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Should Scope 3 emissions reporting become mandatory? An empirical analysis of European listed companies.

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Table of Contents

INTRODUCTION 1

PART 1: LITERATURE REVIEW 4

1. THE CLIMATE CHANGE 4
2. INTERNATIONAL AGREEMENTS ON CLIMATE CHANGE 7
A. THE FIRST WORLD CLIMATE CONFERENCE 7
B. THE MONTREAL PROTOCOL 8
C. CONFERENCE IN RIO DE JANEIRO 8
D. KYOTO PROTOCOL 9
E. THE PARIS AGREEMENT 12
F. FAILURE OF INTERNATIONAL AGREEMENTS 13
3. CARBON MARKET 14
A. CARBON PRICING 14
B. SOCIAL COST OF CARBON 16
C. HARMONIZED CARBON PRICE 17
4. THE ROLE OF FINANCE IN THE FIGHT AGAINST CLIMATE CHANGE 19
A. POWER OF FINANCE AND ALIGNMENT WITH THE PARIS AGREEMENT 19
B. CLIMATE-RELATED FINANCIAL RISKS 20
C. INTEREST FROM THE PRIVATE SECTOR 22
D. EXTRA-FINANCIAL CRITERIA 24
5. A CHALLENGE FOR COMPANIES AND ORGANIZATIONS 27

PART 2: METHODOLOGY 29

1. THE PEARSON COEFFICIENT CORRELATION 32
2. SIMPLE AND MULTIPLE LINEAR REGRESSION 33
3. THE SPEARMAN CORRELATION COEFFICIENT 34
4. SIMPLE AND MULTIPLE NON-LINEAR REGRESSION 34
5. STATISTICAL CLUSTERS 35
6. ECONOMIC CLUSTERS 37

PART 3: EMPIRICAL ANALYSIS 38

1. DATABASES 38
2. RESULTS AND INTERPRETATIONS 39
A. LINEAR ANALYSIS 39
B. NON-LINEAR ANALYSIS 47
C. ANALYSIS OF THE ECONOMIC CLUSTER "SECONDARY" 51
D. ANALYSIS OF THE ECONOMIC CLUSTER "TERTIARY" 55

CONCLUSION 60

1. LIMITS 62

2. RECOMMENDATIONS 63

BIBLIOGRAPHY I

APPENDICES .... A

Glossary

AAU	Assigned Amount Unit
AR6	Sixth Assessment Report
CDM	Clean Development Mechanism
CDP	Carbon Disclosure Project
CER	Certified Emission Reduction
CH_4	Methane
CO_2	Carbon dioxide
COP	Conferences of the Parties
CSRD	Corporate Sustainability Reporting Directive
ERU	Emission Reduction Unit
ESG	Environmental, Social, Governance
ETF	Enhanced Transparency Framework
ETS	Emissions Trading System
EU	European Union
GHG	Greenhouse Gas
GRI	Global Reporting Initiative
IPCC	Intergovernmental Panel on Climate Change
ISSB	International Sustainability Standards Board
JI	Joint Implementation
LT-LEDS	Long Term Low Emission Development Strategies
MDB	Multilateral Development Banks
N_2O	Nitrous Oxide
NDC	Nationally Determined Contributions
NGO	Non-Governmental Organization
ODS	Ozone-Depleting Substances
OECD	Organization for Economic Cooperation and Development
PRI	Principles for Responsible Investment

SASB	Sustainability Accounting Standards Board
SCC	Social Cost of Carbon
SDG	Sustainable Development Goals
SRI	Socially Responsible Investment
TCFD	Taskforce on Climate-related Financial Disclosure
UN	United Nations
UNEP	United Nations Environment Program
UNFCCC	United Nations Framework Convention on Climate Change
WCP	World Climate Program
WMO	World Meteorological Organization

INTRODUCTION

The urgency of tackling climate change is now well understood by society. The continuous increase of greenhouse gas emissions is mainly caused by human activities and is leading to a strong degradation of environmental and social systems across the globe with further impacts extending in the future (IPPC, 2022). According to insurance broker Aon, 2022 was the worst year ever, with over $29 billion weather disasters affecting the world (Masters, 2022). To effectively respond to the threats generated by global warming, collective actions are needed at the global level, which includes the responsibility of companies in the economy (Finke et al., 2016). Companies are therefore experiencing a growing pressure to report, disclose, and reduce their greenhouse gas emissions (Akbaş & Canikli, 2018).

Significant players in carbon disclosure requirements are the governments and the financial sector (Wittevrongel, 2022). On the one hand, governments pressure stimulates companies to measure their emissions and to set reduction targets. Indeed, governments have commitments and obligations at an international level. With the current international agreement in place, the Paris Agreement, the goal is to limit global warming to two degrees Celsius, preferably 1.5. Therefore, the focus of the regulation will be on emissions reduction. In addition, in order to internalize the cost of carbon, government policies have implemented different mechanisms such as carbon tax or emissions trading system. It is in the interest of companies to calculate their carbon emissions and implement reduction strategies for the sake of regulatory compliance and carbon trading and management (Knox-Hayes & Levy, 2011). On the other hand, investors and lenders are very demanding about carbon accounting and reporting. Indeed, corporate carbon emissions assessment represents a key element to evaluate climate change-related risks and opportunities. For example, the way in which companies are considering climate change can have significant financial implications and consequently impact the performance of investments portfolio (Sullivan & Gouldson, 2012). It explains why investors will consider extra-financial indicators such as carbon emissions for their investment decisions.

For companies to be able to consider their emissions, they need guidelines in terms of measurement, reporting and disclosure. The Greenhouse Gas Protocol classifies the emissions in three categories called scopes. Scope 1 emissions refer to direct emissions from sources owned or controlled by the organization. Scope 2 emissions are indirect emissions from the organization's purchased energy consumption. Finally, Scope 3 emissions, also called value chain emissions, are other indirect emissions resulting from the activities, but from sources that are not owned or controlled by the business. For companies to provide a representative overview of their emissions, it is important to consider all emissions, not only Scope 1 and 2 emissions as it is usually the case. The importance of Scope 3 emissions can simply be understood by the fact that they represent the majority of a business carbon emissions (Downie & Stubbs, 2012). However, Scope 3 emissions is the object of much controversy and discussion, mainly because of the non-mandatory dimension of corporate carbon disclosure, especially for Scope 3 emissions, and its complex and ambiguous measurement. Indeed, it is challenging for companies to collect all the data necessary for the calculation of Scopes 3 emissions and more particularly good quality data, i.e. reliable and accurate data (Haberl-Arkhurst & Sternisko, 2020). Given the fact that Scope 3 emissions includes upstream and downstream emissions, it involves gather emissions generated along the value chain, between numerous suppliers and customers, introducing therefore a risk of measurement error (Kaplan & Ramanna, 2021). In addition, including Scope 3 emissions in GHG reporting raises the risk of emissions duplication in accounting which could weaken an accurate representation of the companies' emissions and the related risks (Kaplan & Ramanna, 2021). Moreover, computing scope 3 emissions is a time-consuming process for companies and required a lot of resources, not only financial but also, qualified labor, and adapted technologies (Lee & Ma, 2012). Nevertheless, the CSRD, a new EU regulation on corporate sustainability reporting, states that companies need to anticipate and get prepared to report on Scope 3 emissions (Wajon & Hinrichsen, 2022).

These many reasons lead us to ask questions about the place of scopes emissions in society and, more specifically, the relevance of Scope 3 emissions for companies. In the current literature, the inclusion of Scope 3 emissions is becoming increasingly common but remains unclear. One of the objectives we want to achieve with this master thesis is to find out, for a defined sample of companies, the dependencies or independencies between the three scopes with a focus on Scope 3 emissions. In other words, we want to check whether it is really necessary to publish the scope 3 of one's activity or whether this scope is not a combination of scope 1 and 2 emissions. Finally, we will also discuss how companies can integrate these value chain emissions into their strategies. More specifically, we are addressing the following question:

"Should Scope 3 emissions reporting become mandatory? An empirical analysis of European listed companies"

To answer this question, we combined the relevant information found in the literature and the results obtained when conducting a quantitative approach on the companies' scopes of emissions belonging to the MSCI EMU index-to process data and perform statistical analysis. With RStudio as a statistical tool to perform correlations, regressions, and cluster analyses, it is possible to find out if there are any dependencies between the scopes and more precisely, if Scope 3 is dependent on the other scopes or if it provides important information. With regard to this statistical analysis and in order not to draw any hasty conclusions, several tests were carried out on several different databases throughout our research. This part, which conducts parametric but also non-parametric models, allows to obtain results that concretize the existing or non-existing relationships between scope 1, scope 2 and scope 3. The results will then be interpreted and compared in order to draw conclusions.

This paper is organized into four main parts. First, we realized a review of the literature to cover the topic and illustrate some critics and necessities regarding the way of fighting climate change in the current economy. Then the methodology is presented to understand how our data were selected and processed as well as the explanation of the different statistical models mobilized. After, the results of the empirical analysis are presented and interpreted. In the last chapter, we first outline the statistical methods that have been successful with our data, then we provide our conclusion as the answer to the research question. We also mentioned the limitations of our research and conclusions that are subject to debate, and we finally suggested pathways for future research.

PART 1: LITERATURE REVIEW

1. The Climate Change

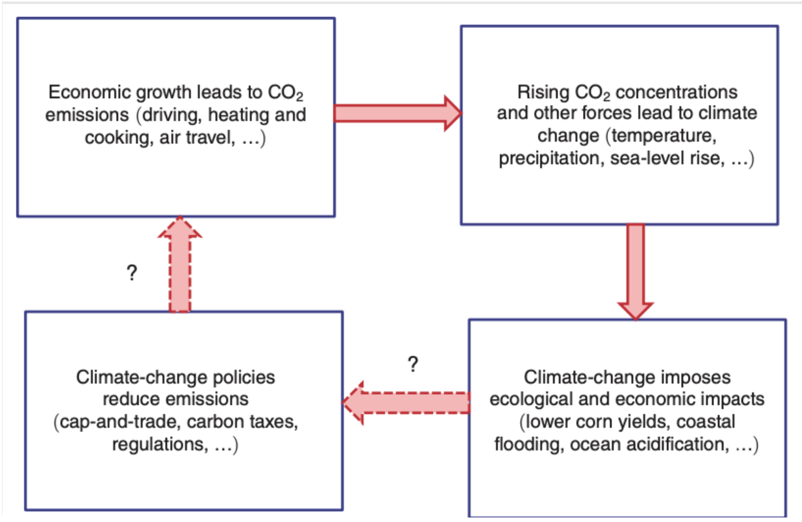
Global warming is due to greenhouse gases (GHG) in the atmosphere. Greenhouse gases include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and trace gases as the group of "F-gases" (HFC_s, CFC_s, SF_6). The greenhouse effect [appendix 1.1: Greenhouse Effect] can be explained by the fact that those gases absorb the heat of the earth's surface and stay in the atmosphere for a certain period of time depending on the gas, increasing therefore the global temperature (*Carbon Dioxide, Methane, Nitrous Oxide, and the Greenhouse Effect*, 2022). Greenhouse gases can be measured in carbon dioxide equivalent (CO_2eq). It is commonly used to assess GHG emissions in order to convert the different impacts of the different gases into a single metric. The respective repartition of gases among greenhouse gases in 2016, measured in carbon dioxide equivalents, is the following: 74.4% of CO_2, 17.3% of CH_4, 6.2% of N_2O, and 2.1% of F-gases, with CO2 as the most contributor gas of greenhouse emissions (Ritchie, 2020). Between 2010 and 2019, the average annual worldwide emissions of greenhouse gases reached their highest levels. However, it can be noted that the growth rate has started to flatten, which is positive and motivating regarding the future (IPPC PRESS RELEASE, 2022).

In the Sixth Assessment Report (AR6) published by the Intergovernmental Panel on Climate Change (IPCC) in 2022, the term "anthropogenic" is used to qualify the sources of this continuous increase of greenhouse emissions. The adjective anthropogenic is used to describe that "something finds its origin in human activity" (Oxford Languages). Scientists, thanks to their knowledge of fundamental physics, ability to compare observations to models, and expertise in identifying the specific patterns of climate change brought on by various natural and human influences, can conclude that recent climate change is largely the consequence of human activity (The National Academy of Sciences; The Royal Society, s.d.). The human activities that are emitting greenhouse emissions are various and specific depending on the gas. First, the burning of fossil fuels used for energy and transportation represents the principal human source of CO_2. Regarding CH_4 emissions resulting from human activity, they are mainly emitted from agriculture, energy and industry, and waste from homes and businesses. For N_2O, the principal human activity producing emissions is agricultural soil management. Finally, the fluorinated gases are used as substitution for Ozone-depleting substances (*Overview of Greenhouse Gases*, 2022).

It is therefore clear that there is human responsibility in the phenomenon of global warming and people seem to perceive the related risks [Appendix 1.2: Global Risk Perception Survey]. In the Global Risk Report 2022 published by the World Economic Forum (2022), the most severe risks on a global scale have been identified. Among the top 10 risks over the next 10 years, five are environmental and the top 3 includes Climate action failure, Extreme weather, and Biodiversity loss. The risks of climate change arise from the interdependence between climate, ecosystems, and human systems. To understand the risks, two variables need to be considered which are the exposure and vulnerability. The exposure is related to the existence of systems that are likely to suffer damage while the vulnerability refers to the sensitivity of systems to respond to those climate changes (IPCC, 2022). Some damages are already or will be soon impossible to reverse such as species extinction and melting glaciers. Those situations where consequences are irreversible as soon as systems have crossed certain thresholds, are called tipping points. Scientists and experts are particularly concerned about those tipping points and early warnings of them are crucial to reduce the related risks (Lenton, 2011). In addition to those tipping points, other damages are noticed. Extreme weather events cause populations to move, exposing them to food and water shortages. Another grave impact of climate change on human systems is that it affects the health and well-being of populations. For example, heat waves, heavy precipitation, and droughts have led to mortality, and new diseases arise in regions usually not affected. In addition, climate changes also have impacted cities, livelihoods, and infrastructure (IPCC, 2022). Besides the observed impacts of climate change, scientific research is also focused on the long-term risks and there is a clear global acceptance that the climate-related impacts will increase in severity and frequency (Malhi et al., 2020). An important point to note is that those climate risks are cascading. To illustrate that, let's take the example of a flood in a city [Appendix 1.3: Example of cascading risks in cities]. The urban infrastructures will be impacted, such as for example the transport system. It will therefore affect the effectiveness of the industry, which will disturb the international trade and supply chain, which will have repercussions on financial markets which will have consequences back on the industry. Consequently, extreme climate events will have impacts on societies and economies that go beyond borders (The Shifters, 2022).

Nicholas Stern is a British economist. He worked as senior vice president of the World Bank from 2000 to 2003. He is particularly known for the Stern Review on the "Economics of Climate Change". In his review (2008), he has proven that the benefits of acting far outweigh the cost of doing nothing regarding global warming. There is still time to limit the negative externalities of climate change, but actions need to be taken at the global level and immediately. From his view, the world is currently facing two transformations coming together. First, the basic structural change. It includes the increase of people in urban areas, the growing energy demand, and the growth of the economy and population that exerts pressure on lands, waters, and forests. This first fundamental change will happen anyway. If those changes or externalities are managed in a short-term vision, consequences will be disastrous and will lead to a sharper increase in GHG emissions, and thus, temperature rises changing the environment even stronger than now. The second transformation is the climate transformation to a low-carbon economy. This change represents an opportunity to take or to lose depending on the initiatives, taken or not, by countries, states, and companies.

William Nordhaus, an American economist, also investigates the fundamental problem of climate change, considering the negative externality, being the greenhouse gas emissions, as a global public good. An important characteristic of public goods is that the costs (or benefits) spread outside the market and are not reflected in market prices. Nordhaus maintains the idea that the response to climate change needs to be global since it affects the whole planet and that individual actions are not sufficient to limit the change. However, he underlines the complexity of addressing it at a global level in terms of governance. It is therefore necessary to implement, design, and enforce cooperative multinational policies to obtain an effective management of GHG emissions (Nordhaus, 2019). To illustrate climate change, Nordhaus developed an Integrated Assessment Model (IAM) in order to integrate elements of different domains (natural, social, and policy sciences) in a single framework. It is called the Dynamic Integrated model of Climate and the Economy or DICE model. In figure 1, the basic structure of his model is presented through the circular flow of global warming science, impacts, and policy. Global warming starts at the top left corner, following the chronological loop of economy-climate-impacts-policies to come back to economy. Nordhaus explicitly dotted the last two arrows with question marks, arguing that these links do not yet exist. In other words, current international agreements on climate change do not lead to effective climate-change policies.



[Figure 1. The Circular Flow of Global Warming Science, Impacts, and Policies]

Source: Nordhaus, W. (2019). Climate Change: The Ultimate Challenge for Economics. *American Economic Review*, *109*(6), 1991-2014. https://doi.org/10.1257/aer.109.6.1991

2. International Agreements on Climate Change

Over time, international agreements on climate change have brought together a number of governments and experts to find global solutions. Currently, the international regulation in force concerning the measures against climate change is the United Nations Framework Convention on Climate Change (UNFCC), which was adopted in 1992. In order to enforce the Convention on Climate Change, the Kyoto protocol was initially implemented, followed by the Paris agreement. The UNFCCC provides a global framework for intergovernmental efforts to tackle the challenge of climate change. It acknowledges that CO_2 and other greenhouse gas emissions from industry and other sources can have an impact on the stability of the climate system, which is a common resource (Kuyper et al., 2018).

A. The First World Climate Conference

Several events have shaped the history of international discussions on climate change since the First World Climate Conference in 1979. This conference was held in Geneva and was organized by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP). Its outcome was a declaration by the participants that the world's governments must address anthropogenic climate change, and the launch of the World Climate Program (WCP), a scientific initiative to better understand the climate system. To carry out this objective, the Intergovernmental Panel on Climate Change was founded in 1988. Most specifically, the IPCC is responsible for the scientific monitoring of global warming processes (*A history of Climate Activities*, 2017).

B. The Montreal Protocol

The Montreal Protocol implements a global phase-out of ozone-depleting substances (ODS's) as a follow-up to the Vienna Convention on the Protection of the Ozone Layer. In 1987, it was signed by 24 nations in Montreal. It was negotiated in response to the hole in the ozone layer that scientists have been able to witness. The Protocol has led to good results thanks to the reduction of global production, consumption, and emissions of ODS's. The Montreal Protocol is not directly related to climate change, but it achieved universal ratification and is therefore a historic environmental agreement and a guide for future climate negotiations. It is considered to be one of the most successful multilateral agreements (Velders et al., 2007).

C. Conference in Rio de Janeiro

In 1992, the third Earth Summit took place in Rio (better known as the Rio Summit). From this conference on Environment and Development organized by the United Nations, three important conventions have come into being: The Convention on Biological Diversity, The United Nations Convention to Combat Desertification, and the United Nations Framework Convention on Climate Change. Those three "Rio Conventions" are intrinsically linked as they deal with interrelated issues (Montanarella & Alva, 2015).

The United Nations Framework Convention on Climate Change was thus established in 1992 and took effect in 1994. For the first time, the existence of climate change and human responsibility to lower greenhouse gas (GHG) concentrations in the atmosphere are acknowledged by this Convention. Indeed, in the Article 1 of the Convention, the definition of climate change is the following: *"Climate change means a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods"* (United Nations Framework Convention on Climate Change, 1992, art. 1). From this definition, human responsibility is clearly highlighted. In addition, in Article 2 of the Convention, the ultimate objective of the Convention is described as the stabilization of greenhouse gas concentrations "*at a level that would prevent dangerous anthropogenic interference with the climate system*" (United Nations Framework Convention on Climate Change, 1992, art.2). It states that "*such a level should be achieved within a time-frame sufficient to allow ecosystems to adapt naturally to climate change, to ensure that food production is not threatened, and to enable economic development to proceed in a sustainable manner*" (United Nations Framework Convention on Climate Change, 1992, art.2). Although reducing CO2 emissions is a global concern, standards of accountability differ from nation to nation due to variations in energy efficiency, productivity, economic development stage, technological innovation, and historical cumulative emissions (Yan et al., 2022). Therefore, in Article 4 of the Convention regarding the Parties' commitments, a difference is highlighted between developed and developing countries. The Convention demands that the more developed nations work to lower their greenhouse gas emissions to bring them back to their 1990 level (United Nations Framework Convention on Climate Change, 1992, art.4, para.2). Historically, it has been proven that industrialized countries are mainly accountable for past and present greenhouse gas emissions (Tsayem Demaze, 2009). Those countries form the Annex I of the Convention and represent the members of the Organization for Economic Cooperation and Development (OECD). They are expected to make the most effort according to the UNFCC. Those efforts are expressed not only in terms of emissions reduction but also in terms of financial support for developing countries (non-Annex I countries) to have the resources to put actions in place to tackle climate change (United Nations Framework Convention on Climate Change, 1992, art.4, para.3). In addition to that, developed countries have also agreed on technology sharing with less-advanced countries. Regarding reporting, the requirements are also not the same between industrialized and developing countries with more detailed and more frequent submissions for countries of Annex I than others. As of right now, 197 nations, including the European Union, and 1 regional economic integration organization, have ratified the Convention on Climate Change, which comes to 198 Parties. It is important to note that, as a framework agreement, it remains general in the obligations it imposes on the parties. Nevertheless, the Conferences of the Parties (COP's) allow negotiations to be further discussed and new agreements to be reached. COPs are conferences organized by the United Nations (UN) that gathers states, regional organizations, and non-state actors. The COPs on climate change are held annually. The role of the COP is to be the supreme decision-making body of the Convention (Hjerpe & Linnér, 2010).

D. Kyoto Protocol

In 1997, the Kyoto Protocol to the United Nations Framework Convention on Climate Change was adopted on the third Conference of Parties (COP3) and came into force in 2005 as soon as 55 countries of the Convention, accountable for at least 55% of the carbon dioxide emissions for 1990 of the Parties included in Annex I, had deposited instruments of ratification, acceptance, approval, or accession. Two periods of commitment were established: the first one from 2008 to 2012 and the second one from 2013 to 2020. The Kyoto Protocol is ratified by 192 parties, excluding the United States that have signed the Protocol, but never ratified it, which frees them from any binding commitment. Although the United States was already an important contributor regarding global greenhouse emissions, their explanation for their refusal to ratify was the conflict of interest between the Protocol requirements and implications and their economic and industrial activities. The fact that the U.S. were able to react like this knowing its GHG contribution was an early indicator of the weakness of the Protocol design (Tsayem Demaze, 2009).

Since the Convention on Climate Change only requires the implementation of policies and measures to tackle climate change, it was clearly not sufficient to ensure effective climate protection as the objective is described in the Article 2 of the Convention. Therefore, the Kyoto Protocol has been set up to operationalize the Convention. It was the first international agreement containing binding greenhouse emission reduction targets, more specifically, for developed countries (Annex B of the Kyoto Protocol includes 37 industrialized countries and economies in transition and the European Union), following the same principle developed in the Convention regarding their global and historical responsibility of GHG emissions in the atmosphere (Kuyper, 2018).

The first commitment period implies to globally reduce between 2008 and 2012 globally reducing the GHG emissions level by 5.2% compared to the 1990 level for developed countries (Annex B Parties) while developing and emerging countries are exempt from binding reductions. The method used is a repartition of quotas among those industrialized countries. The target for the European Union was an 8% GHG emissions reduction. Within the EU, the expectations per country were different depending on the pollution emitted and the advancements made aiming at reducing pollution (Tsayem Demaze, 2009).

The willingness to reconcile positions and to find compromise is integrated in the Protocol through “flexibility mechanisms”, which seek to facilitate the political acceptance of the protocol and reduce the economic costs of implementing the measures adopted (Tsayem Demaze, 2009). The Protocol proposes three market-based mechanisms. The first one is called

“International Emissions Trading”. It gives the possibility to trade or exchange greenhouse gas emission rights. Indeed, Parties with commitments under the Kyoto Protocol (Annex B Parties) have agreed to set emissions reduction/stabilization targets. Those targets are expressed as allowed emissions in the form of assigned amount units (AAU’s). Therefore, this mechanism gives the opportunity to countries that have emissions “to spare” - assigned emissions in surplus since they are not using them - to sell them to countries that are exceeding their level of emissions allowed. Thanks to this system, Carbon is considered as a new commodity that is tracked and traded. In reality, the right term to use would be greenhouse gas instead of carbon. However, since carbon is the most important gas among greenhouse gases, it is called the “Carbon Market”. Other units are tradable on this Carbon market. In addition, it is important to note that the European Union is the most active within this emissions trading mechanism. The second mechanism in place is the Clean Development Mechanism (CDM). It is an arrangement between developed countries (Annex B Parties) and developing countries, where developed countries have the possibility to launch an emission reduction project in developing countries. Implementation of that kind of project allows developed countries to be awarded tradeable certified emission reduction (CER) credits that can be applied to meet Kyoto targets. The CDM is supposed to act as an incentive for sustainable development and at the same time, to give industrialized nations flexibility regarding the way they choose to achieve their emission reduction or limitation goals (Hepburn, 2007). The third mechanism is the Joint Implementation (JI) and allows countries from Annex B to launch emissions reduction projects in other countries from Annex B. Therefore, emissions reduction units (ERU’s) are given to the country initiating the project and can again be applied to meet Kyoto targets (Hepbrun, 2007).

For the second commitment period, the Doha Amendment to the Kyoto Protocol was adopted in Qatar in 2012. It covered further emissions reduction targets, new reporting requirements and adjustments to be applied for the period from 2013 until 2020, more specifically, the Parties committed to a GHG emissions reduction of 18% compared to 1990 levels. The amendment came into force only at the end of 2020 because the necessary number of 144 instruments of acceptance should be achieved. Therefore, the ratification of this amendment has been particularly slow. It is important to mention that the composition of Parties of the second period was different than the first period. In other words, some countries have not renewed their commitments for the second period after the first one, and only a few new countries have been added for the second period of commitment.

E. The Paris Agreement

In 2015, The Paris Agreement was adopted at COP21 in Paris. It is an international binding agreement under the United Nations Framework on Climate Change that came into force in 2016 and counted 194 Parties. The Paris agreement is considered as an outcome of the period of uncertainty that followed the Kyoto protocol (Maréchal, 2016). This agreement is characterized by flexibility since it sets a new international legal regime (Lemoine, 2016) that brings all nations to take actions to both prevent and adapt to climate change.

