                          =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOXX
    600_clean.xlsx',
78.                        sheet_name ='Excess', index_col = 0)
```

```python
79.
80. ESG_CS                                                                    =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
    ts_CS.xlsx',
81.                        sheet_name ='ESG', index_col = 0)
82. E_CS                                                                      =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
    ts_CS.xlsx',
83.                        sheet_name ='E', index_col = 0)
84. S_CS                                                                      =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
    ts_CS.xlsx',
85.                        sheet_name ='S', index_col = 0)
86. G_CS                                                                      =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
    ts_CS.xlsx',
87.                        sheet_name ='G', index_col = 0)
88.
89. ESG_CSts                                                                  =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
    ts_CSts.xlsx',
90.                        sheet_name ='ESG', index_col = 0)
91. E_CSts                                                                    =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
    ts_CSts.xlsx',
92.                        sheet_name ='E', index_col = 0)
93. S_CSts                                                                    =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
    ts_CSts.xlsx',
94.                        sheet_name ='S', index_col = 0)
95. G_CSts                                                                    =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Weigh
    ts_CSts.xlsx',
96.                        sheet_name ='G', index_col = 0)
97.
98. def OLS_reg (returns,ratings,Mkt_rf,SMB,HML,RMW,CMA,WML):
99.     """Given the excees stock returns and ESG score weights, the function
    perform the
100.          monthly OLS regression :
101.          r_t = Lambda_{0,t} * 1_{N,t-1} + Lambda_{1,t} * ESG_{t-1} + e_{t}"""
102.          results = []
103.          for t in ratings.columns:
104.              X                                                           =
    pd.concat([ratings[t],Mkt_rf[t],SMB[t],HML[t],RMW[t],CMA[t],WML[t]],axis=1)
105.              X = sm.add_constant(X)
106.              Y = returns[t]
107.              model = sm.OLS(Y,X,missing='drop')
108.              res = model.fit(cov_type='HAC',cov_kwds={'maxlags':12})
109.              results.append(res)
110.          return results
111.
112.     def lambdas(returns,ratings,Mkt_rf,SMB,HML,RMW,CMA,WML,p=1):
113.          """Given the excess returns and the  ESG weights, compute the OLS
    regression
114.          to define the ESG factor returns"""
115.          coef = []
116.          reg = OLS_reg (returns,ratings,Mkt_rf,SMB,HML,RMW,CMA,WML)
117.          for i in range(len(reg)):
118.              coef.append(reg[i].params[p])
119.          lambdas = pd.Series(coef,index = ratings.columns)
120.          lambdas.index                                                   =
    pd.DatetimeIndex(lambdas.index.values,freq=lambdas.index.inferred_freq)
121.          return lambdas
122.     def model_tests(Y):
123.          """compute CAPM and FF6 regression on factor returns and gives as
    output the coef estimated and
```

```
124.              their p-values
125.              MODIFED: output results objects with all informations"""
126.         FF6                                                            =
     pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
     F_6_Factors.csv'
127.                              , index_col = 0 )
128.         FF6.index = Y.index
129.         RM = FF6[FF6.columns[0]]
130.         FF6.drop(columns = [FF6.columns[-1]], inplace = True)
131.         res_obj1 = []
132.         res_obj2 = []
133.         for col in Y.columns:
134.             y = Y[col]
135.             capm                                                       =
     sm.OLS(y,sm.add_constant(RM)).fit(cov_type='HAC',cov_kwds={'maxlags':12})
136.             ff6                                                        =
     sm.OLS(y,sm.add_constant(FF6)).fit(cov_type='HAC',cov_kwds={'maxlags':12})
137.             res_obj1.append(capm)
138.             res_obj2.append(ff6)
139.         return res_obj1,res_obj2
140.
141.     def Kalman_Filter_CAPM(Y,starter = None ):
142.         """Compute the Kalman filtering for alpha as a local trend
143.         output the regression fitted object
144.         """
145.         FF6                                                            =
     pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
     F_6_Factors.csv'
146.                              , index_col = 0 )
147.         FF6.index = Y.index
148.         RM = FF6[FF6.columns[0]]
149.         results = pd.DataFrame(index = Y.index,columns = Y.columns)
150.         obj_res = []
151.         for col in Y.columns:
152.             mod = sm.tsa.UnobservedComponents(Y[col], 'llevel',exog= RM )
153.             res = mod.fit(start_params = starter )
154.             results[col] = res.level.filtered
155.             obj_res.append(res)
156.         return obj_res
157.
158.     def Kalman_Filter_FF6(Y):
159.         """Compute the Kalman filtering for alpha as a local trend
160.         output the regression fitted object
161.         """
162.         FF6                                                            =
     pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
     F_6_Factors.csv'
163.                              , index_col = 0 )
164.         FF6.drop(columns = 'RF', inplace = True)
165.         FF6.index = Y.index
166.         results = pd.DataFrame(index = Y.index,columns = Y.columns)
167.         obj_res = []
168.         for col in Y.columns:
169.             mod = sm.tsa.UnobservedComponents(Y[col], 'llevel',exog= FF6)
170.             res = mod.fit()
171.             results[col] = res.level.filtered
172.             obj_res.append(res)
173.         return obj_res
174.
