OVERCONFIDENCE AND RISK PREFERENCES OF IMPACT INVESTORS

A Behavioral Analysis of Italian Impact Investors in the Cleantech Sector

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ABSTRACT

This thesis contributes to the impact investing field by adopting a behavioral finance perspective. Given the increased theoretical attention from impact investing scholars and practitioners to the concept of Impact Risk, the study analyses impact investors' risk preferences by focusing on the influence exercised by the overconfidence bias on such preferences when choosing among cleantech carbon reduction investments. Starting from the Impact Investing Framework formulated by Hornsby & Blumberg (2013) and applying an innovative methodology combining the Choice-Based Conjoint Analysis and the Calibration Test, the researchers based their conclusions on a sample of impact investing experts in Italy. On the one hand, through the Choice-Based Conjoint Analysis, the conceptual and empirical separation of the novel concept of Impact Risk from the well-known notion of Financial Risk was demonstrated. On the other hand, through the Calibration Test, the presence of overconfidence among respondents was confirmed. However, no evidence was found on how the overconfidence bias explains impact investors' preferences for the parameters of Financial and Impact Risk.

Table of Contents

CHAPTER 1 - INTRODUCTION

1.1 RELEVANCE OF THE RESEARCH TOPIC

To clarify the reason behind the scope of the thesis, this section is divided in two parts. The first part will discuss the global relevance of impact investing as a means to finance the clean technology sector and to achieve the Climate Action goal. The second part will discuss the topic of impact investing within the cleantech sector but with a narrower geographical perspective: Italy.

1.1.1 Impact Investing, Clean Technologies and The Climate Action Goal

Impact Investing is defined as a new investment strategy combining finance and philanthropy with the intention to *"generate positive, measurable social and environmental impact alongside a financial return"* (GIIN, 2020). This new stream of investing gained critical importance when, in 2015, the 2030 Agenda for Sustainable Development was adopted to emphasize a holistic plan to achieve a global sustainable development (UN, 2020). The agenda includes 17 universal Sustainable Development Goals (SDGs) with the objective of addressing the urgent environmental, political and economic challenges that our world is facing (UNDP, 2020). Moreover, according to the UN, the achievement of the SDGs will allow for US$ 12 trillion in terms of market opportunities and create 380 million new jobs (Vali, 2017). Thus, to reach these ambitious targets globally, an estimated amount of US$ 5-7 trillion a year in terms of financial investments is needed (Vali, 2017). In this sense, impact investing plays a key role in unlocking private capital for the realization of SDGs (Triodos Investment Management, 2020). According to GlobeScan – SustainAbility Survey (2019), among the 17 SDGs, global experts consider Goal Number 13, namely *Climate Action*, the one that requires the most urgent response. In fact, the rising of greenhouse gas (GHG) emissions has been a permanent phenomenon for the past decade, leading to an increase in global warming. In this regard, the European Union is the third biggest emitter of GHG, after China and the US (Center for Climate and Energy Solutions, 2017), with Germany producing the largest share of these emissions, followed by the UK, Poland and Italy (Armstrong, 2019). Moreover, carbon dioxide (CO_2), which accounts for 76% of global GHG emissions, is considered the most significant human-caused emission contributing to climate change (Center for Climate and Energy Solutions, 2017). Additionally, given that global CO_2 is expected to rise to approximately 43.08 billion metric tons in 2050, this could have several implications for global warming (Wang, 2019). Therefore, the 2015 Paris Agreement has set the long-term goal of limiting the global mean temperature increase well below 2°C to strengthen the global response to climate change (EU, 2020). For this reason, to achieve the critical goal set by the Paris Agreement, an estimated amount of US$ 100 billion a year is necessary (Peake &

Ekins, 2016). However, there is a large gap between actual climate-friendly financial flows provided and those needed in order to achieve this ambitious Climate Action goal (Peake & Ekins, 2016). In this sense, it is essential to ensure that not only public investments but also private ones are directed towards climate-related investments (Peake & Ekins, 2016). Hence, the role of impact investing in the achievement of the Climate Action and Paris Agreement goals is fundamental.

