Louvain School of Management
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Impact of greenhouse gas emissions disclosure policy on stock returns of Euronext listed companies

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Aurélien Lambert

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Supervisors:
Prof. Philippe Grégoire
Prof. Emanuele Rizzo

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ABSTRACT

Context - The current lack of standardised reporting framework is a real obstacle for the materiality assessment of ESG data and particularly greenhouse gas (GHG) emissions. Hence, investors must find their way around to make investment decisions.

Purpose - The aim of this study is to understand the companies' incentives to disclose their GHG emissions knowing that such disclosure makes them vulnerable to market reactions.

Methodology - The difference between the baseline valuation computed from a non-disclosing sample and the integrated disclosure policy valuation computed from a disclosing group has been analysed in order to depict the materiality of the GHG emissions disclosure. The performance of both samples has been measured using the alpha computed through the Capital Asset Pricing Model, the Fama-French three-factor model and the Carhart four-factor model.

Findings - Our results suggest that the implementation of a GHG emissions disclosure policy provides a downside protection in times of crisis while limiting the upward potential in bullish periods. Also, less polluting companies perform globally better than polluting ones, except when the latter disclose their environmental information in downward periods.

Implications - The measurement of the GHG emissions disclosure factor and other materiality factors in general, provides a clearer measure of the companies' societal impact since the aggregation of ESG companies affects the entire society.

Keywords - GHG emissions disclosure - Voluntary environmental disclosure - ESG - Carbon Disclosure Project - Alpha - Industries' GHG intensity

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Contents

List of Figures

List of Tables

Abbreviations

CAPM: Capital Asset Pricing Model

CDP: Carbon Disclosure Project

CDSB: Climate Disclosure Standards Board

CR: Corporate Report

CSO: Corporate Sustainability Officer

CSR: Corporate Social Responsibility

D: Disclosing sample

ESG: Environmental Social Governance

FF3M: Fama-French Three-Factor Model

FF5M: Fama-French Five-Factor Model

GHG: Greenhouse Gas

GICS: Global Industry Classification Standard

HML: High Minus Low

KDE: Kernel Density Estimation

MOM: Momentum

ND: Non-Disclosing sample

NP: Non-Polluting group

P: Polluting group

SMB: Small Minus Big

SRI: Socially Responsible Investing

TCFD: Task Force on Climate-related Financial Disclosures

Contents

Introduction

In a context where the discussions around climate change have never been so important, it is time for mankind to react. The problem will not be solved in the short term, but the sooner action is taken, the more likely it is to protect the world, humanity and biodiversity and prevent irreparable consequences from happening. Climate change measures must be integrated into national policies, business strategies and citizens' consumption. Individuals must work together to take concrete action and make this sustainable development objective a success. In this context, the individual investor has an important role to play. There is currently no consensus on the performance of Socially Responsible Investing (SRI) funds. For some, these funds outperform the rest of the market, while for others, this potential outperformance can only be a temporary trend. One of the reasons for the lack of consensus on this type of investment is the lack and scattering of data. This makes it difficult to measure companies' environmental performance and therefore makes it hard for the individual investor to choose which companies to include in his portfolio.

The development of sustainable finance is constantly evolving. Nevertheless, a number of challenges persist and constitute real stakes. Nowadays, more than 250 ratings and benchmarks exist, leading to inconsistencies on data collection, analysis, and reporting. Moreover, the materiality of the data is difficult to assess because ESG issues do not have the same impact depending on company's specific characteristics (industries, countries, etc.). A firm's business model and value drivers, e.g. capital requirements, risk, margins or revenue growth, can be positively or negatively affected by financially material ESG factors. Greenhouse gas (GHG) emissions is one of these factors and is linked to the companies' financial performance. The measurement of GHG emissions and other materiality factors in general, provides a clearer measure of the companies' societal impact since the aggregation of ESG companies affects the entire society.

The company's transparency with its stakeholders on factors that could potentially impact its value is an important step to reduce information asymmetry. The relationship between environmental disclosure and information asymmetry is not explicit in the literature but appears to be related to the companies' value. This is partly due to the lack of standardised regulatory climate scheme. Implementing a disclosure policy can be beneficial for firms that comply with such regulations by providing various stakeholders with the same type of information. For non-compliant companies, non-disclosure of GHG emissions can represent a significant risk. Initiatives such as the Carbon Disclosure Project (CDP) bring homogeneity in the publication of corporate environmental information by providing established frameworks and can be a solution to move towards more transparency while mitigating the risk.

Under these circumstances, the greenhouse gas emissions publication is a fundamental characteristic to assess companies' environmental performance since every firm emits GHG but does not necessarily publish them voluntarily or sometimes without full disclosure. The research question tackled in this work is thus: "*what are the incentives for companies to disclose their greenhouse gas emissions knowing that such disclosure makes them vulnerable to market reactions ?*". This research question will be answered by comparing the financial performance of companies that voluntarily and fully disclose their GHG emissions with companies that do not. For this purpose, two samples each composed of 35 companies listed on the Euronext have been created. The choice to limit the empirical study to the Euronext is driven by the relatively homogeneous institutional context in which companies listed on this market operate. The financial performance will be assessed using the Capital Asset Pricing Model (CAPM), the Fama-French Three-Factor Model (FF3M) and the Carhart four-factor model.

The remainder of this work is organised as follows. First, a summary of the literature will be provided. Second, the empirical research framework will be built and is divided in three parts, data and sample construction, descriptive statistics and research methodology. Third, the results will be presented. Finally, the last section provides a discussion of the results and conclusions.

Literature summary

Previous studies on the subject mention several reasons affecting the choice of implementing a GHG emissions disclosure policy. Companies adapt the information channel used to respond as effectively as possible to stakeholders' expectations, which, depending on the company's visibility, will have a different impact on the company's practices. (Cormier, Ledoux, & Magnan, 2011) argue that the main drivers of Corporate Social Responsibility (CSR) disclosure are companies' characteristics such as leverage capacity and company size, environmental performance, the channel used to convey environmental news, the visibility and the asymmetry of information. These characteristics are often mentioned in the literature for their influence on companies' environmental disclosure practices and will be developed and recontextualised in the following to highlight the impact these may have on company's value.

Firstly, the **characteristics of a company** in terms of structure, size and policy influence the propensity to disclose GHG emissions. (Huang & Kung, 2010) show that firms with a **dispersed ownership structure** and a **large number of employees** are more under pressure to publish their environmental activities which may result in greater information asymmetry. Moreover, the authors highlight the impact **successful leaders** can have in terms of market share by focusing more on environmental performance through greater emphasis on public information release. (Cormier et al., 2011) support this finding by arguing that corporate governance has an impact on CSR disclosure affecting the information asymmetry between managers and stakeholders. Other characteristics - such as the committee size, the number of committee meetings, the committee members' expertise, the potential overlap between environmental and audit committees, and the corporate sustainability officer (CSO) expertise - are also associated with an increased likelihood of disclosing (Peters & Romi, 2014). This is all the more true when the number of employees in the company is large. (Huang & Kung, 2010) argue that **large firms** are subject to stricter government control, resulting in greater environmental transparency. Furthermore, (Peters & Romi, 2014) state that the **presence of a CSO** and **environmental committees** is positively related to GHG emissions disclosure and transparency which, according to (Kılıç & Kuzey,

2019) and (Baalouch, Salma Damak, & Hussainey, 2019), influences the disclosure quality. The **gender diversity** consideration in board committees also has a positive impact on the disclosure quality (Baalouch et al., 2019) and on the firm's value (Muhammad Azeem, Kirkerud, Kim, & Ahsan, 2020) which can be explain by the difference in perception and trust of stakeholder relations. These evidences are nuanced by (Kılıç & Kuzey, 2019) who show that **nationality diversity** within boards has a significant positive impact on carbon disclosure and the companies' ability to respond to the CDP. Finally, (Baalouch et al., 2019) state that the **board's independence** has an impact on the company's disclosure policy, which is confirmed by (Kılıç & Kuzey, 2019) who found that companies with a significant number of independent managers are more likely to respond to the CDP, thereby improving the company's environmental disclosure transparency.

Secondly, companies **adapt** the **amount of information disclosed** according **to their environmental performance**. (Dawkins & Fraas, 2011a) show that firms with poor environmental performance use disclosure policies as a safety net against legislation, while good performing firms use environmental disclosure as an opportunity. The latter may be willing to set the tone and therefore be more inclined to disclose information on their performance. In terms of regulation, (Dawkins & Fraas, 2011b) observed that companies with poorer environmental performance tend to be reactive, while firms with good performance are more proactive. In between, there is a category that is neglected and which benefits from the visibility of companies with extreme results, i.e. good or poor environmental performers. Moreover, in line with their other paper, (Dawkins & Fraas, 2011a) argue that depending on the quality of the companies' environmental performance, the purpose of the information disclosed is different. Good performers will use it as a way to create a competitive advantage, while bad performers tend to use it to protect themselves. Again, firms with extreme performance are under the spotlight and face institutional pressure because of their increased visibility. This dependence between the company's environmental performance and the disclosure policy is also underlined by (Baalouch et al., 2019), who depict the positive relationship between the quality of the information disclosed and the company's environmental performance. The authors verified that their results remain robust after considering the industry sensitivity since the quality of environmental disclosure is indeed impacted by the company's pollution intensity, which in turn depends on its type of activity. For example, companies active in the energy or utilities sector could be those that would like to show that they are leaders in low-carbon transformation to avoid being treated as high climate risk companies because of their industry activities as such (Bingler, Kraus, & Leippold, 2021). (Schiemann & Sakhel, 2019) conclude by arguing that generally, the disclosure of information related to physical climate risks has informational value for investors.

Thirdly and related to the previous point, depending on the company's environmental performance and the information the firm want to communicate to its shareholders, the company will use a different **channel to convey its message**. (Depoers, Jeanjean, & Jérôme, 2016) analyse two channels used by companies to disclose their GHG emissions information, the **corporate report** (CR) and the **Carbon Disclosure Project** (CDP). The study shows that the amount of GHG emissions information disclosed varies depending on the channel used, firms tend to report less in the corporate report than in the CDP. This study also shows that when there is a discrepancy between the two channels, the information disclosed is more easily traceable. Therefore, companies choose the information channel that allows them to better respond to their stakeholders' demands, offering managers flexibility. Firms can use two different techniques to adapt the quantity of information disclosed, either excluding Scope3 (optional in the CDP) when scopes are mentioned or detaching themselves from the guidance provided by the CDP and reporting according to their own standards. In their analysis on the Task Force for Climate-related Financial Disclosures (TCFD) reporting framework, (Bingler et al., 2021) found that the amount of information disclosed is not greater in the sense that companies use the framework to disclose non-material and convenient information. The authors therefore stress the need to convert voluntary disclosure into regulation. To overcome the lack of coherence, the Climate Disclosure Standards Board (CDSB) encourages the production of **integrated reports** providing relevant information to stakeholders on climate change risks and opportunities. The benefits of integrating reports are underlined by (Mervelskemper & Streit, 2017), who show that regardless of the reporting tool used to convey their message, companies publishing ESG reports see their environmental performance positively influenced. It allows investors to more accurately price ESG activities, which in turn impacts favourably the company's value. ESG integrated reporting therefore represents a managerial challenge that prompts the initiative or the renewal of the current reporting policies. Finally, (Mervelskemper & Streit, 2017) also underline the link between firms' environmental performance and their ESG disclosure policy by pointing out that while reporting can be beneficial to good environmental performers for risk mitigation purposes, it can have the opposite effect for bad performers.

Fourth, **media exposure** and **increased climate regulations** are pushing companies under the spotlight by increasing their **visibility**. Businesses are then forced to act to ensure that they do not suffer from excessive information asymmetry or erroneous news. Linked to the environmental performance and the incentives mentioned above, (Dhaliwal, Li, Tsang, & Yang, 2011) show that companies with good CSR performance and disclosing their information tend to attract coverage from institutional investors and analysts, reducing absolute forecast errors and the dispersion following disclosure. However, (Dawkins & Fraas, 2011b) contradict the influence environmental performance may have and point out that regardless of the performance, increased visibility makes it easier for companies to publish information on a voluntary basis. In another study, (Dawkins & Fraas, 2011a) also analyse the impact of visibility on voluntary corporate disclosure and after conducting a survey among executives, image improvement, competitive advantage, cost savings or employee retention have been mentioned as benefits of the media's impact on corporate image. Clearly, there will always be information gaps despite pressure from third party, but participation in a project like the CDP allows companies to mitigate risks. For instance, (Schiemann & Sakhel, 2019) use two components of the CDP questionnaire, i.e. the type of risk and the risk assessment, to assess companies' exposure to climate change physical risks. Furthermore, (Cormier et al., 2011) identify a subsidiarity relation between social and environmental disclosure on top of the additive relation showed in several studies. This subsidiarity reduces information asymmetry as a result of the greater impact of environmental disclosure on debt, risk and litigation. Finally, (Kılıç & Kuzey, 2019)' results support the **stakeholder theory** explaining how organisations manage the interests of different stakeholders by taking action in such a way that it can create value for the company. The growing pressure from third parties related to climate change issues is forcing companies to take action to mitigate the associated risk by voluntarily disclosing GHG-related information in annual reports or in sutainability-related individual reports.

Fifth, and related to the previous points, **companies** may see their **value impacted by a lack of GHG emissions disclosure**. According to the pecking order theory, well-known in Corporate Finance, the main driver of the capital structure choice is the information asymmetry (Berk & DeMarzo, 2020). The information available to managers on the prospects and risks of their company is likely to be greater than the information available to outsiders who finance the firm. Outsiders will always be a bit suspicious since they cannot ascertain by themselves whether they are giving money to a firm that has good prospects or if they are getting swindle due to the asymmetry of information and opinions. (Schiemann & Sakhel, 2019) support this theory by showing that information asymmetry is usually less important when European companies share the physical risks they bear and even more when those are subject to the EU Emissions Trading Scheme. This is a good indication when considered in conjunction with the current development of the EU taxonomy. The discrepancy of information represents a cost for firms needing to raise capital from investors to finance new projects. As a result, a company attempting to issue shares, will see its price reduced since investors will take into account the possibility that the management may be aware of bad news. Hence, the collective awareness of climate change issues is leading companies to communicate on their management of ESG criteria, which in turn may impact their value. (Giese, Lee, Melas, Nagy, & Nishikawa, 2019) argue that the transmission from ESG characteristics to financial value is a multichannel process both through systematic and idiosyncratic risks, underlining that the ESG criteria consideration is not limited to the unidimensional factor investing analysis. Furthermore, (Dhaliwal et al., 2011) state that CSR disclosure is associated with a subsequently lower cost of equity capital and that the likelihood that a firm will disclose its CSR activities is positively related with its previous year cost of equity. The relation between environmental disclosure and company's performance is also analysed by (Griffin, Lont, & Sun, 2017) who argue that the GHG emissions quantity reported under the CDP is negatively associated with equity values. The study shows that the market responds significantly when investors receive new emissions-related information through the negative relationship between equity value and GHG emissions. Finally, the authors modelled this relation and analysed it empirically using an estimation model based on the industrial and operational characteristics of companies that do not disclose their emissions to the CDP. An implicit penalty of $79 per ton of GHG emissions had been found for the median S&P500 companies. This figure represents approximately 1% of the median firm market capitalisation.

To conclude, the five points that have just been developed are linked. Depending on their characteristics, companies will have a better or worse environmental performance and, accordingly, will have to respond to the pressure of growing stakeholder expectations, which will finally positively or negatively impact the company's value. Therefore, the effect of the firm's environmental disclosure policy on its performance depends on these factors nuancing (Muhammad Azeem et al., 2020)' statements, which maintain that environmental disclosure positively influences firm's value.

Empirical research

I. Data and samples

1. Selection criteria

For the purposes of this study, **two samples** have been drawn, **each containing 35 companies** listed on the **Euronext** market. The first includes companies that disclose their GHG emissions on a voluntary basis and the second is made up of companies that do not disclose or where no information can be found on their emissions. To this end, the CDP climate change score, the MSCI rating and the Bloomberg proprietary ESG score have been used as selection criteria. Their definition and usage will be detailed in the following.

1.1 Carbon Disclosure Project (CDP)

a) Definition and use

The project has been created by a group of institutional investors wishing to enhance the value of GHG information. The goal of the CDP is to collect annual carbon emissions reports from large companies, as well as the risks, opportunities and strategy to address climate change issues. During the last 20 years, this initiative has developed a system resulting in an unprecedented worldwide commitment towards environmental challenges (CDP, 2020a).