175.     def lambdas_series(lambdas,capm,ff6):
176.         mean = lambdas.mean()
177.         median = lambdas.quantile(.5)
178.         std = lambdas.std()
179.         minm = lambdas.min()
180.         maxx = lambdas.max()
181.         a_capm = capm.params[0]
```

```
182.            b_capm = capm.params[1]
183.            a_ff6 = ff6.params[0]
184.            return
     pd.Series({'mean':mean*100,'t_mean':np.sqrt(len(lambdas))*mean/std,
185.                            'median':median*100,'std':std*100,'min':minm*100,
     'max':maxx*100,
186.                            'a_capm':a_capm*100,'t_ac':capm.tvalues[0],'p_ac':
     capm.pvalues[0],
187.                            'b_capm':b_capm*100,'t_bc':capm.tvalues[1],'p_bc'
     :capm.pvalues[1],
188.                            'a_ff6':a_ff6*100,'t_af':ff6.tvalues[0],'p_af':ff
     6.pvalues[0],})
189.
190.        lambdas_MCS                                                        =
     pd.DataFrame({'ESG':lambdas(r,ESG_CS,Mkt_rf,SMB,HML,RMW,CMA,WML),
191.                            'E':lambdas(r,E_CS,Mkt_rf,SMB,HML,RMW,CMA,WML
     ),
192.                            'S':lambdas(r,S_CS,Mkt_rf,SMB,HML,RMW,CMA,WML
     ),
193.                            'G':lambdas(r,G_CS,Mkt_rf,SMB,HML,RMW,CMA,WML
     )})
194.
195.        lambdas_MCSts                                                      =
     pd.DataFrame({'ESG':lambdas(r,ESG_CSts,Mkt_rf,SMB,HML,RMW,CMA,WML),
196.                            'E':lambdas(r,E_CSts,Mkt_rf,SMB,HML,RMW,CMA,W
     ML),
197.                            'S':lambdas(r,S_CSts,Mkt_rf,SMB,HML,RMW,CMA,W
     ML),
198.                            'G':lambdas(r,G_CSts,Mkt_rf,SMB,HML,RMW,CMA,W
     ML)})
199.
200.        # CAPM and FF6 test
201.        APT_MCScapm, APT_MCSff6 = model_tests(lambdas_MCS)
202.        APT_MCStscapm,APT_MCStsff6 = model_tests(lambdas_MCSts)
203.
204.        #Kalman Filter CAPM
205.        KLcapm_MCS = Kalman_Filter_CAPM(lambdas_MCS)
206.        KLcapm_MCSts = Kalman_Filter_CAPM(lambdas_MCSts)
207.
208.        #Kalman Filter FF6
209.        KLff6_MCS = Kalman_Filter_FF6(lambdas_MCS)
210.        KLff6_MCSts = Kalman_Filter_FF6(lambdas_MCSts)
211.
212.        TS_capm                                                            =
     pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Results/Alph
     as_capm.csv',
213.                        index_col=0,header=[0,1],parse_dates=True)
214.        TS_ff6                                                             =
     pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Results/Alph
     as_ff6.csv',
215.                        index_col=0,header=[0,1],parse_dates=True)
216.
217.        #################################### SAVE  SOME  DATA  TO  PLOTS
     ####################################
218.        T = pd.date_range(start='2005-01-01',periods = 204,freq='M')
219.        mux                                                                =
     pd.MultiIndex.from_product([['ESG','ESG_c','E','E_c','S','S_c','G','G_c'],
220.                                    ['TS','MCS(1)', 'MCS(TS)']])
221.
222.        ESG_capm_alphas = pd.DataFrame({'MCS(1)':KLcapm_MCS[0].level.filtered,
223.                            'MCS(TS)':KLcapm_MCSts[0].level.filtered
     }, index = T)
224.        E_capm_alphas = pd.DataFrame({'MCS(1)':KLcapm_MCS[1].level.filtered,
225.                            'MCS(TS)':KLcapm_MCSts[1].level.filtered
     }, index = T)
226.        S_capm_alphas = pd.DataFrame({'MCS(1)':KLcapm_MCS[2].level.filtered,
```

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227.                                             'MCS(TS)':KLcapm_MCSts[2].level.filtered
    }, index = T)
228.         G_capm_alphas = pd.DataFrame({'MCS(1)':KLcapm_MCS[3].level.filtered,
229.                                       'MCS(TS)':KLcapm_MCSts[3].level.filtered
    }, index = T)
230.
231.         ESG_capm_alphas = pd.concat([TS_capm.ESG.TS,ESG_capm_alphas],axis=1)
232.         E_capm_alphas = pd.concat([TS_capm.E.TS,E_capm_alphas],axis=1)
233.         S_capm_alphas = pd.concat([TS_capm.S.TS,S_capm_alphas],axis=1)
234.         G_capm_alphas = pd.concat([TS_capm.G.TS,G_capm_alphas],axis=1)
235.