The objective of the Paris Agreement is to limit global warming this century to below 2 degrees Celsius, preferably 1.5, compared to pre-industrial level (Paris Agreement, 2015, art.2.1a). Indeed, in 2018, the IPCC published a special report about global warming of 1.5 degrees Celsius and the difference of impacts with global warming of 2 degrees Celsius. Limiting global warming to 1.5 degrees Celsius instead of 2 degrees Celsius could contribute to a more sustainable and fairer world. Currently, some consequences are already irreversible but if this temperature rise limit is not respected, worse consequences will be unavoidable.

In order to achieve the goal of temperature mentioned above, long-term strategies are adopted. To mitigate climate change, governments must report action plans every five years, with each plan setting more ambitious goals compared to previous national contributions (Paris Agreement, 2015, art.4). Those plans are called Nationally Determined Contributions (NDCs). The NDC communicated by each nation must contain actions to reduce greenhouse gas emissions and actions to build resilience for a better adaptation of the new ecosystem caused by global warming. To improve guidance for the long-term horizon of the NDC's, the Paris agreement advises (not mandatory) Parties to draw up and provide long-term low GHG emission development strategies (LT-LEDS) by 2020. They will facilitate the vision of future development at a national level.

Following the same reflection from the UNFCCC, knowing, developed countries have the responsibility to support developing countries in the fight against climate change and their adaptation to it, the Paris Agreement proposes a framework for financial, technical, and capacity building (Paris Agreement, 2015, art.9,10,11). First, developed countries should give financial support to nations in need and the most exposed to climate risks, while for the first time encouraging voluntary contributions by other Parties. Indeed, climate finance is necessary for both mitigation and adaptation. Secondly, collaborating on the development and transmission of climate-friendly technology is key in order to reduce GHG emissions and to strengthen climate resilience. Thirdly, in terms of capacity, developing countries are sometimes struggling to face the consequences of climate change. Therefore, the Agreement calls on developed countries to increase their support in developing countries for capacity-building actions.

Regarding communication, the Agreement emphasizes transparency in order to "*strengthen mutual trust and promote effective implementation*" (Paris Agreement, 2015, art.13). To do so, an enhanced transparency framework (ETF) has been created. However, the ETF recognizes the differences of capacity depending on the Party in terms of transparent reporting and is thus flexible.

To evaluate the overall progress of the application of the Paris Agreement, it will be assessed through a "global stock take" every five years. The first global stock take will take place in 2023 during COP28. The outcome of this stock take is supposed to help Parties to adapt their actions and strategies.

F. Failure of International Agreements

Dysfunctionalities have been identified in current and past climate policies, which prevent the achievement of their goals in an effective manner. Indeed, the model of Kyoto protocol and the current Paris Agreement is a dead end for international agreements according to Nordhaus (2019). Regarding the Kyoto Protocol, he recognized that reporting requirements as well as the several mechanisms developed such as the cap-and-trade emissions system were important and relevant features. However, the Protocol was not attractive enough to new participants and Parties could withdraw without any consequences, as it was the case for the United States. Additionally, the non-binding structure regarding developing countries, also called middle-income countries, misrepresented the reality since those countries' emissions grew rapidly and were representative of a great proportion of world emissions [Appendix 1.4: Illustration of the growing global emissions' responsibility of developing (or middle-income) countries]. Indeed, when the UNFCCC was established, industrialized countries represented most global emissions. It is the reason why under Kyoto, only developed countries were under compliance. However, over time, the share of responsibility for emissions has changed very quickly and countries such as China, the U.S, or India were starting to emit a lot of emissions without any repercussions since they were not bound by the Kyoto Protocol (Rosen, 2015). This dimension was corrected in the Paris Agreement since all countries were committed to reducing GHG emissions, not only the developed countries. However, those commitments are voluntary. It is voluntary in the sense that there are no penalties if countries do not participate or do not meet their requirements and this, induced the important problem of free riding. It arises because nations only enjoy a small portion of the benefits of their actions, that are usually costly. Therefore, they prefer not to participate and act as a free rider since they decide to put national interests first. On top of that, the Paris Agreement is also described as uncoordinated because even if the countries meet their commitments, the target of 2°C will not be achieved (Nordhaus, 2019). Therefore, the uncoordinated and voluntary characteristics of the Paris Agreement make it ineffective.

Nordhaus (2015) developed an alternative structure for international agreements, called the *Climate Club.* Two main features differ strongly from current agreements. The first one is that the policy target would be a global harmonized carbon price in order to integrate a cost-benefit analysis compared to a quantity target as it is the case with the current emissions limit approach. In other words, the objective would be that all countries of the club agree on a target price of, for example, \$25/ tCO_2. Another study conducted by Weitzman (2017) strengthens this climate club structure. Weitzman' analysis is based on a conceptually "World Climate Assembly" where countries should vote to impose either a universal carbon price or an overall quantity of total worldwide emissions. The outcome is that, based on the majority rule, it will be easier and less distortionary to vote on a single price than a set of country-by-country emission reductions quantity. The second new feature of the Climate Club is mainly implemented to avoid the free riding problem. It consists in the inclusion of tariffs. Therefore, the dues of the climate club are the abatement costs while the penalties for non-participants are trade tariffs (Nordhaus, 2015).

3. Carbon Market

A. Carbon Pricing

Carbon pricing is defined as *"initiatives that put an explicit price on greenhouse gas emissions, ie., a price expressed as a value per ton of carbon dioxide equivalent"* (Tvinnereim & Mehling, 2018, p.185). The reasons behind putting a price on carbon are diverse [Appendix

1.5: Carbon Pricing Basics]. The most popular one is the fact that it will promote emissions reduction in a cost-effective way. The logic is quite simple: the economic agents will opt for emission abatement opportunities that are less costly rather than paying the price. For example, the price will act as an indicator for consumers to identify goods and services that are carbon intensive and therefore, find other alternatives. It will also indicate producers which inputs are carbon-intensive, and which one are low-carbon, causing the firms to shift to low-carbon technologies. Another reason why putting a price on carbon is that it incentivizes cost-saving innovations. In other words, it motivates investors and innovators to fund and develop technologies that lower the cost of reducing emissions in order to commercialize new low-carbon products and processes. Finally, the most persuasive reason to price carbon is to include this latter in climate policy. It will guarantee that the emission reduction targets are met in an effective manner (Boyce, 2018).

It exists different mechanisms such as carbon taxes, emissions trading systems, hybrid carbon pricing systems, and emission crediting mechanisms (Mehling & Tvinnereim, 2018). The two main instruments with which it is possible to set a carbon price are the carbon tax and the emissions trading system (Baranzini et al., 2015). While a carbon tax directly determines the carbon price through a tax on emissions, an emissions trading system (ETS) set a cap on emissions and assigns emission allowances to trade, resulting in a carbon price. Therefore, the major difference between those two mechanisms is that the carbon tax is built around the price while the ETS is built around the quantity (Weitzman, 2017).

Historically, the introduction of a carbon tax was met with great resistance. In general, the public overestimates the negative aspects and underestimates the benefits of taxes (Carattini et al., 2018; Carattini et al., 2019). A study conducted to understand the reluctance of the public regarding carbon taxes states that, in addition to the influence of climate change belief and political trust, the feeling of personal responsibility for trying to reduce climate change represents an important condition for predicting opposition to carbon taxes (Levi, 2021). Moreover, there is pressure from large industrial groups against carbon tax and in favor of ETS since they would like to continue to benefit from free allowances (Tamma & Oroschakkof, 2021).

B. Social Cost of Carbon

An important dimension when raising the price of carbon is the consideration of the impacts of climate change. The idea is to integrate the effects of global warming into economics terms. It will help policymakers and other decision makers to evaluate the economic impacts of their actions, in terms of costs if it leads to an increase in emissions, and in terms of benefits if it leads to a reduction in emissions. This concept is called the Social Cost of Carbon (SCC), or the marginal impact of greenhouse gas emissions (Tol, 2011) and is associated with the optimal price of carbon. It measures the present value of damages resulting from an additional ton of greenhouse gases. Therefore, this value can determine whether a carbon tax or the amount of tradeable emission based on the total equivalent quota (Pindyck, 2017). However, a survey on different forms of pricing in Member States of the OECD and other major economies reveals significant divergences between real-world carbon prices and the social cost of carbon (Mehling & Tvinnereim, 2018).

Estimating the SCC is not an easy task. There are four major steps in order to evaluate the damages of emissions. The first one is to forecast future emissions according to population, economic growth and other factors. It is then required to model climate responses such as increase in temperature and sea level. The next step is the assessment of the impacts caused by those climate changes on the economy. And finally, to calculate total damages, convert the future damages into their present value and sum them up. According to the definition of the SCC, the process is therefore repeated with an additional ton of GHG emissions to see how much it changes the total damages cost and the increase in damages found is equal to the SCC (Rennert & Kingdon, 2019).

In the calculation of the SCC, there are also considerations to highlight. Since it implies computing a present value, a discount rate must be chosen carefully to assess the weight to be placed on impacts that occur in the future. Future impacts are viewed as being significantly less important than present effects when the discount rate is high, while future effects are more or less viewed as being equally important when the discount rate is low. In addition, the causality between carbon and the damage it causes is also marked by considerable uncertainty, which further complicates the calculation of the SCC. The models are therefore run many times with different values for the uncertain variables and parameters. However, it exists hundreds of uncertainty assumptions that will vary the estimation of the SCC in different ways (Guo et al., 2006).

The most spread approach to computing the SCC is the use of Integrated Assessment Models to simulate the path of climate change but there are other approaches. However, regardless of the method used, it is well known that the carbon price needs to be high enough to prompt the necessary adjustments that will permit the achievement of emissions abatement goal (Barazini et al., 2015). Indeed, the higher the value of the social cost of carbon, the more control is guaranteed (Pearce, 2003). An encouraging fact is that the estimated SCC is higher in recent publication years and in peer-reviewed studies. (Wang, 2019). Therefore, a fair value of the SCC allows a more representative way to integrate climate change damages into the cost-benefit analysis of public policies and investments.

C. Harmonized Carbon Price

As mentioned before, carbon pricing will give financial incentives to everyone to take abatement measures and to innovate with the final goal of reducing emissions. However, the carbon price needs to be on the one hand high enough to reach climate objective, and on the other hand harmonized, meaning having a minimum global carbon price. Again, this latter can be determined through both mechanisms, a harmonized carbon tax or a global tax-and-trade system. The importance of a harmonized price is the alignment of each nation on a minimum carbon price. It is challenging since we need to move from a mix of domestic carbon prices to a global and harmonized carbon pricing system and that the mechanism needs to ensure that each agent will face the same climate rules. Indeed, as a matter of competitiveness, it will be complicated for countries to agree on a high enough carbon price if they are individually disadvantaged by a higher carbon price than other countries (Dion, 2015).

The idea would be to set a minimum global price that countries need to implement with the mechanism of their choice. The carbon revenues would be retained internally, with a minimum determined percentage dedicated to global climate mitigation. Therefore, on the one hand, countries will have revenues to invest internally as they see fit, and on the other hand, countries will need to reserve a percentage of their carbon revenues to support developing countries in facing climate change. This percentage will be set according to the country's wealth and the Polluter Pays principle, meaning that if the country' contribution to climate change in terms of emissions is weak, the percentage to be set aside will be lower. It will act as an additional incentive for emissions reduction. This financing will be done through the Green Climate Fund, which is a fund managed by the UNFCCC that aims to transfer funds from more developed countries to more vulnerable countries to help them to fight and mitigate the effects of climate change (Silverstein, 2013).

Regarding the mechanism used to set a global carbon price, scholars[1] tend to prefer the global carbon tax as opposed to a global cap-and-trade system. Weitzman (2014) argues that the negotiating instruments for internalizing the global externality of climate change should have three specific characteristics: *(i) induce cost effectiveness, (ii) be of one dimension centered on a natural focal point to facilitate finding an agreement with relatively low transactions costs, (iii) Embody "countervailing force" against narrow self-interest by automatically incentivizing all negotiating parties to internalize the externality* (Weitzman, 2014, p.32). Regarding the first property, there is no obvious preference between the two mechanisms since they are both cost effective. Regarding the second property, the one-dimensional harmonized carbon tax is advised rather than a n-dimensional harmonized cap-and-trade system. Weitzman proved his argument of low dimensionality in his study in 2017, where the outcome was that it is easier to negotiate a single price than n-quantities. Finally, the third property and probably the most important one, is aiming at fighting the free-riding self-interest issue. A quantity-based global cap-and-trade system lacks this "countervailing force" property, whereas a price-based harmonized system of emissions taxes does. Indeed, in a cap-and-trade regime, it is in the self-interest of countries to aspire to have the larger cap of emissions possible which is not in line with the ultimate goal of reducing emissions. With this configuration, everyone has an interest in free riding. If we consider a harmonized carbon tax, the logic is different. If the carbon price is applied only to one country, this latter would negotiate to have the lowest value possible to limit the abatement costs. However, if the price is imposed uniformly, there is an incentive to set a high carbon price since it implies other nations to reduce their emissions and will therefore increase the benefit of each country from total global carbon reduction. Therefore, this acts as a countervailing force against free riding.

[1]See, for example, session 1 "Why insist on an international carbon price?" of the conference organized by the Yale Center for the study of Globalization in May 2015. In this session 1, Martin Weitzman, Robert Schmidt, and Massimo Tavoni as participants and William Nordhaus as moderator are debating about arguments supporting the hypothesis that, as opposed to the global cap and trade strategy currently being pursued, a successful international regime to address climate change would be one in which the parties agree on a harmonized carbon pricing trajectory. https://ycsg.yale.edu/sites/default/files/files/conference.pdf

4. The Role of finance in the fight against climate change

According to the World Bank and International Monetary Fund, there is a strong need to finance all necessary developments to meet the Sustainable Development Goals (SDGs). Those needs are expected to be very significant at country level but also at corporate and individual levels. The 2030 Agenda containing the SDGs for sustainable development has been created by the UN and adopted by its members in 2015. There are 17 goals to be met around the three pillars of sustainability that are the environment, the society, and the economy (Purvis et al., 2019). Within this framework, traditional finance is pushed aside to make way for sustainable finance. According to the European Commission, sustainable finance refers to "*the process of taking environmental, social and governance (ESG) considerations into account when making investment decisions in the financial sector, leading to more long-term investments in sustainable economic activities and projects"* (*Overview of Sustainable Finance,* 2021). In the case of environmental considerations, they are, among others, related to climate change mitigation and adaptation.

A. Power of finance and alignment with the Paris Agreement

The financial sector has the power to mitigate climate change through its three main functions. First, finance is providing capital to companies, organizations, or individuals to undertake projects. Therefore, financial actors decide whether to finance a project or not depending on the financial performance, the reliability of the accountable agent, but also, and more importantly, the purpose and the impact of what they are financing, either carbon-intensive projects or low-carbon intensive projects. Secondly, they serve as risk assessors who forecast business profitability and investment choices in a world where carbon emissions are becoming increasingly constrained. Moreover, as lenders and shareholders, they have influence on climate-related corporate management and governance (Bowman, 2010). The financial sector must therefore use its functions as incentives (or constraints) to influence companies towards greater environmental responsibility and greener business practices to put all the chances on our side to reach the objectives of the Paris agreement.

The term "Paris alignment" describes how public and private finance flows are coordinated with the goals of the Paris Agreement on climate change. The goal of this alignment is to make "*financial flows consistent with a trajectory toward low greenhouse gas emissions* *and climate change resilient development*" (Paris Agreement, 2015, art.2.1c). The financial flows required to bolster the global response will increase as a result of this alignment. However, work on the Paris alignment need to pick up quickly since the actions taken so far are insufficient. At a strategic level, the actions required leading to a low-carbon economy implies the intervention of different actors including the private finance sector and the public finance sector that must ensure that financial decisions are aligned with the objectives of the Paris Agreement. To do so, the creation of reliable, comparable, and consistent standardized methods and metrics needs to pick up speed right away in order to assess and guide financial decisions. Indeed, incentives to move financial resources to decarbonization are weakened if actors cannot be held responsible for their financial decisions. Regarding public finance, the emergence of a collaboration between Multilateral Development Banks (MBD's) has been put in place to collaboratively develop a unique approach for achieving Paris alignment through different "Building Blocks". Regarding private finance, this sector is working on methods and metrics such as green taxonomies and ESG tools to facilitate the assessment of investments. The private financial sector also developed an interesting outcome-based approach that consists in estimating a temperature pathway related to the climate performance of an asset, portfolio, or investment strategy in relation to the international temperature increase limitation of bellow 2°C. A temperature indicator is used to convey the results, indicating the range of world average temperature increases that the portfolio or business is able to withstand (for example, 2°C, 3°C, or 5°C). As a result, various public and private sector actors will come up with different approaches, but it would be very helpful to establish a set of "minimum standards" for methods and metrics given the fact that "alignment" of finance with the Paris agreement is understood differently by the different actors (Rydge, 2020).

B. Climate-related financial risks

The financial system should contribute to global climate goals by aligning investments decisions to sustainability objectives while evaluating climate-related risks and opportunities. The first important step before assessing risks is to understand them. Climate change exposes economies and businesses to two different types of risks (Battison et al., 2021). The first type of risks, the physical risks, are the results of extreme weather events such as floodings, tornadoes, fires, which have a direct impact on the company's activities as they disrupt its operations. According to the IPCCC, global warming of 1.5-degree Celsius will increase the likelihood of natural catastrophes, which strengthens the relevance of considering those physical risks. The second type of risks, the transition risks, are linked to a lack of consideration for the adjustment associated with the transition to a low-carbon economy. For example, a transition risk can be the depreciation of the value of carbon-intensive assets held by a company, or other transition risks can arise from new policies or regulations that would impose a carbon tax to promote a greener economy (Batten, 2018), or in the form of regulatory sanctions for polluting entities.

Depending on their roles, financial institutions are exposed to different risks. In the insurance sector, for example, climate change affects both the subscription risk and the management risk of the financial portfolio. Therefore, insurance companies must continue to ensure that risk premiums remain appropriate and that reserves are adequate. In other words, they need to cover expected losses caused by physical risks thanks to an appropriate premium price and responsible portfolio management (Boissinot, 2016). Banks also need to consider both types of risks for their credit exposure. Indeed, there is a risk that clients become insolvent (inability to repay the loan) due to a deterioration of their balance sheets caused by climate damages affecting the productivity and the stock of capital for example (Lamperti et al., 2019). Finally, investors[2] are also highly exposed to climate-related risks as companies they are investing in are susceptible to experiencing a deterioration of the balance sheet due to physical or transition risks, which will therefore impact the shareholder value. For example, carbon-intensive assets might become stranded, which would postpone the transition to a low-carbon economy and introduce new financial risks associated with climate change (Monasterolo, 2020). On top of that, all those financial actors run a reputational risk depending on the projects or companies they are financing. Bopp (2020) argues that climate-change related risks amplify the effect of reputational risks. Financial institutions that act in line with the values they claim when doing business get more favorable outcomes than those who provide goods and services in a way that deviates from what consumers would expect based on reputation. This integrity, credibility, and trust gap represent the reputational risk. Parallel to this, financial institutions are increasingly asked to disclose information about governance, strategy, and risks (Bopp, 2020). In other words, they must disclose who their borrowers are and the purpose of those loans, and which companies they invest in based on publicly available investment strategies, according to specific ESG objectives.

[2] The term "investors" is used in the broad sense, including asset managers, institutional investors (pension funds, insurers, and investment funds), private equity firms, business angel, etc.

C. Interest from the private sector

There has been a surge of interest from companies and some large investors in adopting sustainable strategic plans. There are several initiatives and strategies developed to integrate climate issues into the investment process.

The first approach consists of understanding the climate-risk exposure of companies and investments. Given the fact that risk exposures of businesses or investments are related to their ESG considerations, investors usually analyze their ESG profiles. For example, a great amount of investors are signatories of the Principles for Responsible Investment (PRI), which is a United-Nations supported financial network bringing together investors to guide responsible investments through the incorporation of ESG factors. It is interesting because companies that score well on important ESG issues tend to have superior financial performance thanks to its long-term horizon (Khan et al., 2016). More specifically, among the environmental, social, and governmental factors, the environmental one has showed the strongest relation to financial performance (Ahlklo & Lind, 2019), probably justified by the urgency of addressing climate change. By paying attention to ESG criteria, the investors act in a committed way and follow what is called the “engagement” strategy. To assess ESG profiles, investors can use ESG ratings and indices provided by rating agencies while remaining critical. Indeed, investors cannot simply rely on ESG scores but need to perform other analysis, and a strong interpretation of those ESG scores is needed depending on the investment preferences of investors (Schoenmaker, 2018).

The second approach aims to reduce the "carbon footprint" of financial investments made. The investors can follow for example a divestment strategy. Investors decide to divest from fossil fuels companies or from companies whose operations are highly polluting. In this way, they are “decarbonizing” their portfolio. Their motives are on the one hand, moral, and on the other hand, financial, not to mention that the increasing climate policies also influence the investors’ divestment decisions. The moral motive is explained by the fact that the short-term economic benefits of continued investment in fossil fuel production are far less important than their long-term societal and environmental costs (Lajarthe & Zaccai, 2017). In other words, it is considered immoral to continue to finance companies that generate large amounts of carbon emissions since they are the main cause of global warming leading to catastrophic environmental and social consequences. The financial motive mainly lies in the risk of carbon-intensive assets. Indeed, respecting the 2°C objective implies that a limited amount of GHGs can be emitted, which means that a significant part of the fossil energy reserves must remain unexploited. Companies should therefore adjust their balance sheet reflect the fact those assets might not generate future value. However, the effectiveness of divestment strategy regarding climate change is often subject to debate unless all financial actors providing them with financing decide to stop/reduce massively their support. However, there is a lack of trust toward government capacities to legislate strongly and quickly to meet the 2°C target (Griffin et al., 2015), meaning that there is currently no overvaluation of those energy companies and that their assets will be exploited as intended. An alternative and more engaged strategy to reduce the carbon footprint of financial investments is the activist strategy.

The third approach is related to the growing market for green bonds. Forecasts state that in 2023, yearly worldwide issuance will hit $1 trillion USD [Appendix 1.6: Importance of the Green Bonds Market]. They are special bonds ultimately dedicated to finance environmental and climate-friendly projects within the issuing company [Appendix 1.7: Green Bond Principle]. The difference with traditional bonds lies in the commitments made by the issuer, on the one hand, on the precise use of the funds collected, which must concern projects with a favorable impact on the environment, and, on the other hand, on the publication, each year, of a report giving investors an overview of the progress of these projects. Therefore, the administrative and compliance costs of issuing green bonds are higher than for traditional bonds, and more restrictive regarding the use of the obtained capital. The results of the study of Flammer (2021) demonstrates that the issuance of corporate green bonds can be considered as a credible signal for investors regarding the environmental commitment of the company, dismissing any argument of greenwashing[3] or cost of capital (Flammer, 2021). Indeed, the company experiences on the one hand a better environmental performance through higher environmental scores and lower carbon emissions, and on the other hand, a rise in ownership by long-term and green investors.

[3] According to Flammer (2021), the term "greenwashing" refers to the fact of making unfounded or misleading statements regarding the environmental commitment of a company.

D. Extra-financial criteria

Financiers, such as banks, asset managers, and other investors, increasingly examine extra-financial criteria in addition to financial criteria when deciding where to invest (MIT Sloan Management Review, 2016).

(i) ESG scores and Rating Agencies

Investors are seeking indicators to measure and quantify how far entities consider potential externalities in their strategy, and whether they develop ways to handle the related risks and opportunities. In order to perform sustainable investing, investors use, among other analysis, ESG ratings or ESG scores[4] provided by agencies. ESG rating agencies allow investors to select companies based on their ESG performance, just as credit ratings allow them to select companies based on their creditworthiness. The ESG rating agencies are paid by the investors and not by the rated companies as it is the case for creditworthiness rating agencies. The rating agencies create overall ESG scores based on available data by bundling environmental, social, and governance considerations. They defined their scope of ESG considerations through a set of attributes, then they use indicators as measurements, and they weight the relative importance of attributes. For example, a rating agency could analyze the companies' labor practices attribute, using workforce turnover as measurement, giving labor practices a specific weight of importance compared to other ESG attributes. Many different ESG rating agencies exist such as MSCI, Sustainalytics, ISS, Refinitiv, S&P Global Ratings, and others, using different scorings and methodologies [Appendix 1.8: ESG Rating Agencies Comparison]. ESG rating agencies are of great importance for the dissemination of sustainable information to market participants. One the one hand, it helps investors understanding business and investment risk, and on the other hand it also helps companies identifying ESG shortcomings since one of the main strengths of an ESG score is its capacity to highlight opportunities and risks within an organization' ESG strategy.

However, there are some challenges in ESG ratings provided by agencies. First, there is an inconsistency in the terminology of ESG matters as well as ESG performance. The concept

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[4] ESG ratings refer to letter ratings while ESG scores refer to numerical scores. The terms ESG rating and ESG score will be used interchangeably since the goal of the result is the same, knowing, to assess a company's ESG performance.

of ESG is not well defined and is built on values that are constantly evolving. Due to this inconsistency, confusions and risks such as green washing arise (Migliorelli, 2021). All is about interpretation and therefore, subject to debate. Second, there is heterogeneity among the different ESG ratings methodologies since no ESG score regulation exists so far. First, ESG rating agencies do not have the same scope, meaning that one could exclude some attributes that another includes. Second, rating agencies could use different indicators to measure the same attribute. Third, the weights that they give to attributes are different and, to some extent, subjective. It means that a rating agency could consider the same attribute but not with the same importance (Berg et al., 2022). It implies that companies might get high composite ratings even if they perform well in certain areas but cause harm in others. Finally, there is a lack of quality ESG data due to the enormous amount of data to consider as well as the sourcing of those data. The data used by the rating agencies can come from different sources such as companies' reports, sector-specific NGO's, government agencies or trade unions (Jinga, 2021). Therefore, they will inevitably be a gap between analysis and reality, as information is not always public, complete or objective *("Comment connaître le score ESG d'une entreprise?"*, 2021). Data provided by companies can be biased. For example, the greenhouse gas emissions, are mainly provided by the organization in itself, which have an interest in artificially reducing its carbon footprint (Anquetin et al., 2022). However, the firms' ESG reports are usually audited by third parties to mitigate a potential lack of transparency or accuracy. Despite this, investors and rating agencies' access to ESG data is particularly impeded by the lack of ESG reporting standards. Regarding the large amount of data to be managed, the integration of artificial intelligence and machine learning play a key role for rating agencies (Jinga, 2021).