The project offers the possibility to disclose different amounts of information and provides a well-defined structure divided into three distinct areas called scope (Depoers et al., 2016):

- **Scope1** refers to direct GHG emissions coming from company-owned or controlled sources, such as combustion in boilers or furnaces owned or controlled by the company;
- **Scope2** refers to indirect GHG emissions resulting from the electricity production purchased and consumed by the company, heat or steam;
- **Scope3** is an optional reporting category allowing the reporting of other indirect emissions generated from sources that are not owned or controlled by the company, such as employee business travel or outsourced business activities.

Relatively few firms report figures related to the last scope and the lack of consensus on the measure methodology makes it difficult to use it as comparison criterion.

Disclosing companies do not always make their information public and provide it primarily to investors who wish to assess the impact of GHG emissions. As seen in the literature, firms can be classified according to their level of disclosure (Depoers et al., 2016):

- (**1**) companies responding to the CDP questionnaire and making their response public;
- (**2**) companies responding to the CDP questionnaire but not allowing their response to be made public;
- (**3**) companies refusing to respond to the CDP questionnaire or ignoring the invitation.

The CDP is used as a benchmark for worldwide GHG emissions and provides a coherent and uniform methodology by submitting the same questionnaire to all respondents. It can therefore be used in the implementation of corporate governance policies by enabling the company's carbon footprint to be benchmarked against other industry players. Disclosure of this type of information can be costly for a company due to the impact it may have on its stakeholder relationships, cost of capital and the unveiling to competitors and environmental activists (Peters & Romi, 2014). In a context of increasing climate pressure in which stakeholders are requiring more transparency on GHG emissions, GHG reporting constitutes a real challenge and a strategic tool for companies. In this regard, the Carbon Disclosure Project offers a good opportunity for firms seeking to address these growing climate challenges as it is considered as one of the most reliable ratings by specialists.

b) CDP Climate Change Scoring Methodology

The scoring methodology delivers a score evaluating the progress made in environmental management, as described in the company's response to the CDP. The score reflects the degree of detail and completeness of the content, the company's understanding of climate change issues and lastly, the management practices and progress to address climate change. The score is attributed based on the evaluation and the answers provided by the company.

The CDP 2020 questionnaires use a sectoral approach. To this end, each of the CDP questionnaires (Climate Change, Forests and Water Security) includes general questions as well as sectoral-oriented ones for high impact industries. In the aim of studying the impact of the GHG emissions disclosure, the **Climate Change** assessment will be the only one consulted. The three questionnaires have their own individual scoring methodology and the scores are established based on the answers provided by the companies. External sources such as company reports, sustainability reports, websites or other sources are therefore not taken into account in the scoring attribution (CDP, 2020b).

The CDP rating emphasises the CDP's principles and values promoting a sustainable economy by highlighting the underlying economic rationale behind this approach. Companies can use the rating to have a clear vision of where they want to go and thus make the changes required to achieve this. The points allocation contributes to the firm's development process with regard to environmental issues. Participants are asked to provide further details and information on their sustainability strategy and depending on their sustainability maturity, they will be assigned a grade ranging from A to D. As shown on **Figure 1**, there are four main different levels assessed in the following order: **Disclosure** (**D**), **Awareness** (**C**), **Management** (**B**) and **Leadership** (**A**). To move from one level to another, the company must reach a certain minimum score (Appendix 1). The questionnaires are adapted according to the levels. These thresholds are set in advance by the CDP and are reviewed periodically in order to maintain a certain level of representativeness with regard to the answering population.

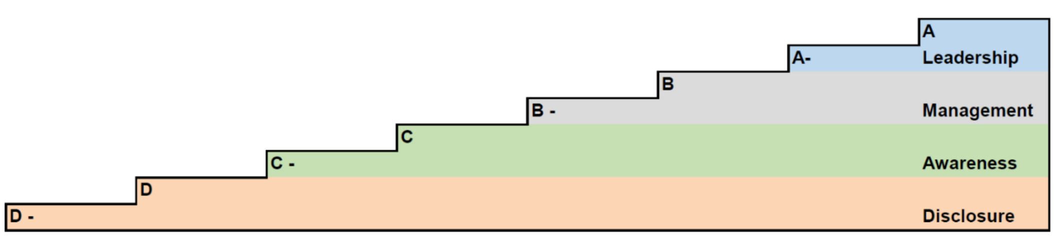


Figure 1. CDP Climate Change Scoring classification

Source: (CDP, 2020b, p.7)

An additional level may be added to the other four since companies that have received a request to respond to the CDP do not necessarily do so. Firms that do not wish to disclose their data or do not provide sufficient information will be considered as belonging to the "**Failure**" level (**F**). This does not mean that the company does not care about and manage environmental issues, it is a matter of disclosure to the CDP. The companies' practices not reported in the CDP questionnaire are therefore not taken into consideration in the score attribution although they are not necessarily harmful to the environment (CDP, 2020b). Nevertheless, (Dawkins & Fraas, 2011b) show that a U-shaped relationship exists between environmental performance and voluntary environmental disclosure as illustrated on **Figure 2**. Extreme performers will therefore disclose more than the category in between.

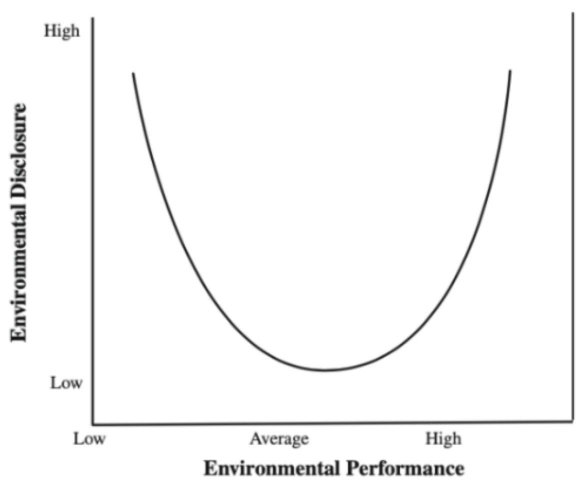


Figure 2. Environmental performance and environmental disclosure relationship

Source: (Dawkins Fraas, 2011b, p.386)

We can therefore **assume** that the non-respondents to the questionnaire are mainly companies in the category at the bottom of the U. This category is neglected and, as mentioned before, benefits from the visibility of companies with extreme results. The presence of an intermediate category is confirmed by (Bennani et al., 2018) who show that best-in-class and worst-in-class companies are respectively rewarded or penalised after integrating ESG criteria. (Depoers et al., 2016) argue that it may also be the result of firms choosing not to use the CDP channel to disclose their GHG emissions. The authors claim that companies tend to report less in the corporate report than in the CDP either by ignoring the optional Scope3 or by detaching themselves from the guidance and choosing to report according to their own standards. Companies opt for the information channel that allows them to better respond to their stakeholders' demands providing management flexibility. It can therefore be **hypothesized** that least rigorous firms in terms of GHG emissions disclosure will opt for flexibility to mitigate negative perceptions caused by a poor environmental performance.

Depending on the questions, the approach used to award points is different. Sometimes it is necessary to complete the entire questionnaire to get points but alternatively, fractions of points can be awarded based on the completeness of the response. This second methodology is based on the number of lines disclosed giving companies incentives to disclose more information. Finally, the third way of awarding points is to cumulate fractions of points for each additional piece of information provided.

1.2 MSCI ESG rating

The MSCI ESG rating provides a measure of a firm's ability to address the long-term environmental, social and governance (ESG) risks of its industry. This rules-based approach aims to identify industry leaders and laggards based on their exposure to ESG risks and how they manage these risks relative to their peers. This method thus makes it possible to assess companies' engagement and leadership. The MSCI ESG rating enables to identify extreme performers who, according to (Dawkins & Fraas, 2011b), tend to disclose more. The methodology followed to build the rating will be described below.

First, the data is collected using the publicly available information, i.e. documents published by firms themselves, various media sources and alternative data, i.e. information disclosed by external sources including government regulations and NGO datasets.

Second, the method used relies on artificial intelligence and new technologies increasing data collection capacity and accuracy. Then, 200 ESG analysts scrutinise the information collected to extract relevant data in order to assess ESG criteria.

Third, with the aim of classifying companies according to the seven different scores, they break down their analysis by industry. Then, analysts compare companies' performance within each sector from a financial risk perspective according to industry's key drivers. The rating can therefore be used for benchmarking purposes. In addition to this, the rating takes into account on the one hand, firm's possible controversial activities and on the other hand, the undertaking of initiatives having a sustainable impact. In other words, analysts use the different strategies that underpin the evaluation of companies' performance against ESG criteria.

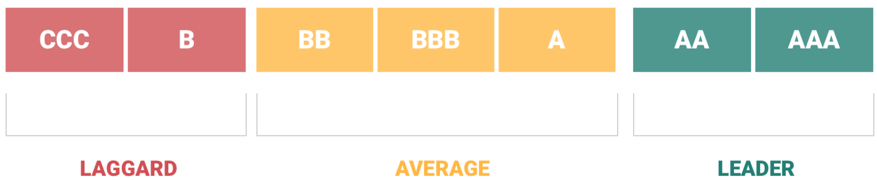


Figure 3. MSCI ESG rating classification

Source: (MSCI, 2019)

Regarding the rating interpretation, the methodology allows to differentiate firms qualified as "**leaders**" from firms qualified as "**laggards**" with intermediate categories as shown on **Figure** 3. These scores are assigned according to company's risk management and company's performance relative to its peers on ESG criteria. This allows the identification of companies having a real desire to incorporate ESG standards (MSCI, 2019).

1.3 Bloomberg proprietary ESG score

Bloomberg provides a company financial analysis according to ESG criteria. Depending on the data availability, the information provided may not be complete. For the purpose of building the samples, the global **ESG disclosure score** and the **environmental disclosure score** related to the publication of GHG emissions, will be taken into consideration. These scores enable to identify the most assiduous companies in terms of environmental publication, thus avoiding any kind of greenwashing.

The Bloomberg ESG score is based on the level of disclosure of companies' ESG information. Firms for which such data is not available will not be scored and will be reported as **NaN**. The same applies to companies that do not disclose GHG emissions information. The scores range from 0.1 for firms that disclose a minimum amount of ESG data to 100 for firms disclosing all the elements collected by Bloomberg. Each data point is weighted according to its importance, e.g. data such as GHG emissions have more weight than other types of disclosure. The scores are also adapted to different sectors meaning that each firm is assessed only on the data that is relevant to its industry. Note that these scores measure the amount of ESG data that a company discloses and not the company's performance on any data point, underlying the importance of using the MSCI ESG rating criterion (Bloomberg, 2021).

This study is focused on firm's total GHG emissions which are expressed in thousands of metric tons of carbon dioxide equivalent (CO2e). Greenhouse gases are defined as gases that contribute to heat trapping in the earth's atmosphere and include carbon dioxide (CO2), methane and nitrous oxide. Total GHG emissions reported are equal to the total corporate emissions in Scope1 and 2 and does not include emissions in Scope3 as mentioned before. The definition of the Scope3 remains subject to numerous interpretations explaining the variability in the data reported by companies which could lead to excessive variations in the total corporate GHG emissions figure. Emissions reported as CO2 only are not taken into account in the Bloomberg ESG score (Bloomberg, 2021).

2. Methodology for data collection and sample creation

The two samples have been initially formed by taking Euronext listed companies referenced in the CDP database with a **CDP climate change score** equivalent to an A or A^- (Leadership level) for the disclosing group and companies with a score equivalent to F (Failure level) for the non-disclosing group.

Then, based on the **MSCI ESG rating**, firms initially present in the non-disclosing sample with a A rating (or more) have been withdrawn. Similarly, firms with no rating (NaN) or a score below A have been removed from the initial disclosing sample.

Finally, the definitive samples have been obtained after considering the **ESG** and the **environmental disclosure score** reported on **Bloomberg**. Due to the pre-selection performed based on the two previous criteria, no adjustment has been made in the non-disclosing sample since the vast majority of the scores were either not available or very low. Regarding the disclosing sample, companies for which data were not available over the last five years and companies with a 5-year average score and 2019-score below one standard deviation from the relative mean, have been removed from the disclosing sample.

Once the samples were created based on the three screening criteria, the **weekly** and **monthly returns** for the **70 companies** have been collected on Bloomberg for the period between 02 January 2015 and 19 March 2021. The samples breakdown can be found in Appendix 2.

II. Descriptive statistics

1. Disclosing sample selection criteria

This section aims to provide descriptive statistics on the last selection criterion, i.e. the Bloomberg proprietary scores for the disclosing sample.

Analysing **Table 1**, it can be seen that 50% of the companies in the disclosing sample have both a 2019 and 5-year average **ESG disclosure score** above 50 out of 100. Regarding the **environmental disclosure score**, the threshold is lower, i.e. 50% of the companies have a 2019 and 5-year score above 44 out of 100.

Percentiles	**2019 score**	**5-year average score**
1%	40.91	40.61
5%	42.54	42.81
10%	44.63	44.30
25%	48.35	47.24
50%	**53.19**	**52.35**
75%	57.64	56.20
90%	63.22	61.49
95%	65.29	63.57
99%	71.07	68.18
Mean:	53.47	52.65
Std. Dev.:	6.80	6.68

(a) ESG disclosure score

Percentiles	**2019 score**	**5-year average score**
1%	24.03	29.30
5%	34.88	32.40
10%	37.21	33.49
25%	41.09	39.84
50%	**44.96**	**44.50**
75%	53.49	52.50
90%	62.79	61.86
95%	64.34	63.41
99%	72.87	67.44
Mean:	47.52	46.11
Std. Dev.:	9.99	9.80

(b) Environmental disclosure score

Table 1. Bloomberg proprietary scores percentiles

Analysing **Table 2** and the annual averages of these two scores over the years, a small and steady increase can be observed over time except in 2019, which may be due to the fact that the information is not yet available for all selected companies.

	2015	**2016**	**2017**	**2018**	**2019**
ESG disclosure score	54.15	54.86	55.72	56.27	55.81
Environmental disclosure score	47.61	48.75	49.88	50.48	50.12

Table 2. Bloomberg proprietary average scores over time

2. Sample comparison

Based on general statistics, **Table 3** suggests that while the samples are of equal size, the disclosing sample has a slightly higher average weekly return and a lower standard deviation than the non-disclosing sample. Detailed descriptive statistics for the 70 companies included in both samples are summarised in Appendix 3.

Non-Disclosers	Disclosers
$n_{ND} = 35$	$n_D = 35$
$\overline{X_{ND}} = .0913\%$	$\overline{X_D} = .0941\%$
$s_{ND} = 3.898\%$	$s_D = 2.899\%$

Table 3. Key sample statistics

Analysing **Figure 4** which represents the cumulative weekly returns over the considered period of time, it can be observed that both samples perform better than their benchmark, the **Euronext 100 index** (N100). The three curves are subject to the same systemic shocks as illustrated by the Covid-19 crisis starting in 2020. Moreover, two distinct periods are identifiable, i.e. an **upward period** going from 2015 until end 2017 followed by a **downward period** starting early 2018 onwards.

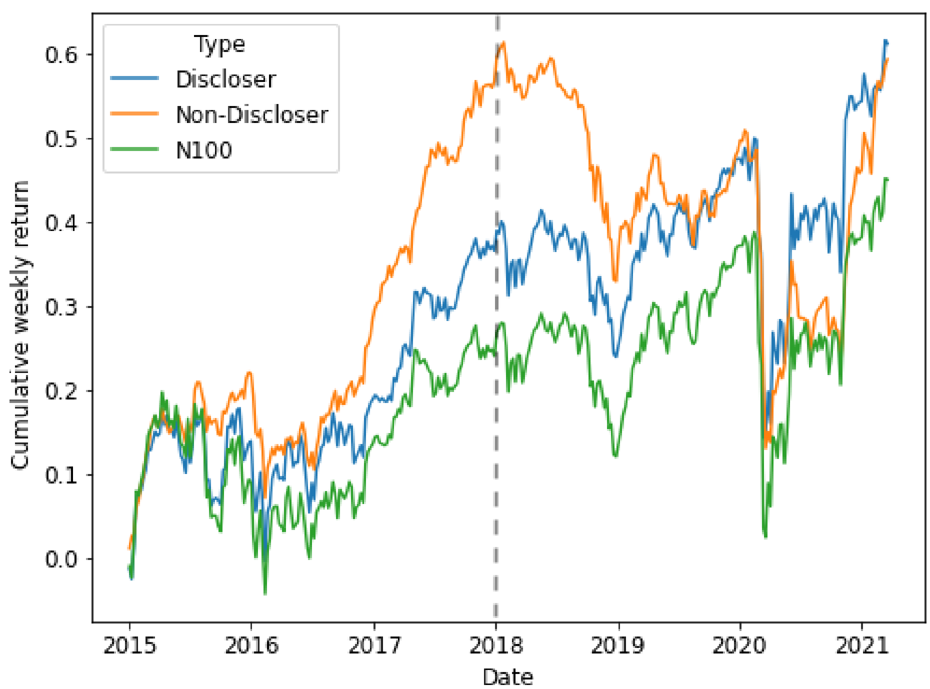


Figure 4. Cumulative weekly returns over time

Based on these observations, the remainder of this study will be carried out in two stages.