236.         Alphas_Mcapm = pd.concat([ESG_capm_alphas,ESG_capm_alphas.cumsum(),
237.                                   E_capm_alphas,E_capm_alphas.cumsum(),
238.                                   S_capm_alphas,S_capm_alphas.cumsum(),
239.                                   G_capm_alphas,G_capm_alphas.cumsum()],axis    =
    1)
240.         Alphas_Mcapm.columns = mux
241.
242.         ESG_ff6_alphas = pd.DataFrame({'MCS(1)':KLff6_MCS[0].level.filtered,
243.                                        'MCS(TS)':KLff6_MCSts[0].level.filtered}
    , index = T)
244.         E_ff6_alphas = pd.DataFrame({'MCS(1)':KLff6_MCS[1].level.filtered,
245.                                      'MCS(TS)':KLff6_MCSts[1].level.filtered}
    , index = T)
246.         S_ff6_alphas = pd.DataFrame({'MCS(1)':KLff6_MCS[2].level.filtered,
247.                                      'MCS(TS)':KLff6_MCSts[2].level.filtered}
    , index = T)
248.         G_ff6_alphas = pd.DataFrame({'MCS(1)':KLff6_MCS[3].level.filtered,
249.                                      'MCS(TS)':KLff6_MCSts[3].level.filtered}
    , index = T)
250.         ESG_ff6_alphas = pd.concat([TS_ff6.ESG.TS,ESG_ff6_alphas],axis=1)
251.         E_ff6_alphas = pd.concat([TS_ff6.E.TS,E_ff6_alphas],axis=1)
252.         S_ff6_alphas = pd.concat([TS_ff6.S.TS,S_ff6_alphas],axis=1)
253.         G_ff6_alphas = pd.concat([TS_ff6.G.TS,G_ff6_alphas],axis=1)
254.
255.         Alphas_Mff6 = pd.concat([ESG_ff6_alphas,ESG_ff6_alphas.cumsum(),
256.                                  E_ff6_alphas,E_ff6_alphas.cumsum(),
257.                                  S_ff6_alphas,S_ff6_alphas.cumsum(),
258.                                  G_ff6_alphas,G_ff6_alphas.cumsum()],axis = 1)
259.         Alphas_Mff6.columns = mux
260.
261.         Alphas_Mff6.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysi
    s/Results/Alphas_Mff6.csv')
262.         Alphas_Mcapm.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analys
    is/Results/Alphas_Mcapm.csv')
263.
264.         ESG_summary=pd.concat([lambdas_series(lambdas_MCS.ESG,APT_MCScapm[0],AP
    T_MCSff6[0]).round(4),
265.                                lambdas_series(lambdas_MCSts.ESG,APT_MCStscapm[0
    ],APT_MCStsff6[0]).round(4)],
266.                               axis=1)
267.         E_summary=pd.concat([lambdas_series(lambdas_MCS.E,APT_MCScapm[1],APT_MC
    Sff6[1]).round(4),
268.                              lambdas_series(lambdas_MCSts.E,APT_MCStscapm[1],
    APT_MCStsff6[1]).round(4)],
269.                             axis=1)
270.         S_summary=pd.concat([lambdas_series(lambdas_MCS.S,APT_MCScapm[2],APT_MC
    Sff6[2]).round(4),
271.                              lambdas_series(lambdas_MCSts.S,APT_MCStscapm[2],
    APT_MCStsff6[2]).round(4)],
272.                             axis=1)
273.         G_summary=pd.concat([lambdas_series(lambdas_MCS.G,APT_MCScapm[3],APT_MC
    Sff6[3]).round(4),
274.                              lambdas_series(lambdas_MCSts.G,APT_MCStscapm[3],
    APT_MCStsff6[3]).round(4)],
275.                             axis=1)
```

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```
276.        summary = pd.concat([ESG_summary,E_summary,S_summary,G_summary],axis=1)
277.        summary.columns                                                         =
     pd.MultiIndex.from_product([['ESG','E','S','G'],['MCS(1)', 'MCS(T)']])
278.        summary.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Ta
     bles/MCS_sum.csv')
```

B.6 Additional multivariate analysis on target portfolios

```
1.  import pandas as pd
2.  import numpy as np
3.  import statsmodels.api as sm
4.
5.  def rating_NPR(rating):
6.      """rating_NPR function compute percentile ranks of row annual scores to
    normalize the rating
7.      distribution and rescale them between 0 and 1 and computing the rating
    monthly values"""
8.      for t in rating.columns:
9.          rating[t].loc[rating[t].notna()]=
    (rating[t].rank(numeric_only=True).dropna()-np.dot(-
    .5,np.ones(rating[t].count())))/rating[t].count()
10.     return rating
11.
12. def OLS_reg (returns,ratings,Mkt_rf,SMB,HML,RMW,CMA,WML):
13.     """Given the excees stock returns and ESG score weights, the function
    perform the
14.     monthly OLS regression :
15.     r_t = Lambda_{0,t} * 1_{N,t-1} + Lambda_{1,t} * ESG_{t-1} + e_{t}"""
16.     results = []
17.     for t in ratings.columns:
18.         X                                                                  =
    pd.concat([ratings[t],Mkt_rf[t],SMB[t],HML[t],RMW[t],CMA[t],WML[t]],axis=1)
19.         X = sm.add_constant(X)
20.         Y = returns[t]
21.         model = sm.OLS(Y,X,missing='drop')
22.         res = model.fit(cov_type='HAC',cov_kwds={'maxlags':12})
23.         results.append(res)
24.     return results
25.