All those challenges lead to a significant divergence among rating agencies that strongly requires critical approach. Therefore, Schoenmaker (2018) argues that focus should not be solely on ESG ratings but rather use them as a starting point in the sustainability analysis. Investors are the final decision-makers regarding their investments and should look at what matters the most for them. To help investors to globally assess the ESG implication and performance of companies, the International Financial Reporting Standards have created in November 2021 the International Sustainability Standards Board (ISSB) for a global harmonization of sustainability disclosure standards. The goal of the ISSB is to provide investors with comprehensive global disclosure baseline that outlines risks and opportunities associated with sustainability for corporations (*International Sustainability Standards Board*, 2022).

(ii) Corporate Carbon Disclosure

To address carbon risk, investors will consider the environmental factor “E”. It examines how a company is affecting the environment through its direct operations and across their supply chains. In other words, how a corporation discloses its environmental impact and attempts to cut carbon emissions (*“Understanding the “E” in ESG”*, 2019). The environmental considerations of financiers will indirectly incentivize companies to reduce their carbon footprint by making their access to non-sustainable financing needs more difficult and/or more costly. The companies’ response of reducing their scope emissions will then help achieving the goal of the Paris Agreement of limiting the temperature below 2°C above pre-industrial level (Jinga, 2022). It is therefore increasingly relevant to accurately assess the carbon emissions of companies and organizations, not to mention the pressure from other stakeholders on companies to operate in an environmentally friendly manner, and the strategic interest of companies to limit their carbon emissions.

The International Greenhouse Gas Protocol provides a uniform methodology for measuring and reporting GHG emissions and is the most widely used tool for that purpose (Hertwich & Wood, 2018). The emissions are therefore classified into scopes 1, 2, and 3. Scope 1 emissions refer to direct emissions coming from sources managed by the organization. Scope 2 emissions are indirect emissions from the organization's purchased energy consumption. Finally, Scope 3 emissions, also called value emissions, are other indirect emissions resulting from the activities, upstream and downstream, but from sources that are not controlled by the company (WRI/WBCSD, 2004). It is important to highlight that Scope 1 and Scope 2 emissions measurement and management procedures are well known, whereas Scope 3 emissions are not as well understood and defined and therefore, difficult to assess (Shrimali, 2022).

The real challenge is to actually make carbon disclosure mandatory with a standardized clear framework. Indeed, to limit something, in that case, GHG emissions, it is necessary to have access to data and to be able to measure it (Kalesnik et al., 2020). In addition, this would make a significant amount of the data needed by policymakers and asset managers to manage the risks associated with the carbon transition available (Bolton et al., 2021). However, despite some initiatives on sustainability reporting and disclosure framework and standards such as the Global Reporting Initiative (GRI) Standards, the Sustainability Accounting Standards Board (SASB), the Carbon Disclosure Project (CDP), and the Taskforce on Climate-related Financial

Disclosure (TCFD) recommendations, there is an absence of mandatory carbon reporting. The lack of a unified regulatory model that imposes a strict framework for the reporting of carbon emissions represents an obstacle to assessing companies' environmental commitment (Anquetin et al., 2022). At the European level, the Corporate Sustainability Reporting Directive (CSRD) was adopted by the European Commission in November 2022 leading to more precise sustainability requirements such as specific format and standards for reports and a required third-party auditing. Its application will start between 2024 and 2028 for about 50,000 EU companies. It is important to notice that non-EU companies that have a presence (a branch of their activity or a subsidiary) in the EU will also need to comply with the legislation. The standards proposed for the CSRD include the interaction between companies and climate change, and very importantly, include value chain sustainability factors (Wajon & Hinrichsen, 2022). In other words, companies' Scope 3 emissions will be mandatory to report. Therefore, this new legislation could have the potential to play a key function in the corporate carbon disclosure and therefore, in the fight against climate change for companies, investors, and many other stakeholders.

5. A challenge for Companies and Organizations

As mentioned before, companies obviously face pressure regarding their responsibility to mitigate climate change. It stimulates, and sometimes legally requires corporations to measure their emissions and set target in terms of greenhouse gases reduction (Kolk & Pinkse, 2007).

The reduction of greenhouse gases has become a new management focus, associated with strategies, instruments, and technologies. However, the consideration of such a long-time issue is a real challenge for companies because it goes beyond their traditional management horizon (Aggeri & Cartel, 2017). The tendency of companies to favor short-term can be explained by the traditional shareholder model developed by Friedman (1970) that is opposed to the stakeholder model developed by Freeman that favors long-term perspectives (Freeman & McVea, 2001). The shareholder theory states that the only objective of companies is profit and that the objective of managers is to maximize shareholder wealth while the stakeholder theory supports the need to create value for each of the people involved, directly or indirectly, in the activities of companies. Based on the definition of stakeholders provided by Freeman (1984): "*any group or individual who is affected by or can affect the achievement of an* *organization's objectives*", there is a claim that the natural environment can be considered as a stakeholder (Mitchell & al., 1997). It is clear that the environment is affected by corporate activity, and that company's objectives can be seriously disrupted by changing weather patterns or even natural disasters (Kolk & Pinkse, 2007). However, the direct pressure of climate change is not as significant as the indirect pressure other stakeholders exert on companies (Kumarasiri, 2017). Among those stakeholders to consider, there are governments, investors, but also non-governmental organizations (NGO's), suppliers, consumers, and competitors that are also sources of pressure and must be considered in a certain order of salience that each company will define depending on its exposure (Kolk & Pinkse, 2007).

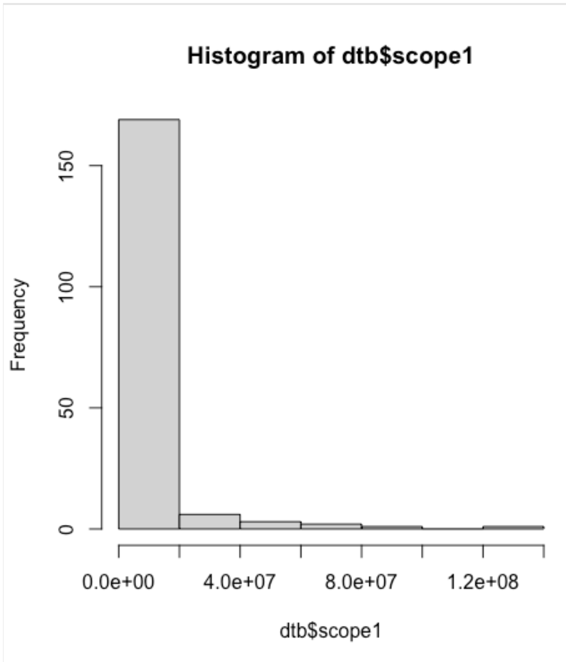
In addition to this long-term horizon, it is known that computing emissions is not an easy task. Currently, companies usually disclose scope 1 and 2 emissions, but it is much less frequent for Scope 3 emissions. First, this is due to the difficulty of accessing reliable, accurate, and specific data along their supply chain (Haberl-Arkhurst & Sternisko, 2020). Second, the process of calculating value chain emissions is time-consuming and requires different resources, not only financial but also qualified labor and adapted technologies (Lee & Ma, 2012). Third, the lack of standardized methodology, especially for Scope 3 emissions, can discourage companies from undertaking the process. Even though it represents a challenge for companies, there are multiple reasons to consider and therefore evaluate Scope 3 emissions. Indeed, they represent the majority of an organization's emissions (Downie & Stubbs, 2012). In addition, computing Scope 3 emissions represents a valuable risk-management tool to assess risks and opportunities along the supply chain and take decisions accordingly (Sundin, 2002). Finally, in addition to the voluntary emissions disclosure, companies in many jurisdictions also face mandatory requirements to report on their GHG emissions (Tang & Demeritt, 2017). The mandatory reporting of scope 1 and scope 2 emissions is relatively common, as these are considered to be under the direct control of a company and are therefore easier to measure and report (Huang et al., 2009). Regarding Scope 3 emissions, the regulation is more progressive due to its complexity, but it is increasing. For example, in October 2022, the ISSB voted and confirmed scope 3 emissions mandatory disclosure with specific assistance and more time for companies to meet the requirements (« ISSB unanimously confirms Scope 3 GHG emissions disclosure requirements with strong application support, among key decisions », 2022).

PART 2: METHODOLOGY

Now that the topics embracing the research subject have been studied and explored in literary ways, it is time to get to the heart of the matter and answer our research question. Given the growing importance of corporate greenhouse gas emissions reporting, which is increasingly considered in investments, in the creation of new laws, and in the regulation of their reporting, it is of interest to know what may be behind these emissions in order to have a better quantitative perspective and a deeper understanding other than qualitative. More specifically, this research aims to learn more about scope 1, scope 2 and scope 3 and the relationships between them. These three terms, which quantify the greenhouse gas emissions used in a company's carbon or GHG footprint, will be our three quantitative variables on which the statistical analysis is done. With the intention of having robust results and therefore enough observations, we agreed to take as observations the companies belonging to the MSCI EMU stock index. This index, following more than 200 companies, allowed us to build a database of 182 observations after cleaning and 3 quantitative variables being the scopes. Given the quantitative nature of our data, performing statistical analyses is an excellent way to discover potential relationships between these scopes, to answer the hypotheses posed and finally to answer our research question. First, the methodology followed was to statistically test this database containing the 182 companies belonging to the MSCI EMU stock index with their scope 1, scope 2 and scope 3.

To do so, a first parametric study was carried out with the objective of finding linear relationships between our variables, which will be demonstrated by the Pearson correlation coefficient and by simple and multiple linear regressions. Here, we assumed that our data are normally distributed and we, therefore, used probability density functions to compute p-values.

In a second and intermediate step, we assumed that the distribution was not normal. If we make this assumption, it is important to match the probability density function to whatever our data behave like. In econometrics studies, the known transformations in order to obtain a generalized linear model are the Poisson transformation or the logarithmic transformation but there are, of course, other possible transformations. We observe in figure 1 that the scopes 1 of our observations are not normally distributed. And in order not to make a mistake in our model and not to perform regular linear models on data that are not normally distributed, it is very important to modify our data to constrain them to follow a normal distribution.



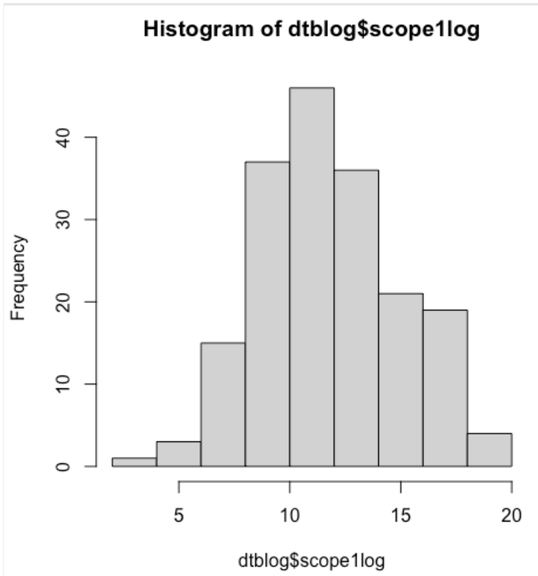
[Figure 2. Histogram of the distribution of scope 1 of the *dtb* database]
Source: Empirical analysis

The choice in this work was whether to do a log transformation or a Poisson transformation. According to figure 1 which shows that we have a skewed discrete distribution and according to the fact that we have count variables and no negative data, the obvious choice would have been to do a Poisson transformation. The following formula represents the link function of a Poisson.

$$\lambda = e^{b0+b1X} \tag{1}$$

However, we decided to perform a log-transformation on our database. This popular transformation makes it possible to handle situations where the relationships are non-linear between the independent and dependent variables, while preserving the linear model as explained by Benoit Kenneth in his paper on *Linear Regression Models with Logarithmic Transformations*. Indeed, this transformation has the advantage of being able to transform an asymmetric variable into a variable following a normal distribution, as we can see in figure 2 below. Furthermore, the 7th edition of William H. Green's Econometrics Analysis states that *by using logarithms [...], the regression model can accommodate a wide variety of functional* *forms in the data*. In addition, the same book confirms that some models that appear to be nonlinear become linear after a transformation, in this case after taking logarithms. As explained and as visually observed with the help of plots, the distribution of scope 1 is strongly skewed to the right while the histogram of the logarithm of scope 1 provides a plot following the normal distribution as expected. This significant change between the two figures proves that we are moving towards a consistent study with the new log transformed database called *dtblog*. Here is the formula applied for logit transformation.

$$logit = \frac{e^{b0+b1X}}{1+e^{b0+b1X}} \qquad (2)$$



[Figure 3. Histogram of the distribution of scope 1 of the *dtblog* database]

Source: Empirical analysis

In conclusion, we might have performed a Poisson transformation, but we decided otherwise. For the sake of clarity, this choice was made because the log transformation is easier to use and understand, that it does not distort the results obtained given the large sample size and is also more widely used.

After these first two parametric studies, we found it interesting to continue the analysis in a non-parametric way. To accomplish this, we used non-linear models such as the Spearman correlation or non-linear regression. The linear relationship allows us to validate a relationship between variables and to explain it with a straight line, whereas a non-linear regression explain it with a curve, we will refer to the Gauss-Newton algorithm. Indeed, performing non-linear methods on our database has the advantage of looking for non-linear relationships between scope 1, scope 2 and scope 3. Performing non-linearity means that we no longer make assumptions or hypotheses about the nature of the relationships between our three variables.

Finally, with the desire to go further, other analyses were conducted on statistical or economic sub-databases. From a statistical point of view, for example, we carried out a cluster analysis, and we created a new database without the companies that do not belong to the majority cluster. From an economic point of view, we divided the 182 companies according to their sector of activity, secondary or primary, and we reiterated the models to these new databases.

To facilitate a good understanding and interpretation of results, it is important to have in mind the formulas and theory of these linear and non-linear models. This also provides a justification for the choice of the methods used. The following methodology therefore creates the red line of our empirical research, explains what stands behind the models and clarifies some aspects of our work.

1. The Pearson coefficient correlation

As a first step, and in order to get an initial idea of the relationship that may exist between the three scopes, we performed a Pearson correlation. The coefficient of this correlation is a linear coefficient and allows us to measure both the strength and the direction of a relationship between two variables. The formula for the linear correlation coefficient between two random variables is as follows:

$$\rho(a,b) \;=\; \frac{E(ab)}{\sigma a \sigma b} \tag{3}$$

Where ρ (*a, b*) is the linear correlation coefficient, E(*ab*) is the cross-correlation between *a* and *b* and where $\sigma^2 a$ and $\sigma^2\, b$ are the variances of variables *a* and *b* given the equation which states that the standard deviation is obtained by calculating the square root of the variance:

$$\sigma \;=\; \sqrt{\left(\frac{\Sigma(x_i - m)^2}{n-1}\right)} \tag{4}$$

Where x_i is our quantitative variable, m represents the mean and $\frac{1}{n-1}$ is the standard deviation estimator.

One of the most important properties of the Pearson correlation coefficient (PCC) is that $0 \leq \rho^2 (a, b) \leq 1$. Indeed, this coefficient varies from -1 to +1 and if no association exists, it will be equal to 0 and this will mean that the variables are independent, uncorrelated. A coefficient close to +1 means that the association between the two variables is strong and behaves in the same way, we will speak of an increasing affine function. We will obtain an affine and decreasing function if the coefficient is close to -1. Nevertheless, this PCC only gives an indication of the linear dependencies between two variables, and therefore, later in our research, we will carry out the non-linear correlation known as Spearman's correlation.

2. Simple and multiple linear regression

Simple linear regression is a widely used statistical method for finding a linear relationship between an or several explanatory variable X and a variable to be explained Y. More precisely, it consists in considering Y as an affine function of X. For our statistical analysis, we assumed the relationship between a statistical variable Y, called the variable to be explained, and an explanatory variable X to be linear. With this in mind, we performed the simple linear regression between our three variables, with for example Scope 1 as the explanatory variable and Scope 3 as the variable to be explained. The double objective of this model is to know the relationship between the variable Y and variable X but also to make predictions of the explained variable according to the explanatory variables. A linear regression follows the formula:

$$y = \beta_0 + \beta_1 x \quad (5)$$

Where y is the variable to be explained, x is the explanatory variable, the parameter β_0 indicates the intercept and β_1 the director of the line.

In order to get a first idea of the graphical representation of the data, a scatter plot should be constructed. Indeed, this type of plot allows to display the values of two variables with Cartesian coordinates for a set of data. The data are displayed as a collection of points, each with the value of one variable determining the position on the horizontal x-axis, which represents the variable to be explained and the value of the other variable, the explanatory variable, determining the position on the vertical y-axis.

In the interest of taking our research further, we have extended simple linear regression with the multiple linear regression method, which allows us to describe the variations of an independent variable (the variable to be explained) associated with the variations of several explanatory variables.

3. The Spearman correlation coefficient

In our non-parametric analysis, we apply the Spearman correlation coefficient as a measure of non-parametric statistical dependence between two variables. Indeed, in the case where our data do not follow a normal distribution and do not respect the linearity conditions, the Spearman correlation coefficient, ρ, is used as a substitute for the Pearson correlation coefficient. This non-linear correlation is used when two statistical variables appear to be correlated without the relationship between the two variables being of the affine type, and therefore consists in measuring the strength and direction of association between two ranked variables and not between the values taken by the two variables but between the ranks of these values. The rank of a variable means that the RStudio program will rank each data in scope 1 in descending order and will do the same for data in scope 2 and scope 3. Once this step, which provides the ranks of all the variables in the database, has been completed, the correlation between the three scopes can be measured. As with the Pearson correlation coefficient, ρ varies from -1 to 1. A correlation equal to 0 means that the data are independent, and the closer this coefficient is to 1, the stronger the relationship and the more it goes in the same direction, the closer it is to -1, the stronger the relationship linking the data but in opposite directions.

4. Simple and multiple non-linear regression

In order to further develop our non-linear model, we will then perform simple and multiple non-linear regressions. Indeed, linear regressions determine, with the help of statistical models, a relationship between two variables, x and y, according to an estimation function called predictor *f*. However, in our case now, we assume that there is no estimating function associated with our model and that it is not known which predictor is the most suitable. With this assumption, we decide to perform a non-parametric regression. Non-parametric regression, also called non-linear, is in fact a regression in which the estimating function does not take a predetermined form. The estimating function with its predictor *f* will be constructed from the data provided, this requires the variables to be of large sizes. Indeed, the regression model is based directly on the data, in other words, the richer the scatterplot, the more efficient the regression.

5. Statistical clusters

Thanks to the paper *A cautious note on the use of panel models to predict financial crises* written jointly by Jeroen van den Berg, Bertrand Candelon and Jean-Pierre Urbain (2008), we know that we can avoid the naive analysis of all our data together. Indeed, it may be recommended to perform a preliminary analysis that would identify subgroups in our database, and this would greatly improve the prediction quality (van den Berg, Candelon & Urbain, 2008). Within a sample, there may be similarities or differences between data. To find out whether there are subgroups within our database of 182 companies belonging to the MSCI EMU stock index, we performed a cluster analysis. Examining the homogeneity of the predictive power of scope 3 with respect to companies is also possible using methods for calculating the optimal number of clusters in a database. Indeed, on the one hand, if the optimal number of clusters is equal to the number of companies, i.e. 182, then this cluster analysis shows that the results on the predictive power of scope 3 are very heterogeneous from one company to another. On the other hand, if the optimal number of clusters is equal to one, the results can be considered very homogeneous (Hasse & Lajaunie, 2022). A second aim is to gather similar data into a sub-database and thus differentiate different variables by grouping them into several different sub-databases. However, a cluster analysis sometimes implies that we know in advance how many clusters we want to obtain, this is the case with k-means classification that we performed. In order to determine this number of clusters, methods exist to provide the optimal number of clusters in the database. In order to ensure a high degree of reliability, we have performed four different methods: the elbow method, the silhouette analysis, the gap statistics and the consensus-based algorithm.

The first method used to determine the optimal number of clusters is the elbow method. This method works by minimizing the sum of the squares of the gaps within the clusters, in other words the Weighted Sum Statistic (WSS). More precisely, this method examines the total distance of the data points from their respective cluster centroids and extracts the total within-cluster sum of squares value from each model.

The second method used to confirm or not the results of the elbow method is the silhouette analysis method. The silhouette index (Rousseeuw, 1987) is a measure of the quality of a clustering and estimates a measure of the position of each point in its cluster. This coefficient varies from -1 to 1 for each observation in your data and the score is interpreted as follows: if the value is close to 1, it implies that the observation is well matched to the assigned cluster. A value close to 0 suggests that the observation is on the borderline of two-cluster correspondence and if it is close to -1, it means that the observations may be attributed to the wrong cluster. For this method, the optimal number of clusters in the data is the maximum value of the index, which will therefore be the closest to 1.

The gap-statistic (Tibishirani, Walther and Hastie, 2001) is the third method realized to find the number of clusters for the k-means clustering method. The gap statistic compares the total variation within a cluster for different values of k with their expected values under a null-reference distribution of the data, i.e., a distribution without obvious clustering (Krishna, S. T., V., Babu, Y. A. & Kumar, K. R, 2018). The optimal number of clusters is the one that maximizes the variance statistic.

Once these three methods have been carried out, we will be able to fix the number of clusters we want and then carry out our cluster analysis using the supervised k-means method. This method is widely used in many R packages for statistical computing and is one of the most popular partitioning algorithms. The method behind this algorithm is to minimize the sum of squares within a cluster for a predefined number of clusters (MacQueen 1967; Hartigan and Wong 1979). With an iterative operation, the algorithm starts by estimating the center of the clusters, and the observations are assigned to the cluster it is closest to. Then there is a second estimation of the cluster centers, and the process is repeated until the cluster centers do not move. In other words, once the desired number of clusters is known, the algorithm will create initial cluster centers and associate each observation with a center, at which point temporary clusters are obtained. In order to reiterate the process, the center of the temporary clusters become the centers of the new clusters and the estimation calculation is repeated until the sum of squares within a cluster is minimized.

6. Economic clusters

After having analyzed statistical clusters, economic clusters have been used in a concern of complementarity. In statistical clustering, the organization tool is an algorithm that measures the proximity between each element while with economic clusters, we have done the choice to classify our database according to an economic factor that is relevant within the framework of our study. Since greenhouse gas emissions are more or less important depending on sectors of activity (Ritchie, 2020), we have divided our database following the three-sector model. Defined by the British economist and statistician Colin Clark in his book The Conditions of Economic Progress (1947), the economy is divided into three sectors: primary, secondary, and tertiary. The primary sector, being related to the exploitation of natural resources (agriculture, fishing, forestry), the secondary sector broadly includes manufacturing and industry, and finally, the tertiary sector that encompasses services. However, the classification of the three-sector model is not rigid and often subject to debate (Bouchard & Al, 2009).

According to our database and the three-sector model, there are no companies classified in the primary sector. Consequently, the first economic cluster, being the one corresponding to the companies belonging to the secondary sector as we defined it. It includes Aeronautics, Food & Beverage, Automotive, Building and public works, Electrical engineering, Mechanical engineering, Chemical industry, Pharmaceutical industry, Household appliances, Energy industry, Textile industry, Paper industry, and Energy production. The second economic cluster, being the one corresponding to the companies belonging to the tertiary sector as we defined it. It includes Insurance, Auditing, Banking, Business & Commerce, Communication, Consulting, Education, Finance, Horeca (Hotels, Restaurants, Cafés), Leisure industry, Health & Medicine, Legal Services, Telecommunications, and Transport. It is important to note that some companies in our database, being parent companies, or having diversified their activities into several business units, are thus involved in both sectors, secondary and tertiary. However, for the classification, we decided to analyze which activity the company operated the most. This was used as a reference to classify the company into one of two sectors, i.e., in a unique cluster.

PART 3: EMPIRICAL ANALYSIS

1. Databases

For the sake of clarity, it is necessary to refer to the databases used throughout our research. As you know, our empirical study is based on the three scopes of greenhouse gas emissions of a panel of companies. At the beginning of our research and in order to analyze comparable European companies, we first selected the 50 companies belonging to the EURO STOXX 50 index. However, after having cleaned this database, we ended up with a panel of 42 companies. The analysis conducted on 42 companies gave us non-relevant results due to the low amount of data. Due to the constraints, we chose another stock market index with more companies. However, thanks to the access given by the Louvain School of Management, we found another database with the 233 companies belonging to the MSCI EMU stock index which also provided the different scopes for almost all these companies. We had to check it and clean it up and we removed for example companies that did not publish their scope 3 or some companies that were duplicates. Our final database to start our statistical analysis, named *dtb*, therefore has 182 observations (the remaining 182 companies) with their scope 1, scope 2 and scope 3 for the year 2019 expressed in tCO2eq. This unit means that the scopes are expressed in tons of carbon dioxide and *eq* for *carbon equivalent* which measures only the weight of carbon, i.e. the chemical element C, contained in the CO2 emitted.

In table 1, it is possible to see the head of the *dtb* database. This database has been greatly simplified as a lot of the work was only on the scopes. However, in total we have worked on five different databases. The first one [Appendix 3.1: *dtb* database] is the one gathering the 182 companies belonging to the MSCI EMU stock market index, which we simply called *dtb* as a diminutive of the word *database*. The second is the transformation of the dtb database by calculating the log of the variables. Thanks to the RStudio software and the *data.frame()* command, we were able to create a database containing the logs of the three scopes of the *dtb* database [Appendix 3.2 : *dtblog* database]. The second is the one created following the cluster analysis and includes the 177 companies. Indeed, as we shall see, there are two clusters in our database, one of which is made up of 5 companies that we have removed from the 182 observations. This implies that the third database contains 177 observations and is called *dtb177* [Appendix 3.3: *dtb177* database]. In addition, during our work, we added a qualitative variable and more precisely a nominal variable. Indeed, we have assigned to each company its sector of activity, secondary or tertiary, as you will see later in our analyses. To deepen our research on these economic clusters, we have created the last two databases: *Secondary* [Appendix 3.4: *Secondary* database] and *Tertiary* [Appendix 3.5: *Tertiary* database]. Each of which gathers the companies belonging to their sector. We will obtain 92 companies from the secondary sector and 90 companies from the tertiary sector.

In addition to these 4 variables, there is of course the qualitative variable that identifies the companies. This was the ISIN, International Securities Identification Numbers, of the company which allowed us, thanks to its unique international identification system of twelve characters, to identify the companies belonging to the MSCI EMU index.

Table 1: The scope of companies belonging to the MSCI EMU stock index
Head of the database

Scope 1	**Scope 2**	**Scope 3**
26600	800	648000
50144	201473	32813
23362	31997	3866
5231	8392	1833
1930000	1560000	8940000
124300	377300	40634700

<u>Source</u>: Empirical Analysis

2. Results and interpretations

A. *Linear analysis*

As can easily be seen in these two following tables, which show the correlation coefficients between the scopes of our initial database, labelled *dtb*, and our logarithmically transformed database, called *dtblog*, an evident relationship appears between scope 1 and scope 2. However, in table 2, it is more complicated to say that our data are dependent on each other given the extremely small values close to 0 for the relationship between scope 1 and scope 3 and the relationship between scope 2 and scope 3. Nevertheless, thanks to the logarithmic transformation that handles situations where the relationships are non-linear and verifies the linearity conditions of our variables, the Pearson correlation coefficients in table 3 confirm that linear relationships do exist between scope 1 and scope 3 but also between scope 2 and scope 3.