- First, the statistical tests will be performed over a single period going from January 2015 until mid-March 2021.

- Second, the tests will be performed distinguishing two periods, an "upward period" (2015-2018) and a "downward period" (2018-2021).

The objective is to be able to quantify and check empirically the impact of the pandemic crisis (and crisis in general) on the results. According to (Whelan, Atz, & Clark, 2021), ESG investing allows investors to limit the risk and protect their portfolio, particularly in times of crisis and adverse market conditions.

Finally, re-analysing **Figure 4**, it can be seen that the non-disclosing sample has overall higher but more volatile cumulative weekly returns. It would therefore be interesting to analyse the **Sharpe ratio**, i.e. the risk-adjusted performance of both samples over the single and two periods of time. The ratio is defined as follows:

$$SR = \frac{R_p - R_f}{\sigma_p} \tag{1}$$

where R_p is the portfolio return, R_f the risk-free rate and σ_p the standard deviation of the portfolio's excess return (Bodie, Kane, & Marcus, 2014).

The Sharpe ratio is based on the assumption that returns are normally distributed. It has no intrinsic interpretation and serves for comparative purposes. A high ratio is good since returns per unit of risk are higher compared to similar portfolios or funds. The measure depends on the average return but also on the aggregate risk of the companies making up the portfolio. Hence the importance of diversification, allowing the overall risk to be reduced.

	2015-2021		*2015-2018*		*2018-2021*	
	Non-Disclosers	Disclosers	Non-Disclosers	Disclosers	Non-Disclosers	Disclosers
Sharpe ratio	**3.911**	**2.453**	**16.657**	**5.209**	**-.069**	**1.366**

Note: by assumption, $R_f = 0\%$

Table 4. Sharpe ratios

Comparing the ratios listed in **Table 4**, it can be observed that the risk-adjusted performance is better for non-disclosing firms during the **single period** of time. Considering the two periods, the Sharpe ratio is considerably higher for non-disclosers than for disclosers during the **upward period** whereas, during the **downward period**, the risk-adjusted performance is better for disclosers than for non-disclosers whose ratio is even negative despite the assumed risk-free rate of 0%.

III. Methodology

The **Euronext 100 index** will be used as the **market proxy** in this research because of its representativity of the companies composing both samples and the market of interest in this study, i.e. the Euronext. The index is updated quarterly and includes the major and most liquid shares traded on the Euronext (Euronext, 2021). Furthermore, due to the very low market rates experienced over the last few years, a **risk-free rate** of 0% will be used in the analyses to simplify the calculations.

In this section, the Capital Asset Pricing Model and some of the criticisms often associated with it will be briefly discussed and then some extensions such as the FF3M or the Carhart four-factor model, which address some of the CAPM limitations, will be developed.

1. Capital Asset Pricing Model (CAPM)

The Capital Asset Princing Model is a set of forecasts of equilibrium expected returns on risky assets. It is based on the idea that the appropriate risk premium on an asset will be determined by its contribution to the risk of all investors' portfolios, since investors want to be compensated for the risk they bear. The model relies on several assumptions listed in Appendix 4 yielding to the following CAPM equation (Bodie et al., 2014):

$$E[R_i - R_f] = \beta_{iM} E[(R_M - R_f)] \tag{2}$$

where: $\beta_{iM} = \frac{cov(R_i, R_M)}{\sigma^2 R_M}$

This single period model can be extended to a multi-period world in which investors are allowed to have heterogeneous horizon periods and in which securities trading takes place continuously over time. Note that β_{iM} is implicitly assumed to be stationary over time (Jensen, 1968).

$$E[R_{i,t} - R_{f,t}] = \beta_{iM} E[(R_{M,t} - R_{f,t})] \tag{3}$$

One way to assess the relevance of the model is to analyse the r-squared indicating how much of the dependent variable variance is explained by the model. In the CAPM context, the variance of an asset can be split into a systematic component and an idiosyncratic component (4) which, according to (Giese et al., 2019), are two channels whereby ESG affects the valuation and companies' performance (Appendix 5). In a world where the CAPM is true, differences in expected returns across assets are fully explain by the beta on the market, i.e. by the co-movement of the asset and the market portfolio (Bodie et al., 2014).

$$Var(R_{i,t} - R_{f,t}) = \underbrace{\beta_{i,M}^2 Var(R_{M,t} - R_{f,t})}_{\text{Systematic risk}} + \underbrace{Var(\epsilon_{i,t})}_{\text{Idiosyncratic risk}} \tag{4}$$

1.1 Jensen's alpha

The theoretical CAPM equation (3) is an ex-ante model describing investors' return expectations depending on their risk aversion, the risk-free rate and the beta. To test the CAPM empirically, the model needs to be transformed from an expectation form (ex-ante) into ex-post form using the actual observed data. To this end, the efficient market hypothesis should be applied implying that on average, for large samples, the expected return on an asset equals its actual return and can be expressed mathematically as follows (Bodie et al., 2014):

$$R_{i,t+1} = E[R_{i,t+1}] + \epsilon_{i,t+1} \tag{5}$$

where $R_{i,t+1}$ is the actual return, $E[R_{i,t+1}]$ the expected return and $\epsilon_{i,t+1}$ the difference between actual and expected returns. Assuming that $\epsilon_{i,t+1}$ is an independent normally distributed random variable and that returns probability distributions do no change significantly over time, equation (5) can be rewritten as follows (Jensen, 1968):

$$E[\epsilon_{i,t+1}] = E[R_{i,t+1} - E[R_{i,t+1}]] = 0 \tag{6}$$

Taking the expectation of the regression formula (7) allowing for the possible existence of a non-zero constant, equation (8) can be obtained. The expectation of the error term is equal to 0 by assumption following our previous reasoning.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{iM}(R_{M,t} - R_{f,t}) + \epsilon_{i,t} \tag{7}$$

$$E[R_{i,t} - R_{f,t}] = \alpha_i + \beta_{iM} E[(R_{M,t} - R_{f,t})] \tag{8}$$

Comparing equation (8) with the key CAPM equation (3), we can observe that α_i is missing in the latter. So, in a world where the CAPM is true, alpha is equal to 0 because stock expected returns are perfectly explained by the beta on the market. So, the Jensen's alpha, isolated in the following equation (9), measures the average excess return over the one predicted by the CAPM.

$$\alpha_i = (\overline{R}_i - R_f) - \beta_i(\overline{R}_M - R_f) \tag{9}$$

As a result, it must be true that the expected excess return of an asset is fully explained by the market risk premium. If not, it means that there is an additional factor, i.e. alpha, which can either mean that the stock is mispriced or that the model is wrong due to its inability to reflect other sources of risks. The Jensen's alpha can therefore be defined as the average return on the portfolio above the one implied by the Capital Asset Pricing Model given the portfolio's beta and the average market return. It can also be interpreted in a multifactor framework such as the Fama-French three-factor model which will be developed in the following (Bodie et al., 2014).

1.2 Hypothesis testing

The aim of this research is to test any significant difference between the average alphas of the two samples. To this end, an hypothesis test testing the difference between two means with equal variances will be carried out. From a theoretical perspective, the samples' sampling distribution mean is equivalent to the population mean for large and independent samples. Therefore, the point estimator of $(\mu_1 - \mu_2)$ can be expressed as $(\overline{X_1} - \overline{X_2})$ where the two samples are respectively the non-disclosing and disclosing one (Wackerly, Mendenhall, & Scheaffer, 2008). If the random samples are independent, these results imply that:

$$E(\overline{X_1} - \overline{X_2}) = E(\overline{X_1}) - E(\overline{X_2}) = \mu_1 - \mu_2 \tag{10}$$

Assuming that the null hypothesis (11) is true, the p-value can be found, i.e. the proportion of repeated samples, under the null hypothesis, that would be as extreme as the test statistic generated. If it is bellow some threshold, called the significance alpha, the null will be rejected in favor of the alternative. In other words, the p-value is the smallest level of significance alpha for which the null hypothesis can be rejected.

$$\begin{cases} H_0 : \mu_{ND} - \mu_D = 0 \\ H_1 : \mu_{ND} - \mu_D \neq 0 \end{cases} \tag{11}$$

This hypothesis can be tested using a student test to determine whether the disclosers' average alpha (μ_D) is significantly greater than the non-disclosers' one (μ_{ND}). The two-sided alternative allows to identify either the case in which $\mu_{ND} > \mu_D$ or oppositely $\mu_D > \mu_{ND}$ (in both cases, H_0 is rejected). Given that the point estimator satisfies the assumptions necessary to develop a large-sample test, the test statistic used to test H_0 is given by (Wackerly et al., 2008):

$$T = \frac{\overline{X_{ND}} - \overline{X_D} - 0}{S_p\sqrt{\frac{1}{n_{ND}} + \frac{1}{n_D}}} \tag{12}$$

where:

$$S_p^2 = \frac{(n_{ND} - 1)S_{ND}^2 + (n_D - 1)S_D^2}{n_{ND} + n_D - 2} \tag{13}$$

Numerous empirical studies conducted on this statistical test by sampling from non-normally distributed populations have shown that generally the probability distributions of statistical tests are relatively unchanging despite small deviation from normality. The two-sample t-test is therefore relatively insensitive to violations of the normality hypothesis, hence it is often qualified as robust. The test is also robust to the homoscedasticity assumption when samples are of equal size (Wackerly et al., 2008).

For sufficiently large degrees of freedom, the student distribution converges to a normal distribution. Typically, the t-distribution is identical to the normal one for more than 120 degrees of freedom (Wackerly et al., 2008).

Finding significance does not necessarily mean that there are abnormal returns. This may be due to a CAPM limitation and the omission of one or multiple factors explaining stock returns that may have ended up in the idiosyncratic part of the risk. The CAPM is based on several assumptions which are therefore important to be aware of, but the real test of a model is not the realism of its assumptions but its ability to predict reality.

Many studies have been carried out on the Capital Asset Pricing Model to test its validity. It appears that the model in its most basic form does not explain well variation in average returns across assets. Some of the most powerful evidence to this conclusion comes from Fama and French (1992) arguing that there exist additional dimensions of risk that investors care about on top of the market factor.

2. Fama-French three-factor model

2.1 Alpha

As part of their research, they have developed the Fama-French three-factor model by adding two additional factors to the CAPM, i.e. the **company size** measured in terms of market capitalisation and the **book-to-market value**. These two additional terms are systematic factors not captured by the CAPM and could potentially be reflected in the alpha. Finding an alpha on a given asset pricing model can either mean that the stock is mispriced or be an indication that other sources of risks are not captured by the model. Fama and French intuition is founded on the fact that small firms historically outperformed big firms and high book-to-market firms historically outperformed low book-to-market firms. The key CAPM equation (3) has therefore been extended as follows (Bodie et al., 2014):

$$E[R_{i,t} - R_{f,t}] = \alpha_i + \beta_{iM}E[(R_{M,t} - R_{f,t})] + \beta_{iSMB}E[SMB] + \beta_{iHML}E[HML] \tag{14}$$

where (French, 2021):

- SMB= $\frac{1}{3}$ (Small Value + Small Neutral + Small Growth) -$\frac{1}{3}$ (Big Value + Big Neutral + Big Growth)
- HML= $\frac{1}{2}$ (Small Value + Big Value) -$\frac{1}{2}$ (Small Growth + Big Growth)

The **small minus big** (SMB) and **high minus low** (HML) factors have been obtained by taking the difference between two portfolios' returns. The SMB factor reflects the difference between a portfolio composed of small market capitalisation firms minus larger capitalisation firms and the HML factor reflects the difference between a portfolio composed of high book-to-market value companies (value firms) minus low book-to-market value companies (growth firms). The book-to-market value can be high or low depending on the company's growing expectations with respect to market value (Bodie et al., 2014).

2.2 Hypothesis testing and CAPM extensions

The alphas can be tested in a similar way using the FF3M, i.e. following the same methodology to compute the alphas and using the hypothesis test testing the difference between the two-sample averages:

$$\begin{cases} H_0 : \mu_{ND} - \mu_D = 0 \\ H_1 : \mu_{ND} - \mu_D \neq 0 \end{cases} \tag{15}$$

The CAPM can be further extended by adding new factors to capture risk that the model is not able to explain. In 1997, Mark Carhart proposed an extension of the FF3M by adding the **momentum** factor (MOM), thereby developing the Carhart four-factor model. The MOM factor reflects the trend for past high (low) performance stocks to continue to perform well (poorly) in the near term. Similarly to the SMB and HML factors, the momentum factor has been obtained by going long on positive momentum and short on negative momentum (Carhart, 1997):

- MOM= $\frac{1}{2}$ (Small High + Big High) -$\frac{1}{2}$ (Small Low + Big Low)

Additional parameters could be added indefinitely in order to improve the model's predictability, as illustrated by the FF5M. This would have no impact on the parameters' biasedness but would affect their variance, which in turn would affect the statistical test. (Giese et al., 2019) propose a comparative analysis between the impact of the MSCI ESG rating and the one of more traditional factors, such as momentum, on companies' financial performance. The differences are analysed based on their **intensity** (financial impact per unit of time) and **longevity** (how long the signal persists). The authors show that the financial impact of ESG ratings is lower than common factors. However, traditional factors have a short-term influence while the MSCI ESG rating has a greater longevity, underlining its relevance for benchmark creation. As a conclusion, (Giese et al., 2019) argue that associating classical factors with ESG criteria might lead to both the **short-term** performance benefits of quantitative factors and the **medium to long term** risk reduction potential of ESG ratings. This will be verified empirically in the course of this study.

2.3 Data collection

The data on the factors added by Fama and French and latter by Carhart, applicable for European companies, i.e. SMB, HML and MOM, have been collected on the Fama-French website (French, 2021). As weekly data for these three factors are not available, they have been collected at a **monthly** frequency, hence avoiding any returns conversion. It is therefore important to keep in mind that the alphas obtained through the three models have been calculated in the same way using weekly returns for the CAPM and monthly returns for the FF3M and Carhart four-factor model. For the sake of comparability between alphas, Appendix 6 contains the geometric conversion of weekly, monthly and annual returns.

Results

I. Empirical tests and findings

1. Introduction

The aim of this study is to test whether the financial performance of GHG emissions disclosing firms is significantly different relative to non-disclosing ones. To this end, the alpha of both samples has been computed through the CAPM, the FF3M and the Carhart four-factor model. The results obtained with the four-factor model are almost identical to the Fama-French three-factor model, i.e. considering the momentum factor does not influence the results found with the FF3M. For the sake of readability, the results obtained with the model developed by Carhart will not be detailed in the below analysis but are incorporated in the global results summary (III. Summary of results). Note also that all the results point in the same direction and present same levels of significance after controlling for outliers.

From this study's aim, we will thus test the potential statistical difference in performance between non-disclosing and disclosing firms using the test statistic developed in the above section (12). The **null hypothesis** states that the difference between the average alpha of the non-disclosing sample (μ_{ND}) and the one of the disclosing sample (μ_D) is equal to 0. A positive (negative) difference means that the non-disclosers' alpha is more (less) important than the disclosers' one.

The **t-statistic** can be either positive or negative, the sign indicating the side of the distribution. If t < 0, $\mathbf{P(T < t)}$ is the probability of observing a value of the t-statistic that is more negative than t and if t > 0, $\mathbf{P(T > t)}$ is the probability of having a value of the t-statistic that is more positive than t. For the purpose of this study, a two tailed test has been conducted where $\mathbf{P(|T| > |t|)}$ is the probability of observing a value of the t-statistic greater in absolute value than t (Wackerly et al., 2008).