26. def lambdas(returns,ratings,Mkt_rf,SMB,HML,RMW,CMA,WML):
27.     """Given the excess returns and the  ESG weights, compute the OLS regression
28.     to define the ESG factor returns"""
29.     coef = []
30.     reg = OLS_reg (returns,ratings,Mkt_rf,SMB,HML,RMW,CMA,WML)
31.     for i in range(len(reg)):
32.         coef.append(reg[i].params[1])
33.     lambdas = pd.Series(coef,index = ratings.columns)
34.     lambdas.index                                                          =
    pd.DatetimeIndex(lambdas.index.values,freq=lambdas.index.inferred_freq)
35.     return lambdas
36.
37. def model_tests(Y):
38.     """compute CAPM and FF6 regression on factor returns and gives as output
    the coef estimated and
39.     their p-values
40.     MODIFED: output results objects with all informations"""
41.     FF6                                                                    =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
    F_6_Factors.csv'
42.                            , index_col = 0 )
43.     FF6.index = Y.index
44.     RM = FF6[FF6.columns[0]]
45.     FF6.drop(columns = [FF6.columns[-1]], inplace = True)
46.     res_obj1 = []
47.     res_obj2 = []
```

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48.     for col in Y.columns:
49.         y = Y[col]
50.         capm                                                              =
   sm.OLS(y,sm.add_constant(RM)).fit(cov_type='HAC',cov_kwds={'maxlags':12})
51.         ff6                                                               =
   sm.OLS(y,sm.add_constant(FF6)).fit(cov_type='HAC',cov_kwds={'maxlags':12})
52.         res_obj1.append(capm)
53.         res_obj2.append(ff6)
54.     return res_obj1,res_obj2
55.
56. def Kalman_Filter_CAPM(Y,starter = None ):
57.     """Compute the Kalman filtering for alpha as a local trend
58.     output the regression fitted object
59.     """
60.     FF6                                                                   =
   pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
   F_6_Factors.csv'
61.                         , index_col = 0 )
62.     FF6.index = Y.index
63.     RM = FF6[FF6.columns[0]]
64.     results = pd.DataFrame(index = Y.index,columns = Y.columns)
65.     obj_res = []
66.     for col in Y.columns:
67.         mod = sm.tsa.UnobservedComponents(Y[col], 'llevel',exog= RM )
68.         res = mod.fit(start_params = starter )
69.         results[col] = res.level.filtered
70.         obj_res.append(res)
71.     return obj_res
72.
73. def Kalman_Filter_FF6(Y):
74.     """Compute the Kalman filtering for alpha as a local trend
75.     output the regression fitted object
76.     """
77.     FF6                                                                   =
   pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/F-
   F_6_Factors.csv'
78.                         , index_col = 0 )
79.     FF6.drop(columns = 'RF', inplace = True)
80.     FF6.index = Y.index
81.     results = pd.DataFrame(index = Y.index,columns = Y.columns)
82.     obj_res = []
83.     for col in Y.columns:
84.         mod = sm.tsa.UnobservedComponents(Y[col], 'llevel',exog= FF6)
85.         res = mod.fit()
86.         results[col] = res.level.filtered
87.         obj_res.append(res)
88.     return obj_res
89.
90. def lambdas_series(lambdas,capm,ff6):
91.     mean = lambdas.mean()
92.     median = lambdas.quantile(.5)
93.     std = lambdas.std()
94.     minm = lambdas.min()
95.     maxx = lambdas.max()
96.     a_capm = capm.params[0]
97.     b_capm = capm.params[1]
98.     a_ff6 = ff6.params[0]
99.     return pd.Series({'mean':mean*100,'t_mean':np.sqrt(len(lambdas))*mean/std,
100.                         'median':median*100,'std':std*100,'min':minm*100,
   'max':maxx*100,
101.                         'a_capm':a_capm*100,'t_ac':capm.tvalues[0],'p_ac':
   capm.pvalues[0],
102.                         'b_capm':b_capm*100,'t_bc':capm.tvalues[1],'p_bc'
   :capm.pvalues[1],
103.                         'a_ff6':a_ff6*100,'t_af':ff6.tvalues[0],'p_af':ff
   6.pvalues[0],})
```

```python
104.
105.        ESG                                                                          =
      pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
      gs.xlsx',
106.                              sheet_name = 'ESG', index_col = 0)
107.
108.        E                                                                            =
      pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
      gs.xlsx',
109.                              sheet_name = 'E', index_col = 0)
110.
111.        S                                                                            =
      pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
      gs.xlsx',
112.                              sheet_name = 'S', index_col = 0)
113.
114.        G                                                                            =
      pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
      gs.xlsx',
115.                              sheet_name = 'G', index_col = 0)
116.