Table 2: Pearson linear correlation

	Scope 1	Scope 2	Scope 3
Scope 1	1	0.427	0.094
Scope 2		1	0.049
Scope 3			1

Model: cor(dtb, method = « pearson »)
Source: Database dtb

Table 3: Pearson linear correlation

	Scope 1	Scope 2	Scope 3
Scope 1	1	0.683	0.733
Scope 2		1	0.516
Scope 3			1

Model: cor(dtblog, method = « pearson »)
Source: Database dtblog

This first test means that the research can go further. Indeed, knowing that a dependency exists, it is now interesting to learn more about the relationship between our data. To accomplish this, we performed simple and multiple linear regressions between the scopes. In our hypotheses, we assume that scope 1 is always an explanatory variable, that scope 2 is either an explanatory or a variable to be explained and that scope 3 is always a variable to be explained.

As we could guess from the correlations between the scopes in our database *dtb*, the only simple linear regression that gives a result to consider is the regression that explains scope 2 in relation to scope 1 as shown in table 4. Indeed, the other two linear regressions that concern *scope 3 ~ scope 1* and *scope 3 ~ scope 2* [Appendix 2: Results of empirical analysis] have p-values greater than 5% and it is the same result for the multiple linear regression of *scope 3 ~ scope 1 + scope* 2, as shown in Table 5. Those p-values mean that we do not reject the null hypothesis that guarantees that there are no links between our data. In other words, if the p-value is greater than 5%, it means that there is no significant effect and that this model is therefore not interesting. On the other hand, if the p-value is less than 5%, it means that the null hypothesis which maintains that there is no significant link between the explanatory variables and the dependent variable to be explained must be rejected. Rejecting the null hypothesis means that there is a linear relationship between the variables.

Table 4: Simple linear regression dtb$scope2 ~dtb$scope1

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	4.392e+05	1.308e+05	3.357	0.000963
dtb$scope1	5.097e-02	8.051e-03	6.331	1.89e-09

Model: dtb$scope2 ~dtb$scope1 (182 observations)
Residual standard deviation: 1685000 (df=180)
Adjusted R-squared: 0.1776
Source: Database dtb

Table 5: Multiple linear regression dtb$scope3 ~dtb$scope2 + dtb$scope1

Coefficients	**Estimate**	**SE**	**T-value**	**p-value**
(Intercept)	3.097e+07	1.057e+07	3.174	0.00177**
dtb$scope2	6.993e-01	1.331e+01	1.086	0.2789
dtb$scope1	7.020e-01	1.511e+00	0.130	0.8966

Model: dtb$scope3 ~dtb$scope2 + dtb$scope1 (182 observations)
Residual standard deviation: 1.219e+08 (df = 179)
Adjusted R-squared: -0.0022
p-value: 0.4487
Source: Database dtb

Given the weak results obtained in the linear regressions performed with the *dtb* database, we will proceed with a different approach using the log-transformed database hoping for more successful results.

Table 6: Simple linear regression dtblog$scope3log ~dtblog$scope2log

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	3.76	0.721	5.216	5e-07 ***
dtblog$scope1log	0.86	0.059	14.465	< 2e-17 ***

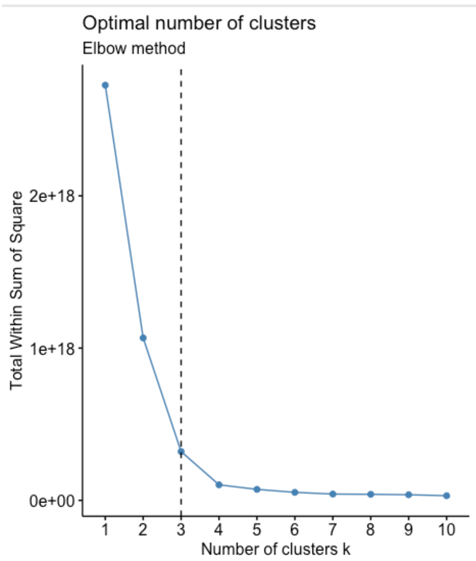
Model: dtblog$scope3log ~dtblog$scope2log (182 observations)
Residual standard deviation: 2.5 (df=180)
Adjusted R-squared: 0.535
Source: Database dtblog

Table 6 showing the simple linear regression of the logarithm of scope 3 explained in relation to the logarithm of scope 1 shows much better results. Firstly, because the p-value is significant and less than 5%. Here, the null hypothesis is rejected, and this model confirms that scope 3 can be related to scope 1 and is therefore not independent. Secondly, because the adjusted R-squared of this regression with its 0.535 result is significant. Indeed, this adjusted R-squared means that 54% of the logarithm of scope 3 is explained by the logarithm of scope 1.

For the other linear regressions [Appendices 2: Results of empirical analysis], we could have expected more satisfactory results that would easily demonstrate the relationship between the scopes. Nevertheless, all regressions have becoming interesting thanks to the log transformation because their p-values are now each time lower than 5% contrary to the linear regressions of the *dtb* database which implied that the scopes were independent. This proves that this second approach is necessary in order to handle the data in our database that do not follow a normal distribution and, as already mentioned above and to handle situations where there is a non-linear relationship between independent and dependent variables while maintaining a linear model.

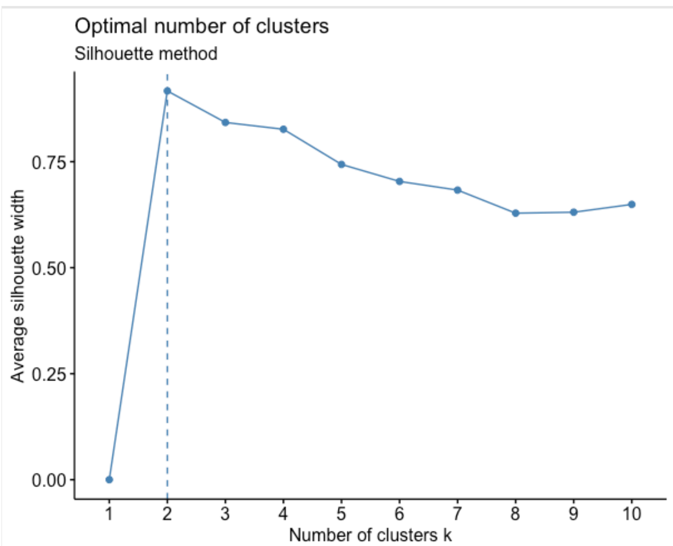
In order to go further, a cluster analysis will be carried out with the aim of finding clusters in our database as a first step. Further and in a second step, a non-parametric study will be conducted on the same database. The statistical clustering method we will use for our work is the k-means algorithm method. This method implies, as mentioned above, that the optimal number of clusters is known in advance. Several methods with the ability to find this optimal number of clusters exist and in order to obtain the most reliable result possible, we have tested several of them.

The elbow method is the first one applied on our *dtb* database. We have seen that with this method, the optimal number of clusters is the number where the elbow is located on the graph. Considering this, we can conclude that this method proposes to have 3 clusters as shown in figure 4.



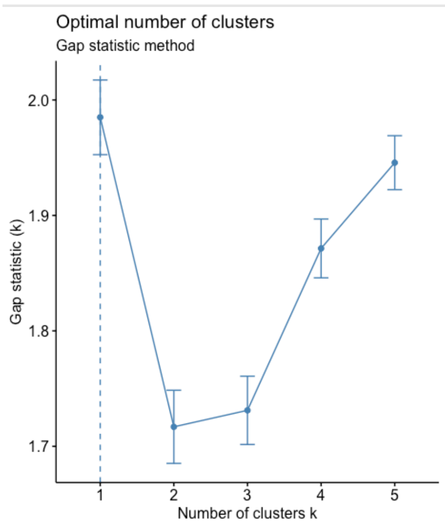
[Figure 4. Optimal number of clusters based on the elbow method]
Source: Empirical analysis

Afterwards, it was the turn of the silhouette analysis method to be realized. Again, based on the graph, we are able to determine the optimal number of clusters that maximizes the average width of the silhouette. This method gives us 2 clusters as the optimal number of clusters to have according to figure 5.



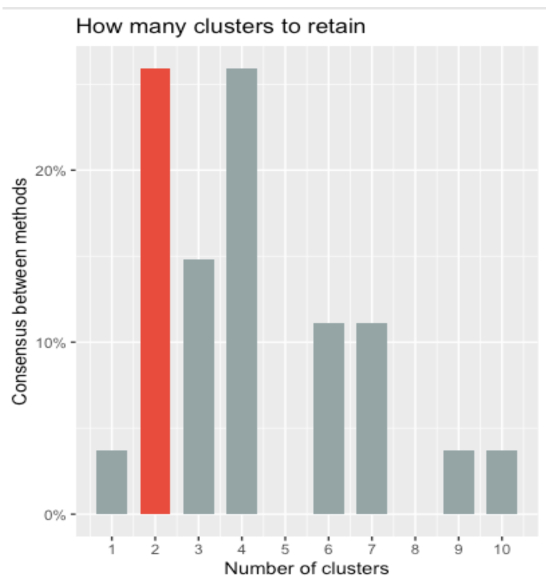
[Figure 5. Optimal number of clusters based on the silhouette analysis method]
Source: Empirical analysis

Lastly, we performed the gap statistic method which unfortunately did not give us a satisfactory result. In our work and as shown in figure 6, this method suggests only 1 cluster as an optional number of clusters to have, so this result indicates an unnecessary cluster.



[Figure 6. Optimal number of clusters based on the gap statistic method]
Source : Empirical analysis

We can conclude that these three methods do not always give the same result. Indeed, the elbow method suggests that the optimal number of clusters is 3 while the silhouette analysis method gives us 2 clusters. As for the gap statistic method, we cannot interpret its result being a single cluster, which makes the cluster useless as it is equivalent to the total database. An alternative that can be done when the result is not convincing, is to test the consensus-based algorithm. This alternative method is in fact a concentration of many methods, meaning that it will run many methods and pick the number of clusters that is subject to the highest agreement, or consensus.



[Figure 7. Optimal number of clusters based on the consensus-based algorithm]
Source: Empirical analysis

The consensus-based algorithm method will turn the scales in favor of having two clusters in total as shown in figure 6. Indeed, according to this algorithm, the choice of two clusters is supported by seven methods out of 27 methods including Elbow, Silhouette, Duda, Beale, PtBiserial, Mcclain, Dunn, etc. In other words, a quarter of the methods advise us to have two clusters for our *dtb* database.

We are now at the phase where we can perform the cluster analysis with the k-means method. By imposing the number of clusters $k = 2$, we will, obviously, obtain two clusters composing our database. A first major cluster composed of 177 data and a second small cluster containing the 5 other companies. With the help of RStudio, we are able to view the second cluster which is the one shown in table 7 where the unit of the scopes is still the tCO2eq.

Table 7 : Database of companies in the minority cluster

ISIN	COMPANY	SCOPE 1	SCOPE 2	SCOPE 3
NL0000235190	Airbus	562000	265000	464746000
BE0974293251	AB InBev	2590500	1318800	23652933
FR0000120271	Total Energies	33000000	2000000	370000000
DE0007236101	Siemens AG	386000	208000	469271000
DE000ENER6Y0	Siemens Emery AG	206000	67000	1373924000

Once the 5 companies in the cluster are known, we will obtain two databases, one above that gathers the five companies and a much larger one keeping the other 177 companies that we have called *dtb177*. First, we tried to find out why these five companies were in the second cluster by analyzing them for similarities and differences with the other 177 companies. Unfortunately, no apparent observations could be made either in terms of the value of their scopes or within the company itself (their turnover, the nationality and background of their CEO, the location of their head office, their seniority, etc.). Also, since a sample of 5 data is too small to analyze and will not produce reliable results, we will concentrate the continuation of our research on the database with the 177 companies in order to reiterate our linear search.

For this new database, we immediately observe that the linear correlations are much stronger than the linear correlations of our first database (Table 8). Indeed, the correlation between scope 1 and 3 is equal to 0.342 in the *dtb177* whereas the correlation between these same scopes in the initial database, *dtb*, was 0.094. This also implies that there must have been outliers in the 5 companies removed.

Table 8: Pearson linear correlation

	Scope 1	**Scope 2**	**Scope 3**
Scope 1	1	0.338	0.342
Scope 2		1	0.184
Scope 3			1

Model: cor(dtb177, method = 'spearman')
Source: Database dtb177

By performing simple linear regressions between the three variables of the reduced database of 177 firms, a significative improvement is perceived as can be seen in the results tables in the appendices 2.6, 2.7, 2.8 and 2.9. With the cluster analysis and the small reduction of the database, we could guess that the results would lead to a better result. Indeed, these three linear regressions have p-values below 5%. Which implies that we reject the null hypothesis and the hypothesis that a relation exists between the variables can be maintained. However, the adjusted R-squared obtained are not sufficient because of their very low values of 12% *for scope 3 ~ scope 1* [Appendix 2: Results of empirical analysis] and *only 3% for scope 3 ~ scope 2 1* [Appendix 2: Results of empirical analysis]. This does not change the dependence between the variables, but it implies that there are other factors to take into account to explain scope 3.

To conclude this first linear analysis, it is easily observable that the statistical analyses performed on the initial database of 182 companies are not conclusive given the weak correlations and the independence between the variables as expressed by the p-values above 5%. Nevertheless, and in order not to stop there, we had the possibility to transform our data thanks to the log function which allows us to analyze them from another point of view. This transformation was very beneficial given the strong positive correlations between our three quantitative data, the regressions implying that the scopes were dependent on each other and given the rather high percentage of variability explained by the adjusted R-squared. In the third place, the cluster analysis has also improved the results of this parametric study. Indeed, thanks to the k-means method, we knew that our database had two distinct statistical clusters, one of which was too small to be statistically analyzed. The second larger cluster composed of the 177 other companies also underwent statistical analysis which provided much better results in terms of correlation and dependency of the variables with p-values lower than 5% as mentioned earlier.

B. Non-linear analysis

In the case where there is no linear function associated with our model, non-linear tests, in this case correlations and regressions, can be conducted with the objective of still analyzing the relationships between the three scopes, but where the estimation function will no longer be a predetermined form, but is directly based on the data. In a non-parametric search, the correlation coefficient to be calculated is the Spearman's coefficient. Here, the able 9 shows very strong and positive correlations between the scopes of the original database. This is in contrast to the low, if not almost zero, Pearson correlation coefficient in table 2. This is explained by the fact that the Pearson coefficient only analyses the strength of the linear relationship between x and y. However, we have seen above that the variables of our *dtb* database do not follow a normal distribution, this implies that it is the Spearman correlation that must be calculated. As a reminder, this correlation does not use the values of the scopes but their rank and finally the interpretation of the results remains the same.

Table 9: Spearman non-linear correlation

	Scope 1	**Scope 2**	**Scope 3**
Scope 1	1	0.798	0.747
Scope 2		1	0.632
Scope 3			1

Model: cor(dtb, method = "spearman")
Source: Database dtb

Concerning the regressions, the first one in table 10 studying scope 2 in relation to scope 1 is significant. The p-value lower than 5% confirms the dependence of scope 2 which is explained by 18% by scope 1. The regression of scope 3 against scope 1 remains interesting given the p-value of 0.019 but scope 3 is only explained by 2% of scope 1 and this is very low (Table 11). The results are much better than those obtained for the linear regression of scope 3 and 1 in the same database which had a p-value greater than 5% and therefore implied that scope 3 was independent of scope 1. However, improvements can still be made to our research. For the last non-linear regression, table 12 shows that the null hypothesis is retained and that there is no dependence of scope 3 from scope 2. The same conclusion can be drawn for the non-linear multiple regression since it also obtains a p-value higher than 5% as shown in table 13.

Table 10: Simple non-linear regression dtb$scope2 ~dtb$scope1 + I(dtb$scope1^2)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	3.987e+05	1.345e+05	2.964	0.0034 **
dtb$scope1	7.309e-02	1.927e-02	2.794	0.0002 ***
I(dtb$scope1^2)	-2.530-10	2.003e-10	-1.263	0.2081

Model: dtb$scope2 ~dtb$scope1 + I(dtb$scope1^2) (182 observations)
Residual standard deviation: 1682000 (df=179)
Adjusted R-squared: 0.1803
p-value: 6.944e-09
Source: Database dtb

Table 11: Simple non-linear regression dtb$scope3 ~dtb$scope1 + I(dtb$scope1^2)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	2.664e+07	9.637e+06	2.764	0.0063 **
dtb$scope1	3.267e+00	1.380e+00	2.367	0.019*
I(dtb$scope1^2)	-2.896-08	1.435e-08	-2.018	0.0451 *

Model: dtb$scope3 ~dtb$scope1 + I(dtb$scope1^2) (182 observations)
Residual standard deviation: 1.205e+08 (df=179)
Adjusted R-squared: 0.02
p-value: 0.06
Source: Database dtb

Table 12: Simple non-linear regression dtb$scope3 ~dtb$scope2+ I(dtb$scope2^2)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	2.718e+07	1.045e+07	2.600	0.0101 *
dtb$scope1	1.575e+01	1.059e+01	1.487	0.1388
I(dtb$scope1^2)	-8.067e-07	6.048e-07	-1.334	0.1839

Model: dtb$scope3 ~dtb$scope2+ I(dtb$scope2^2) (1822 observations)
Residual standard deviation: 1.217e+08 (df=179)
Adjusted R-squared: 0.0011
p-value: 0.3332
Source: Database dtb

Table 13: Multiple non-linear regression dtb$scope3 ~dtb$scope1 + I(dtb$scope1²) + dtb$scope2 + I(dtb$scope2²)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	2.386e+07	1.057e+07	2.257	0.0252 *
dtb$scope1	2.931e+00	1.511e+00	1.941	0.0539
I(dtb$scope1²)	-2.829e-08	1.450e-08	-1.951	0.0526
dtb$scope2	9.278e+00	1.331e+01	0.697	0.4868
I(dtb$scope2²)	-5.480e-07	6.959e-07	-0.787	0.4321

Model: dtb$scope3 ~dtb$scope1 + I(dtb$scope1²) + dtb$scope2 + I(dtb$scope2²) (182 observations)
Residual standard deviation: 1.21e+08 (df=177)
Adjusted R-squared: 0.01245
p-value: 0.1842
Source: Database dtb

For the purpose of depth, non-parametric analysis was also performed on the log-transformed database. The Spearman correlation coefficients obtained for the *dtblog* database are identical to those obtained for the initial database. That is, according to this model, the scopes would be strongly positively related since the coefficients are worth more than 0.6

Table 14: Spearman non-linear correlation

	Scope 1	**Scope 2**	**Scope 3**
Scope 1	1	0.798	0.748
Scope 2		1	0.632
Scope 3			1

Model: cor(dtblog, method = "spearman")
Source: Database dtblog

The results of the non-parametric and simple or multiple regressions applied to the logarithm of the scopes show much better results, as our appendices 2 shown than the non-linear regressions between the untransformed scopes. Here, all three regressions have p-values below 5% and we interpret this as knowing that our variables are not independent of each other, which should be kept in consideration because it is very relevant for our research. Moreover, the percentage of variability explained is high with values close to 50%. These results are therefore very promising and the non-linear search of the database of our logarithmically transformed variables could go further.

Once this was done, we performed a cluster analysis and it is now the time to analyze, still in a non-parametric way, the *dtb177* database. As far as the correlations are concerned in table 15, they are almost similar to those obtained with the full database, so no improvement appears at this stage.

Table 15: Spearman non-linear correlation

	Scope 1	**Scope 2**	**Scope 3**
Scope 1	1	0.793	0.750
Scope 2		1	0.637
Scope 3			1

Model: cor(dtb177, method = "spearman")
Source: Database dtb177

The non-linear regression between scope 2 and scope 1 [Appendix 2: Results of empirical analysis] does not add anything, as its p-value is also less than 5% and its adjusted R-squared is 17%, which is very close to the results obtained with the same regression done in the database of 182 companies. However, a very important improvement will be in the non-parametric regression between scope 3 and scope 1 [Appendix 2: Results of empirical analysis]. Indeed, the p-value is still below 5% which is a good thing, but the adjusted R-squared has increased from 2% to 22%. Having done this cluster analysis is an excellent thing regarding the relationship between scope 3 and scope 1. The non-parametric regression between scope 3 and scope 2 [Appendix 2: Results of empirical analysis] is also better with our *dtb177* database. Indeed, here the p-value is less than 5% and the adjusted R-squared is 11%, which is not huge, but it implies that we are heading in the right direction. Finally, the results of the non-linear and multiple regression [Appendix 2: Results of empirical analysis] with the three scopes are also better than expected. The overall p-value of this model is below 5% and scope 3 is explained by 24% by scope 1 and scope 2.

Our cluster analysis is therefore quite useful given the significant improvements between the same non-parametric statistical studies between the *dtb* database and the reduced *dtb177* database.

C. *Analysis of the economic cluster "Secondary"*

As explained above, in order to test different approaches and in the hope of getting new results, we tested statistical cluster models but also created economic clusters. For this second approach, we started from the initial database with 182 companies and identified for each of them their sector of activity. Given that there are three-sector model (Colin Clark, 1947) of activity: primary, secondary and tertiary, we expected to obtain three databases. But in the end, after studying closely the definitions of these concepts and after analyzing our 188 companies, we associated each company with a sector, and we obtained only companies in the secondary or tertiary sector. There were no companies belonging to the primary sector.

About the secondary sector, 92 companies out of the 180 represent mainly this sector involving the transformation of raw materials. Statistical analyses were carried out on our new database called *Secondary* in order to try to find more significant relationships between these 92 companies.

The correlation between scope 1 and scope 2 again has the best coefficient with 0.385 while the other two correlations involving scope 3 are not significant. Indeed, the coefficient is 0.028 for the one looking at scope 3 compared to scope 1, which is too close to 0 and means that scope 3 is independent of scope 1. In addition, the coefficient of the linear correlation relating scope 3 to scope 2 is negative and close to 0 with a coefficient of -0.014 as we can see in table 16, which also means that scope 2 does not influence scope 3.

Table 16: Pearson linear correlation

	Scope 1	**Scope 2**	**Scope 3**
Scope 1	1	0.385	0.028
Scope 2		1	-0.014
Scope 3			1

Model: cor(secondary, method = "pearson")
Source: Database Secondary

For the simple linear regressions of the database of secondary sector companies, the results are close to those of the same regressions of the original database and the interpretations are therefore similar. That is to say, once again, here the only result to be kept and interpreted is that of the regression between scope 1 as an explanatory variable and scope 2 as a variable to be explained which has a p-value of less than 5% as shown in table 17. Unfortunately, the adjusted R-squared of this model is not representative as less than one fifth of scope 2 is explained by scope 1 given the result of 14% as shown in table 17. Concerning the two other simple regressions and the multiple linear regression, we observe in the table 18, the table 19 and the table 20 that their p-values are higher than 5% which predicts an independence of the variables.

Table 17: Simple linear regression secondary$scope2 ~secondary$scope1

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	7.354e+05	2.579e+05	2.852	0.005 **
secondary$scope1	4.523e-02	1.141e-02	3.963	0.000148 ***

Model: secondary$scope2 ~secondary$scope1 (92 observations)
Residual standard deviation: 2275000 (df=90)
Adjusted R-squared: 0.139
Source: Database Secondary

Table 18: Simple linear regression secondary$scope3 ~secondary$scope1

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	6.132e+07	1.885e+07	3.253	0.0016 **
secondary$scope1	2.218e-01	8.345e-01	0.266	0.791***

Model: secondary$scope3 ~secondary$scope1 (92 observations)
Residual standard deviation: 166300000 (df=90)
Adjusted R-squared: 0.0103
Source: Database Secondary

Table 19: Simple linear regression secondary$scope3 ~secondary$scope2

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	6.442e+07	1.914e+07	3.367	0.0011 **
secondary$scope2	-9.974e-01	7.113	-0.140	0.8888

Model: secondary$scope3 ~secondary$scope2 (92 observations)
Residual standard deviation: 166400000 (df=90)
Adjusted R-squared: -0.011
Source: Database Secondary

Table 20: Multiple linear regression secondary$scope3 ~secondary$scope2 + secondary$scope1

Coefficients	Estimate	SE	T-value	p-value
(Intercept)	6.281e+07	1.979e+07	3.175	0.0021**
secondary$scope1	3.135e-01	9.091e-01	0.34	0.731
secondary$scope2	-2.027e+00	7.746e+00	-0.262	0.794

Model: secondary$scope3 ~secondary$scope2 + secondary$scope1 (92 observations)
Residual standard deviation: 1672e+05 (df = 89)
Adjusted R-squared: -0.021
p-value: 0.9332
Source: Database Secondary

From a non-parametric approach and by comparing the results of the Pearson correlation with the results of the non-linear Spearman correlation, a major improvement can be seen. In table 21, the correlations between the scopes are all positive and significant, even for the correlation between scope 3 and scope 2 with its coefficient of 0.492. Whereas in our previous parametric study of the same database, the only positive correlation but with a relatively low coefficient of 0.385 was the one linking scope 1 and scope 2. We can conclude, for the moment, that the non-parametric method is more consistent with our database.

Table 21: Spearman non-linear correlation

	Scope 1	Scope 2	Scope 3
Scope 1	1	0.762	0.591
Scope 2		1	0.492
Scope 3			1

Model: cor(secondary, method =”spearman”)
Source: Secondary

Despite this very positive improvement, all the non-linear regressions between the scopes in the *Secondary* database have p-values higher than 5% as we can easily observe in the following four tables. In each case, the null hypothesis of independence is therefore to be kept and the analysis cannot go further. Indeed, if the results of the regressions imply that the data are independent of each other, it is not possible to find any relationship between the scopes despite what the correlation coefficients might suggest.