Based on the cumulative returns analysis done earlier (**Figure 4**), a two-stage analysis will be carried out. The first stage consists in assessing the financial performance of the two samples over a single period of time going from January 2015 until mid-March 2021. The second stage consists in calculating the alpha in the same way but over two periods, an upward period starting from 2015 to end 2017 and a downward period from 2018 until mid-March 2021.

2. Single period analysis (2015-2021)

The results reported in **Table 5** indicate that non-disclosing companies have a **significantly** higher average alpha than disclosing ones when the **CAPM** is used over the single period. The weekly alphas difference between the two samples is **.03591%** towards non-disclosers. However, when the **FF3M** is used, results indicate that disclosing firms have a **non-significantly** higher monthly average alpha than non-disclosing ones, which is not conclusive. As a reminder, the CAPM and FF3M results have been obtained based on weekly and monthly returns respectively (for ease of comparison, see Appendix 6).

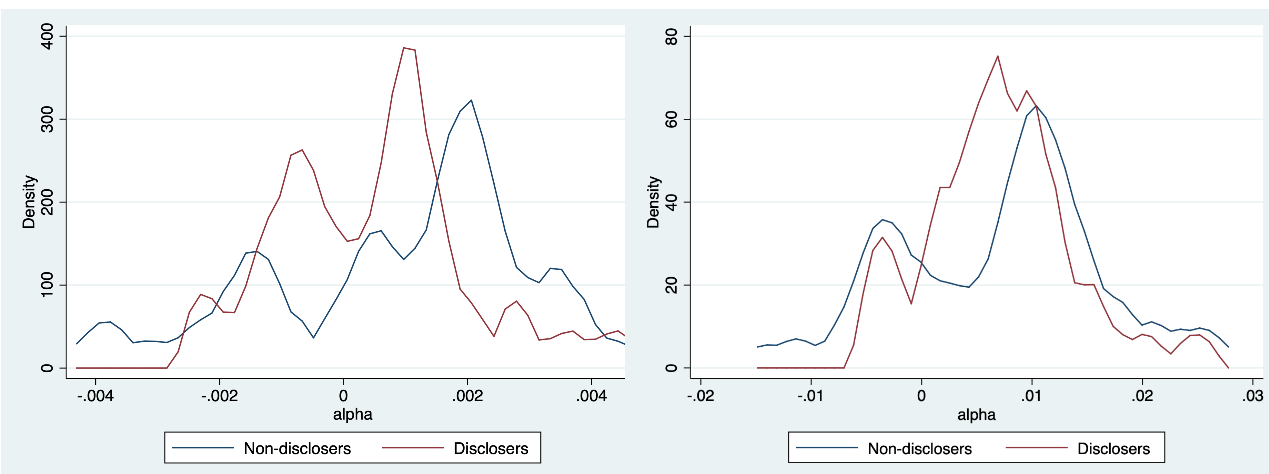
	CAPM				FF3M			
Group	Obs	Mean	t-stat	P> $\|t\|$	Obs	Mean	t-stat	P> $\|t\|$
Non-Disclosers	11375	.0008416			2590	.007049		
Disclosers	11375	.0004825			2590	.0070535		
$H_0 : \mu_{ND} - \mu_D = 0$		**.0003591**	14.8747	**0.0000*****		**-4.46e-06**	-0.0203	**0.9838**

*Note: the results reported for the CAPM and the FF3M are respectively based on **weekly** and **monthly** returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 5. Single period: alphas two-sample t test

The results are not the same depending on the model used. On the one hand, the difference in average alphas above the one implied by the Capital Asset Pricing Model is positive and highly significant meaning that non-disclosing companies tend to perform financially better than disclosing ones over the single period. On the other hand, the difference in average alphas above the one implied by the Fama-French three-factor model goes in the opposite direction, i.e. disclosing firms perform financially better, but is not significant and close to zero. This difference in results between the CAPM and the FF3M could be explained by the presence of additional factors in the latter that better capture the returns on top of the ones implied by the CAPM.

In the following analysis, **kernel density estimation** (KDE) plots will be used. The kernel density estimator is a function that is generally smooth and symmetric such as a Gaussian. Basically, the KDE smoothes each data point into a small density bumps and then sum all these small bumps together to obtain the final density estimate (Y.Chen, 2018). The x-axis represents the values of the average alphas of non-disclosing and disclosing companies and the y-axis represents the density estimate. Probability density functions can be used to assess the risk/return trade-off as they provide a measure of the likelihood of a certain outcome.



(a) CAPM (b) FF3M

Figure 5. Single period: average alphas KDE

The **Figure 5** provides a better understanding of the results obtained so far, i.e. a significant alphas difference of .03591% and a non-significant alphas difference of -.000446% when the CAPM and FF3M are used respectively. On the one hand, the distribution of non-disclosing firms is centred on higher values of alphas than the distribution of disclosers when the CAPM is used. On the other hand, the two distributions are relatively centered and overlap with the FF3M. Furthermore, the different curves display a **bimodal pattern**, i.e. the probability distributions exhibit two different modes. There could therefore be a criterion distinguishing these two groups allowing for a better understanding of the difference in performance between the two samples.

3. Two-period analysis

3.1 Upward period (2015-2018)

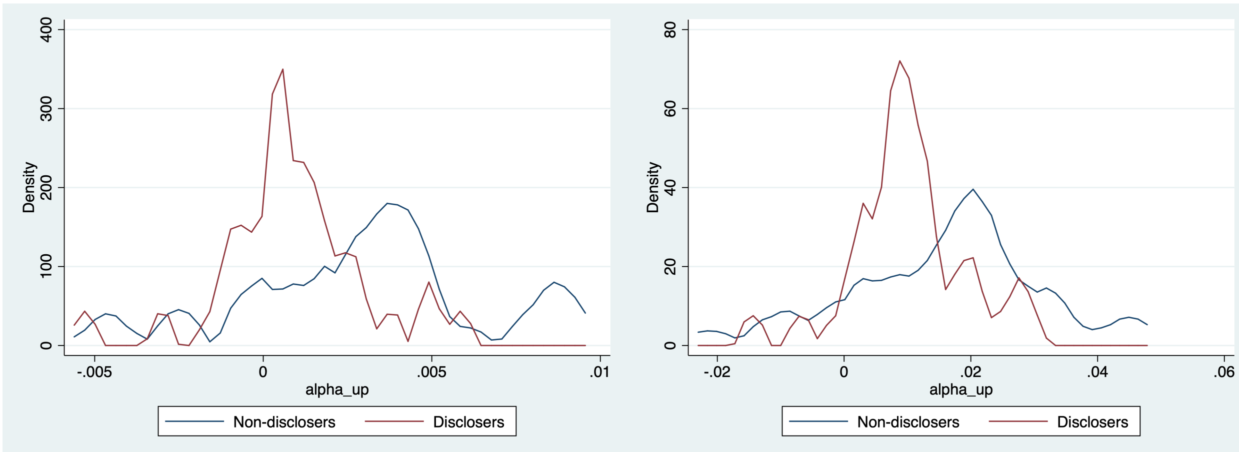
The results reported in **Table 6** indicate that non-disclosing companies have a **significantly** higher average alpha than disclosing ones when the **CAPM** is used over the upward period. The alphas difference between the two samples is **.19553%** towards non-disclosers. Results point in the same direction when the **FF3M** is used and indicate that non-disclosing companies have a **significantly** higher average alpha than disclosing ones. The alphas difference between the two samples is **.54994%** towards non-disclosers (for ease of comparison between weekly and monthly results, see Appendix 6). The difference in average alphas above the one implied by the two models is positive and significant, meaning that non-disclosing companies perform financially better during the upward period.

	CAPM				**FF3M**			
Group	Obs	Mean	t-stat	P> $\|t\|$	Obs	Mean	t-stat	P> $\|t\|$
Non-Disclosers	11375	.0028704			2590	.0157244		
Disclosers	11375	.000915			2590	.010225		
$H_0 : \mu_{ND} - \mu_D = 0$		**.0019553**	51.4464	**0.0000*****		**.0054994**	16.1391	**0.0000*****

Note: the results reported for the CAPM and the FF3M are respectively based on ***weekly*** *and* ***monthly*** *returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 6. Upward period: alphas two-sample t test

Analysing **Figure 6**, it can be observed that the curve of non-disclosing firms for both models exhibit positive Kurtosis meaning that the distributions have more extreme possible values (outliers) than a normal distribution and thus fatter tails. These extreme values lie more on the positive side explaining the results observed in **Table 6**. Finally, the previously observed bimodal pattern is less pronounced.



(a) CAPM

(b) FF3M

Figure 6. Upward period: average alphas KDE

3.2 Downward period (2018-2021)

The results reported in **Table 7** indicate that disclosing companies have a **significantly** higher average alpha than non-disclosing ones when the **CAPM** is used over the downward period. The alphas difference between the two samples is **.10825%** towards disclosers. Results point in the same direction when the **FF3M** is used and indicate that disclosing companies have a **significantly** higher average alpha than non-disclosing ones. The alphas difference between the two samples is **.49334%** towards disclosers (for ease of comparison between weekly and monthly results, see Appendix 6). The results point therefore in the opposite direction to those found during the upward period, i.e. the difference in average alphas is significantly negative meaning that disclosing firms perform financially better during the downward period.

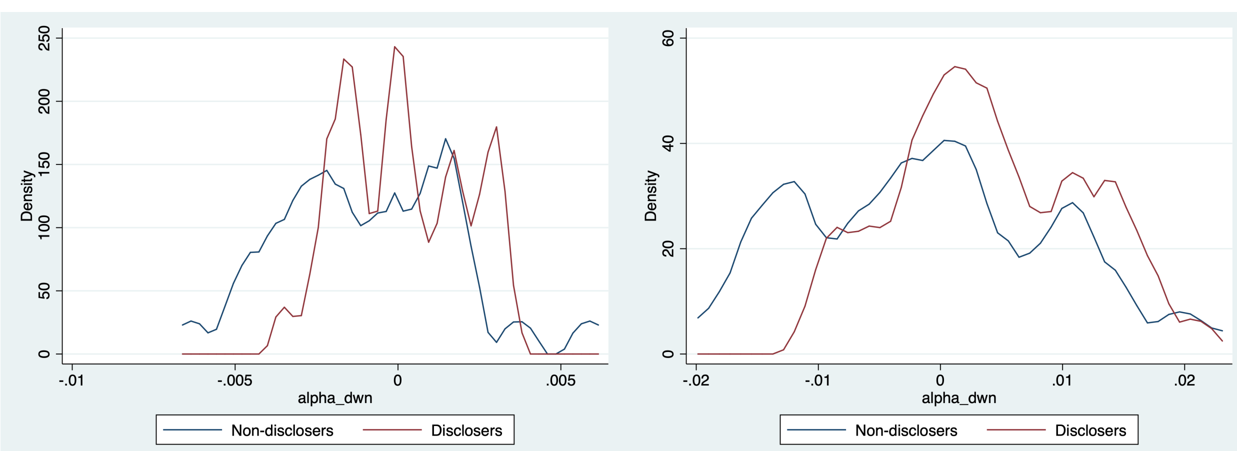
In their meta-analysis aggregating more than 1000 studies, (Whelan et al., 2021) affirm that ESG investments provide an overall downward protection, specifically in periods of crisis. Our results are consistent with these findings and will be discussed further in the last part of this study.

	CAPM				FF3M			
Group	Obs	Mean	t-stat	P> $\|t\|$	Obs	Mean	t-stat	P> $\|t\|$
Non-Disclosers	11375	-.0009361			2590	-.0008948		
Disclosers	11375	.0001464			2590	.0040386		
$H_0 : \mu_{ND} - \mu_D = 0$		**-.0010825**	-35.7168	**0.0000*****		**-.0049334**	-19.6908	**0.0000*****

Note: the results reported for the CAPM and the FF3M are respectively based on ***weekly*** *and* ***monthly*** *returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 7. Downward period: alphas two-sample t test

Analysing **Figure 7**, it can be observed that the curve for disclosing firms for both models has a higher density than the non-disclosing one. Hence, the distribution of disclosing companies has a higher probability of having an equivalent positive alpha value, which is consistent with the observations made in **Table 7**. However, the KDE distributions obtained with the FF3M are not unimodal reiterating the question previously raised. From the literature, it appears that the type of industry in which a company is active influences the environmental disclosure policy (Cormier et al., 2011). Therefore, the question of *whether the industry in which these firms operate can explain a difference in performance* will be examined in the second part of this study (II. Industry sensitivity analysis) in order to determine if the results obtained previously are robust.



(a) CAPM (b) FF3M

Figure 7. Downward period: average alphas KDE

II. Industry sensitivity analysis

1. Introduction

Following the above observations and based on the literature, we will conduct an industry sensitivity analysis. Numerous studies show that the industry in which a company is active influences its GHG emissions disclosure policy. According to (Schiemann & Sakhel, 2019), contextual factors, e.g. the industry, may indeed explain the difference in financial performance between carbon-intensive and other companies. Moreover, (Bingler et al., 2021) highlight the fact that firms active in the energy and utilities sectors disclose more than in other industries, thus constituting an important part of the TCFD in the risk materiality assessment. In their study based on European firms, (Muhammad Azeem et al., 2020) show that the association between ESG disclosure and market value is stronger among firms operating within sensitive industries. Furthermore, (Cormier et al., 2011) underline the link between the company's environmental performance and its pollution level by stating that the more a company pollutes, the more its environmental performance has an impact on its CSR disclosure. This can be explained by the fact that firms working in more polluting industries tend to be more under pressure (Huang & Kung, 2010).

This section is organised as follows. First, the selection criteria used to introduce the additional research dimension, i.e. the industries' pollution intensity, will be developed using the GHG intensity Bloomberg equity screening tool. Then, following the same logic used in the previous section, a two-stage analysis will be conducted considering the two dimensions, first over the single period and then over the two periods of time.

2. Polluting industry selection criteria

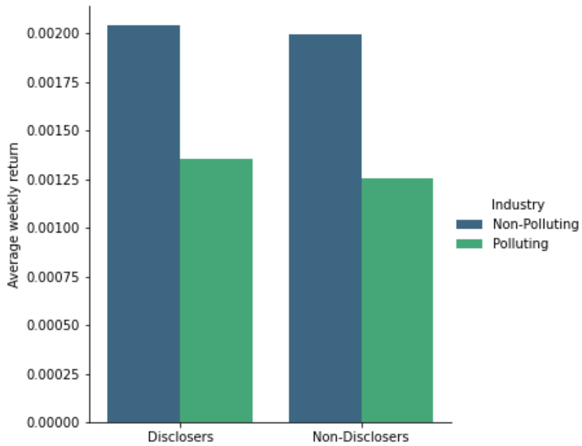
For comparative purposes, the Global Industry Classification Standard (GICS) has been used for the 70 companies (Appendix 2). Each firm is assigned a single GICS at the sub-industry level according to its principal business activity (MSCI, 2021). The structure is composed of 11 sectors, 24 industry groups and 69 industries detailed in Appendix 8b. The GICS industries' GHG intensity per unit sales for European companies reported in **Table 8**, has been used as selection criterion to create two subgroups within the initial samples. The numbers in brackets represent the number of securities in the filtered universe. This will allow us to differentiate, beyond the distinction between disclosers and non-disclosers, polluting firms from non-polluting ones.