117.        r
      =    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/ST
      OXX600_clean.xlsx',
118.                              sheet_name = 'Excess', index_col = 0)
119.        betas
      =pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Charat
      eristics.csv',
120.                      index_col=0,header=[0,1],          parse_dates            =
      True,infer_datetime_format=True)
121.        betas.dropna(how='all',inplace=True)
122.        betas.drop(index = betas.index[0],inplace=True)
123.
124.        ESG = ESG -ESG.mean()
125.        E = E - E.mean()
126.        S = S - S.mean()
127.        G = G - G.mean()
128.
129.        ESG_brown =  ESG/ESG.quantile(.25)
130.        E_brown =  E/E.quantile(.25)
131.        S_brown =  S/S.quantile(.25)
132.        G_brown =  G/G.quantile(.25)
133.
134.        ESG_green =  ESG/ESG.quantile(.75)
135.        E_green =  E/E.quantile(.75)
136.        S_green =  S/S.quantile(.75)
137.        G_green =  G/G.quantile(.75)
138.
139.        ESG_h =  ESG/ESG.quantile(.9)
140.        E_h =  E/E.quantile(.9)
141.        S_h =  S/S.quantile(.9)
142.        G_h =  G/G.quantile(.9)
143.
144.        Mkt_rf = betas.iloc[:,0:betas.shape[1]:6].T
145.        SMB = betas.iloc[:,1:betas.shape[1]:6].T
146.        HML = betas.iloc[:,2:betas.shape[1]:6].T
147.        RMW = betas.iloc[:,3:betas.shape[1]:6].T
148.        CMA = betas.iloc[:,4:betas.shape[1]:6].T
149.        WML = betas.iloc[:,5:betas.shape[1]:6].T
150.        stocks = Mkt_rf.index.unique(0)
151.        Mkt_rf.index = stocks
152.        SMB.index = stocks
153.        HML.index = stocks
154.        RMW.index = stocks
155.        CMA.index = stocks
156.        WML.index = stocks
```

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157.        Mkt_rf = (rating_NPR(Mkt_rf) - rating_NPR(Mkt_rf).mean())
158.        SMB = (rating_NPR(SMB) - rating_NPR(SMB).mean())
159.        HML = (rating_NPR(HML) - rating_NPR(HML).mean())
160.        RMW = (rating_NPR(RMW) - rating_NPR(RMW).mean())
161.        CMA = (rating_NPR(CMA) - rating_NPR(CMA).mean())
162.        WML = (rating_NPR(WML) - rating_NPR(WML).mean())
163.
164.        lambdas_brown                                                    =
    pd.DataFrame({'ESG':lambdas(r,ESG_brown,Mkt_rf,SMB,HML,RMW,CMA,WML),
165.                                   'E':lambdas(r,E_brown,Mkt_rf,SMB,HML,RMW,CMA,
    WML),
166.                                   'S':lambdas(r,S_brown,Mkt_rf,SMB,HML,RMW,CMA,
    WML),
167.                                   'G':lambdas(r,G_brown,Mkt_rf,SMB,HML,RMW,CMA,
    WML)})
168.
169.        lambdas_green                                                    =
    pd.DataFrame({'ESG':lambdas(r,ESG_green,Mkt_rf,SMB,HML,RMW,CMA,WML),
170.                                   'E':lambdas(r,E_green,Mkt_rf,SMB,HML,RMW,CMA,
    WML),
171.                                   'S':lambdas(r,S_green,Mkt_rf,SMB,HML,RMW,CMA,
    WML),
172.                                   'G':lambdas(r,G_green,Mkt_rf,SMB,HML,RMW,CMA,
    WML)})
173.
174.        lambdas_h                                                        =
    pd.DataFrame({'ESG':lambdas(r,ESG_h,Mkt_rf,SMB,HML,RMW,CMA,WML),
175.                                   'E':lambdas(r,E_h,Mkt_rf,SMB,HML,RMW,CMA,WML)
    ,
176.                                   'S':lambdas(r,S_h,Mkt_rf,SMB,HML,RMW,CMA,WML)
    ,
177.                                   'G':lambdas(r,G_h,Mkt_rf,SMB,HML,RMW,CMA,WML)
    })
178.
179.        APT_bcapm,APT_bff6 = model_tests(lambdas_brown)
180.        APT_gcapm, APT_gff6 = model_tests(lambdas_green)
181.        APT_hcapm,APT_hff6 = model_tests(lambdas_h)
182.
183.        #Kalman Filter CAPM
184.        KLcapm_b = Kalman_Filter_CAPM(lambdas_brown)
185.        KLcapm_g = Kalman_Filter_CAPM(lambdas_green)
186.        KLcapm_h = Kalman_Filter_CAPM(lambdas_h)
187.
188.        #Kalman Filter FF6
189.        KLff6_b = Kalman_Filter_FF6(lambdas_brown)
190.        KLff6_g = Kalman_Filter_FF6(lambdas_green)
191.        KLff6_h = Kalman_Filter_FF6(lambdas_h)
192.
193.        # Saving Lambdas
194.        writer                                                           =
    pd.ExcelWriter('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Results/M
    Factor_Returns_Chasing.xlsx',
195.                                  engine='xlsxwriter')
196.