Table 22: Simple non-linear regression secondary$scope2 ~secondary$scope1 + I(secondary$scope1^2)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	6.899e+05	2.725e+05	2.531	0.0131 *
secondary$scope1	5.921e-02	2.856e-02	2.073	0.0411 *
I(secondary$scope1^2)	-1.543e-10	2.871e-10	-0.534	0.5946

Model: secondary$scope2 ~secondary$scope1 + I(secondary$scope1^2) (92 observations)
Residual standard deviation: 2284000 (df=89)
Adjusted R-squared: 0.1322
p-value: 0.0006758
Source: Database Secondary

Table 23: Simple non-linear regression secondary$scope3 ~secondary$scope1 + I(secondary$scope1^2)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	5.491e+07	1.984e+07	2.768	0.0068 **
secondary$scope1	2.190e+00	2.079e+00	1.054	0.294
I(secondary$scope1^2)	-2.16e-08	2.090e-08	-1.034	0.304

Model: secondary$scope3 ~secondary$scope1 + I(secondary$scope1^2) (92 observations)
Residual standard deviation: 1663e+05 (df=89)
Adjusted R-squared: -0.0095
p-value: 0.5677
Source: Database Secondary

Table 24: Simple non-linear regression secondary$scope3 ~secondary$scope2 + I(secondary$scope2^2)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	6.047e+07	2.230e+07	2.712	0.00803 **
secondary$scope1	4.579e+00	1.746e+01	0.262	0.793
I(secondary$scope1^2)	-3.291e-07	9.401e-07	-0.350	0.727

Model: secondary$scope3 ~secondary$scope2 + I(secondary$scope2^2) (92 observations)
Residual standard deviation: 1672e+05 (df=89)
Adjusted R-squared: -0.021
p-value: 0.9315
Source: Database Secondary

Table 25: Multiple non-linear regression secondary\$scope3 ~ secondary\$scope1 + I(secondary\$scope1^2) + secondary\$scope2 + I(secondary\$scope2^2)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	5.463e+07	2.234+07	2.351	0.021 *
secondary\$scope1	2.225+00	2.231	0.997	0.321
I(secondary\$scope1^2)	-2.197e-08	2.115e-08	-1.039	0.302
Secondary\$scope2	1.499	2.234e+01	0.067	0.947
I(secondary\$scope2^2)	-2.135e-07	1.122e-06	-0.190	0.849

Model: secondary\$scope3 ~ secondary\$scope1 + I(secondary\$scope1^2) + secondary\$scope2 + I(secondary\$scope2^2) (92 observations)
Residual standard deviation: 1.68e+08 (df=87)
Adjusted R-squared: -0.031
p-value: 0.868
Source: Database Secondary

To conclude the analysis of the secondary economic cluster, we can state that the scopes are independent of each other for the sample of 92 companies in the database analyzed in this 3rd part of the statistical analysis. This result is surprising when compared to previous analyses. For example, our previous non-parametric analysis has each time shown a dependence between our variables whereas this time, the non-parametric study on the Secondary database shows the opposite when we interpret the p-values of the regressions.

D. Analysis of the economic cluster "Tertiary"

If our first cluster, which includes companies from the secondary sector, is composed of 92 companies, and knowing that none of our companies belong to the primary sector, it is quite logical that our last analyzed database, which includes companies from the tertiary sector, is composed of the remaining 90 companies.

The scopes of the 90 companies belonging to the tertiary sector are positively and moderately correlated given the coefficients collected in table 26. Compared to the correlations of the scopes of the secondary sector companies, better results are observed. In particular, the relationship between scope 1 and scope 2 was almost non-existent in our study of companies in the *Secondary* database, whereas now the coefficient between these two scopes is 0.33. As for the correlation between scope 2 and scope 3, the coefficient remains low but becomes significant and is positive. As with our other studies, we will now carry out simple and multiple linear regressions to learn more about the potential relationships between the three scopes.

Table 26: Pearson linear correlation

	Scope 1	Scope 2	Scope 3
Scope 1	1	0.482	0.333
Scope 2		1	0.131
Scope 3			1

Model: cor(tertiary, method =”pearson”)
Source: Database Tertiary

Still using the *Tertiary* database, the regressions performed give different results. The simple regressions of scope 2 explained by scope 1 or of scope 3 explained by scope 1 show that these variables are dependent given significant p-values below 5% as shown the table 27 and table 28. However, their respective R-squared adjustments do not show a strong percentage of variability as they are 22% and 10% as shown in table 27 and table 28 whereas we assume a good result when variable Y is explained by at least 50% of variable X.

Table 27: Simple linear regression tertiary$scope2 ~tertiary$scope1

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	1.65e+05	6.360e+04	2.46	0.0158 *
tertiary$scope1	9.303e-02	1.803e-02	5.16	1.51e-06 ***

Model: tertiary$scope2 ~tertiary$scope1 (90 observations)
Residual standard deviation: 589300 (df=88)
Adjusted R-squared: 0.224
Source: Database Tertiary

Table 28: Simple linear regression tertiary$scope3 ~tertiary$scope1

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	4.22e+06	2.169e+06	1.946	0.05488
tertiary$scope1	2.039	6.149e-01	3.316	0.00133 **

Model: tertiary$scope3 *~tertiary$scope1* (90 observations)
Residual standard deviation: 20100000 (df=88)
Adjusted R-squared: 0.1
Source: Database Tertiary

Concerning the linear regression between scope 3 and scope 2 (table 29) or the multiple regression of scope 3 explained by scope 1 and scope 2 (table 30), the p-values of these regressions are higher than 5% and this implies that for this database the scopes are independent of each other.

Table 29: Simple linear regression: tertiary$scope3 ~tertiary$scope2

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	4.819e+06	2.353e+06	2.048	0.0436 *
tertiary$scope1	4.162	3.349	1.243	0.2173

Model: tertiary$scope3 ~tertiary$scope2 (90 observations)
Residual standard deviation: 21130000 (df=88)
Adjusted R-squared: 0.006
Source: Database Tertiary

Table 30: Multiple linear regression tertiary$scope3 ~tertiary$scope1 + tertiary$scope2

Coefficients	**Estimate**	**SE**	**T-value**	**p-value**
(Intercept)	4.409e+06	2.254e+06	1.956	0.0536
tertiary$scope1	2.151e+00	7.053e-01	3.050	0.003 **
tertiary$scope2	-1.208e+00	3.654+00	-0.331	0.742

Model: tertiary$scope3 ~tertiary$scope1 + tertiary$scope2 (90 observations)
Residual standard deviation: 202e+05 (df = 87)
Adjusted R-squared: 0.09
p-value: 0.0056
Source: Database Tertiary

To finish the statistical analysis on our last database and to follow the logic of our work, we also performed non-parametric test on the *Tertiary* database. This starts with a correlation calculation using the Spearman method. If we compare the Pearson correlation coefficients, table 26, with those obtained with Spearman, table 31, an improvement is obvious. For companies in the service sector and in a non-linear approach, we can conclude that the scopes are much more strongly and positively correlated. These results motivate us to go further by performing the regressions now.

Table 31: Spearman non-linear correlation

	Scope 1	**Scope 2**	**Scope 3**
Scope 1	1	0.715	0.615
Scope 2		1	0.431
Scope 3			1

Model: cor(tertiary, method = "spearman")
Source: Database Tertiary

The two simple regressions involving scope 1 which try to explain either scope 2 or scope 3 imply a dependence of the variables given the p-values smaller than 5% as shown in table 33 and 34. We can even say that scope 1 explains 30% of scope 2 and 19% of scope 3. For the third simple regression, there is still no dependence between scope 2 and scope 3, table 35 shows that these two variables are independent, and this is very often the case in the research done throughout this work. Finally, regarding the non-parametric multiple regression, the overall p-value of the model is less than 5% but if we look closely at table 36, we will see that the p-value of scope 2 in this model remains above 5%.

Table 33: Simple non-linear regression

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	1.877e+05	6.143e+04	3.055	0.00299 **
tertiary$scope1	-7.424e-02	5.595e-02	-1.327	0.1879
I(tertiary$scope1²)	7.671e-09	2.442e-09	3.142	0.002 **

Model: tertiaty$scope2 ~tertiary$scope1 + I(tertiary $scope1²) (90 observations)
Residual standard deviation: 561700 (df=87)
Adjusted R-squared: 0.29
p-value: 9.472e-08
Source: Database Tertiary

Table 34: Simple non-linear regression

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	3.121e+06	2.087e+06	1.496	0.1384
tertiary$scope1	7.934e+00	1.900e+00	4.175	7.06e-05 ***
I(tertiary$scope1²)	-2.703e-07	8.294e-08	-3.259	0.0016 **

Model: tertiaty$scope3 ~tertiary$scope1 + I(tertiary $scope1²) (90 observations)
Residual standard deviation: 1908e+04 (df=87)
Adjusted R-squared: 0.189
p-value: 3.977e-05
Source: Database Tertiary

Table 35: Simple non-linear regression

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	3.269e+06	2.599e+06	1.258	0.2118
tertiary$scope2	1.877+01	1.113e+01	1.686	0.0954
I(tertiary$scope2²)	-3.572e-06	2.598e-06	-1.375	0.1727

Model: tertiaty\$scope3 ~tertiary\$scope2 + I(tertiary \$scope2^2) (90 observations)
Residual standard deviation: 2102e+04 (df=87)
Adjusted R-squared: 0.016
p-value: 0.184
<u>Source</u>: Database Tertiary

Table 36: Multiple non-linear regression

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	2.006e+06	2.417+06	0.830	0.409
tertiary\$scope1	7.947e+00	1.953e+00	4.069	0.000105 ***
I(tertiary\$scope1^2)	-2.857e-07	8.842e-08	-3.231	0.001755 **
tertiary\$scope2	9.041+00	1.077e+01	0.839	0.404
I(tertiary\$scope2^2)	-2.135e-07	2.424e-06	-0.631	0.529

Model: tertiary\$scope3 ~ tertiary\$scope1 + I(tertiary\$scope1^2) + tertiary\$scope2 + I(tertiary\$scope2^2) (90 observations)
Residual standard deviation: 1.92e+07 (df=85)
Adjusted R-squared: 0.1794
p-value: 0.00032
<u>Source</u>: Database Tertiary

CONCLUSION

As we have seen in the literature review, the scope 3 remains globally complex and not mandatory, but still, very important. And thus, it is because scope 3 is ambiguous, that we decided to focus our research on it. The empirical analysis allows us to statistically analyze and then demonstrate the potential correlations between scope 1, scope 2 and scope 3 greenhouse gas emissions of the companies of the MSCI EMU index.

The first outcomes identified are with regards to statistics and more particularly the relevance of clustering. Indeed, at the beginning of our analysis, we performed a cluster analysis using the k-means algorithm and this analysis was successful. As we saw, the regressions applied on the *dtb177* give much better results than those applied on the *dtb* database. This can be justified by the fact that the company Siemens Energy AG, which belongs to the minority scope of the 5 companies, was removed. Indeed, as a general observation, when the company Siemens Energy AG is present in the database on which we are working on, the results are less good. In parallel to this cluster analysis, we also performed a log transformation of our variables. Indeed, in the doubt where our data did not follow a normal distribution but in the desire to carry out linear models, we decided to take the logarithm of the scopes of the 182 companies. As a reminder, this transformation allows to handle situations where the relationships are non-linear between the independent and dependent variables, while preserving the linear model. We can observe that the analyses performed on the *dtb177* and *dtblog* database allow us to reject the hypothesis of independence. In these two situations, scope 3 is dependent on scope 1 and scope 2. However, this does not allow us to generalise about any dependency but these situations can be interesting. For a future study that would like to work on the dependence of scope 3 on the other two scopes, our analyses on these two databases could become a starting point for a future research. Finally, after these three approaches and in order to push our study further, the initial database was divided into two sub-databases according to an economic cluster. After reflection and analysis of the companies we had, we decided to classify the 182 companies according to their economic activity sector defined by the British economist and statistician Colin Clark. This cluster provides us with two databases, the first including 92 companies belonging to the secondary sector of activity and a second including the other 90 companies of the tertiary sector of activity. The results obtained for the tests carried out on the *Secondary* database were not conclusive as they led to a total independence of the scopes between them, so we decided to stop this research at this stage. Nevertheless, the second economic cluster, which brings together companies from the tertiary sector, allows us to consider a dependence between scope 3 and scope 1. Once again, we justify the poor results obtained with the secondary database because of the data from the company Siemens Energy AG. The situation here is similar to the one described above between *dtb* and *dtb177*. Siemens Energy AG belongs to the secondary sector and, once again, the results are not consistent because this company, with its large scope 3, distorts the results. For the sake of clarity and to summarize the results, there is no obvious dependency between scope 3 and scopes 1 and 2, although there are some cases where scope 3 is dependent on scope 1. Therefore, based on our statistical analysis, we can say that scope 3 makes a contribution and should not be neglected because it is not directly correlated with the other two scopes.

After this detailed empirical analysis, we have drawn up a conclusion based on the general outcome we found which is that there is no significant correlation between Scope 1 & 2 and Scope 3 GHG emissions. Given the independence of scope 3 versus scope 1 and 2, we therefore conclude that its disclosure should be mandatory and integrated into companies' carbon footprint reduction strategies as it brings additional value. Several important elements of the literature support our conclusion. Indeed, given the prominent risks of climate change and its anthropogenic source, there is a clear necessity of reducing carbon emissions. Even though the current international policy design does not appear to be effective and that there is no unified regulatory model that imposes a strict framework for the reporting of carbon emissions, there is a growing pressure from investors as well as all other stakeholders on companies' responsibility regarding climate change. To be able to reduce carbon emissions, corporations obviously need to compute them. According to the GHG Protocol, the total emissions of an entity include scope 1, 2, and 3. We argue that Scope 3 emissions should not be set aside as it is usually the case today and that consequently, its reporting should be mandatory. First, Scope 3 emissions usually represent the largest proportion of company's emissions, excluding them would give an inaccurate picture of a company carbon footprint. Secondly, as the Scope 3 emissions represent the value chain emissions, they are a valuable risk-management tool. It will help companies to understand in which part of their value chain they are using carbon-intensive processes or products and therefore, which parts of their value chain are the most vulnerable in facing the potential risks of increasing prices due to a changing regulation such as the implementation of a carbon tax for example. Also, Scope 3 emissions need to be considered as part of the evaluation of the transition risks of climate change. For example, upstream emissions can be exposed to policy risk and downstream emissions to market, technology, and legal risks. A clear roadmap to net-zero emissions across the value chain is prerequisite for future access to debt or equity financing. The transition to a low-carbon economy is coming and countries are more and more committed to net-zero targets, which implies an increasing focus from the financial sector and governments on value chain emissions. Considering Scope 3 emissions allows companies to identify areas for business innovation and collaboration with industry and suppliers, leading to transformative change and providing them competitive advantages. Finally, even though Scope 3 emissions is being mandated, we are realistic about the current situation and its "voluntary" nature. Things will only really change when it will become mandatory and with an understandable standardized methodology and framework. Overall, given the relevance of scope 3 emissions that we have been able to demonstrate through this research, we support the argument for mandatory scope 3 reporting for companies despite its current complexity in terms of measurement and reporting.

1. Limits

This thesis has encountered a few limitations in the course of its writing. The first one is that our research is only based on companies belonging to the MSCI EMU index. The results obtained are only correct for the panels we used, and the conclusions of the results are not representative on a global scale. In addition, the initial database chosen had to be cleaned as some companies do not publish their Scope 3 emissions. We consider our results to be correct only for the database in question and not for all companies belonging to the MSCI EMU index, as we only kept 182 companies out of the 233.

Regarding our conclusion, there are also limitations that are subject to debate. Indeed, although we consider that it is only a matter of time for the mandatory calculation and reporting of Scope 3 emissions, attention should be paid to the feasibility of what the Scope 3 calculation represents in the sense of not penalizing companies. Indeed, the fact that companies must calculate and report their Scope 3 carbon emissions is undoubtedly positive for limiting climate change as well as for the strategic positioning of companies. As mentioned before, this can be a competitive advantage since it is highly valued by stakeholders such as investors, governments, consumers, competitors, partners, etc. However, for companies with fewer resources, the challenge is even bigger since the process is time-consuming and resource intensive. Moreover, it does not only depend on the company in itself but also on the many partners along its supply chain. Create understandable methodology and framework is as important as making Scope 3 disclosure mandatory. The limitation emphasized here is the fact that it is not effective to make Scope 3 emissions disclosure mandatory if it is unfeasible for companies to do so due to its complexity. Therefore, the mandatory dimension of Scope 3 emissions disclosure should be perhaps adapted to the size, sector, and structure of companies but still with a predefined uniform methodology and framework in order to avoid competitiveness issues.

2. Recommendations

This thesis allowed us to conduct initial statistical analysis on a defined sample of companies to find out more about their scopes. However, as explained in the limits, this only applies to the different databases used throughout the research. Given our results, it will be interesting to reiterate this research on other panels of companies in order to detect similarity or not of the relationships between the scopes. In order to help the continuation of this work, it may be useful and interesting to consider further questions. Since theoretically, Scope 3 emissions of a company is the sum of scope 1 emissions of other companies along its supply chain, we could assume that in a situation where all companies correctly measure and report scope 1 emissions, the calculation and report of scope 3 emissions would be easier to do. One could therefore investigate the following question: “In which case is scope 3 dependent on scope 1?”. In addition, since specific sectors are generating more GHG emissions than the average, the following question could also be investigated: “Do scope 3 emissions depend on the sector of activity of the company concerned?”. Finally, given the fact that the EU is the best-in-class regarding its involvement in implementing policies and measures limiting GHG emissions, another line of research could answer the following question: “Will the results be similar for a panel of non-EU companies?”

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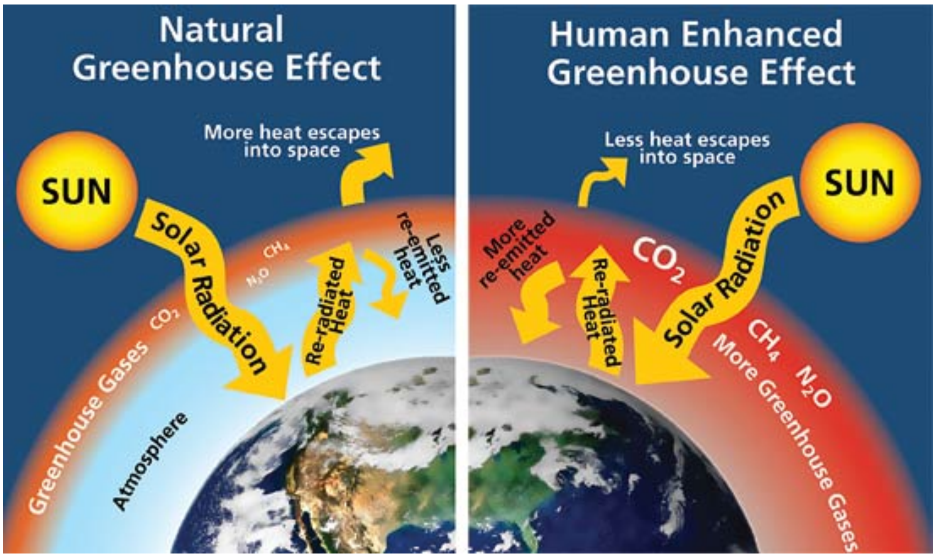
APPENDICES

Appendices 1	**Literature Review**
Appendix 1.1	Greenhouse Effect
Appendix 1.2	Global Risks Perception Survey
Appendix 1.3	Example of cascading risks in cities
Appendix 1.4	Illustration of the growing global emissions' responsibility of developing (or middle-income) countries
Appendix 1.5	Carbon Pricing Basics
Appendix 1.6	Importance of the Green Bonds Market
Appendix 1.7	Green Bond Principle
Appendix 1.8	ESG Rating Agencies Comparison
Appendices 2	**Results of empirical analysis**
Appendices 3	**Databases**
Appendix 3.1	*dtb* database
Appendix 3.2	*dtblog* database
Appendix 3.3	*dtb177* database
Appendix 3.4	*Secondary* database
Appendix 3.5	*Tertiary* database

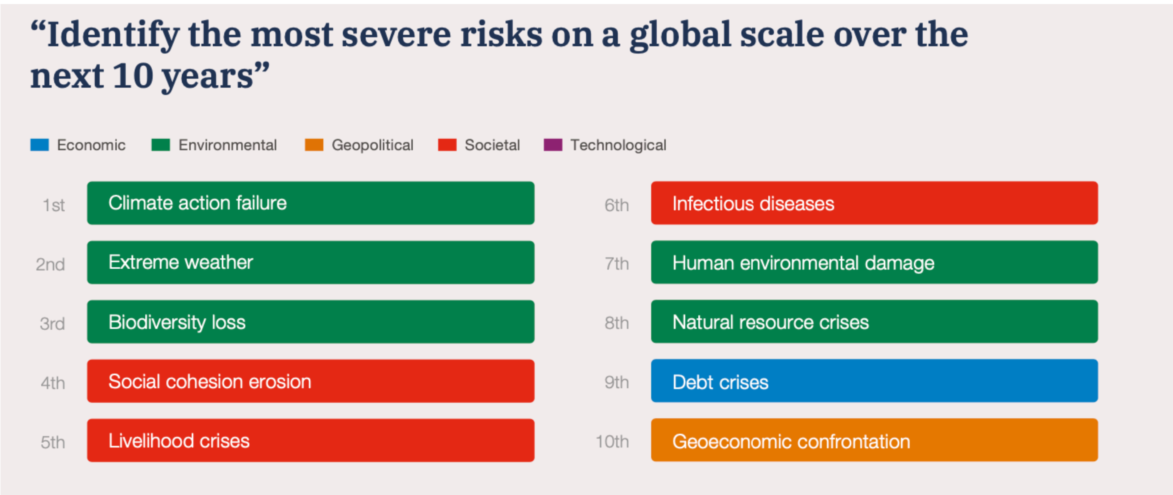
A. *Appendices 1: Literature Review*

Appendix 1.1: Greenhouse Effect



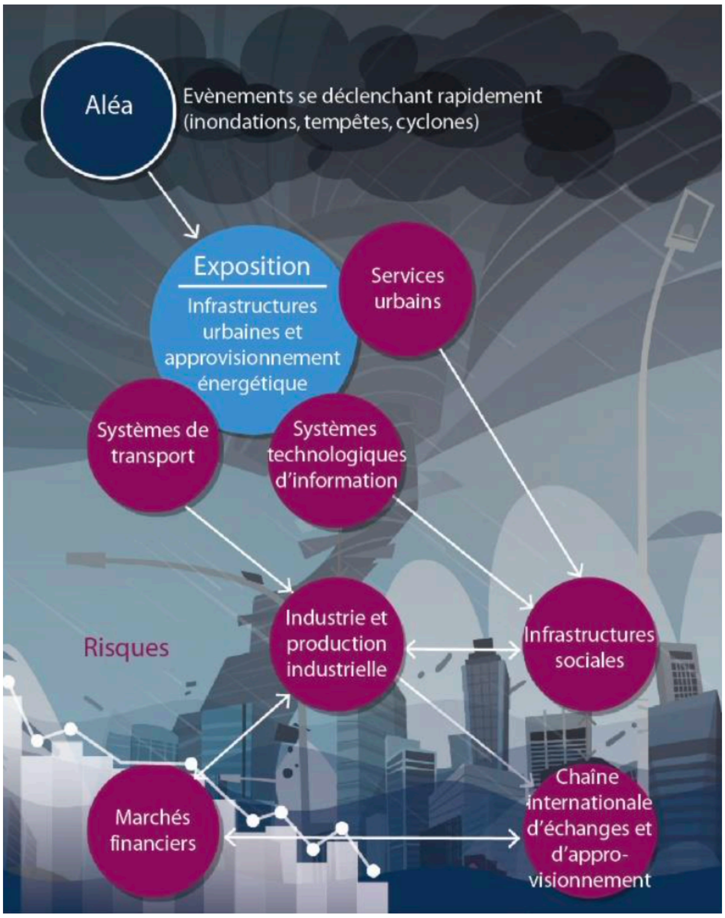
<u>Source</u>: *Carbon Dioxide, Methane, Nitrous Oxide, and the Greenhouse Effect.* (2022).

Appendix 1.2: Global Risks Perception Survey



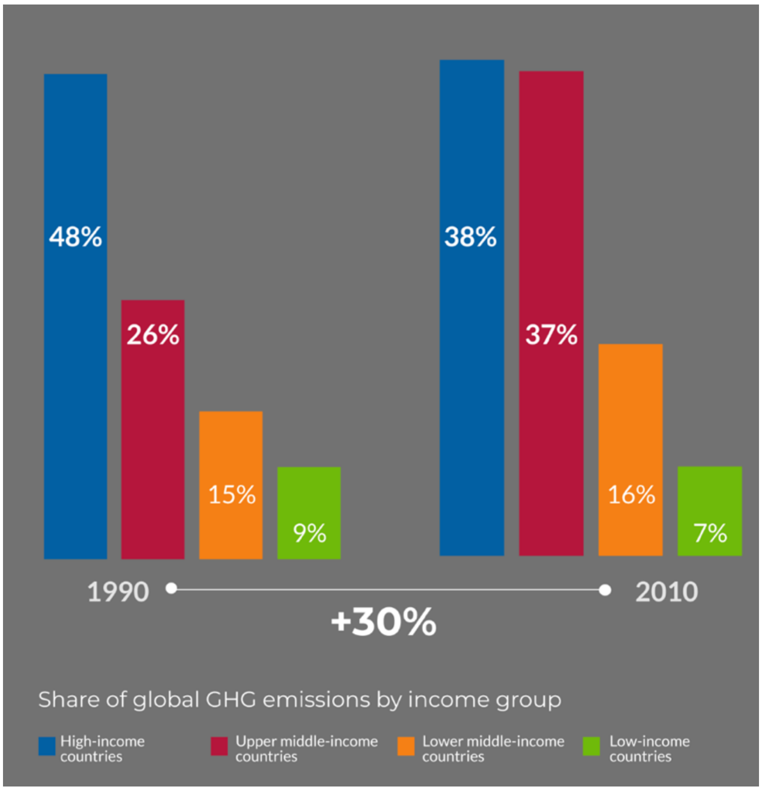
<u>Source</u>: World Economic Forum. (2022). *The Global Risk Report 2022.*

Appendix 1.3: Example of cascading risks in cities



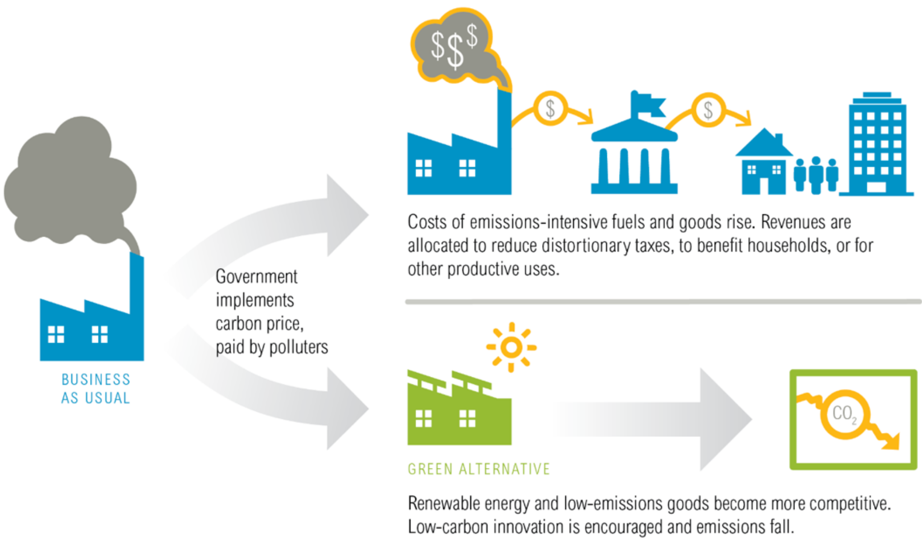
<u>*Source*</u>: The Shifters. (2022). *Synthèse du Rapport AR6 du GIEC publié le 28/02/2022.*

Appendix 1.4: Illustration of the growing global emissions' responsibility of developing (or middle-income) countries



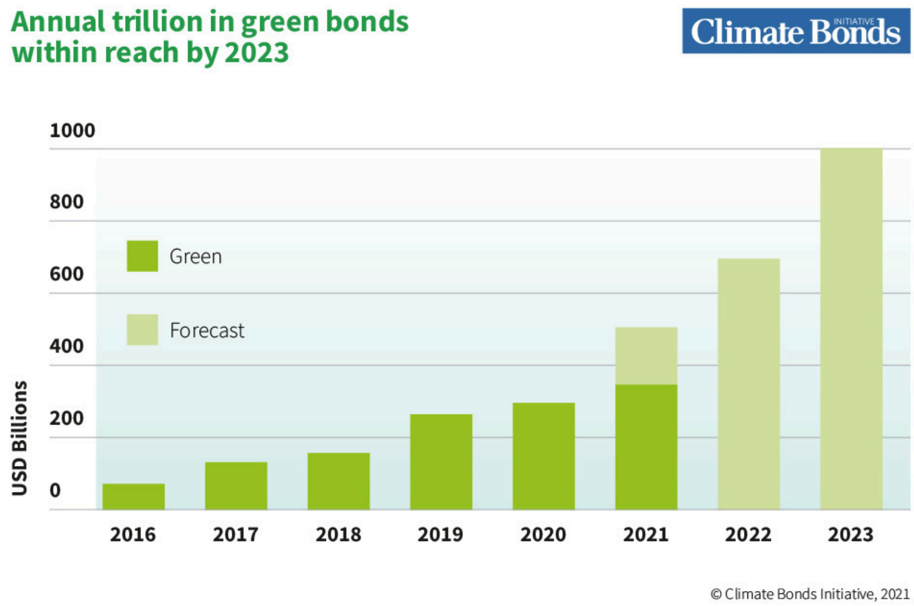
<u>Source</u>: *Timeline of Climate Action*. (2016).