GICS industry	**GHG intensity per unit sales (thousands of metric tons)**
Utilities (33)	801.62
Materials (50)	726.64
Energy (16)	371.63
Consumer Staples (48)	79.53
Industrials (113)	73.67
Consumer Discretionary(64)	47.42
Real Estate (41)	43.63
Health Care (53)	39.78
Communication Services (38)	23.58
Information Technology (37)	14.57
Financials (100)	5.11

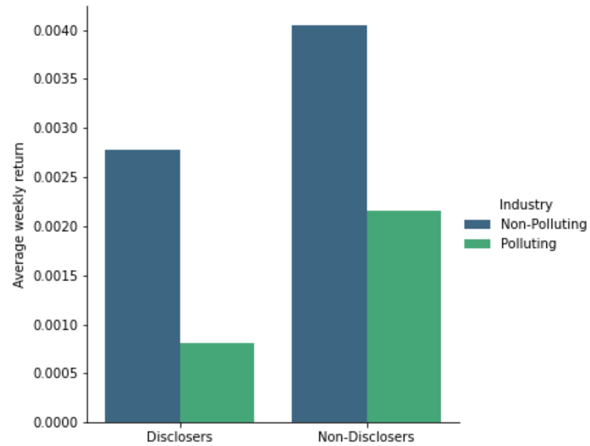
Table 8. Bloomberg European equity screening: GHG intensity by GICS industry

Source: (Bloomberg, 2021)

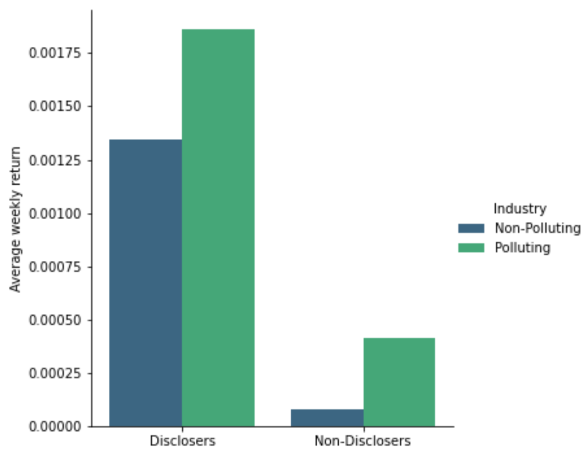
Given that the first three industries, i.e. **utilities**, **materials** and **energy** account for more than 85% of the GHG intensity metric (**Table 8**), companies active in these sectors are aggregated under the "**polluting**" group (P). Hence, firms active in the other sectors will be classified in the "**non-polluting**" group (NP). Based on (Ritchie & Roser, 2020)' research which gives a general idea of the most polluting industries worldwide in terms of GHG emissions, we can confirm our classification by matching the sectors included in their analysis (Appendix 8a) with the industries listed in the GICS framework (Appendix 8b).



(a) Single period: 2015-2021



(b) Upward period: 2015-2018



(c) Downward period: 2018-2021

Figure 8. Industry sensitivity analysis: average weekly returns

The table presented in Appendix 9 provides key statistics after including the industries' pollution intensity dimension according to the time period analysed. The **average weekly returns** of the disclosers and non-disclosers by type of industry reported in this table are represented on **Figure** 8. The firm's GHG emissions disclosure policy seems to have a different impact depending on the time period considered. There is no difference between the non-disclosing and the disclosing group over the **single period** of time, i.e. firms active in less polluting sectors have a higher average weekly return regardless of the disclosure policy. Considering the two-period analysis, it seems that during the **upward period** the non-polluting group continues to perform better than companies operating in environmentally damaging industries and that non-disclosers have a higher average weekly return than disclosers. However, during the **downward period** the situation is reversed, i.e. disclosers appear to perform much better than non-disclosers which have an average return close to 0% regardless of the GHG intensity of their industry and the polluting group has a higher average weekly return than the non-polluting one.

Analysing **Figure 9** by type of industry over the **single period**, companies active in non-polluting industries have globally higher cumulative weekly returns than polluting firms regardless their disclosure policy (green and blue curves). The same observation can be made considering the **upward period** only. However, during the **downward period**, less GHG-intensive companies have still higher cumulative returns no matter the disclosure policy but the polluting companies' performance has changed considerably compared to the upward period. Firms implementing a disclosure policy (orange curve) have higher cumulative returns than their benchmark (purple curve) whereas the reverse situation can be noticed for non-disclosing firms (red curve). The scenario is thus the opposite of what can be observed during the upward period for the polluting group taking the N100 index as reference.

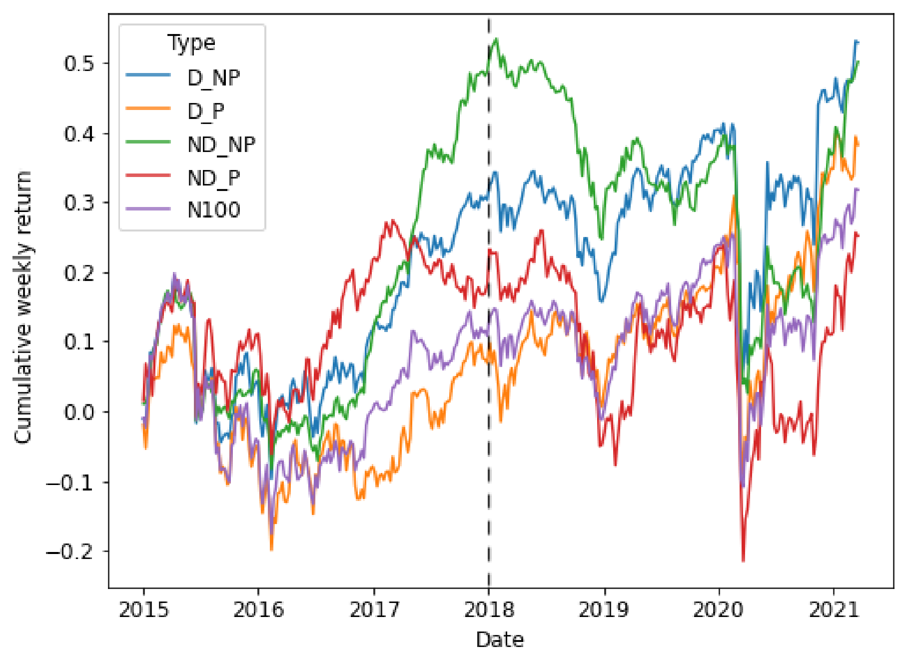


Figure 9. Industry sensitivity analysis: cumulative weekly returns over time

However, these observations are purely descriptive and do not take into account the underlying risk. Keeping these in mind, the remainder of this study will aim to test empirically whether the industry in which companies operate can explain a difference in performance between non-disclosing and disclosing firms and determine if the results obtained previously are robust. To this end, a similar test statistic as the one implemented in the previous section will be used (12). The **null hypothesis** states that the difference between the average alpha of non-polluting firms and the one of polluting firms is equal to 0. A positive (negative) difference means that the non-polluters' alpha is more (less) important than the polluters' one. This test will be conducted twice, for the non-disclosing and disclosing companies.

3. Single period analysis (2015-2021)

3.1 Non-Disclosers

The results reported in **Table 9** for non-disclosers indicate that companies active in non-polluting industries have a **significantly** higher average alpha than companies active in polluting sectors when the **CAPM** is used over the single period. The alphas difference between the two types of industries is **.12877%** towards the non-polluting group. Results point in the same direction when the **FF3M** is used and indicate that companies active in non-polluting industries have a **significantly** higher average alpha than firms active in polluting ones. The alphas difference between the two types of industries is **.47659%** towards the non-polluting group (for ease of comparison between weekly and monthly results, see Appendix 6). The combined row corresponds to the results found for the non-disclosing firms in **Table 5** when carrying out the one-dimension analysis on the sole GHG disclosure policy (this remark is valid for the following tables and can be used for verification purposes).

	CAPM				**FF3M**			
Group	Obs	Mean	t-stat	P> $\|t\|$	Obs	Mean	t-stat	P> $\|t\|$
Non-Polluters	8775	.0011359			1998	.0081384		
Polluters	2600	-.0001518			592	.0033725		
combined	11375	.0008416			2590	.007049		
$H_0 : \mu_{NP} - \mu_P = 0$		**.0012877**	28.8176	**0.0000*** **		**.0047659**	11.3847	**0.0000*** **

Note: the results reported for the CAPM and the FF3M are respectively based on ***weekly*** *and* ***monthly*** *returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 9. Single period: non-disclosers alphas two-sample t test by industry

3.2 Disclosers

The results reported in **Table 10** for disclosers indicate that firms active in non-polluting industries have a **significantly** higher average alpha than firms active in polluting sectors when the **CAPM** is used over the single period. The weekly alphas difference between the two types of industries is **.06645%** towards the non-polluting group. Results point in the same direction when the **FF3M** is used and indicate that companies active in non-polluting industries have a **significantly** higher average alpha than companies active in polluting ones. The monthly alphas difference between the two types of industries is **.2625%** towards the non-polluting group (for ease of comparison between weekly and monthly results, see Appendix 6).

	CAPM				**FF3M**			
Group	Obs	Mean	t-stat	P> $\|t\|$	Obs	Mean	t-stat	P> $\|t\|$
Non-Polluters	8775	.0006344			1998	.0076535		
Polluters	2600	-.0000301			592	.0050285		
combined	11375	.0004825			2590	.0070535		
$H_0 : \mu_{NP} - \mu_P = 0$		**.0006645**	19.8140	**0.0000*** **		**.002625**	8.8241	**0.0000*** **

*Note: the results reported for the CAPM and the FF3M are respectively based on **weekly** and **monthly** returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 10. Single period: disclosers alphas two-sample t test by industry

3.3 Comparison and interpretation

The results of the statistical tests confirm the previous observations that companies active in non-polluting industries have a significantly higher average alpha than firms active in polluting ones regardless of their disclosure policy. The implementation of a GHG emissions disclosure policy does not have any effect on the companies' financial performance depending on the industry in which they operate when we consider the single period of time.

For visualisation purposes, the alphas distributions of the four groups for the CAPM and FF3M can be found in Appendix 10a.

4. Two-period analysis

4.1 Upward period (2015-2018)

4.1.1 Non-Disclosers

Results reported in **Table 11** for non-disclosers indicate that firms active in non-polluting industries have a **significantly** higher average alpha than firms active in polluting sectors when the **CAPM** is used over the upward period. The alphas difference between the two types of industries is **.20219%** towards the non-polluting group. Results point in the same direction when the **FF3M** is used and indicate that companies active in non-polluting industries have a **significantly** higher average alpha than companies active in polluting ones. The alphas difference between the two types of sectors is **.94505%** towards the non-polluting group (for ease of comparison between weekly and monthly results, see Appendix 6).

	CAPM				FF3M			
Group	Obs	Mean	t-stat	P> $\|t\|$	Obs	Mean	t-stat	P> $\|t\|$
Non-Polluters	8775	.0033325			1998	.0178846		
Polluters	2600	.0013106			592	.008434		
combined	11375	.0028704			2590	.0157244		
$H_0 : \mu_{NP} - \mu_P = 0$		**.0020219**	27.0386	**0.0000*****		**.0094505**	14.0806	**0.0000*****

*Note: the results reported for the CAPM and the FF3M are respectively based on **weekly** and **monthly** returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 11. Upward period: non-disclosers alphas two-sample t test by industry

4.1.2 Disclosers

The results reported in **Table 12** for disclosers indicate that firms active in non-polluting industries have a **significantly** higher average alpha than firms active in polluting sectors when the **CAPM** is used over the upward period. The alphas difference between the two types of industries is **.20972%** towards the non-polluting group. Results point in the same direction when the **FF3M** is used and indicate that companies active in non-polluting sectors have a **significantly** higher average alpha than companies active in polluting ones. The alphas difference between the two types of industries is **.85005%** towards the non-polluters.

	CAPM				FF3M			
Group	Obs	Mean	t-stat	P> $\|t\|$	Obs	Mean	t-stat	P> $\|t\|$
Non-Polluters	8775	.0013944			1998	.012168		
Polluters	2600	-.0007028			592	.0036675		
combined	11375	.000915			2590	.010225		
$H_0 : \mu_{NP} - \mu_P = 0$		**.0020972**	48.6912	**0.0000*****		**.0085005**	22.2579	**0.0000*****

*Note: the results reported for the CAPM and the FF3M are respectively based on **weekly** and **monthly** returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 12. Upward period: disclosers alphas two-sample t test by industry

4.2 Downward period (2018-2021)

4.2.1 Non-Disclosers

The results reported in **Table 13** for non-disclosers indicate that companies active in non-polluting industries have a **significantly** higher average alpha than companies active in polluting sectors when the **CAPM** is used over the downward period. The alphas difference between the two types of industries is **.0625%** towards the non-polluting group. However, when the **FF3M** is used, results indicate that firms active in non-polluting sectors have a **non-significantly** higher average alpha than firms active in polluting ones, which is not conclusive (for ease of comparison between weekly and monthly results, see Appendix 6).

	CAPM				FF3M			
Group	Obs	Mean	t-stat	P> $\|t\|$	Obs	Mean	t-stat	P> $\|t\|$
Non-Polluters	8775	-.0007933			1998	-.0007285		
Polluters	2600	-.0014183			592	-.001456		
combined	11375	-.0009361			2590	-.0008948		
$H_0 : \mu_{NP} - \mu_P = 0$		**.000625**	10.6469	**0.0000*****		**.0007276**	1.5351	**0.1249**

*Note: the results reported for the CAPM and the FF3M are respectively based on **weekly** and **monthly** returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 13. Downward period: non-disclosers alphas two-sample t test by industry

4.2.2 Disclosers

The results reported in **Table 14** for disclosers indicate that companies active in polluting industries have a **significantly** higher average alpha than companies active in non-polluting sectors when the **CAPM** is used over the downward period. The alphas difference between the two types of industries is **.0598%** towards the polluting group. Results point in the same direction when the **FF3M** is used and indicate that firms active in polluting industries have a **significantly** higher average alpha than firms active in non-polluting ones. The alphas difference between the two types of industries is **.2916%** towards the polluting group.

	CAPM				FF3M			
Group	Obs	Mean	t-stat	P> $\|t\|$	Obs	Mean	t-stat	P> $\|t\|$
Non-Polluters	8775	9.69e-06			1998	.0033721		
Polluters	2600	.0006076			592	.0062881		
combined	11375	.0001464			2590	.0040386		
$H_0 : \mu_{NP} - \mu_P = 0$		**-.000598**	-14.5084	**0.0000*****		**-.002916**	-8.1497	**0.0000*****

*Note: the results reported for the CAPM and the FF3M are respectively based on **weekly** and **monthly** returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 14. Downward period: disclosers alphas two-sample t test by industry

4.3 Comparison and interpretation

Non-polluting companies perform better than polluting ones during the upward period regardless of their disclosure policy, which confirms the results obtained so far. However, during the downward period, the implementation of a GHG emissions disclosure policy is of interest, i.e. firms active in polluting industries perform better than firms active in non-polluting ones when they disclose their GHG information. This confirms the observations made on **Figure 8**. For non-disclosers, the alphas difference is not statistically significant during the downward period when the FF3M is used. This difference in results between the two models could again be explained by the presence of additional factors in the model developed by Fama and French.

Firms active in polluting sectors are therefore less penalised if they disclose their GHG emissions information when the market is not performing well [FF3M: -.1456% (ND) vs. .62881% (D)]. (Bingler et al., 2021) argue that companies active in these industries could use this opportunity to show that they are leaders in low-carbon transformation so that they are not seen as high climate risk companies because of their sectoral activities as such. Our results are consistent with these findings and will be discussed further in the last part of this study.

A more detailed visualisation of the the alphas distributions can be found in Appendix 10b. These graphs identify the four groups enabling to discern the impact of implementing a GHG emissions disclosure policy while considering the industries' pollution intensity over different time periods.