197.        lambdas_brown.to_excel(writer, sheet_name='MCS(25)')
198.        lambdas_green.to_excel(writer, sheet_name='MCS(75)')
199.        lambdas_h.to_excel(writer, sheet_name='MCS(90)')
200.
201.        writer.save()
202.
203.        T = pd.date_range(start='2005-01-01',periods = 204,freq='M')
204.        mux                                                              =
    pd.MultiIndex.from_product([['ESG','ESG_c','E','E_c','S','S_c','G','G_c'],
205.                                      ['MCS(25)', 'MCS(75)', 'MCS(90)']])
206.
207.        ESG_capm_alphas = pd.DataFrame({'TS':KLcapm_b[0].level.filtered,
```

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208.                                    'UCS(1)':KLcapm_g[0].level.filtered,
209.                                    'UCS(TS)':KLcapm_h[0].level.filtered},
    index = T)
210.        E_capm_alphas = pd.DataFrame({'TS':KLcapm_b[1].level.filtered,
211.                                    'UCS(1)':KLcapm_g[1].level.filtered,
212.                                    'UCS(TS)':KLcapm_h[1].level.filtered},
    index = T)
213.        S_capm_alphas = pd.DataFrame({'TS':KLcapm_b[2].level.filtered,
214.                                    'UCS(1)':KLcapm_g[2].level.filtered,
215.                                    'UCS(TS)':KLcapm_h[2].level.filtered},
    index = T)
216.        G_capm_alphas = pd.DataFrame({'TS':KLcapm_b[3].level.filtered,
217.                                    'UCS(1)':KLcapm_g[3].level.filtered,
218.                                    'UCS(TS)':KLcapm_h[3].level.filtered},
    index = T)
219.        Alphas_capm = pd.concat([ESG_capm_alphas,ESG_capm_alphas.cumsum(),
220.                                E_capm_alphas,E_capm_alphas.cumsum(),
221.                                S_capm_alphas,S_capm_alphas.cumsum(),
222.                                G_capm_alphas,G_capm_alphas.cumsum()],axis    =
    1)
223.        Alphas_capm.columns = mux
224.        Alphas_capm.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysi
    s/Results/Alphas_Mcapm_chasing.csv')
225.
226.        ESG_ff6_alphas = pd.DataFrame({'UCS(25)':KLff6_b[0].level.filtered,
227.                                    'UCS(75)':KLff6_g[0].level.filtered,
228.                                    'UCS(90)':KLff6_h[0].level.filtered},
    index = T)
229.        E_ff6_alphas = pd.DataFrame({'UCS(25)':KLff6_b[1].level.filtered,
230.                                    'UCS(75)':KLff6_g[1].level.filtered,
231.                                    'UCS(90)':KLff6_h[1].level.filtered},
    index = T)
232.        S_ff6_alphas = pd.DataFrame({'UCS(25)':KLff6_b[2].level.filtered,
233.                                    'UCS(75)':KLff6_g[2].level.filtered,
234.                                    'UCS(90)':KLff6_h[2].level.filtered},
    index = T)
235.        G_ff6_alphas = pd.DataFrame({'UCS(25)':KLff6_b[3].level.filtered,
236.                                    'UCS(75)':KLff6_g[3].level.filtered,
237.                                    'UCS(90)':KLff6_h[3].level.filtered},
    index = T)
238.        Alphas_ff6 = pd.concat([ESG_ff6_alphas,ESG_ff6_alphas.cumsum(),
239.                                E_ff6_alphas,E_ff6_alphas.cumsum(),
240.                                S_ff6_alphas,S_ff6_alphas.cumsum(),
241.                                G_ff6_alphas,G_ff6_alphas.cumsum()],axis = 1)
242.        Alphas_ff6.columns = mux
243.        Alphas_ff6.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis
    /Results/Alphas_Mff6_chasing.csv')
244.
245.        ESG_summary=pd.concat([lambdas_series(lambdas_brown.ESG,APT_bcapm[0],AP
    T_bff6[0]).round(4),
246.                                lambdas_series(lambdas_green.ESG,APT_gcapm[0],AP
    T_gff6[0]).round(4),
247.                                lambdas_series(lambdas_h.ESG,APT_hcapm[0],APT_hf
    f6[0]).round(4)],
248.                                axis=1)
249.        E_summary=pd.concat([lambdas_series(lambdas_brown.E,APT_bcapm[1],APT_bf
    f6[1]).round(4),
250.                                lambdas_series(lambdas_green.E,APT_gcapm[1],APT_
    gff6[1]).round(4),
251.                                lambdas_series(lambdas_h.E,APT_hcapm[1],APT_hff6
    [1]).round(4)],
252.                                axis=1)
253.        S_summary=pd.concat([lambdas_series(lambdas_brown.S,APT_bcapm[2],APT_bf
    f6[2]).round(4),
254.                                lambdas_series(lambdas_green.S,APT_gcapm[2],APT_
    gff6[2]).round(4),
```

```
255.                                lambdas_series(lambdas_h.S,APT_hcapm[2],APT_hff6
     [2]).round(4)],
256.                                axis=1)
257.        G_summary=pd.concat([lambdas_series(lambdas_brown.G,APT_bcapm[3],APT_bf
     f6[3]).round(4),
258.                                lambdas_series(lambdas_green.G,APT_gcapm[3],APT_
     gff6[3]).round(4),
259.                                lambdas_series(lambdas_h.G,APT_hcapm[3],APT_hff6
     [3]).round(4)],
260.                                axis=1)
261.        summary = pd.concat([ESG_summary,E_summary,S_summary,G_summary],axis=1)
262.        summary.columns                                                        =
     pd.MultiIndex.from_product([['ESG','E','S','G'],['25', '75','90']])
263.        summary.to_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Ta
     bles/MCS_chasing_sum.csv')
```

B.7 Plots

```
1.  import pandas as pd
2.  import numpy as np
3.  import statsmodels.api as sm
4.  import matplotlib.pyplot as plt
5.