Appendix 1.5: Carbon Pricing Basics



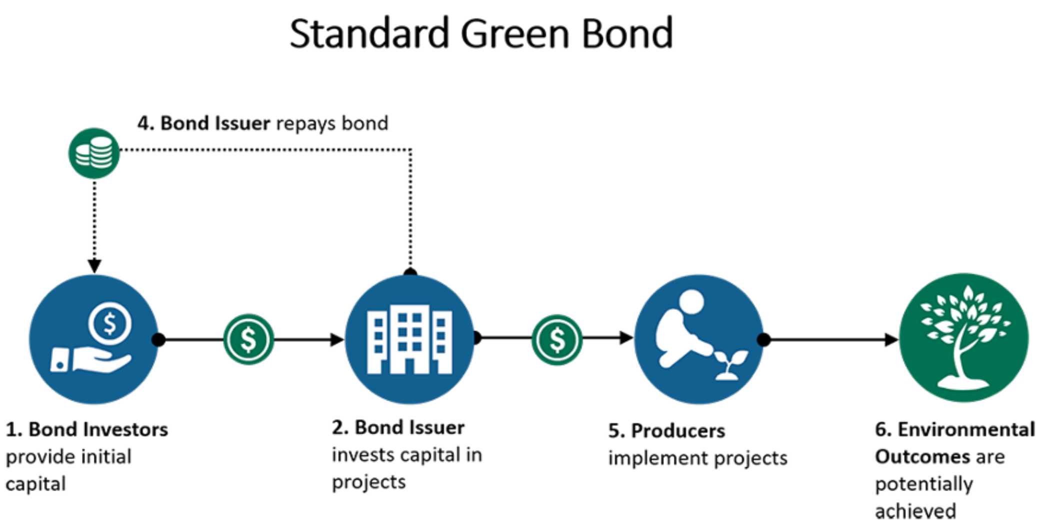
<u>Source</u>: World Resources Institute. (2015).

Appendix 1.6: Importance of the Green Bonds Market



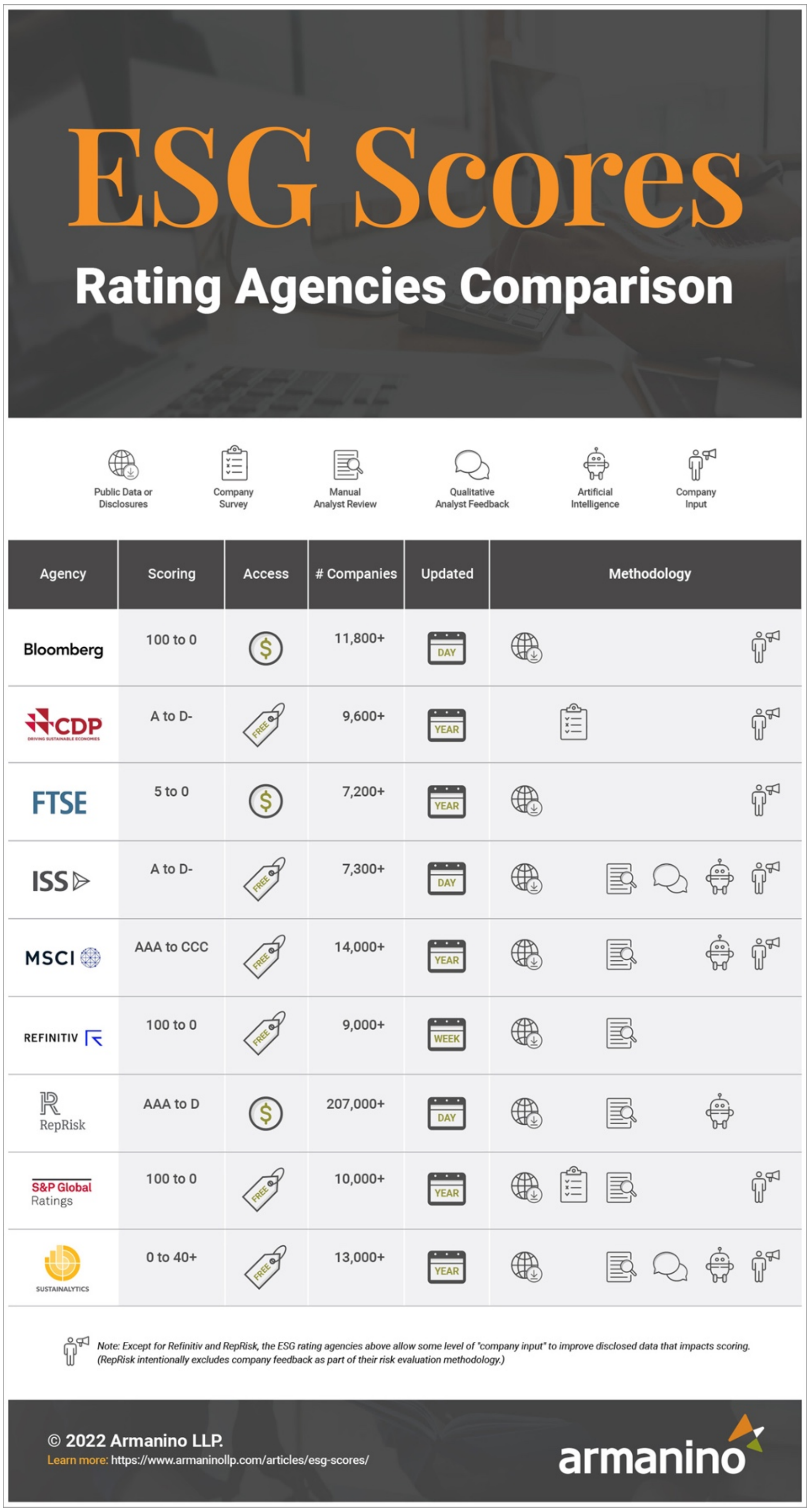
<u>Source</u>: *2021 Already a Record Year for Green Finance with over $350bn Issued !* (2021).

Appendix 1.7: Green Bond Principle



<u>Source</u>: *Green Bonds and Pay for Performance - Pay for Performance Toolkit*. (2021).

Appendix 1.8: ESG Rating Agencies Comparison



Agency	Scoring	Access	# Companies	Updated	Methodology
Bloomberg	100 to 0	$	11,800+	DAY	Public Data or Disclosures; Company Input
CDP	A to D-	FREE	9,600+	YEAR	Company Survey; Company Input
FTSE	5 to 0	$	7,200+	YEAR	Public Data or Disclosures; Company Input
ISS	A to D-	FREE	7,300+	DAY	Public Data or Disclosures; Manual Analyst Review; Qualitative Analyst Feedback; Artificial Intelligence; Company Input
MSCI	AAA to CCC	FREE	14,000+	YEAR	Public Data or Disclosures; Manual Analyst Review; Artificial Intelligence; Company Input
REFINITIV	100 to 0	FREE	9,000+	WEEK	Public Data or Disclosures; Manual Analyst Review
RepRisk	AAA to D	$	207,000+	DAY	Public Data or Disclosures; Manual Analyst Review; Artificial Intelligence
S&P Global Ratings	100 to 0	FREE	10,000+	YEAR	Public Data or Disclosures; Company Survey; Manual Analyst Review; Company Input
SUSTAINALYTICS	0 to 40+	FREE	13,000+	YEAR	Public Data or Disclosures; Manual Analyst Review; Qualitative Analyst Feedback; Artificial Intelligence; Company Input

Source: *ESG Scores & Rating Agencies*. (2022).

B. Appendices 2: Results of empirical analysis

Below are the tables of results not included in the text itself for various reasons. In order to avoid overloading the text or showing redundant results.

Table 1*:* Simple linear regression dtb$scope3 ~dtb$scope1

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	3.128e+07	9.439e+06	3.313	0.00111 **
dtb$scope1	7.351e-01	5.808e-01	1.266	0.20728

Model: dtb$scope3 ~dtb$scope1 (182 observations)
Residual standard deviation: 121500000 (df=180)
Adjusted R-squared: 0.1776
<u>Source</u>: Database dtb

Table 2: Simple linear regression dtb$scope3 ~dtb$scope2

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	3.264e+07	9.638e+06	3.387	0.000868 ***
dtb$scope1	3.201e+00	4.879e+00	0.656	0.5126

Model: dtb$scope3 ~dtb$scope2 (182 observations)
Residual standard deviation: 121900000 (df=180)
Adjusted R-squared: -0,003
<u>Source</u>: Database dtb

Table 3: Simple linear regression dtblog$scope2log ~dtblog$scope1log

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	4.2494	0.5912	7.188	1.7e-11 ***
dtblog$scope1log	0.6118	0.0488	12.536	<2e-16 ***

Model: dtblog$scop2log ~dtblog$scope1log (182 observations)
Residual standard deviation: 2.05 (df=180)
Adjusted R-squared: 0.4632
<u>Source</u>: Database dtblog

Table 4: Simple linear regression dtblog$scope3log ~dtblog$scope1log

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	3.76077	0.72104	5.216	5e-07 ***
dtblog$scope1log	0.86095	0.05952	14.465	<2e-16 ***

Model: dtblog$scope3log ~dtblog$scope1log (182 observations)

Residual standard deviation: 2.5 (df=180)
Adjusted R-squared: 0.535
Source: Database dtblog

Table 5: Multiple linear regression dtblog$scope3log ~dtblog$scope1log + dtblog$scope2log

Coefficients	Estimate	SE	T-value	p-value
(Intercept)	3.60471	0.81991	4.396	1.88e-05 ***
dtblog$scope1log	0.83848	0.08165	10.269	<2e-16 ***
dtblog$scope2log	0.03672	0.09112	0.403	0.687

Model: dtblog$scope3log ~dtblog$scope1log + dtblog$scope2log (182 observations)
Residual standard deviation: 2.506 (df = 179)
Adjusted R-squared: 0.5328
p-value: <2e-16
Source: Database dtblog

Table 6: Simple linear regression dtb177$scope2 ~dtb177$scope1

Coefficients	Estimate	SE	t-value	p-value
(Intercept)	4.727e+05	1.405e+06	3.364	0.000945 ***
dtb$scope1	5.137e-02	1.080e-02	4.756	4.12e-06 ***

Model: dtb177$scope2 ~dtb177$scope1 (177 observations)
Residual standard deviation: 1774000 (df=175)
Adjusted R-squared: 0.1094
Source: Database dtb177

Table 7: Simple linear regression dtb177$scope3 ~dtb177$scope1

Coefficients	Estimate	SE	t-value	p-value
(Intercept)	1.537e+07	3.410e+06	4.507	1.20e-05***
dtb$scope1	1.262e+00	2.621e-01	4.814	3.18e-06 ***

Model: dtb177$scope2 ~dtb177$scope1 (177 observations)
Residual standard deviation: 43040000 (df=175)
Adjusted R-squared: 0.1119
Source: Database dtb177

Table 8: Simple linear regression dtb177$scope3 ~dtb177$scope2

Coefficients	Estimate	SE	t-value	p-value
(Intercept)	1.751e+07	3.602e+06	4.859	2.6e-06***
dtb$scope1	4.469e+00	1.806e+00	2.475	0.0143*

Model: dtb177$scope3 ~dtb177$scope1 (177 observations)

Residual standard deviation: 45020000 (df=175)
Adjusted R-squared: 0.0283
<u>Source</u>: Database dtb177

Table 9: Multiple linear regression dtb177$scope3 ~dtb177$scope1 + dtb177$scope2

Coefficients	**Estimate**	**SE**	**T-value**	**p-value**
(Intercept)	1.449e+07	3.518e+06	4.117	5.92e-05 ***
dtb177$scope1	01.166e+00	2.785e-01	4.186	4.51e-05 ***
dtb177$scope2	1.872e+00	1.834e+00	01.021	0.309

Model: dtb177$scope3 ~dtb177$scope1 + dtb177$scope2 (772 observations)
Residual standard deviation: 2.506 (df = 174)
Adjusted R-squared: 0.1121
p-value: 1.189e-05
<u>Source</u>: Database dtb177

Table 10: Simple non-linear regression dtblog$scope2 ~ dtblog$scope1 + I(dtblog $scope1^2)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	2.34643	1.81227	1.295	0.19707
dtblog$scope1	0.95380	0.31176	3.059	0.00256 **
I(dtblog$scope1^2)	-0.01432	0.01289	-1.111	0.26818

Model: dtblog$scope2 ~ dtblog$scope1 + I(dtblog $scope1^2) (182 observations)
Residual standard deviation: 2.049 (df=179)
Adjusted R-squared: 0.4698
p-value: <2.2e-16
<u>Source</u>: Database dtblog

Table 11: Simple non-linear regression dtblog$scope3 ~ dtblog$scope1 + I(dtblog $scope1^2)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	-0.92261	2.18671	-0.422	0.6736
dtblog$scope1	1.70268	0.37617	4.526	1.09e-05 ***
I(dtblog$scope1^2)	-0.03524	0.01555	-2.266	0.0247 *

Model: dtblog$scope3 ~ dtblog$scope1 + I(dtblog $scope1^2) (182 observations)
Residual standard deviation: 2.472 (df=179)
Adjusted R-squared: 0.5454
p-value: <2.2e-16
<u>Source</u>: Database dtblog

Table 12: Simple non-linear regression dtblog$scope3 ~ dtblog$scope2 + I(dtblog $scope2²)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	8.305184	0.993158	8.362	1.68e-14***
dtblog$scope12	-0.073126	0.156359	-0.468	0.641
I(dtblog$scope2²)	0.046151	0.008368	5.515	1.20e-07 ***

Model: dtblog$scope3 ~ dtblog$scope1 + I(dtblog $scope1²) (182 observations)
Residual standard deviation: 2.921 (df=179)
Adjusted R-squared: 0.3654
p-value: <2.2e-16
<u>Source</u>*: Database dtblog*

Table 13: Multiple nonlinear regression dtblog$scope3 ~ dtblog $scope1 + I(dtblog $scope1²) + dtblog $scope2 + I(dtblog $scope2²)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	-0.493967	2.260713	-0.219	0.8273
dtblog $scope1	1.643191	0.389405	4.220	3.9e-05***
I(dtblog $scope1²)	-0.035381	0.015660	-2.259	0.0251*
dtblog $scope2	-0.071952	0.133168	-0.540	0.5897
I(dtblog $scope2²)	0.008044	0.008549	0.941	0.3480

Model: dtblog $scope3 ~ dtblog $scope1 + I(dtblog $scope1²) + dtblog $scope2 + I(dtblog $scope2²) (92 observations)
Residual standard deviation: 2.479 (df=177)
Adjusted R-squared: 0.5427
p-value: <2e-16

<u>Source</u>*: Database dtblog*

Table 14: Simple non-linear regression dtb177$scope3 ~ dtb177$scope1 + I(dtb177$scope1²)

Coefficients	**Estimate**	**SE**	**t-value**	**p-value**
(Intercept)	3.370e+05	1.404e+05	2.401	0.017423*
dtb177$scope1	1.518e-01	2.888e-02	5.258	4.23e-07***
I(dtb177$scope1²)	-1.641e-09	4.398e-10	-3.731	0.000258***

Model: dtb177$scope3 ~ dtb177$scope1 + I(dtb177$scope1²) (182 observations)
Residual standard deviation: 1712000(df=174)
Adjusted R-squared: 0.1706
p-value: 3.164e-08
<u>Source</u>*: Database dtb177*

Table 15: Simple non-linear regression dtb177$scope3 ~ dtb177$scope1 + I(dtb177$scope1²)

Coefficients	Estimate	SE	t-value	p-value
(Intercept)	1.104e+07	3.306e+06	3.339	0.00103**
dtb177$scope1	4.472e+00	6.799e-01	6.578	5.37e-10 ***
I(dtb177$scope1²)	-5.244e-08	1.036e-08	-5.064	1.04e-06 ***

Model: dtb177$scope3 ~ dtb177$scope1 + I(dtb177$scope1²) (182 observations)
Residual standard deviation: 40300000 (df=174)
Adjusted R-squared: 0.2215
p-value: 1.279e-10
Source: Database dtb177

Table 16: Simple non-linear regression dtb177$scope3 ~ dtb177$scope2 + I(dtb177$scope2²)

Coefficients	Estimate	SE	t-value	p-value
(Intercept)	-1.141e+07	3.731e+06	3.057	0.00259**
dtb177$scope1	1.868e+01	3.789e+00	4.942	1.81e-06 ***
I(dtb177$scope1²)	-9.099e-07	2.154e-07	-4.225	3.85e-05 ***

Model: dtb177$scope3 ~ dtb177$scope2 + I(dtb177$scope2²) (182 observations)
Residual standard deviation: 4.3e+07 (df=174)
Adjusted R-squared: 0.1136
p-value: 1.025e-05
Source: Database dtb177

Table 17: Multiple nonlinear regression dtb177$scope3 ~ dtb177$scope1 + I(dtb177$scope1²) + dtb177$scope2 + I(dtb177$scope2²)

Coefficients	Estimate	SE	t-value	p-value
(Intercept)	8.694e+06	3.500e+06	2.484	0.0140*
dtb177 $scope1	4.065e+00	7.547e-01	5.387	2.33e-07***
I(dtb177 $scope1²)	-4.973e-08	1.077e-08	-4.618	7.56e-06***
dtb177 $scope2	8.168e+00	4.149e+00	1.969	0.0506
I(dtb177 $scope2²)	-5.097e-07	2.199e-07	-2.318	0.0216 *

Model: dtb177$scope3 ~ dtb177$scope1 + I(dtb177$scope1²) + dtb177$scope2 + I(dtb177$scope2²) (177 observations)
Residual standard deviation: 39900000 (df=172)
Adjusted R-squared: 0.2367
p-value: 2.576e-10

Source: Database dtb177

C. *Appendices 3: Databases*

Appendix 3.1 = *dtb* database

Once the database of 233 companies belonging to the MSCI EMU index was cleaned, we obtained a new database with 182 companies on which we will conduct our research. These 182 companies are the ones that are unduplicated and for which we had information on their three scopes and this database is simply called *dtb*.

ISIN	COMPANY	SCOPE 1	SCOPE 2	SCOPE 3
BE0003810273	PROXIMUS	26600	800	648000
FR0000131104	BNP PARIBAS	50144	201473	32813
FR0000120628	AXA	23362	31997	3866
IT0004056880	AMPLIFON	5231	8392	1833
DE000BAY0017	BAYER AG	1930000	1560000	8940000
FI0009000681	NOKIA OYJ	124300	377300	40634700
FI0009005961	STERV, STORA ENSO OYJ R	2180000	340000	6310000
FR0000125338	CAPGEMINI	9187	84995	66786
FR0000120172	CARREFOUR	698700	965100	337200
FR0000120073	AIR LIQUIDE	15536000	20829000	22247000
FR0000045072	CREDIT AGRICOLE S.A.	14475	70052	143006638
IE0001827041	CRH PLC	33400000	2600000	12000000
NL0000235190	AIRBUS	562000	265000	464746000
FR0000121667	ESSILOR LUXOTTICA	46011	696843	194955
FR0000064578	COVIVO	2216	2443	43990
FR0010040865	GECINA	7097	7219	12455
ES0144580Y14	IBERDROLA	13207008	2161983	53898339
PTJMT0AE0001	JERÓNIMO MARTINS, SGPS, S.A.	246863	787100	27363835
IT0005239360	UNICREDIT	44016	138496	1471
NL0011821202	ING GROEP N.V.	12000	4000	8000
FR0000121964	KLEPIERRE	11341	56417	1185162
FR001400AJ45	MICHELIN	1204534	1589000	165810462
AT0000743059	OMV AG	13900000	1100000	156400000
NL0000395903	WOLTERS KLUWER	4691	13641	27480
FR0000073272	SAFRAN	146655	268333	24195000
FR0013176526	VALEO	170600	787910	8521000
DE000ENAG999	E.ON SE	3710000	3900000	100380000
DE0008232125	DEUTSCHE LUFTHANSA AG	13823320	139496	4667549

FR0006174348	BUREAU VERITAS	68779	83545	485189
FR0000133308	ORANGE	282526	990554	14729
ES0130960018	ENAGÁS, S.A.	263517	46368	825211
FR0000121147	FAURECIA	117000	662000	24256000
NL0000009165	HEINEKEN N.V.	970218	755287	18107286
DE000CBK1001	COMMERZBANK AG	28313	12263	43472
ES0148396007	INDITEX	12986	472510	14888171
FR0000121485	KERING	14256	106226	2095574
AT0000606306	RAIFFEISEN BANK INT	4827	41064	30925
FR0000131906	RENAULT	498611	451493	72234633
AT0000937503	VOESTALPINE AG	12440680	809378	54572232
IT0000062072	ASSICURAZIONI GENERALI	24466	47022	25296
FR0013280286	BIOMÉRIEUX	20000	36000	277100
FR0000120503	BOUYGUES	1876200	302100	20421700
DE0006969603	PUMA SE	4179	29839	211108
DE0007664005	VOLKSWAGEN AG	4740000	2420000	337387768
FI0009007132	FORTUM OYJ	69100000	650700	120228000
DE000A1EWWW0	ADIDAS AG	6748	56134	11636342
DE0005140008	DEUTSCHE BANK AG	41458	207288	1603304
DE0006602006	GEA GROUP AG	30394	34286	3602
FR0000125007	SAINT GOBAIN	8400000	1900000	21300000
FR0010242511	ELECTRICITE DE FRANCE (EDF)	27690997	320773	106649250
FR0000130452	EIFFAGE S.A.	594485	43636	5957965
ES0171996087	GRIFOLS, S.A.	147669	117152	44733
FR0000052292	HERMES INTL	21257	16124	490057
BE0974293251	ANHEUSER-BUSCH INBEV	2590500	1318800	23652933
NL0000009827	ROYAL DSM N.V.	873219	586781	11600000
AT0000746409	VERBUND AG	653000	406000	335000
NL0000009538	PHILIPS NV	27000	3000	489000
NL0000379121	RANDSTAD NV	48135	15822	3277
IT0003497168	TELECOM ITALIA	127810	405235	5276891
FR0000120271	TOTALENERGIES	33000000	2000000	370000000
FR0000120578	SANOFI	467780	192701	4738904
DE000SYM9999	SYMRISE AG	299119	1360	1747178
FR0010220475	ALSTOM	53898	74197	21782971
DE0005200000	BEIERSDORF	93057	86818	1096289
FI0009003305	SAMPO OYJ	1515	2886	6925
PTEDP0AM0009	EDP - ENERGIAS DE PORTUGAL	9311000	594000	11572000
DE0005190003	BMW AG	642885	84257	65100863
DE0005439004	CONTINENTAL AG	820000	1845138	107700000
DE0006047004	HEIDELBERGCEMENT AG	69490000	5060000	20000000
IT0003506190	ATLANTIA	115186	74501	1007160