III. Summary of results

	One dimension analysis: GHG emissions disclosure policy		
	2015-2021	*2015-2018*	*2018-2021*
	Non-Disclosers - Disclosers	Non-Disclosers - Disclosers	Non-Disclosers - Disclosers
$\mu_{ND} - \mu_D$	**.03591 %** (.00241%)	**.19553%** (.0038%)	**-.10825%** (.00303%)
t-test	**14.8747*****	**51.4464*****	**-35.7168*****
N	11375+11375	11375+11375	11375+11375

	Two dimensions analysis: GHGe disclosure policy & industries' pollution intensity					
	Non-Disclosers NP - P	Disclosers NP - P	Non-Disclosers NP - P	Disclosers NP - P	Non-Disclosers NP - P	Disclosers NP - P
$\mu_{NP} - \mu_P$	**.12877%** (.00447%)	**.06645%** (.00335%)	**.20219%** (.00748%)	**.20972%** (.00431%)	**.0625%** (.00587%)	**-.0598%** (.00412%)
t-test	**28.8176*****	**19.8140*****	**27.0386*****	**48.6912*****	**10.6469*****	**-14.5084*****
N	8775+2600	8775+2600	8775+2600	8775+2600	8775+2600	8775+2600

*Note: the results reported are based on **weekly** returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 15. CAPM: summary of the results

	One dimension analysis: GHG emissions disclosure policy		
	2015-2021	*2015-2018*	*2018-2021*
	Non-Disclosers - Disclosers	Non-Disclosers - Disclosers	Non-Disclosers - Disclosers
$\mu_{ND} - \mu_D$	**-4.46e-04%** (.02202%)	**.54994%** (.03408%)	**-.49334%** (.02505%)
t-test	**-0.0203**	**16.1391*** **	**-19.6908*** **
N	2590+2590	2590+2590	2590+2590

	Two dimensions analysis: GHGe disclosure policy & industries' pollution intensity					
	Non-Disclosers NP - P	Disclosers NP - P	Non-Disclosers NP - P	Disclosers NP - P	Non-Disclosers NP - P	Disclosers NP - P
$\mu_{NP} - \mu_P$	**.47659%** (.04186%)	**.2625%** (.02975%)	**.94505%** (.06712%)	**.85005%** (.03819%)	**.07276%** (.04739%)	**-.2916%** (.03578%)
t-test	**11.3847*** **	**8.8241*** **	**14.0806*** **	**22.2579*** **	**1.5351**	**-8.1497*** **
N	1998+592	1998+592	1998+592	1998+592	1998+592	1998+592

Note: the results reported are based on ***monthly*** *returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 16. FF3M: summary of the results

	One dimension analysis: GHG emissions disclosure policy		
	2015-2021	*2015-2018*	*2018-2021*
	Non-Disclosers - Disclosers	Non-Disclosers - Disclosers	Non-Disclosers - Disclosers
$\mu_{ND} - \mu_D$	**-4.47e-04%** (.02202%)	**.54994%** (.03408%)	**-.49334%** (.02505%)
t-test	**-0.0203**	**16.1391*** **	**-19.6909*** **
N	2590+2590	2590+2590	2590+2590

	Two dimensions analysis: GHGe disclosure policy & industries' pollution intensity					
	Non-Disclosers NP - P	Disclosers NP - P	Non-Disclosers NP - P	Disclosers NP - P	Non-Disclosers NP - P	Disclosers NP - P
$\mu_{NP} - \mu_P$	**.4766%** (.04186%)	**.2625%** (.02975%)	**.94505%** (.06712%)	**.85005%** (.03819%)	**.07276%** (.04739%)	**-.2916%** (.03578%)
t-test	**11.3847*** **	**8.8240*** **	**14.0806*** **	**22.2579*** **	**1.5351**	**-8.1497*** **
N	1998+592	1998+592	1998+592	1998+592	1998+592	1998+592

Note: the results reported are based on ***monthly*** *returns*
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 17. Carhart four-factor model: summary of the results

Discussion and conclusion

I. Discussion

The increased availability of ESG data and reporting regulations are putting more and more pressure on companies' practices, thus raising investors' attention. Reporting regulations are constantly evolving, e.g. the EU issued a directive on non-financial reporting (NFRD) requiring companies to disclose on ESG matters in 2014 and more recently, the European Green Deal has been voted in 2020. The emergence of new reporting directives will hopefully reduce companies' incentives to perform cherry picking according to their own environmental performance as outlined in the literature summary. To set a framework in this evolving context, this study has been conducted on Euronext listed companies in order to keep a certain coherence with (Bennani et al., 2018)' statement who argue that ESG dimensions have both a time and region varying impact on performance and risk. The difference between the baseline valuation computed from the non-disclosing sample and the integrated GHG emissions disclosure policy valuation computed from the disclosing sample depicts the materiality of the GHG disclosure factor. According to (Whelan et al., 2021), ESG disclosure on its own does not drive financial valuation. Beyond simply measuring ESG performance indicators, companies must come up with a concrete strategy. Therefore, the MSCI rating and the Bloomberg proprietary ESG score have been used in addition to the Carbon Disclosure Project to identify companies that are implementing ESG-related issues appropriately. Firms included in the disclosing sample can thus also be considered as good ESG performers.

The Capital Asset Pricing model has been used initially to compute the alpha of the non-disclosing and disclosing samples to answer the research question. However, the CAPM suffers from a number of limitations, including the limited ability of the predictor variable to explain the variance of the dependent variable. For this reason and to deal with the capitalisation differential between the two samples, the Fama-French three-factor model has been implemented. Companies with a disclosure policy and valuing ESG criteria have a higher capitalisation than the companies in the non-disclosing sample (Appendix 7). This difference in capitalisation between the two samples is consistent with the findings of (Huang & Kung, 2010) and (Peters & Romi, 2014) who show that firms with a larger number of employees and larger management committees result in greater information asymmetry and are more under pressure to publish their environmental activities. Moreover, (Dawkins & Fraas, 2011b) argue that increased visibility, implied by the higher market capitalisation, makes it easier for companies to publish information on a voluntary basis. The Fama-French SMB factor captures the part of the returns related to this size differential, not explained by the CAPM. The majority of the findings point in the same direction using either model. Finally, the Carhart four-factor model has been implemented to ensure that the observed results were robust, thereby verifying that the obtained alphas were not attributable to the companies' past performance. The findings are almost identical to the ones obtained with the FF3M. This indicates that the financial performance associated with the implementation or not of a GHG emissions disclosure policy is not attributable to the companies' historical performance. Consequently, the **results discussed** in the remainder **are those obtained with the Fama-French three-factor model based on monthly returns**.

Considering first the **GHG emissions disclosure policy** dimension **only** over the **single period** going from 2015 until mid-March 2021, a slightly negative and **non-significant** alphas difference has been found which is not conclusive after considering the two additional Fama-French factors. As for the two-period analysis, the implementation of a GHG emissions disclosure policy has a different impact on the alpha depending on the period considered. During the **upward period**, a positive and **significant** alphas difference of **.54994%** has been found indicating that non-disclosing companies perform better when the market is performing well whereas during the **downward period**, the situation is reversed, i.e. disclosing firms perform better with a negative and **significant** alphas difference of **.49334%**. In other words, **disclosing companies perform better when the market is bearish whereas non-disclosing firms perform better when the market is bullish**.

Results suggest that the implementation of a GHG emissions disclosure policy by ESG performers provides a downside protection while limiting their upward potential. The relationship between the reported GHG quantity and the companies' financial performance is unclear, as outlined in the literature summary. (Benlemlih, Shaukat, Qiu, & Trojanowski, 2016) shed light on this by analysing the impact of environmental and social disclosure on the companies' systematic and idiosyncratic risk. Their results indicate that although the disclosure policy may increase firm's value, it is not explained by a reduction of the systematic risk. The authors find that the implementation of a disclosure policy according to the environmental and social criteria can improve the firm's reputation leading to a higher growth rate, higher cash flows and idiosyncratic risk mitigation. In their meta-analysis aggregating more than 1000 studies, (Whelan et al., 2021) affirm that ESG investments provide an overall downside protection, specifically in periods of crisis. A large majority of the sub-studies demonstrate a strong correlation between lower sustainability-related risk and better financial performance. (Hale, 2020) confirms this in his article in which he analyses the results of US equity funds during the first quarter of 2020 impacted by the pandemic. Despite inevitable losses, sustainable funds end up performing better than traditional funds. In (Hale, 2020)'s view, beyond this short-term performance, the longer-term impact of ESG investing should be borne in mind, as demand to integrate ESG criteria is expected to grow in the coming years. (Wade, 2018) highlights the importance this type of asset could have in an investment core strategy. According to this author and confirmed by (Bingler et al., 2021), this will become even more relevant since the portfolio inclusion of ESG performing assets will be inevitable in the future. To avoid investors rushing to include such positions in their portfolio, it is best to navigate through the challenging market conditions, understand the corporate governance strategy and engage with bondholders to include ESG performing assets in investors' portfolio and reduce the risk of being in trouble once climate risks materialize.

Furthermore, the increasing climate regulations are pushing companies under the spotlight. Businesses are then forced to respond to it to ensure that they do not suffer from excessive information asymmetry or erroneous news. Recent European directives such as the EU

Green Deal and Paris agreement illustrate this phenomenon and could therefore explain the lower performance of poor ESG-performers during the most recent period, i.e. the downward period. (Dhaliwal et al., 2011) confirm that companies with good ESG performance and disclosing their information tend to attract coverage from institutional investors and analysts, reducing the absolute forecast errors and the dispersion following disclosure. This underlines the importance of implementing an environmental disclosure policy and complying with ESG criteria. The visibility is even greater in GHG intensive industries reinforcing the association between sustainability disclosure and market value (Muhammad Azeem et al., 2020). The industries' pollution intensity is therefore worth considering.

In the second part of this study, the **industries' pollution intensity** dimension has been added on top of the GHG emissions disclosure policy. Companies operating in more polluting sectors may have more incentive to publish their GHG emissions due to the higher visibility they are usually given. Considering the **single period**, results do not seem to indicate that the implementation of a voluntary disclosure policy makes a difference taking into account the type of industry in which companies are active, i.e. companies operating in less polluting industries perform better regardless the GHG emissions disclosure policy implementation. The alphas difference for non-disclosers and disclosers is respectively of **.47659%** [.81384% (NP) - .33725% (P)] and **.2625%** [.76535% (NP) - .50285% (P)] with a relatively similar alpha for the non-polluting group (.81384% vs. .76535%) but a better performance for the polluting firms disclosing their information (.33725% vs. .50285%). Considering the two-period analysis, the same observations can be made during the **upward period** with an even greater and more significant difference in favour of the non-polluting group. The alphas difference increases to **.94505%** and to **.85005%** respectively for the non-disclosing and disclosing group. However, in line with the observations made on **Figure 8**, companies operating in more GHG intensive industries perform better when they implement a GHG emissions disclosure policy during the **downward period**. The alphas difference is statistically not significant when companies choose not to implement a GHG emissions disclosure policy but is significant and of **.2916%** towards the polluting group when firms disclose their information.

The results obtained after considering the industries' pollution intensity confirm globally the observations made previously, i.e. **the downside protection provided by ESG integrated policies when the market is not performing well and the upward limitation in more bullish markets**. Considering the results over the **single period**, the alphas difference between the non-polluting group and the polluting one is smaller when companies implement a disclosure policy due to the higher performance of polluting firms when they decide to disclose their information compared to those that do not. Exposures to GHG intensive sectors are often excluded from sustainable funds, thus improving their financial performance (Hale, 2020). The non-polluting portfolio has been constructed in a similar way, i.e. by excluding the most polluting firms, which can explain the overall better performance of the non-polluting group. However, we observe that, despite being active in polluting sectors, ESG integration reduces information asymmetry and gives companies the opportunity to be among the best ESG performers in these controversial sectors. Considering the two-period results, the environmental disclosure policy implementation limits the upside potential during the **upward period** but is of real interest during the **downward period**. **Being more ESG conscious reduces the risk associated with more polluting firms when the market is not performing well**. In other words, companies active in more GHG intensive sectors are less penalised when they disclose their GHG emissions information during downward periods. According to (Huang & Kung, 2010), they are subject to greater pressure and are therefore more likely to disclose this information. (Bingler et al., 2021) argue that companies active in polluting industries could use this opportunity to show that they are leaders in low-carbon transformation so that they are not seen as high climate risk companies because of their sectoral activities as such.

Beyond the directly measurable ESG-related characteristics impacting firm's value, their implementation may take some time to be valued. In their meta-analysis, (Whelan et al., 2021) argue that as time goes by, the financial performance of companies integrating ESG criteria is increasingly improved. Moreover, (Giese et al., 2019) state that the transmission from ESG characteristics to financial value is a multichannel process (Appendix 5) and insist on the longevity of ESG ratings' financial impact. ESG-related features, such as the presence of a CSO or gender diversity, have been increasingly integrated into companies over the past few years influencing their environmental disclosure policy. According to (Kılıç & Kuzey, 2019) and (Baalouch et al., 2019), the inclusion of a CSO and environmental committee is positively related to voluntary GHG emissions divulgation and impacts the disclosure quality. The gender diversity consideration in board committees also has a positive effect on the disclosure quality as per (Baalouch et al., 2019) and (Muhammad Azeem et al., 2020) further claim that it has an influence on firm's value.

Finally, taking a step back from the literature and considering alpha from a risk perspective, one could explain the fact that by investing in riskier stocks, depending on the risk factors considered, e.g. regulatory risk, the alpha is higher. The non-disclosing group may be perceived to be riskier due to the lack of ESG consideration in a growing climate change regulatory framework. Riskier stocks pay up when investors need money the least and suffer losses when investors really need it. This could explain the higher performance of the non-disclosing sample when the overall market is doing well and alternatively its lower performance when the market is doing poorly. However, considering alpha from a risk perspective can be difficult to differentiate from the increasingly widespread factor investing strategies. In order to convince investors to invest in companies implementing disclosure policies, they need to be compensated with higher returns. From a societal perspective, this can be beneficial because if their price actually goes up, companies incurring environmental protection costs will not have to pay much to investors, firms will grow and end up becoming more and more important in the economy. There could be other reasons for the performance of the disclosing group during the most recent period. Individuals are forced to stay at home with the pandemic context, increase their savings and may be more prone to invest their money. In a context where climate issues are constantly being discussed, ESG investments can therefore constitute a good opportunity.

II. Conclusion

The aim of this study was to compare the financial performance of companies that voluntarily and fully disclose their greenhouse gas emissions with companies that do not. To this end, two samples each composed of 35 companies listed on the Euronext have been created based on three selection criteria: the Carbon Disclosure Project, the MSCI ESG rating and the Bloomberg proprietary ESG score. The objective was initially to understand the companies' incentives to disclose their GHG emissions in a context where climate-related regulations are exercising an increasing pressure and knowing that such disclosure makes companies vulnerable to market reactions. Subsequently, an industry sensitivity analysis has been conducted in order to examine whether the industry in which these firms operate can explain a difference in performance. To answer these research questions, the financial performance of the two groups has been measured using the alpha computed through three models, the Capital Asset Pricing Model, the Fama-French three-factor model and the Carhart four-factor model. The difference between the baseline valuation computed from the non-disclosing sample and the integrated disclosure policy valuation computed from the disclosing sample depicts the materiality of the GHG emissions disclosure factor. The average alpha of both samples has been initially computed over a single period of time going from 2015 until mid-March 2021 and then over two periods, an upward period starting from 2015 to end 2017 and a downward period going from 2018 until mid-March 2021.

Our results show that the implementation of a GHG emissions disclosure policy provides a downside protection in times of crisis while restricting the upward potential when the market is performing well. Considering the company industries' GHG intensity dimension in our analysis, results indicate that less polluting companies have generally a higher average alpha than polluting ones regardless the GHG emissions disclosure policy. However, the environmental policy implementation is of real interest for GHG intensive firms during downward periods, i.e. polluting companies perform better than less polluting ones in bear markets when they choose to disclose their GHG information. ESG integration offers a long-term perspective in a context of increasing climate awareness and regulation, thereby reducing information asymmetry and the penalty that comes with it.

This study presents certain limitations, notably in the sampling method. The selection criteria led to a relatively large difference in market capitalisation between the two samples requiring to consider the Fama-French SMB factor. Moreover, the disclosers' counter-group, i.e. the non-disclosing sample, has been built using several criteria questioning the impact of the sole GHG emissions disclosure policy on firm valuation. The MSCI ESG rating and the Bloomberg ESG score have been used on top of the CDP to identify ESG best performers for two main reasons. First, given that the company's environmental performance impacts the disclosure policy. Second, to avoid including firms publishing their GHG emissions for greenwashing purposes. Furthermore, GHG emissions as materiality criterion, do not have the same relevance depending on the industry considered. Subsequent researches could use materiality maps to select companies that are more likely to see their valuation impacted by the GHG emissions disclosure. Finally, ESG incorporation within companies may be more complex than the simple ratings or scores consideration. Future studies could therefore focus on incorporating greenhouse gas emissions into company valuation using a multi-factor model or by engaging directly with companies, thereby enabling a better assessment of their ESG policies and the firm's real intent.

Despite the disparity in capitalisation between the two samples which may impact some of the results, this study provides a real perspective on the importance for companies to incorporate environmental, social and governmental criteria somehow in the future. Whether it is in the form of screening, impact-driven, valuation integration, or active ownership and engagement, ESG incorporation is necessary for the survival of all businesses and for the achievement of global climate change objectives. Furthermore, the large amount of reporting frameworks and the current lack of standardised regulatory scheme is a real barrier to the development of sustainable finance. Companies opt for the framework that suits them best and investors must find their way around to make investment decisions. This lack of standardisation is therefore a real obstacle to the materiality of ESG data. The future EU taxonomy implementation will serve as classification tool allowing investors to take more informed decisions. It could therefore be relevant to reconduct this study in a couple of years. Firms will have to disclose their information for regulatory risk mitigation purposes and therefore position themselves towards ESG-related issues. The difference between firms disclosing their GHG emissions and the others will therefore be more exploitable. This will provide companies incentives to reduce their environmental footprint in order to avoid negative market reactions and may as well be part of their sustainability strategy. All companies will have an interest in publishing their figures, especially start-ups which have a headstart over more developed firms in the sense that they can implement sustainable policies at an early stage of their growth and with lower costs. This process requires engagement and active ownership to get them on board to incorporate ESG criteria. The environmental disclosure policy implementation should definitely be part of any company's risk management.