6.  from cycler import cycler
7.  plt.rc('font',**{'family':'sans-serif','sans-serif':['Cambria']})
8.  plt.rc('axes',prop_cycle=(cycler(color=['#1f77b4',
     '#ff7f0e','#c7b842','#d62784',
9.                                          '#2ca02c','#d62728','#8c564b',
     '#e377c2', '#7f7f7f',
10.                                         '#bcbd22', '#17becf'])))
11.
12. l2_norm = pd.concat([l2_norm_TS,l2_norm_CSts],axis=1)
13. Assets = pd.concat([Assets_TS,Assets_CSts],axis=1)
14. mux = pd.MultiIndex.from_product([['T.S.','UCS(T.S.)'], ['ESG','E','S','G']])
15. l2_norm.columns,Assets.columns = [mux,mux]
16.
17. plt.figure(facecolor='white',figsize=(16,15),dpi=100)
18. plt.subplots_adjust(hspace=0.2)
19. scores = l2_norm.columns.unique(0)
20. titles = ['Standard error of T.S. factors','Standard error of UCS(T.S.) factors',
21.           'Number of T.S. assets','Number of UCS(T.S.) assets']
22.
23. for n,score in enumerate(scores):
24.     ax = plt.subplot(2,2,n+1)
25.     l2_norm[score].loc[l2_norm[score].index.year >= 2004].plot(ax=ax)
26.     ax.set_title(titles[n], fontdict={'fontsize': 16},fontweight ='medium')
27.     ax.set_ylabel('Std. Error',fontdict={'fontsize': 12})
28.     ax.tick_params(direction='in',labelsize=12)
29.     ax.grid(True,which='major',linestyle='--')
30.     ax.legend(loc='best');
31.
32.     ax = plt.subplot(2,2,n+3)
33.     Assets[score].plot(ax=ax)
34.     ax.set_title(titles[n+2], fontdict={'fontsize': 16},fontweight ='medium')
35.     ax.set_ylabel('Assets',fontdict={'fontsize': 12})
36.     ax.tick_params(direction='in',labelsize=12)
37.     ax.grid(True,which='major',linestyle='--')
38.     ax.legend(loc='best');
39.
40. #################### Alphas #############################################
41. Alphas_capm                                                            =
     pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Results/Alph
     as_Mff6.csv',
42.                  index_col=0,header=[0,1],parse_dates=True)
43. plt.figure(facecolor='white',figsize=(16,30),dpi=100)
```

```python
44. plt.subplots_adjust(hspace=0.2)
45. scores = Alphas_capm.columns.unique(0)
46. titles = ['Bloomberg alphas from ESG ', 'Bloomberg cumulative alphas from ESG',
47.           'Bloomberg alphas from E','Bloomberg cumulative alphas from E',
48.           'Bloomberg alphas from S','Bloomberg cumulative alphas from S',
49.           'Bloomberg alphas from G','Bloomberg cumulative alphas from G']
50.
51. for n,score in enumerate(scores):
52.     if (n % 2) == 0:
53.         ax = plt.subplot(4,2,n+1)
54.         (Alphas_capm[score]*100).plot(ax=ax)
55.         ax.axhline(y = 0, color = 'gray', linestyle = '-',alpha=0.7)
56.         ax.set_title(titles[n], fontdict={'fontsize': 16},fontweight ='medium')
57.         ax.set_ylabel('Alphas',fontdict={'fontsize': 12})
58.         ax.tick_params(direction='in',labelsize=12)
59.         ax.set_xlim(ax.get_xlim()[0]+2,ax.get_xlim()[1])
60.         ax.set_ylim(ax.get_ylim()[0]-0.05,ax.get_ylim()[1]+0.05)
61.         ax.grid(True,which='major',linestyle='--')
62.         ax.legend(loc='best');
63.     else:
64.         ax = plt.subplot(4,2,n+1)
65.         (Alphas_capm[score]).plot(ax=ax)
66.         ax.set_title(titles[n], fontdict={'fontsize': 16},fontweight ='medium')
67.         ax.set_ylabel('Cumulative alphas',fontdict={'fontsize': 12})
68.         ax.set_xlim(ax.get_xlim()[0]+2,ax.get_xlim()[1])
69.         ax.set_ylim(ax.get_ylim()[0]-0.05,ax.get_ylim()[1]+0.05)
70.         ax.tick_params(direction='in',labelsize=12)
71.         ax.grid(True,which='major',linestyle='--')
72.         ax.legend(loc='lower left');
73.