ES0116870314	NATURGY ENERGY GROUP, S.A.	12965240	487067	136450026
IT0003128367	ENEL	51570000	4310000	69150000
ES0143416115	SIEMENS GAMESA RENEWABLE ENERGY, S.A.	26788	2017	856082
FR0000130809	SOCIETE GENERALE	23195	116642	81854
FR0010259150	IPSEN	15408	9907	32412
NL0000303709	AEGON	5557	16366	2101
US73328P1066	PORSCHE AUTOMOBIL HOLDING	2313220	1492400	196642951
BE0003470755	SOLVAY	9590000	1600000	25831000
LU0156801721	TENARIS S.A.	1900000	800000	1700000
FR0000121329	THALES	86000	110000	9620
ES0167050915	ACS	323889	103637	2637182
NL0010273215	ASML	19300	165100	8830000
FR0010340141	AEROPORTS DE PARIS (ADP)	75434	24159	2626821
NL0013267909	AKZO NOBEL	57160	168200	12600000
DE0008404005	ALLIANZ SE	28699	138746	55359
LU1598757687	ARCELORMITTAL	131100000	7500000	8100000
FR0010313833	ARKEMA	2268000	1103000	11194000
DE000BASF111	BASF SE	17721000	3670000	122000000
ES0113211835	BANCO BILBAO VIZCAYA ARGENTARIA	49639	252131	9432
ES0113900J37	BANCO SANTANDER, S.A.	25672	269615	35420
FR0000039299	BOLLORÉ SE	256317	72664	7242202
FR0000120222	CNP ASSURANCES	1519	2815	58918
ES0140609019	CAIXABANK, S.A.	3262	280	14228
DE0007100000	MERCEDES-BENZ GROUP AG	681000	466000	98326000
FR0014003TT8	DASSAULT SYSTÈMES SE	4629	15331	561226
DE0005810055	DEUTSCHE BÖRSE AG	4931	1805	4510
DE0005552004	DEUTSCHE POST AG	6580000	190000	20610000
DE0005557508	DEUTSCHE TELEKOM AG	235261	4815423	13881000
IT0003132476	ENI SPA	40080000	810000	196500000
ES0130670112	ENDESA, S.A.	10702129	470773	21737472
FR0000121121	EURAZEO SE	577998	212078	2587370
BE0974264930	AGEAS SA	10317	52996	7116
PTGAL0AM0009	GALP ENERGIA, SGPS, S.A.	3060000	40000	46930000
FR0010208488	ENGIE	38589016	2330625	134001033
BE0003797140	GROUPE BRUXELLES LAMBERT SA	36723	139668	10407600
FR0000120644	DANONE	683000	936882	23734000
FR0010533075	GETLINK SE	39703	11658	2225319
DE0008402215	HANNOVER RÜCK SE	24	1859	1772
NL0000008977	HEINEKEN HOLDING	951000	352000	16151000
DE0006048408	HENKEL AG & CO KGAA	343000	132000	43572000
DE0006231004	INFINEON TECHNOLOGIES AG	298246	695432	1190267

BE0003565737	KBC GROUPE NV	19511	34632	13473
FI0009000202	KESKOB, Kesko Oyj B	38538	128358	7736700
IE0004927939	KINGSPAN GROUP PLC	291771	65772	5043030
FI0009013403	KONE OYJ	118700	10200	15906600
NL0000009082	ROYAL KPN N.V	13000	0	793000
FR0000120321	L'OREAL	43134	133578	11168803
DE0005470405	LANXESS AG	1284000	1562000	16876000
FR0000121014	LVMH - Moët Hennessy Louis Vuitton	71055	219123	830253
FR0010307819	LEGRAND	57000	91000	3297690
IT0000062957	MEDIOBANCA	3929	163	1527
DE0006599905	MERCK KGAA	1706000	304000	308000
DE0008430026	MUNICH RE	47598	47751	6015
FI0009013296	NESTE OYJ	1828000	519000	35300000
IE00BWT6H894	FLUTTER ENTERTAINMENT PLC	854	10288	3853
FR0000130577	PUBLICIS GROUPE SA	7351	40146	140622
NL0012169213	QIAGEN	10068	15854	32429
DE0007037129	RWE AG	86900000	2700000	23000000
DE0007010803	RATIONAL AG	2083	1484	898
FR0000130395	RÉMY COINTREAU	7581	612	83825
ES0173516115	REPSOL S.A.	22000000	400000	157000000
FR0000121709	SEB S.A.	72173	145142	15801683
NL0000226223	STMICROELECTRONICS N.V.	486304	781847	593529
FR0000121972	SCHNEIDER ELECTRIC SE	142149	321153	65701766
DE0007236101	SIEMENS AG	386000	208000	469271000
IE00B1RR8406	SMURFIT KAPPA GROUP PLC	2500000	553000	491900
IT0003153415	SNAM S.P.A.	1397000	31000	995000
FR0000121220	SODEXO	71000	20000	6160233
IT0003242622	TERNA S.P.A.	58793	1612109	623
ES0178430E18	TELEFÓNICA, S.A.	212682	1396941	1082541
FR0000051807	TELEPERFORMANCE SE	1779	148278	11642
BE0003739530	UCB	27777	5450	33813
FI0009005987	UPM-KYMMENE OYJ	2730000	2650000	6160000
US90459E1064	UNIBAIL-RODAMCO-WE	21236	24367	2456515
DE0005089031	UNITED INTERNET AG	3074	13880	2788
FR0000124141	VEOLIA ENVIRONNEMENT	26700000	3800000	20900000
FR0000125486	VINCI	2005622	295077	13928809
FR0000127771	VIVENDI SE	14764	23430	111622
FI0009003727	WÄRTSILÄ OYJ	54711	25350	93810
IT0003796171	POSTE ITALIANE S.P.A.	165508	142966	178737
DE000EVNK013	EVONIK INDUSTRIES AG	4802000	2594000	23110000
ES0127797019	EDP RENOVÁVEIS, S.A.	2405	28425	1289

NL0011540547	ABN AMRO BANK N.V.	3490	3160	26288000
ES0109067019	AMADEUS IT GROUP, S.A.	1961	11767	366
NL0013654783	PROSUS N.V.	6330	6900	780987
ES0118900010	FERROVIAL, S.A.	761314	36752	2849892
DE000A1J5RX9	TELEFÓNICA DEUTSCHLAND HOLDING AG	5623	285695	896
NL0010773842	NN GROUP N.V.	1000	4000	8000
IT0000072170	FINECOBANK S.P.A.	461	1150	2334
DE000A1ML7J1	VONOVIA SE	487059	417182	149121
DE000KGX8881	KION GROUP AG	106641	83363	29125
FR0004125920	AMUNDI	540	3132	1740
FR0011981968	WORLDLINE	3615	1106	450608
NL0006294274	EURONEXT N.V.	270	1600	16600
DE0007164600	SAP SE	96000	112000	10061000
ES0105066007	CELLNEX TELECOM, S.A.	3494	328720	349430
DE000ZAL1111	ZALANDO SE	10429	60571	4477570
FR0014000MR3	EUROFINS SCIENTIFIC SE	59000	93000	253000
IT0005090300	INFRASTRUTTURE WIRELESS ITALIA (INWIT)	1542	168991	9546
DE0006062144	COVESTRO AG	980000	4400000	21791000
DE000A12DM80	SCOUT24 SE	232	636	1335
GB00BDCPN049	COCA-COLA EUROPACIFIC PARTNERS PLC	205244	123838	3074649
DE000UNSE018	UNIPER SE	42600000	714202	21065065
NL0012015705	JUSTE EAT TAKEAWAY N.V.	2479	1991	151886
DE000A161408	HELLOFRESH SE	5286	14756	76268
DE000SHL1006	SIEMENS HEALTHINEERS AG	106000	206000	3243000
IT0005366767	NEXI S.P.A	1075	3281	1247
NL0012969182	ADYEN N.V.	223	2341	6064
DE000A2E4K43	DELIVERY HERO SE	1274	3103	278361
DE000A1DAHH0	BRENNTAG SE	194491	52651	18923226
NL0014332678	JDE PEET'S N.V.	378987	181354	8113802
DE000ENER6Y0	SIEMENS ENERGY AG	206000	67000	1373924000

Appendix 3.2 = *dtblog* database

ISIN	COMPANY	SCOPE 1	SCOPE 2	SCOPE 3
BE0003810273	PROXIMUS	10.188666	6.684612	13.381646
FR0000131104	BNP PARIBAS	10.822654	12.213411	10.398580
FR0000120628	AXA	10.058866	10.373397	8.259976
IT0004056880	AMPLIFON	8.562358	9.035034	7.513709
DE000BAY0017	BAYER AG	14.473031	14.260196	16.006046

FI0009000681	NOKIA OYJ	11.730453	12.840796	17.520133
FI0009005961	STERV, STORA ENSO OYJ R	14.594835	12.736701	15.657646
FR0000125338	CAPGEMINI	9.125545	11.350348	11.109249
FR0000120172	CARREFOUR	13.456977	13.779987	12.728432
FR0000120073	AIR LIQUIDE	16.558670	16.851857	16.917718
FR0000045072	CREDIT AGRICOLE S.A.	9.580178	11.156993	18.778402
IE0001827041	CRH PLC	17.324066	14.771022	16.300417
NL0000235190	AIRBUS	13.239257	12.487485	19.957002
FR0000121667	ESSILOR LUXOTTICA	10.736636	13.454315	12.180524
FR0000064578	COVIVO	7.703459	7.800982	10.691718
FR0010040865	GECINA	8.867427	8.884472	9.429877
ES0144580Y14	IBERDROLA	16.396258	14.586536	17.802610
PTJMT0AE0001	JERÓNIMO MARTINS, SGPS, S.A.	12.416589	13.576111	17.124733
IT0005239360	UNICREDIT	10.692308	11.838597	7.293698
NL0011821202	ING GROEP N.V.	9.392662	8.294050	8.987197
FR0000121964	KLEPIERRE	9.336180	10.940526	13.985390
FR001400AJ45	MICHELIN	14.001603	14.278615	18.926356
AT0000743059	OMV AG	16.447399	13.910821	18.867927
NL0000395903	WOLTERS KLUWER	8.453401	9.520835	10.221214
FR0000073272	SAFRAN	11.895838	12.499984	17.001657
FR0013176526	VALEO	12.047077	13.577139	15.958044
DE000ENAG999	E.ON SE	15.126542	15.176487	18.424474
DE0008232125	DEUTSCHE LUFTHANSA AG	16.441868	11.845791	15.356145
FR0006174348	BUREAU VERITAS	11.138654	11.333141	13.092294
FR0000133308	ORANGE	12.551526	13.806020	9.597574
ES0130960018	ENAGÁS, S.A.	12.481873	10.744365	13.623394
FR0000121147	FAURECIA	11.669929	13.403021	17.004175
NL0000009165	HEINEKEN N.V.	13.785276	13.534853	16.711825
DE000CBK1001	COMMERZBANK AG	10.251076	9.414342	10.679872
ES0148396007	INDITEX	9.471627	13.065814	16.516078
FR0000121485	KERING	9.564933	11.573324	14.555338
AT0000606306	RAIFFEISEN BANK INT	8.481980	10.622887	10.339320
FR0000131906	RENAULT	13.119582	13.020315	18.095430
AT0000937503	VOESTALPINE AG	16.336482	13.604021	17.815036
IT0000062072	ASSICURAZIONI GENERALI	10.105040	10.758371	10.138402
FR0013280286	BIOMÉRIEUX	9.903488	10.491274	12.532134
FR0000120503	BOUYGUES	14.444759	12.618513	16.832109
DE0006969603	PUMA SE	8.337827	10.303572	12.260125
DE0007664005	VOLKSWAGEN AG	15.371548	14.699278	19.636743
FI0009007132	FORTUM OYJ	18.051065	13.385804	18.604900
DE000A1EWWW0	ADIDAS AG	8.817001	10.935497	16.269644
DE0005140008	DEUTSCHE BANK AG	10.632436	12.241864	14.287577

DE0006602006	GEA GROUP AG	10.322000	10.442492	8.189245
FR0000125007	SAINT GOBAIN	15.943742	14.457364	16.874218
FR0010242511	ELECTRICITE DE FRANCE (EDF)	17.136618	12.678489	18.485056
FR0000130452	EIFFAGE S.A.	13.295451	10.683638	15.600240
ES0171996087	GRIFOLS, S.A.	11.902729	11.671228	10.708467
FR0000052292	HERMES INTL	9.964442	9.688064	13.102277
BE0974293251	ANHEUSER-BUSCH INBEV	14.767361	14.092233	16.978998
NL0000009827	ROYAL DSM N.V.	13.679942	13.282407	16.266516
AT0000746409	VERBUND AG	13.389332	12.914108	12.721886
NL0000009538	PHILIPS NV	10.203592	8.006368	13.100118
NL0000379121	RANDSTAD NV	10.781765	9.669157	8.094684
IT0003497168	TELECOM ITALIA	11.758300	12.912222	15.478848
FR0000120271	TOTALENERGIES	17.312018	14.508658	19.729014
FR0000120578	SANOFI	13.055753	12.168895	15.371316
DE000SYM9999	SYMRISE AG	12.608597	7.215240	14.373512
FR0010220475	ALSTOM	10.894849	11.214479	16.896639
DE0005200000	BEIERSDORF	11.440967	11.371569	13.907441
FI0009003305	SAMPO OYJ	7.323171	7.967627	8.842893
PTEDP0AM0009	EDP - ENERGIAS DE PORTUGAL	16.046707	13.294635	16.264099
DE0005190003	BMW AG	13.373721	11.341627	17.991448
DE0005439004	CONTINENTAL AG	13.617060	14.428065	18.494860
DE0006047004	HEIDELBERGCEMENT AG	18.056693	15.436877	16.811243
IT0003506190	ATLANTIA	11.654303	11.218568	13.822645
ES0116870314	NATURGY ENERGY GROUP, S.A.	16.377782	13.096157	18.731469
IT0003128367	ENEL	17.758451	15.276448	18.051789
ES0143416115	SIEMENS GAMESA RENEWABLE ENERGY, S.A.	10.195709	7.609367	13.660121
FR0000130809	SOCIETE GENERALE	10.051692	11.666865	11.312692
FR0010259150	IPSEN	9.642642	9.200997	10.386284
NL0000303709	AEGON	8.622814	9.702961	7.650169
US73328P1066	PORSCHE AUTOMOBIL HOLDING	14.654151	14.215896	19.096900
BE0003470755	SOLVAY	16.076231	14.285514	17.067086
LU0156801721	TENARIS S.A.	14.457364	13.592367	14.346139
FR0000121329	THALES	11.362103	11.608236	9.171600
ES0167050915	ACS	12.688156	11.548650	14.785221
NL0010273215	ASML	9.867860	12.014307	15.993666
FR0010340141	AEROPORTS DE PARIS (ADP)	11.231013	10.092412	14.781285
NL0013267909	AKZO NOBEL	10.953610	12.032909	16.349207
DE0008404005	ALLIANZ SE	10.264618	11.840400	10.921595
LU1598757687	ARCELORMITTAL	18.691471	15.830414	15.907375
FR0010313833	ARKEMA	14.634409	13.913544	16.230888
DE000BASF111	BASF SE	16.690261	15.115702	18.619532

ES0113211835	BANCO BILBAO VIZCAYA ARGENTARIA	10.812532	12.437704	9.151863
ES0113900J37	BANCO SANTANDER, S.A.	10.153156	12.504750	10.475032
FR0000039299	BOLLORÉ SE	12.454170	11.193601	15.795436
FR0000120222	CNP ASSURANCES	7.325808	7.942718	10.983902
ES0140609019	CAIXABANK, S.A.	8.090096	5.634790	9.562967
DE0007100000	MERCEDES-BENZ GROUP AG	13.431318	13.051941	18.403799
FR0014003TT8	DASSAULT SYSTÈMES SE	8.440096	9.637632	13.237879
DE0005810055	DEUTSCHE BÖRSE AG	8.503297	7.498316	8.414052
DE0005552004	DEUTSCHE POST AG	15.699545	12.154779	16.841287
DE0005557508	DEUTSCHE TELEKOM AG	12.368451	15.387334	16.446032
IT0003132476	ENI SPA	17.506388	13.604790	19.096173
ES0130670112	ENDESA, S.A.	16.185953	13.062131	16.894548
FR0000121121	EURAZEO SE	13.267326	12.264709	14.766152
BE0974264930	AGEAS SA	9.241548	10.877972	8.870101
PTGAL0AM0009	GALP ENERGIA, SGPS, S.A.	14.933925	10.596635	17.664168
FR0010208488	ENGIE	17.468478	14.661647	18.713358
BE0003797140	GROUPE BRUXELLES LAMBERT SA	10.511159	11.847023	16.158047
FR0000120644	DANONE	13.434250	13.750313	16.982419
FR0010533075	GETLINK SE	10.589182	9.363748	14.615411
DE0008402215	HANNOVER RÜCK SE	3.178054	7.527794	7.479864
NL0000008977	HEINEKEN HOLDING	13.765269	12.771386	16.597493
DE0006048408	HENKEL AG & CO KGAA	12.745486	11.790557	17.589925
DE0006231004	INFINEON TECHNOLOGIES AG	12.605674	13.452289	13.989688
BE0003565737	KBC GROUPE NV	9.878734	10.452533	9.508443
FI0009000202	KESKOB, Kesko Oyj B	10.559400	11.762579	15.861486
IE0004927939	KINGSPAN GROUP PLC	12.583725	11.093949	15.433518
FI0009013403	KONE OYJ	11.684355	9.230143	16.582245
NL0000009082	ROYAL KPN N.V	9.472705	-9.210340	13.583579
FR0000120321	L'OREAL	10.672067	11.802441	16.228635
DE0005470405	LANXESS AG	14.065491	14.261478	16.641403
FR0000121014	LVMH - Moët Hennessy Louis Vuitton	11.171210	12.297388	13.629486
FR0010307819	LEGRAND	10.950807	11.418615	15.008733
IT0000062957	MEDIOBANCA	8.276140	5.093750	7.331060
DE0006599905	MERCK KGAA	14.349662	12.624783	12.637855
DE0008430026	MUNICH RE	10.770546	10.773755	8.702012
FI0009013296	NESTE OYJ	14.418733	13.159659	17.379394
IE00BWT6H894	FLUTTER ENTERTAINMENT PLC	6.749931	9.238733	8.256607
FR0000130577	PUBLICIS GROUPE SA	8.902592	10.600278	11.853831
NL0012169213	QIAGEN	9.217117	9.671177	10.386808
DE0007037129	RWE AG	18.280269	14.808762	16.951005

DE0007010803	RATIONAL AG	7.641564	7.302496	6.800170
FR0000130395	RÉMY COINTREAU	8.933400	6.416732	11.336487
ES0173516115	REPSOL S.A.	16.906553	12.899220	18.871756
FR0000121709	SEB S.A.	11.186821	11.885468	16.575627
NL0000226223	STMICROELECTRONICS N.V.	13.094589	13.569414	13.293841
FR0000121972	SCHNEIDER ELECTRIC SE	11.864631	12.679673	18.000636
DE0007236101	SIEMENS AG	12.863593	12.245293	19.966691
IE00B1RR8406	SMURFIT KAPPA GROUP PLC	14.731801	13.223113	13.106031
IT0003153415	SNAM S.P.A.	14.149838	10.341742	13.810498
FR0000121220	SODEXO	11.170435	9.903488	15.633625
IT0003242622	TERNA S.P.A.	10.981778	14.293054	6.434547
ES0178430E18	TELEFÓNICA, S.A.	12.267553	14.149795	13.894822
FR0000051807	TELEPERFORMANCE SE	7.483807	11.906844	9.362375
BE0003739530	UCB	10.231964	8.603371	10.428601
FI0009005987	UPM-KYMMENE OYJ	14.819812	14.790070	15.633587
US90459E1064	UNIBAIL-RODAMCO-WE	9.963453	10.100985	14.714254
DE0005089031	UNITED INTERNET AG	8.030735	9.538204	7.933080
FR0000124141	VEOLIA ENVIRONNEMENT	17.100174	15.150512	16.855260
FR0000125486	VINCI	14.511465	12.594992	16.449470
FR0000127771	VIVENDI SE	9.599947	10.061773	11.622873
FI0009003727	WÄRTSILÄ OYJ	10.909820	10.140534	11.449027
IT0003796171	POSTE ITALIANE S.P.A.	12.016775	11.870362	12.093671
DE000EVNK013	EVONIK INDUSTRIES AG	15.384543	14.768712	16.955776
ES0127797019	EDP RENOVÁVEIS, S.A.	7.785305	10.255024	7.161622
NL0011540547	ABN AMRO BANK N.V.	8.157657	8.058327	17.084623
ES0109067019	AMADEUS IT GROUP, S.A.	7.581210	9.373054	5.902633
NL0013654783	PROSUS N.V.	8.753056	8.839277	13.568314
ES0118900010	FERROVIAL, S.A.	13.542801	10.511948	14.862792
DE000A1J5RX9	TELEFÓNICA DEUTSCHLAND HOLDING AG	8.634621	12.562680	6.797940
NL0010773842	NN GROUP N.V.	6.907755	8.294050	8.987197
IT0000072170	FINECOBANK S.P.A.	6.133398	7.047517	7.755339
DE000A1ML7J1	VONOVIA SE	13.096141	12.941278	11.912513
DE000KGX8881	KION GROUP AG	11.577223	11.330960	10.279352
FR0004125920	AMUNDI	6.291569	8.049427	7.461640
FR0011981968	WORLDLINE	8.192847	7.008505	13.018353
NL0006294274	EURONEXT N.V.	5.598422	7.377759	9.717158
DE0007164600	SAP SE	11.472103	11.626254	16.124177
ES0105066007	CELLNEX TELECOM, S.A.	8.158802	12.702962	12.764059
DE000ZAL1111	ZALANDO SE	9.252346	11.011572	15.314591
FR0014000MR3	EUROFINS SCIENTIFIC SE	10.985293	11.440355	12.441145
IT0005090300	INFRASTRUTTURE WIRELESS ITALIA (INWIT)	7.340836	12.037601	9.163877

DE0006062144	COVESTRO AG	13.795308	15.297115	16.897008
DE000A12DM80	SCOUT24 SE	5.446737	6.455199	7.196687
GB00BDCPN049	COCA-COLA EUROPACIFIC PARTNERS PLC	12.231955	11.726730	14.938701
DE000UNSE018	UNIPER SE	17.567365	13.478921	16.863127
NL0012015705	JUSTE EAT TAKEAWAY N.V.	7.815611	7.596392	11.930886
DE000A161408	HELLOFRESH SE	8.572817	9.599405	11.242009
DE000SHL1006	SIEMENS HEALTHINEERS AG	11.571194	12.235631	14.992009
IT0005366767	NEXI S.P.A	6.980076	8.095904	7.128496
NL0012969182	ADYEN N.V.	5.407172	7.758333	8.710125
DE000A2E4K43	DELIVERY HERO SE	7.149917	8.040125	12.536674
DE000A1DAHH0	BRENNTAG SE	12.178141	10.871441	16.755901
NL0014332678	JDE PEET'S N.V.	12.845257	12.108206	15.909077
DE000ENER6Y0	SIEMENS ENERGY AG	12.235631	11.112448	21.040937

Appendix 3.3 = *dtb177* database

Database, obtained after the cluster analysis, with the 5 companies belonging to the small cluster

ISIN	COMPANY	SCOPE 1	SCOPE 2	SCOPE 3
NL0000235190	AIRBUS	562000	265000	464746000
BE0974293251	ANHEUSER-BUSCH-InBev	2590500	1318800	23652933
FR0000120271	TOTALENERGIES	33000000	2000000	370000000
DE0007236101	SIEMENS AG	386000	208000	469271000
DE000ENER6Y0	SIEMENS ENERGY AG	206000	67000	1373924000

Database, obtained after the cluster analysis, with the 177 companies belonging to the majority cluster

ISIN	COMPANY	SCOPE 1	SCOPE 2	SCOPE 3
BE0003810273	PROXIMUS	26600	800	648000
FR0000131104	BNP PARIBAS	50144	201473	32813
FR0000120628	AXA	23362	31997	3866
IT0004056880	AMPLIFON	5231	8392	1833
DE000BAY0017	BAYER AG	1930000	1560000	8940000
FI0009000681	NOKIA OYJ	124300	377300	40634700
FI0009005961	STERV, STORA ENSO OYJ R	2180000	340000	6310000

FR0000125338	CAPGEMINI	9187	84995	66786
FR0000120172	CARREFOUR	698700	965100	337200
FR0000120073	AIR LIQUIDE	15536000	20829000	22247000
FR0000045072	CREDIT AGRICOLE S.A.	14475	70052	143006638
IE0001827041	CRH PLC	33400000	2600000	12000000
FR0000121667	ESSILOR LUXOTTICA	46011	696843	194955
FR0000064578	COVIVO	2216	2443	43990
FR0010040865	GECINA	7097	7219	12455
ES0144580Y14	IBERDROLA	13207008	2161983	53898339
PTJMT0AE0001	JERÓNIMO MARTINS, SGPS, S.A.	246863	787100	27363835
IT0005239360	UNICREDIT	44016	138496	1471
NL0011821202	ING GROEP N.V.	12000	4000	8000
FR0000121964	KLEPIERRE	11341	56417	1185162
FR001400AJ45	MICHELIN	1204534	1589000	165810462
AT0000743059	OMV AG	13900000	1100000	156400000
NL0000395903	WOLTERS KLUWER	4691	13641	27480
FR0000073272	SAFRAN	146655	268333	24195000
FR0013176526	VALEO	170600	787910	8521000
DE000ENAG999	E.ON SE	3710000	3900000	100380000
DE0008232125	DEUTSCHE LUFTHANSA AG	13823320	139496	4667549
FR0006174348	BUREAU VERITAS	68779	83545	485189
FR0000133308	ORANGE	282526	990554	14729
ES0130960018	ENAGÁS, S.A.	263517	46368	825211
FR0000121147	FAURECIA	117000	662000	24256000
NL0000009165	HEINEKEN N.V.	970218	755287	18107286
DE000CBK1001	COMMERZBANK AG	28313	12263	43472
ES0148396007	INDITEX	12986	472510	14888171
FR0000121485	KERING	14256	106226	2095574
AT0000606306	RAIFFEISEN BANK INT	4827	41064	30925
FR0000131906	RENAULT	498611	451493	72234633
AT0000937503	VOESTALPINE AG	12440680	809378	54572232
IT0000062072	ASSICURAZIONI GENERALI	24466	47022	25296
FR0013280286	BIOMÉRIEUX	20000	36000	277100
FR0000120503	BOUYGUES	1876200	302100	20421700
DE0006969603	PUMA SE	4179	29839	211108
DE0007664005	VOLKSWAGEN AG	4740000	2420000	337387768
FI0009007132	FORTUM OYJ	69100000	650700	120228000
DE000A1EWWW0	ADIDAS AG	6748	56134	11636342
DE0005140008	DEUTSCHE BANK AG	41458	207288	1603304
DE0006602006	GEA GROUP AG	30394	34286	3602
FR0000125007	SAINT GOBAIN	8400000	1900000	21300000