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Appendices

Appendix 1 - CDP 2020 Climate Change scoring

Level	**Climate change**	**Score band**
Disclosure	1-44%	D^-
	45-79%	D
Awareness	1-44%	C^-
	45-79%	C
Management	1-44%	B^-
	45-79%	B
Leadership	1-44%	A^-
	45-79%	A

Table 18. CDP Climate Change scoring: disclosure level thresholds

Source: (CDP, 2020b, p.7)

Appendix 2 - Samples

1. Non-Disclosing sample

	Company	Ticker	Country	GICS industry
1	ACCELL GROUP	ACCEL	Netherlands	Consumer Discretionary
2	PHARMING GROUP	PHARM	Netherlands	Health Care
3	HUNTER DOUGLAS	HDG	Netherlands	Consumer Discretionary
4	ORANJEWOUD A	ORANW	Netherlands	Industrials
5	EXMAR	EXM	Belgium	Energy
6	VAN DE VELDE	VAN	Belgium	Consumer Discretionary
7	KBC ANCORA	KBCA	Belgium	Financials
8	AGFA-GEVAERT	AGFB	Belgium	Health Care
9	KINEPOLIS GROUP	KIN	Belgium	Communication Services
10	BENETEAU	BEN	France	Financials
11	NICOX	COX	France	Health Care
12	IRISH CONT. GP.	IR5B	Ireland	Industrials
13	MINCON GROUP PLC	MIO	Ireland	Industrials
14	DATALEX PLC	DLE	Ireland	Information Technology
15	ALTRI, SGPS	ALTR	Portugal	Information Technology
16	NOVABASE,SGPS	NBA	Portugal	Information Technology
17	IMPRESA,SGPS	IPR	Portugal	Communication Services
18	GLINTT	GLINT	Portugal	Information Technology
19	IBERSOL,SGPS	IBS	Portugal	Consumer Discretionary
20	COFINA,SGPS	CFN	Portugal	Communication Services
21	FINATIS	FNTS	France	Consumer Staples
22	CATERING INTL SCES	CTRG	France	Industrials
23	ACTIA GROUP	ATI	France	Materials
24	OCEAN YIELD	OCY	Norway	Energy
25	FRONTLINE	FRO	Norway	Energy
26	NEDAP	NEDAP	Netherlands	Information Technology
27	IDI	IDIP	France	Financials
28	ESI GROUP	ESI	France	Materials
29	GROUPE OPEN	OPN	France	Information Technology
30	LACROIX SA	LACR	France	Information Technology
31	DERICHEBOURG	DBG	France	Industrials
32	SERGEFERRARI GROUP	SEFER	France	Materials
33	GROUPE CRIT	CEN	France	Utilities
34	OENEO	SBT	France	Materials
35	VAA VISTA ALEGRE	VAF	Portugal	Consumer Discretionary

Table 19. Non-Disclosing sample

	Company	CDP climate score	MSCI ESG rating	Bloomberg proprietary scores (all)
1	ACCELL GROUP	F	NaN	NaN
2	PHARMING GROUP	F	NaN	NaN
3	HUNTER DOUGLAS	F	NaN	NaN
4	ORANJEWOUD A	F	NaN	NaN
5	EXMAR	F	NaN	NaN
6	VAN DE VELDE	F	NaN	NaN
7	KBC ANCORA	F	NaN	NaN
8	AGFA-GEVAERT	F	NaN	NaN
9	KINEPOLIS GROUP	F	NaN	NaN
10	BENETEAU	F	NaN	NaN
11	NICOX	F	NaN	NaN
12	IRISH CONT. GP.	F	NaN	NaN
13	MINCON GROUP PLC	F	NaN	NaN
14	DATALEX PLC	F	NaN	NaN
15	ALTRI, SGPS	F	NaN	NaN
16	NOVABASE,SGPS	F	NaN	NaN
17	IMPRESA,SGPS	F	NaN	NaN
18	GLINTT	F	NaN	NaN
19	IBERSOL,SGPS	F	NaN	NaN
20	COFINA,SGPS	F	NaN	NaN
21	FINATIS	F	NaN	NaN
22	CATERING INTL SCES	F	NaN	NaN
23	ACTIA GROUP	F	NaN	NaN
24	OCEAN YIELD	F	NaN	NaN
25	FRONTLINE	F	NaN	NaN
26	NEDAP	F	NaN	NaN
27	IDI	F	NaN	NaN
28	ESI GROUP	F	NaN	NaN
29	GROUPE OPEN	F	NaN	NaN
30	LACROIX SA	F	NaN	NaN
31	DERICHEBOURG	F	NaN	NaN
32	SERGEFERRARI GROUP	F	NaN	NaN
33	GROUPE CRIT	F	NaN	NaN
34	OENEO	F	NaN	NaN
35	VAA VISTA ALEGRE	F	NaN	NaN

Table 20. Non-Disclosing sample (2)

2. Disclosing sample

	Company	Ticker	Country	GICS industry
1	PHILIPS KON	PHIA	Netherlands	Health Care
2	ENGIE	ENGI	France	Utilities
3	JC DECAUX SA.	DEC	France	Communication Services
4	PERNOD RICARD	RI	France	Consumer Staples
5	KERING	KER	France	Consumer Discretionary
6	SAINT GOBAIN	SGO	France	Industrials
7	SCHNEIDER ELEC.	SU	France	Industrials
8	L'OREAL	OR	France	Consumer Staples
9	ICADE	ICAD	France	Real Estate
10	IPSEN	IPN	France	Health Care
11	LEGRAND	LR	France	Industrials
12	TOTAL	FP	France	Energy
13	EDP	EDP	Portugal	Utilities
14	ARKEMA	AKE	France	Materials
15	VALEO	FR	France	Consumer Discretionary
16	VEOLIA ENVIRON.	VIE	France	Utilities
17	CAPGEMINI	CAP	France	Information Technology
18	DANONE	BN	France	Consumer Staples
19	KLEPIERRE	LI	France	Consumer Discretionary
20	EDF	EDF	France	Utilities
21	COVIVIO	COV	France	Real Estate
22	AXA	CS	France	Financials
23	DSM KON	DSM	Netherlands	Materials
24	WORLDLINE	WLN	France	Information Technology
25	HEINEKEN	HEIA	Netherlands	Consumer Staples
26	REMY COINTREAU	RCO	France	Consumer Staples
27	NN GROUP	NN	Netherlands	Financials
28	ING GROEP N.V.	INGA	Netherlands	Financials
29	AIR LIQUIDE	AI	France	Information Technology
30	ORANGE	ORA	France	Communication Services
31	SUEZ	SEV	France	Utilities
32	ALSTOM	ALO	France	Industrials
33	BNP PARIBAS ACT.A	BNP	France	Financials
34	KPN KON	KPN	Netherlands	Communication Services
35	VINCI	DG	France	Consumer Discretionary

Table 21. Disclosing sample

	Company	CDP climate score	MSCI ESG rating	Bloomberg ESG score (2019)	Bloomberg E score (2019)	Bloomberg 5-year avg. ESG score	Bloomberg 5-year avg. E score
1	PHILIPS KON	A	A	58.68	57.36	56.61	53.64
2	ENGIE	A	A	55.79	51.16	55.45	50.54
3	JC DECAUX SA.	A	AAA	59.81	56.25	55.89	52.50
4	PERNOD RICARD	A	AA	56.62	62.02	59.84	61.86
5	KERING	A	AA	63.64	65.62	61.15	63.96
6	SAINT GOBAIN	A	A	71.07	72.87	68.18	67.44
7	SCHNEIDER ELEC.	A	AAA	59.09	51.94	61.07	57.05
8	L'OREAL	A	AAA	61.16	57.36	60.91	57.36
9	ICADE	A-	A	50.83	43.41	49.26	40.47
10	IPSEN	A-	A	55.79	55.04	56.20	54.26
11	LEGRAND	A-	AA	58.26	53.49	53.82	45.54
12	TOTAL	A-	A	65.56	63.64	63.57	61.49
13	EDP	A-	AAA	65.29	62.79	65.04	63.41
14	ARKEMA	A-	A	63.22	62.02	61.49	59.85
15	VALEO	A	AAA	62.40	64.34	62.07	63.41
16	VEOLIA ENVIRON.	A-	A	54.13	47.29	55.29	47.13
17	CAPGEMINI	A	AA	53.31	47.29	51.49	44.96
18	DANONE	A	AAA	53.31	48.84	53.31	48.37
19	KLEPIERRE	A-	AA	51.24	48.06	55.12	45.12
20	EDF	A	A	52.07	42.64	52.23	44.34
21	COVIVIO	A-	AA	47.93	44.19	49.26	43.88
22	AXA	A-	AAA	49.56	45.54	48.60	44.64
23	DSM KON	A-	AAA	49.59	37.98	50.58	39.84
24	WORLDLINE	A-	A	52.89	44.19	51.82	44.34
25	HEINEKEN	A	AA	53.72	43.41	52.56	42.02
26	REMY COINTR.	A-	A	51.24	43.41	51.65	45.43
27	NN GROUP	A	AA	50.88	38.39	51.84	38.75
28	ING GROEP N.V.	A	A	57.02	43.75	55.70	43.75
29	AIR LIQUIDE	A	A	55.79	44.96	56.78	48.68
30	ORANGE	A	AAA	52.67	44.72	52.35	42.76
31	SUEZ	A	A	53.31	44.96	52.98	44.50
32	ALSTOM	A-	AA	54.13	44.96	54.46	46.36
33	BNP PARIBAS	A-	AA	53.07	38.39	55.00	43.39
34	KPN KON	A	AAA	47.74	42.28	47.24	40.33
35	VINCI	A-	A	50.83	39.53	49.50	37.83

Table 22. Disclosing sample (2)

Appendix 3 - Samples descriptive statistics

a) Non-Disclosers

	Minimum	Maximum	Mean	Std. Dev.	Skewness	Kurtosis
ACCEL	(.328)	.216	.005	.044	(.16)	13.053
PHARM	(.236)	.394	.006	.07	1.062	7.243
HDG	(.16)	.255	.003	.033	1.314	15.896
ORANW	(.089)	.134	.001	.03	.424	5.126
EXM	(.405)	.276	(.018)	.058	(.367)	11.932
VAN	(.153)	.142	(.0003)	.039	(.004)	5.327
KBCA	(.223)	.239	.002	.044	(.026)	8.638
AGFB	(.214)	.139	.003	.047	(.868)	5.935
KIN	(.194)	.223	(.002)	.05	(.265)	7.27
BEN	(.235)	.186	(.002)	.054	(.173)	5.734
COX	(.276)	.436	(.001)	.067	1.291	12.204
IR5B	(.143)	.176	.002	.041	.275	5.078
MIO	(.25)	.2	.003	.055	(.3)	5.659
DLE	(.679)	.607	.002	.079	(1.27)	34.847
ALTR	(.28)	.241	.004	.054	(.11)	6.443
NBA	(.132)	.212	.002	.042	1.292	8.718
IPR	(.256)	.33	(.003)	.071	.821	5.906
GLINT	(.28)	.323	(.002)	.07	1.489	9.296
IBS	(.234)	.775	.002	.0602	6.61	89.659
CFN	(.321)	.275	(.001)	.055	.142	8.802
FNTS	(.382)	.722	(.0002)	.082	3.227	32.587
CTRG	(.219)	.143	(.0002)	.049	(.345)	5.806
ATI	(.228)	.281	(.0002)	.061	(.116)	5.88
OCY	(.401)	.188	(.002)	.046	(1.831)	20.819
FRO	(.255)	.483	(.002)	.079	1.013	7.9642
NEDAP	(.18)	.222	.003	.034	.21	10.511
IDIP	(.121)	.127	.002	.028	.228	7.53
ESI	(.19)	.296	.003	.049	1.024	8.944
OPN	(.205)	.425	.003	.053	1.49	16.721
LACR	(.183)	.239	.002	.051	.454	6.217
DBG	(.201)	.28	.005	.061	.476	5.888
SEFER	(.208)	.183	(.003)	.0433	(.407)	7.297
CEN	(.184)	.181	.003	.044	(.089)	5.643
SBT	(.176)	.132	.003	.036	(.268)	6.78
VAF	(.25)	.375	.006	.097	.553	3.99

Note: the numbers in brackets are negative

Table 23. Non-Disclosers descriptive statistics

b) Disclosers

	Minimum	Maximum	Mean	Std. Dev.	Skewness	Kurtosis
PHIA	(.181)	.107	.003	.034	(.577)	5.745
ENGI	(.298)	.14	(.001)	.039	(1.048)	13.082
DEC	(.188)	.485	(.0001)	.049	2.989	31.782
RI	(.187)	.1	.002	.031	(.727)	7.82
KER	(.162)	.152	.005	.043	.206	4.802
SGO	(.259)	.198	.002	.044	(.139)	9.7
SU	(.203)	.14	.003	.037	(.243)	6.096
OR	(.149)	.09	.003	.028	(.434)	5.696
ICAD	(.203)	.348	(.0005)	.04	1.757	22.831
IPN	(.289)	.175	.003	.047	(1.018)	10.068
LR	(.215)	.115	.002	.032	(.824)	10.497
FP	(.299)	.29	(.0006)	.042	(.077)	17.925
EDP	(.188)	.112	.002	.035	(.555)	6.232
AKE	(.197)	.156	.002	.0391	(.291)	5.95
FR	(.33)	.229	.001	.06	(.046)	7.343
VIE	(.322)	.117	.002	.036	(2.112)	21.917
CAP	(.234)	.2	.003	.041	(.229)	8.483
BN	(.118)	.095	(.0007)	.028	(.128)	5.108
LI	(.363)	.634	(.0004)	.068	2.927	32.296
EDF	(.263)	.150	(.0006)	.053	(.494)	6.187
COV	(.303)	.341	(.0007)	.043	.611	25.201
CS	(.233)	.223	.001	.043	.185	8.465
DSM	(.136)	.136	.004	.031	(.237)	5.757
WLN	(.208)	.233	.006	.045	.164	6.441
HEIA	(.151)	.113	.002	.031	(.396)	6.056
RCO	(.157)	.138	.004	.036	(.071)	4.723
NN	(.252)	.135	.002	.037	(.783)	10.697
INGA	(.316)	.228	(.001)	.051	(.2)	9.202
AI	(.146)	.099	.002	.028	(.623)	6.411
ORA	(.206)	.159	(.0004)	.033	(.306)	9.286
SEV	(.314)	.236	.001	.04	(1.082)	18.502
ALO	(.132)	.163	.002	.035	.282	5.687
BNP	(.177)	.213	(.001)	.05	(.052)	5.424
KPN	(.161)	.194	.001	.037	.422	6.507
DG	(.23)	.198	.002	.036	(.241)	11.924

Note: the numbers in brackets are negative

Table 24. Disclosers descriptive statistics

Appendix 4 - CAPM assumptions

a) Individual behavior

- Investors are rational, mean-variance optimizers.
- Their planning horizon is a single period.
- Investors have homogeneous expectations (identical input lists).

b) Market structure

- All assets are publicly held and trade on public exchanges, short positions are allowed and investors can borrow or lend at a common risk-free rate.
- All information is publicly available.
- No taxes.
- No transaction costs.

Source: (Bodie et al., 2014, p.304)

Appendix 5 - ESG impact on equity valuation

Figure 10. Idiosyncratic risk transmission channel

Source: (Giese et al., 2019, p.73)

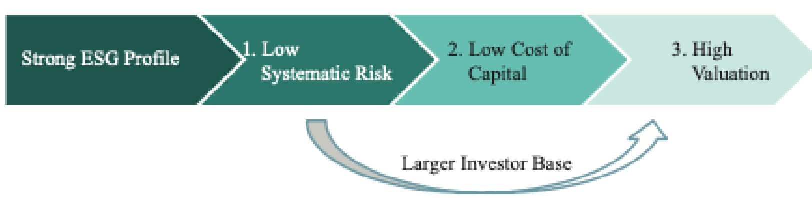


Figure 11. Systematic risk transmission channel

Source: (Giese et al., 2019, p.75)

Appendix 6 - Returns conversion table

This table is indicative and has been constructed using a geometric conversion, e.g. considering a constant weekly return of **0.010%** is equivalent to a monthly return of about **0.040%** or an annual return of about **0.501%**.