74. #predictability of sustainablity ratings
75. r2adj                                                                          =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Results/r2ad
    j_rawESG.csv',
76.                   index_col= 0, parse_dates = True)
77. plt.figure(facecolor='white',figsize=(16,15),dpi=100)
78. plt.subplots_adjust(hspace=0.2)
79. titles = ['ESG rating','E rating','S rating','G rating']
80. p = r2adj.loc[r2adj.index.year>=2004
81.             ]
82. for n, score in enumerate(r2adj.columns):
83.     ax = plt.subplot(2,2,n+1)
84.     (p[score]).plot(ax = ax)
85.     ax.axhline(y = r2adj[score].mean() , color = 'r', linestyle = '-',alpha=
    1, linewidth = 2 )
86.     ax.set_title(titles[n],fontdict={'fontsize': 16},fontweight ='medium')
87.     ax.set_ylabel('Adjusted-'r'$R^2$',fontdict={'fontsize': 12})
88.     ax.tick_params(direction='in',labelsize=12)
89.     ax.grid(True,which='major',linestyle='--')
90.
91. # Ratings C.S.
92. Ratings_rhos                                                                   =
    pd.read_csv('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Results/Rati
    ngs_rhos.csv',
93.                   index_col= 0,header= [0,1], parse_dates = True)
94.
95. plt.figure(facecolor='white',figsize=(16,15),dpi=150)
96. plt.subplots_adjust(hspace=0.2)
97. titles = ['ESG ','E ','S ','G ']
98. scores = Ratings_rhos.columns.unique(0)
99. for n, score in enumerate(scores):
100.        ax = plt.subplot(2,2,n+1)
101.        Ratings_rhos[score].plot(ax = ax)
102.        ax.set_title(titles[n],fontdict={'fontsize':          16},fontweight
    ='medium')
103.        ax.set_ylabel('Rating',fontdict={'fontsize': 12})
```

```
104.            ax.tick_params(direction='in',labelsize=12)
105.            ax.grid(True,which='major',linestyle='--')
```

B.8 Tables

```
1.  import numpy as np
2.  import pandas as pd
3.
4.  ESG                                                                  =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
5.                     sheet_name = 0, index_col = 0)
6.  E                                                                    =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
7.                     sheet_name = 1, index_col = 0)
8.  S                                                                    =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
9.                     sheet_name = 2, index_col = 0)
10. G                                                                    =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/Ratin
    gs.xlsx',
11.                    sheet_name = 3, index_col = 0)
12. stocksMkt_cap                                                        =
    pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/STOXX
    600_clean.xlsx',
13.                    sheet_name = 'Capitalization', index_col = 0)
14. stocksExcess
    =   pd.read_excel('C:/Users/nece5/Desktop/File/Università/TM/4_Analysis/Data/ST
    OXX600_clean.xlsx',
15.                    sheet_name = 'Excess', index_col = 0)
16. table=pd.concat([ESG.describe(percentiles=[.05,.25,.5,.75,.95]).mean(1),
17.         E.describe(percentiles=[.05,.25,.5,.75,.95]).mean(1),
18.         S.describe(percentiles=[.05,.25,.5,.75,.95]).mean(1),
19.         G.describe(percentiles=[.05,.25,.5,.75,.95]).mean(1),
20.         stocksExcess.describe(percentiles=[.05,.25,.5,.75,.95]).mean(1)],axis
    =1).T
21. table.drop(columns=['count','min','max'],inplace=True)
22. table
23.
24. large_ESG=pd.DataFrame(columns=stocksMkt_cap.columns)
25. large_S=pd.DataFrame(columns=stocksMkt_cap.columns)
26. large_E=pd.DataFrame(columns=stocksMkt_cap.columns)
27. large_G=pd.DataFrame(columns=stocksMkt_cap.columns)
28. large_excees=pd.DataFrame(columns=stocksMkt_cap.columns)
29.
30. for t in stocksMkt_cap.columns:
31.     stocks                                                           =
    stocksMkt_cap[t].loc[stocksMkt_cap[t]>=stocksMkt_cap[t].quantile(.7)].index
32.     large_ESG[t]=ESG[t][stocks].describe(percentiles=[.05,.25,.5,.75,.95])
33.     large_E[t]=E[t][stocks].describe(percentiles=[.05,.25,.5,.75,.95])
34.     large_S[t]=S[t][stocks].describe(percentiles=[.05,.25,.5,.75,.95])
35.     large_G[t]=G[t][stocks].describe(percentiles=[.05,.25,.5,.75,.95])
36.     large_excees[t]=stocksExcess[t][stocks].describe(percentiles=[.05,.25,.5,.
    75,.95])
37.
38. table2=pd.concat([large_ESG.mean(1),large_E.mean(1),large_S.mean(1),
39.         large_G.mean(1),large_excees.mean(1)],axis=1).T
40. table2.drop(columns=['count','min','max'],inplace=True)
41. table2.T
```

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