FR0010242511	ELECTRICITE DE FRANCE (EDF)	27690997	320773	106649250
FR0000130452	EIFFAGE S.A.	594485	43636	5957965
ES0171996087	GRIFOLS, S.A.	147669	117152	44733
FR0000052292	HERMES INTL	21257	16124	490057
NL0000009827	ROYAL DSM N.V.	873219	586781	11600000
AT0000746409	VERBUND AG	653000	406000	335000
NL0000009538	PHILIPS NV	27000	3000	489000
NL0000379121	RANDSTAD NV	48135	15822	3277
IT0003497168	TELECOM ITALIA	127810	405235	5276891
FR0000120578	SANOFI	467780	192701	4738904
DE000SYM9999	SYMRISE AG	299119	1360	1747178
FR0010220475	ALSTOM	53898	74197	21782971
DE0005200000	BEIERSDORF	93057	86818	1096289
FI0009003305	SAMPO OYJ	1515	2886	6925
PTEDP0AM0009	EDP - ENERGIAS DE PORTUGAL	9311000	594000	11572000
DE0005190003	BMW AG	642885	84257	65100863
DE0005439004	CONTINENTAL AG	820000	1845138	107700000
DE0006047004	HEIDELBERGCEMENT AG	69490000	5060000	20000000
IT0003506190	ATLANTIA	115186	74501	1007160
ES0116870314	NATURGY ENERGY GROUP, S.A.	12965240	487067	136450026
IT0003128367	ENEL	51570000	4310000	69150000
ES0143416115	SIEMENS GAMESA RENEWABLE ENERGY, S.A.	26788	2017	856082
FR0000130809	SOCIETE GENERALE	23195	116642	81854
FR0010259150	IPSEN	15408	9907	32412
NL0000303709	AEGON	5557	16366	2101
US73328P1066	PORSCHE AUTOMOBIL HOLDING	2313220	1492400	196642951
BE0003470755	SOLVAY	9590000	1600000	25831000
LU0156801721	TENARIS S.A.	1900000	800000	1700000
FR0000121329	THALES	86000	110000	9620
ES0167050915	ACS	323889	103637	2637182
NL0010273215	ASML	19300	165100	8830000
FR0010340141	AEROPORTS DE PARIS (ADP)	75434	24159	2626821
NL0013267909	AKZO NOBEL	57160	168200	12600000
DE0008404005	ALLIANZ SE	28699	138746	55359
LU1598757687	ARCELORMITTAL	131100000	7500000	8100000
FR0010313833	ARKEMA	2268000	1103000	11194000
DE000BASF111	BASF SE	17721000	3670000	122000000
ES0113211835	BANCO BILBAO VIZCAYA ARGENTARIA	49639	252131	9432
ES0113900J37	BANCO SANTANDER, S.A.	25672	269615	35420

FR0000039299	BOLLORÉ SE	256317	72664	7242202
FR0000120222	CNP ASSURANCES	1519	2815	58918
ES0140609019	CAIXABANK, S.A.	3262	280	14228
DE0007100000	MERCEDES-BENZ GROUP AG	681000	466000	98326000
FR0014003TT8	DASSAULT SYSTÈMES SE	4629	15331	561226
DE0005810055	DEUTSCHE BÖRSE AG	4931	1805	4510
DE0005552004	DEUTSCHE POST AG	6580000	190000	20610000
DE0005557508	DEUTSCHE TELEKOM AG	235261	4815423	13881000
IT0003132476	ENI SPA	40080000	810000	196500000
ES0130670112	ENDESA, S.A.	10702129	470773	21737472
FR0000121121	EURAZEO SE	577998	212078	2587370
BE0974264930	AGEAS SA	10317	52996	7116
PTGAL0AM0009	GALP ENERGIA, SGPS, S.A.	3060000	40000	46930000
FR0010208488	ENGIE	38589016	2330625	134001033
BE0003797140	GROUPE BRUXELLES LAMBERT SA	36723	139668	10407600
FR0000120644	DANONE	683000	936882	23734000
FR0010533075	GETLINK SE	39703	11658	2225319
DE0008402215	HANNOVER RÜCK SE	24	1859	1772
NL0000008977	HEINEKEN HOLDING	951000	352000	16151000
DE0006048408	HENKEL AG & CO KGAA	343000	132000	43572000
DE0006231004	INFINEON TECHNOLOGIES AG	298246	695432	1190267
BE0003565737	KBC GROUPE NV	19511	34632	13473
FI0009000202	KESKOB, Kesko Oyj B	38538	128358	7736700
IE0004927939	KINGSPAN GROUP PLC	291771	65772	5043030
FI0009013403	KONE OYJ	118700	10200	15906600
NL0000009082	ROYAL KPN N.V	13000	0	793000
FR0000120321	L'OREAL	43134	133578	11168803
DE0005470405	LANXESS AG	1284000	1562000	16876000
FR0000121014	LVMH - Moët Hennessy Louis Vuitton	71055	219123	830253
FR0010307819	LEGRAND	57000	91000	3297690
IT0000062957	MEDIOBANCA	3929	163	1527
DE0006599905	MERCK KGAA	1706000	304000	308000
DE0008430026	MUNICH RE	47598	47751	6015
FI0009013296	NESTE OYJ	1828000	519000	35300000
IE00BWT6H894	FLUTTER ENTERTAINMENT PLC	854	10288	3853
FR0000130577	PUBLICIS GROUPE SA	7351	40146	140622
NL0012169213	QIAGEN	10068	15854	32429
DE0007037129	RWE AG	86900000	2700000	23000000
DE0007010803	RATIONAL AG	2083	1484	898
FR0000130395	RÉMY COINTREAU	7581	612	83825

ES0173516115	REPSOL S.A.	22000000	400000	157000000
FR0000121709	SEB S.A.	72173	145142	15801683
NL0000226223	STMICROELECTRONICS N.V.	486304	781847	593529
FR0000121972	SCHNEIDER ELECTRIC SE	142149	321153	65701766
IE00B1RR8406	SMURFIT KAPPA GROUP PLC	2500000	553000	491900
IT0003153415	SNAM S.P.A.	1397000	31000	995000
FR0000121220	SODEXO	71000	20000	6160233
IT0003242622	TERNA S.P.A.	58793	1612109	623
ES0178430E18	TELEFÓNICA, S.A.	212682	1396941	1082541
FR0000051807	TELEPERFORMANCE SE	1779	148278	11642
BE0003739530	UCB	27777	5450	33813
FI0009005987	UPM-KYMMENE OYJ	2730000	2650000	6160000
US90459E1064	UNIBAIL-RODAMCO-WE	21236	24367	2456515
DE0005089031	UNITED INTERNET AG	3074	13880	2788
FR0000124141	VEOLIA ENVIRONNEMENT	26700000	3800000	20900000
FR0000125486	VINCI	2005622	295077	13928809
FR0000127771	VIVENDI SE	14764	23430	111622
FI0009003727	WÄRTSILÄ OYJ	54711	25350	93810
IT0003796171	POSTE ITALIANE S.P.A.	165508	142966	178737
DE000EVNK013	EVONIK INDUSTRIES AG	4802000	2594000	23110000
ES0127797019	EDP RENOVÁVEIS, S.A.	2405	28425	1289
NL0011540547	ABN AMRO BANK N.V.	3490	3160	26288000
ES0109067019	AMADEUS IT GROUP, S.A.	1961	11767	366
NL0013654783	PROSUS N.V.	6330	6900	780987
ES0118900010	FERROVIAL, S.A.	761314	36752	2849892
DE000A1J5RX9	TELEFÓNICA DEUTSCHLAND HOLDING AG	5623	285695	896
NL0010773842	NN GROUP N.V.	1000	4000	8000
IT0000072170	FINECOBANK S.P.A.	461	1150	2334
DE000A1ML7J1	VONOVIA SE	487059	417182	149121
DE000KGX8881	KION GROUP AG	106641	83363	29125
FR0004125920	AMUNDI	540	3132	1740
FR0011981968	WORLDLINE	3615	1106	450608
NL0006294274	EURONEXT N.V.	270	1600	16600
DE0007164600	SAP SE	96000	112000	10061000
ES0105066007	CELLNEX TELECOM, S.A.	3494	328720	349430
DE000ZAL1111	ZALANDO SE	10429	60571	4477570
FR0014000MR3	EUROFINS SCIENTIFIC SE	59000	93000	253000
IT0005090300	INFRASTRUTTURE WIRELESS ITALIA (INWIT)	1542	168991	9546
DE0006062144	COVESTRO AG	980000	4400000	21791000
DE000A12DM80	SCOUT24 SE	232	636	1335

GB00BDCPN049	COCA-COLA EUROPACIFIC PARTNERS PLC	205244	123838	3074649
DE000UNSE018	UNIPER SE	42600000	714202	21065065
NL0012015705	JUSTE EAT TAKEAWAY N.V.	2479	1991	151886
DE000A161408	HELLOFRESH SE	5286	14756	76268
DE000SHL1006	SIEMENS HEALTHINEERS AG	106000	206000	3243000
IT0005366767	NEXI S.P.A	1075	3281	1247
NL0012969182	ADYEN N.V.	223	2341	6064
DE000A2E4K43	DELIVERY HERO SE	1274	3103	278361
DE000A1DAHH0	BRENNTAG SE	194491	52651	18923226
NL0014332678	JDE PEET'S N.V.	378987	181354	8113802

Appendix 3.4 = *Secondary* database

Database including the 92 companies belonging to the secondary activity sector.

ISIN	COMPANY	INDUSTRY	SCOPE 1	SCOPE 2	SCOPE 3
DE000BAY0017	BAYER AG	Pharmaceuticals	1930000	1560000	8940000
FI0009000681	NOKIA Oyj	Communications Equipment	124300	377300	40634700
FI0009005961	STERV, STORA ENSO OYJ R	Paper Product / Forest Product	2180000	340000	6310000
FR0000120073	AIR LIQUIDE	Industrial Gases	15536000	20829000	22247000
IE0001827041	CRH PLC	Building Products	33400000	2600000	12000000
NL0000235190	AIRBUS	Aerospace & Defense / Defense	562000	265000	464746000
FR0000121667	ESSILOR LUXOTTICA	Health Care Supplies	46011	696843	194955
ES0144580Y14	IBERDROLA	Electric Utilities	13207008	2161983	53898339
FR001400AJ45	MICHELIN	Tires & Rubber	1204534	1589000	165810462
AT0000743059	OMV AG	Integrated Oil & Gas	13900000	1100000	156400000
FR0000073272	SAFRAN	Aerospace & Defense	146655	268333	24195000
FR0013176526	VALEO	Auto Parts & Equipment	170600	787910	8521000
DE000ENAG999	E.ON SE	Multi-Utilities	3710000	3900000	100380000
ES0130960018	ENAGÁS, S.A.	Gas Utilities	263517	46368	825211
FR0000121147	FAURECIA	Auto Parts & Equipment	117000	662000	24256000
NL0000009165	HEINEKEN N.V.	Brewers	970218	755287	18107286
ES0148396007	INDITEX	Apparel Retail	12986	472510	14888171
FR0000131906	RENAULT	Automobile Manufacturers	498611	451493	72234633

AT0000937503	VOESTALPINE AG	Steel	12440680	809378	54572232
FR0000120503	BOUYGUES	Construction & Engineering	1876200	302100	20421700
DE0006969603	PUMA SE	Footwear / Apparel, Accessories & Luxury Goods	4179	29839	211108
DE0007664005	VOLKSWAGEN AG	Automobile Manufacturers	4740000	2420000	337387768
FI0009007132	FORTUM OYJ	Electric Utilities	69100000	650700	120228000
DE000A1EWWW0	ADIDAS AG	Apparel, Accessories & Luxury Goods / Footwear	6748	56134	11636342
DE0006602006	GEA GROUP AG	Industrial Machinery	30394	34286	3602
FR0000125007	SAINT GOBAIN	Building Products	8400000	1900000	21300000
FR0010242511	ELECTRICITE DE FRANCE (EDF)	Electric Utilities	27690997	320773	106649250
FR0000130452	EIFFAGE S.A.	Construction & Engineering	594485	43636	5957965
FR0000052292	HERMES INTL	Apparel, Accessories & Luxury Goods	21257	16124	490057
BE0974293251	ANHEUSER-BUSCH INBEV	Brewers	2590500	1318800	23652933
NL0000009827	ROYAL DSM N.V.	Specialty Chemicals	873219	586781	11600000
AT0000746409	VERBUND AG	Electric Utilities	653000	406000	335000
NL0000009538	PHILIPS NV	Health Care Equipment	27000	3000	489000
FR0000120271	TOTALENERGIES	Integrated Oil & Gas	33000000	2000000	370000000
FR0000120578	SANOFI	Pharmaceuticals	467780	192701	4738904
DE000SYM9999	SYMRISE AG	Specialty Chemicals	299119	1360	1747178
FR0010220475	ALSTOM	Construction Machinery & Heavy Trucks	53898	74197	21782971
DE0005200000	BEIERSDORF	Personal Products	93057	86818	1096289
PTEDP0AM0009	EDP - ENERGIAS DE PORTUGAL	Electric Utilities	9311000	594000	11572000
DE0005190003	BMW AG	Automobile Manufacturers	642885	84257	65100863
DE0005439004	CONTINENTAL AG	Tires & Rubber	820000	1845138	107700000
DE0006047004	HEIDELBERGCEMENT AG	Building Products	69490000	5060000	20000000
IT0003128367	ENEL	Electric Utilities	51570000	4310000	69150000
ES0143416115	SIEMENS GAMESA RENEWABLE ENERGY, S.A.	Heavy Electrical Equipment	26788	2017	856082
FR0010259150	IPSEN	Pharmaceuticals	15408	9907	32412
US73328P1066	PORSCHE AUTOMOBIL HOLDING	Automobile Manufacturers	2313220	1492400	196642951
BE0003470755	SOLVAY	Diversified Chemicals / Specialty Chemicals	9590000	1600000	25831000

LU0156801721	TENARIS S.A.	Oil & Gas Equipment & Services	1900000	800000	1700000
ES0167050915	ACS	Construction & Engineering	323889	103637	2637182
NL0010273215	ASML	Semiconductor Equipment	19300	165100	8830000
NL0013267909	AKZO NOBEL	Specialty Chemicals	57160	168200	12600000
LU1598757687	ARCELORMITTAL	Steel	131100000	7500000	8100000
FR0010313833	ARKEMA	Specialty Chemicals / Commodity Chemicals	2268000	1103000	11194000
DE000BASF111	BASF SE	Diversified Chemicals / Commodity Chemicals	17721000	3670000	122000000
DE0007100000	MERCEDES-BENZ GROUP AG	Automobile Manufacturers	681000	466000	98326000
IT0003132476	ENI SPA	Integrated Oil & Gas	40080000	810000	196500000
ES0130670112	ENDESA, S.A.	Electric Utilities	10702129	470773	21737472
PTGAL0AM0009	GALP ENERGIA, SGPS, S.A.	Integrated Oil & Gas	3060000	40000	46930000
FR0010208488	ENGIE	Multi-Utilities	38589016	2330625	134001033
NL0000008977	HEINEKEN HOLDING	Brewers	951000	352000	16151000
DE0006048408	HENKEL AG & CO KGAA	Household Products	343000	132000	43572000
DE0006231004	INFINEON TECHNOLOGIES AG	Semiconductors	298246	695432	1190267
IE0004927939	KINGSPAN GROUP PLC	Building Products	291771	65772	5043030
FI0009013403	KONE OYJ	Industrial Machinery	118700	10200	15906600
FR0000120321	L'OREAL	Personal Products	43134	133578	11168803
DE0005470405	LANXESS AG	Diversified Chemicals	1284000	1562000	16876000
FR0010307819	LEGRAND	Electrical Components & Equipment	57000	91000	3297690
DE0006599905	MERCK KGAA	Pharmaceuticals	1706000	304000	308000
FI0009013296	NESTE OYJ	Oil & Gas Refining & Marketing	1828000	519000	35300000
NL0012169213	QIAGEN	Life Sciences Tools & Services	10068	15854	32429
DE0007037129	RWE AG	Electric Utilities	86900000	2700000	23000000
DE0007010803	RATIONAL AG	Industrial Machinery	2083	1484	898
FR0000130395	RÉMY COINTREAU	Distillers & Vintners	7581	612	83825
ES0173516115	REPSOL S.A.	Integrated Oil & Gas	22000000	400000	157000000
FR0000121709	SEB S.A.	Household Appliances	72173	145142	15801683
NL0000226223	STMICROELECTRONICS N.V.	Semiconductors	486304	781847	593529
FR0000121972	SCHNEIDER ELECTRIC SE	Electrical Components & Equipment	142149	321153	65701766
DE0007236101	SIEMENS AG	Industrial Conglomerates	386000	208000	469271000
IE00B1RR8406	SMURFIT KAPPA GROUP PLC	Paper Packaging	2500000	553000	491900

IT0003242622	TERNA S.P.A.	Electric Utilities	58793	1612109	623
BE0003739530	UCB	Biotechnology / Pharmaceuticals	27777	5450	33813
FI0009005987	UPM-KYMMENE OYJ	Paper Products	2730000	2650000	6160000
FR0000125486	VINCI	Construction & Engineering	2005622	295077	13928809
FI0009003727	WÄRTSILÄ OYJ	Industrial Machinery	54711	25350	93810
DE000EVNK013	EVONIK INDUSTRIES AG	Specialty Chemicals	4802000	2594000	23110000
ES0127797019	EDP RENOVÁVEIS, S.A.	Renewable Electricity	2405	28425	1289
DE000KGX8881	KION GROUP AG	Construction Machinery & Heavy Trucks	106641	83363	29125
DE0006062144	COVESTRO AG	Specialty Chemicals	980000	4400000	21791000
GB00BDCPN049	COCA-COLA EUROPACIFIC PARTNERS PLC	Soft Drinks	205244	123838	3074649
DE000UNSE018	UNIPER SE	Independent Power Producers & Energy Traders	42600000	714202	21065065
NL0014332678	JDE PEET'S N.V.	Packaged Foods & Meats	378987	181354	8113802
DE000ENER6Y0	SIEMENS ENERGY AG	Industrial Machinery / Conventional Electricity / Industrial Machinery	206000	67000	1373924000

Appendix 3.5 = *Tertiary* database

Database including the 90 companies belonging to the tertiary activity sector.

ISIN	COMPANY	INDUSTRY	SCOPE 1	SCOPE 2	SCOPE 3
BE0003810273	PROXIMUS	Integrated Telecommunication Services	26600	800	648000
FR0000131104	BNP PARIBAS	Banks	50144	201473	32813
FR0000120628	AXA	Multi-line Insurance	23362	31997	3866
IT0004056880	AMPLIFON	Health Care Supplies / Health Care Services	5231	8392	1833
FR0000125338	CAPGEMINI	IT Consulting & Other Services	9187	84995	66786
FR0000120172	CARREFOUR	Hypermarkets & Super Centers	698700	965100	337200
FR0000045072	CREDIT AGRICOLE S.A.	Diversified Banks	14475	70052	143006638

FR0000064578	COVIVIO	Diversified REITs / Residential REITs	2216	2443	43990
FR0010040865	GECINA	Diversified REITs	7097	7219	12455
PTJMT0AE0001	JERÓNIMO MARTINS, SGPS, S.A.	Food Retail	246863	787100	27363835
IT0005239360	UNICREDIT	Diversified Banks	44016	138496	1471
NL0011821202	ING GROEP N.V.	Diversified Banks	12000	4000	8000
FR0000121964	KLEPIERRE	Retail REITs	11341	56417	1185162
NL0000395903	WOLTERS KLUWER	Research & Consulting Services	4691	13641	27480
DE0008232125	DEUTSCHE LUFTHANSA AG	Airlines	13823320	139496	4667549
FR0006174348	BUREAU VERITAS	Research & Consulting Services	68779	83545	485189
FR0000133308	ORANGE	Integrated Telecommunication Services	282526	990554	14729
DE000CBK1001	COMMERZBANK AG	Diversified Banks	28313	12263	43472
FR0000121485	KERING	Apparel, Accessories & Luxury Goods	14256	106226	2095574
AT0000606306	RAIFFEISEN BANK INT	Diversified Banks	4827	41064	30925
IT0000062072	ASSICURAZIONI GENERALI	Multi-line Insurance	24466	47022	25296
FR0013280286	BIOMÉRIEUX	Biotechnology	20000	36000	277100
DE0005140008	DEUTSCHE BANK AG	Diversified Banks	41458	207288	1603304
ES0171996087	GRIFOLS, S.A.	Biotechnology	147669	117152	44733
NL0000379121	RANDSTAD NV	Human Resource & Employment Services	48135	15822	3277
IT0003497168	TELECOM ITALIA	Integrated Telecommunication Services	127810	405235	5276891
FI0009003305	SAMPO OYJ	Multi-line Insurance	1515	2886	6925
IT0003506190	ATLANTIA	Airport Services / Highways & Railtracks	115186	74501	1007160
ES0116870314	NATURGY ENERGY GROUP, S.A.	Gas Utilities	12965240	487067	136450026
FR0000130809	SOCIETE GENERALE	Diversified Banks	23195	116642	81854
NL0000303709	AEGON	Life & Health Insurance / Asset Management & Custody Banks	5557	16366	2101

FR0000121329	THALES	Aerospace & Defense	86000	110000	9620
FR0010340141	AEROPORTS DE PARIS (ADP)	Airport Services	75434	24159	2626821
DE0008404005	ALLIANZ SE	Asset Managers / Life Insurance	28699	138746	55359
ES0113211835	BANCO BILBAO VIZCAYA ARGENTARIA	Diversified Banks / Asset Managers / Life Insurance	49639	252131	9432
ES0113900J37	BANCO SANTANDER, S.A.	Diversified Banks	25672	269615	35420
FR0000039299	BOLLORÉ SE	Broadcasting / Movies & Entertainment	256317	72664	7242202
FR0000120222	CNP ASSURANCES	Multi-line Insurance	1519	2815	58918
ES0140609019	CAIXABANK, S.A.	Diversified Banks	3262	280	14228
FR0014003TT8	DASSAULT SYSTÈMES SE	Application Software	4629	15331	561226
DE0005810055	DEUTSCHE BÖRSE AG	Financial Exchanges & Data	4931	1805	4510
DE0005552004	DEUTSCHE POST AG	Transportation Services	6580000	190000	20610000
DE0005557508	DEUTSCHE TELEKOM AG	Integrated Telecommunication Services	235261	4815423	13881000
FR0000121121	EURAZEO SE	Asset Management & Custody Banks	577998	212078	2587370
BE0974264930	AGEAS SA	Multi-line Insurance	10317	52996	7116
BE0003797140	GROUPE BRUXELLES LAMBERT SA	Multi-Sector Holdings / Industrial Conglomerates	36723	139668	10407600
FR0000120644	DANONE	Packaged Foods & Meats	683000	936882	23734000
FR0010533075	GETLINK SE	Highways & Railtracks	39703	11658	2225319
DE0008402215	HANNOVER RÜCK SE	Reinsurance	24	1859	1772
BE0003565737	KBC GROUPE NV	Diversified Banks / Multi-line Insurance	19511	34632	13473
FI0009000202	KESKOB, Kesko Oyj B	Home Improvement Retail / Food Retail	38538	128358	7736700
NL0000009082	Royal KPN N.V	Wireless Telecommunication Services / Integrated Telecommunication Services	13000	0	793000

FR0000121014	LVMH - Moët Hennessy Louis Vuitton	Apparel, Accessories & Luxury Goods	71055	219123	830253
IT0000062957	MEDIOBANCA	Diversified Banks	3929	163	1527
DE0008430026	MUNICH RE	Reinsurance	47598	47751	6015
IE00BWT6H894	FLUTTER ENTERTAINMENT PLC	Casinos & Gaming	854	10288	3853
FR0000130577	PUBLICIS GROUPE SA	Advertising	7351	40146	140622
IT0003153415	SNAM S.P.A.	Gas Utilities	1397000	31000	995000
FR0000121220	SODEXO	Restaurants	71000	20000	6160233
ES0178430E18	TELEFÓNICA, S.A.	Integrated Telecommunication Services	212682	1396941	1082541
FR0000051807	TELEPERFORMANCE SE	Research & Consulting Services	1779	148278	11642
US90459E1064	UNIBAIL-RODAMCO-WE	Retail REITs	21236	24367	2456515
DE0005089031	UNITED INTERNET AG	Integrated Telecommunication Services	3074	13880	2788
FR0000124141	VEOLIA ENVIRONNEMENT	Multi-Utilities	26700000	3800000	20900000
FR0000127771	VIVENDI SE	Broadcasting	14764	23430	111622
IT0003796171	POSTE ITALIANE S.P.A.	Industrial Conglomerates	165508	142966	178737
NL0011540547	ABN AMRO BANK N.V.	Diversified Banks	3490	3160	26288000
ES0109067019	AMADEUS IT GROUP, S.A.	IT Consulting & Other Services / Business Support Services	1961	11767	366
NL0013654783	PROSUS N.V.	Internet & Direct Marketing Retail	6330	6900	780987
ES0118900010	FERROVIAL, S.A.	Construction & Engineering	761314	36752	2849892
DE000A1J5RX9	TELEFÓNICA DEUTSCHLAND HOLDING AG	Integrated Telecommunication Services	5623	285695	896
NL0010773842	NN GROUP N.V.	Life & Health Insurance	1000	4000	8000
IT0000072170	FINECOBANK S.P.A.	Diversified Banks	461	1150	2334
DE000A1ML7J1	VONOVIA SE	Real Estate Operating Companies	487059	417182	149121

FR0004125920	AMUNDI	Asset Management & Custody Banks	540	3132	1740
FR0011981968	WORLDLINE	Data Processing & Outsourced Services	3615	1106	450608
NL0006294274	EURONEXT N.V.	Financial Exchanges & Data	270	1600	16600
DE0007164600	SAP SE	Application Software	96000	112000	10061000
ES0105066007	CELLNEX TELECOM, S.A.	Communications Equipment	3494	328720	349430
DE000ZAL1111	ZALANDO SE	Internet & Direct Marketing Retail	10429	60571	4477570
FR0014000MR3	EUROFINS SCIENTIFIC SE	Life Sciences Tools & Services	59000	93000	253000
IT0005090300	INFRASTRUTTURE WIRELESS ITALIA (INWIT)	Wireless Telecommunication Services	1542	168991	9546
DE000A12DM80	SCOUT24 SE	Interactive Media & Services	232	636	1335
NL0012015705	JUST EAT TAKEAWAY	Internet & Direct Marketing Retail	2479	1991	151886
DE000A161408	HELLOFRESH SE	Food Retail	5286	14756	76268
DE000SHL1006	SIEMENS HEALTHINEERS AG	Health Care Equipment	106000	206000	3243000
IT0005366767	NEXI S.P.A	Diversified Banks	1075	3281	1247
NL0012969182	ADYEN N.V.	Data Processing & Outsourced Services	223	2341	6064
DE000A2E4K43	DELIVERY HERO SE	Internet & Direct Marketing Retail	1274	3103	278361
DE000A1DAHH0	BRENNTAG SE	Specialty Chemicals	194491	52651	18923226

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