Weekly return	Monthly return	Annual return
0.010%	0.040%	0.501%
0.020%	0.080%	1.005%
0.030%	0.120%	1.511%
0.040%	0.160%	2.020%
0.050%	0.200%	2.531%
0.060%	0.240%	3.045%
0.070%	0.280%	3.561%
0.080%	0.320%	4.079%
0.090%	0.360%	4.601%
0.100%	0.401%	5.124%
0.110%	0.441%	5.651%
0.120%	0.481%	6.180%
0.130%	0.521%	6.711%
0.140%	0.561%	7.246%
0.150%	0.601%	7.782%
0.160%	0.642%	8.322%
0.170%	0.682%	8.864%
0.180%	0.722%	9.409%
0.190%	0.762%	9.956%
0.200%	0.802%	10.506%
0.210%	0.843%	11.059%
0.220%	0.883%	11.614%
0.230%	0.923%	12.173%
0.240%	0.963%	12.733%
0.250%	1.004%	13.297%

Table 25. Returns conversion table

Appendix 7 - Sample market capitalisation

Company	Market Capitalisation
ACCELL GROUP	810.851M
PHARMING GROUP	733.126M
HUNTER DOUGLAS	2.261B
ORANJEWOUD A	389.812M
EXMAR	176.258M
VAN DE VELDE	288.532M
KBC ANCORA	2.714B
AGFA-GEVAERT	641.648M
KINEPOLIS GROUP	951.297M
BENETEAU	936.652M
NICOX	166.266M
IRISH CONT. GP.	757.269M
MINCON GROUP PLC	232.843M
DATALEX PLC	44.034M
ALTRI, SGPS	1.091B
NOVABASE,SGPS	107.28M
IMPRESA,SGPS	23.436M
GLINTT	17.914M
IBERSOL,SGPS	165.888M
COFINA,SGPS	23.693M
FINATIS	227.981M
CATERING INTL SCES	84.643M
ACTIA GROUP	61.272M
OCEAN YIELD	4.395B
FRONTLINE	11.32B
NEDAP	329.094M
IDI	298.918M
ESI GROUP	243.888M
GROUPE OPEN	116.656M
LACROIX SA	119.369M
DERICHEBOURG	934.863M
SERGEFERRARI GROUP	85.132M
GROUPE CRIT	692.69M
OENEO	742.709M
VAA VISTA ALEGRE	154.238M

(a) Non-Disclosers

Company	Market Capitalisation
PHILIPS KON	42.31B
ENGIE	32.011B
JC DECAUX SA.	3.701B
PERNOD RICARD	42.274B
KERING	68.316B
SAINT GOBAIN	22.816B
SCHNEIDER ELEC.	69.152B
L'OREAL	172.549B
ICADE	4.388B
IPSEN	6.113B
LEGRAND	20.889B
TOTAL	92.479B
EDP	20.019B
ARKEMA	6.812B
VALEO	7.931B
VEOLIA ENVIRON.	12.769B
CAPGEMINI	21.297B
DANONE	34.543B
KLEPIERRE	5.135B
EDF	33.047B
COVIVIO	6.331B
AXA	45.896B
DSM KON	25.505B
WORLDLINE	21.09B
HEINEKEN	51.015B
REMY COINTR.	7.806B
NN GROUP	11.363B
ING GROEP N.V.	30.589B
AIR LIQUIDE	64.588B
ORANGE	26.125B
SUEZ	10.786B
ALSTOM	16.369B
BNP PARIBAS	55.05B
KPN KON	11.201B
VINCI	49.081B

(b) Disclosers

Table 26. Sample market capitalisation

Source: (Bloomberg Finance L.P.)

Appendix 8 - Industry sensitivity analysis: selection criteria

a) GHG emissions by sector

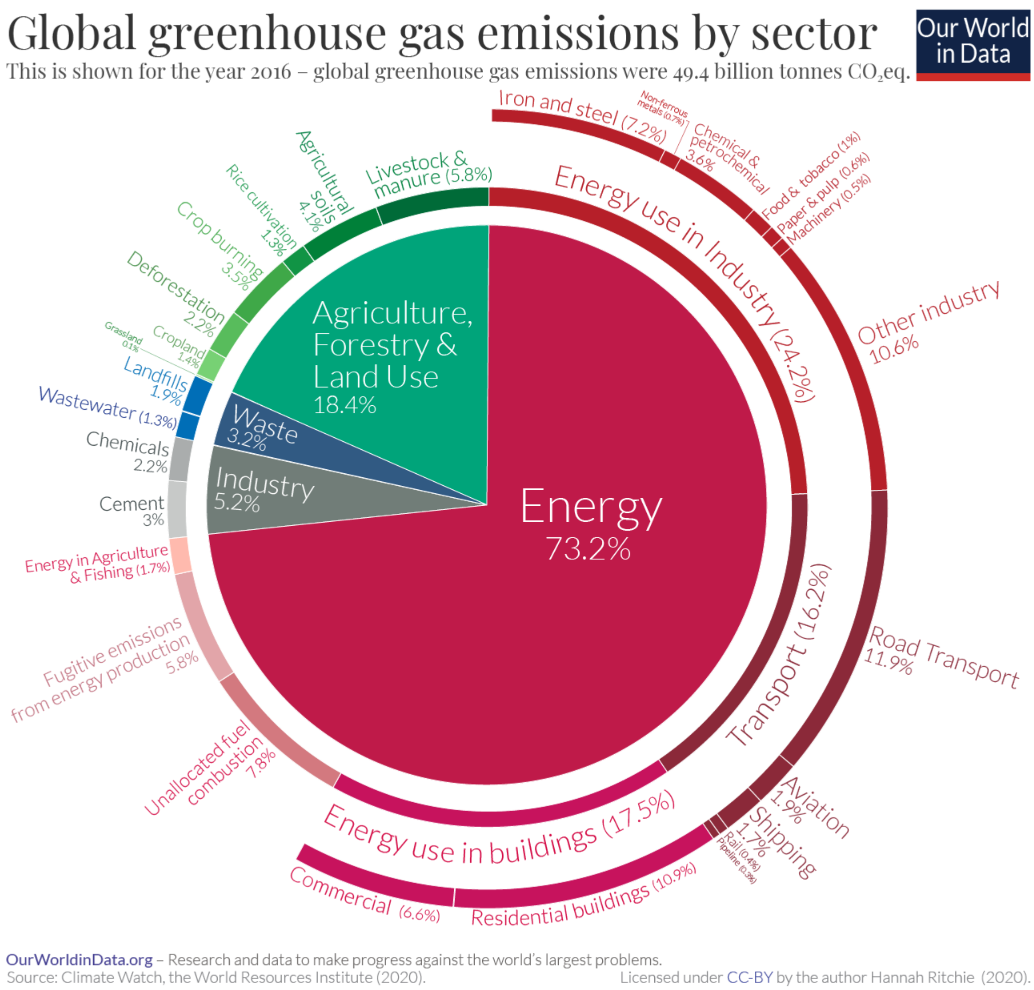


Figure 12. Global GHG emissions by sector

Source: (Ritchie & Roser, 2020)

b) GICS framework

Sector	Industry Group	Industry
Energy	Energy	- Energy Equipment & Services - Oil, Gas & Consumable Fuels
Materials	Materials	- Construction Materials - Metals & Mining - Paper & Forest Products - Chemicals
Industrials	Capital Goods	- Aerospace & Defence - Construction & Engineering - Electrical Equipment - Industrial Conglomerates - Trading Companies & Distributors - Machinery - Building Products
	Commercial & Professional Services	- Commercial Services & Supplies - Professional Services
	Transportation	- Air Freight & Logistics - Marine - Transport Infrastructure - Airlines - Road & Rail
Consumer Discretionary	Automobiles & Components	- Auto Components - Automobiles
	Consumer Durables & Apparel	- Household Durables - Textiles & Luxury Goods - Leisure Products
	Consumer Services	- Hotels, Restaurants & Leisure - Diversified Consumer Services
	Media	- Media
	Retailing	- Distributors - Specialty Retail - Internet & Direct Marketing Retail - Multiline Retail
Consumer Staples	Food & Staples Retailing	- Food & Staples Retailing
	Food, Beverage & Tobacco	- Beverages - Food Products - Tobacco
	Household & Personal Products	- Household Products - Personal Products
Healthcare	Health Care Equipment & Services	- Health Care Equipment & Supplies - Health Care Providers & Services - Health Care Technology
	Pharmaceuticals, Biotech & Life Sciences	- Biotechnology - Life Sciences Tools & Services - Pharmaceuticals
Financials	Banks	- Thrifts & Mortgage Finance - Banks
	Diversified Financials	- Capital Markets - Diversified Financial Services - Mortgage Real Estate Investment - Consumer Finance
	Insurance	- Insurance
Information Technology	Software & Services	- IT Services - Internet Software & Services - Software
	Technology Hardware & Equipment	- Communications Equipment - Technology Hardware & Peripherals - Electronic Equipment & Components
	Semiconductors	- Semiconductors
Telecommunication Services	Telecommunication Services	- Diversified Telecommunication Services - Wireless Telecommunication Services
Utilities	Utilities	- Electric Utilities - Gas Utilities - Independent Power & Renewables - Multi-Utilities - Water Utilities
Real Estate	Real Estate	- REITS - Real Estate Management & Development

Figure 13. GICS framework

Source: (Mahmood, 2018)

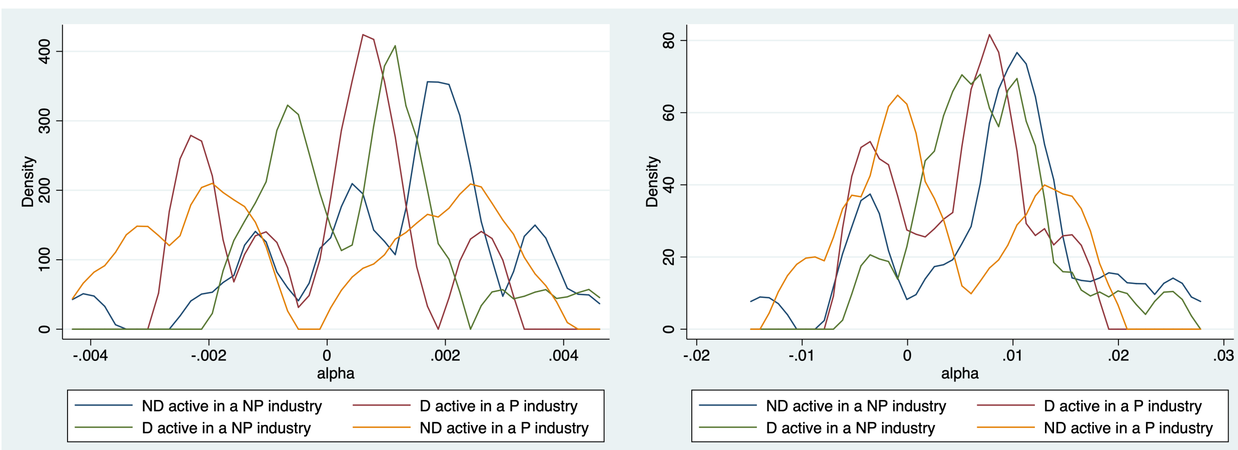
Appendix 9 - Industry sensitivity analysis: sample description

	2015-2021				*2015-2018*				*2018-2021*			
	Non-Disclosers		Disclosers		Non-Disclosers		Disclosers		Non-Disclosers		Disclosers	
	NP	P	NP	P	NP	P	NP	P	NP	P	NP	P
N	27	8	27	8	27	8	27	8	27	8	27	8
$\overline{X_i}$	.200%	.125%	.204%	.135%	.405%	.215%	.278%	.081%	.008%	.041%	.134%	.186%
s_i	3.343%	1.953%	2.550%	1.337%	2.084%	1.076%	1.371%	.811%	2.644%	1.646%	2.172%	1.075%

Table 27. Industry sensitivity analysis: sample description

Appendix 10 - Industry sensitivity analysis: alphas distributions

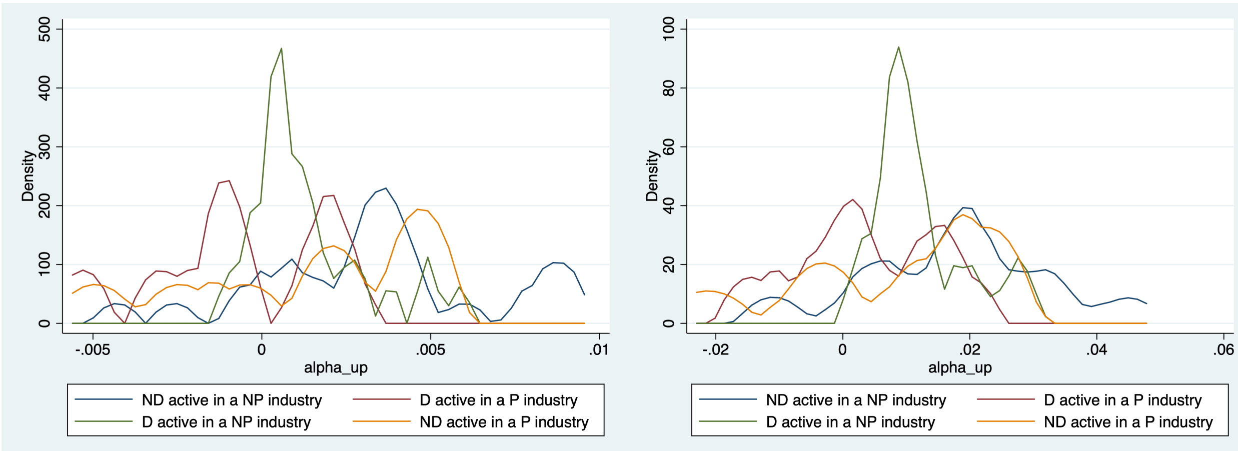
a) Single period analysis



(a) CAPM (b) FF3M

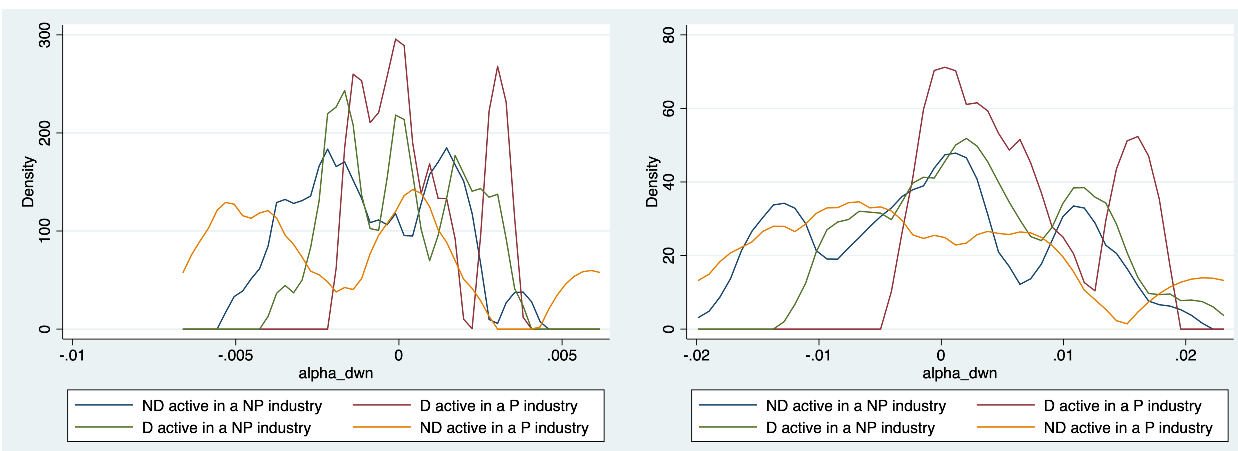
Figure 14. Single period: average alphas KDE by industry

b) Two-period analysis



(a) CAPM (b) FF3M

Figure 15. Upward period: average alphas KDE by industry



(a) CAPM (b) FF3M

Figure 16. Downward period: average alphas KDE by industry

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management
Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve, Belgique | **www.uclouvain.be/lsm**