Among the climate-friendly solutions required to attain the Climate Action goal, the development of low-carbon energy technologies plays a key role (Peake & Ekins, 2016). In fact, the International Renewable Energy Agency estimates that by 2050 the accelerated deployment of clean technologies can contribute 90% of the emission reductions needed to achieve the climate goals defined by the Paris Agreement (IRENA, 2017). Therefore, to reach the ambitious goal of Climate Action and CO2 reduction, it is particularly important to direct investments towards the clean technology industry (UN, 2020). In particular, the term clean technology investment *"encompasses innovative technologies and/or business sectors which include clean energy, environmental, sustainable or green products and services"* (Dikeman, 2015). Hence, it refers to investments towards any product, process or service that reduces environmental impacts in a variety of markets, including three categories: Energy and Power, Agriculture and Food, Mobility and Transportation (Dikeman, 2018).

1.1.2 Impact Investing and Clean Technologies in Italy

With regard to the Italian market, although impact investing has developed quite recently, it is considered an important trend. In fact, as stated by Marco Gerevini, managing director at Fondazione Housing Sociale, despite impact investing being at its initial phase in Italy, there are good prospects of growth (Triboli, 2019). This is attracting many investors to contribute with capital into organizations whose purpose is to solve social or environmental challenges (Triboli, 2019). More precisely, Italy represents an important country when considering investments in low-carbon energy technologies to address the Climate Action SDG globally. In fact, the Energy & Strategy Group from Politecnico di Milano stated that the clean technology sector in Italy represents a valuable business of over 30 billion euros (Il Sole 24 Ore, 2016). Moreover, according to GreenItaly 2015, over 370 thousand Italian enterprises have been investing within the cleantech sector (Il Sole 24 Ore, 2016).

Given the role that Italy has in addressing the Climate Action SDG through its valuable cleantech sector, the researchers selected Italy as the context of this research project. Moreover, the researchers decided to focus on Italy because, due to their nationality, they could contribute to provide new insights on a new investment trend within their home country and avoid language barriers during the data collection process. Additionally, Italy has been recently advancing many initiatives to enhance the development of the impact investing field within the national territory (Chiodo & Michelucci, 2016). One of these initiatives is *Cottino Social Impact Campus* in Turin

(Italy), which represents a network of experts and professionals within the impact investing and sustainability sectors. More specifically, it aims at expanding the awareness around impact investing with the goal of promoting it as an instrument to address urgent environmental and social challenges the world is facing (Torino Social Impact Campus, 2020). Therefore, due to the relevance of this initiative, the researchers decided to take advantage of such wide network of professionals to investigate the impact investing trend in the cleantech sector. Hence, thanks to the collaboration with Cottino Social Impact Campus, the researchers identified this opportunity as an additional motive in choosing Italy as the geographical focus of this research project.

1.2 PROBLEM DEFINITION AND RESEARCH QUESTIONS

This section is divided into three parts to provide more clarity regarding the problem definition and the resulting research questions. In the first part, the researchers will discuss the lack of a single framework to address the financial decision-making process for impact investments. Thereafter, by adopting the comprehensive Impact Investing Framework formulated by Hornsby & Blumberg (2013), the researchers will explain the importance of addressing the new dimension of *Impact Risk*. In the second part, the importance of human psychology and cognitive biases as factors affecting the financial decision-making process of impact investors will be discussed. More precisely, by adopting the behavioral finance perspective, the researchers will focus on the overconfidence bias as it allows to gain more insights on impact investors' risk preferences. Lastly, in the third part, the researchers will formulate the research questions by integrating the Impact Investing Framework with the Behavioral Finance theory.

1.2.1 Impact Investing Framework: The New Dimension of Impact Risk

Considering the potential growing trend of the impact investing sector as a means to finance the development of the clean technologies' industry in Italy, it is relevant to address the issue that the field of impact investing has not yet embraced a single formal framework for addressing these new types of investments (Emerson, 2018). In this regard, the most relevant financial decision-making framework which extensively addresses the most important dimensions within an impact investment has been developed by Hornsby & Blumberg (2013). Due to its comprehensive nature, the researchers chose this framework as the frame of reference within this thesis. In fact, the two authors state that an impact investment is not only characterized by a financial risk/return profile, but also by an impact risk/return one (Hornsby & Blumberg, 2013). Therefore, according to this framework, impact investors have to consider four key parameters during the investment decision-making process, the first two arising from the traditional finance framework, and the other two from the impact investing field. They respectively are:

1) *Financial Return*, **2)** *Financial Risk*, **3)** *Impact Return*, and **4)** *Impact Risk* (Hornsby & Blumberg, 2013). More precisely, the researchers concentrated on *Impact Risk* as, unlike the other parameters, it has not received a large theoretical and empirical attention from the academic literature of impact investing. In fact, although Hornsby & Blumberg (2013) define it as a separate concept from the well-known *Financial Risk*, some practitioners still consider it as a concept implicitly included in the notion of *Financial Risk* (Saltuk & El Idrissi, 2012; Emerson, 2012). Therefore, by adopting the innovative framework proposed by Hornsby & Blumberg (2013), which considers the two risk parameters separately, the researchers will be able to provide a deeper and holistic understanding of impact investors' preferences for the new dimension of *Impact Risk* as a stand-alone parameter.

1.2.2 Cognitive Biases as Key Drivers Within the Decision-Making Process of Impact Investors

According to Duiker *et al*. (2016), the development of the impact investing sector as a means to address the Climate Action goal depends on four main drivers, namely **1)** the *organizational driver*, **2)** the *market driver*, **3)** the *regulation driver* and **4)** the *individual behavior driver*. These four drivers are summarized by *Table 1* below:

Drivers of the Development of the Impact Investing Sector	
Organisational Driver	It includes all the factors (i.e. leadership, culture and investment beliefs) that favour a larger adoption of impact investing strategies within financial organisations.
Market Driver	It includes all the factors (i.e. market perception of impact investing, standardisation of impact measurement, organisational capacity of the market) that influence the impact investing role within the financial markets.
Regulation Driver	It includes all the legal and regulatory requirements relative to impact investing that are imposed by the national central banks.
Individual Behaviour Driver	It includes all the so-called "cognitive biases" within human psychology that affect the individual financial decision-making process of impact investors.

Table 1 - Drivers of the Development of the Impact Investing Sector

Although these four drivers are essential to the development of the impact investing sector, one of them, namely the *individual behavior driver*, often receives the least attention (Duiker *et al.*, 2016). However, the consideration of such driver is particularly important because actual investment decisions take place at the individual level within the singular investor (Duiker *et al.*, 2016). Hence, by taking into account human psychology, further considerations about the personal preferences within the individual financial decision-making process of impact investors can be provided. In this regard, the behavioral finance literature provides the most appropriate framework because it discusses the effect of human psychology on the investment decision-making process (Ackert & Deaves, 2018). In fact, this new finance field studies "*cognitive biases*" (also known as "*behavioral biases*"), which represent systematic and deeply rooted patterns of thoughts that can cause irrational and inconsistent investment choices (Duiker *et al.*, 2016). In particular, among the numerous cognitive biases identified by Behavioral Finance theory, the researchers will concentrate on the overconfidence bias because it is considered one of the most powerful biases playing an important role in explaining impact investors' risk preferences, which represent the focus of this thesis (*see page 78*). Hence, while the overconfidence bias effects have been largely discussed among traditional investors as leading them towards a larger propensity to choose riskier investments (Barber & Odean, 2001; Broihanne *et al.*, 2014; Nosić & Weber 2010), no evidence has been found on how this common bias influences the risk preferences of impact investors.

1.2.3 Bridging Impact Investing and Behavioral Finance to Explain Impact Investors' Risk Preferences

Bringing the perspectives of Impact Investing and Behavioural Finance together and grounding the research in the Italian impact investing industry, this thesis will address two main issues. Firstly, the researchers will empirically test whether Impact Risk, proposed within the Impact Investing Framework of Hornsby & Blumberg (2013), is considered as a new and significant parameter separated from Financial Risk. Secondly, the researchers will empirically test the presence of the overconfidence bias among impact investors and whether such bias influences their risk preferences. More precisely, the researchers will address the three research questions reported in *Table 2* below.

Research Question 1	*Do impact investors consider Impact Risk as an important factor within the investment decision-making process?*
Research Question 2	*Are impact investors overestimating the precision of their knowledge? In other words, are impact investors on average overconfident?*
Research Question 3	*Are impact investors' preferences for risk affected by the overconfidence bias?*

Table 2 - Research Questions

1.3 RESEARCH STRUCTURE

To answer the research questions, the thesis adopts both a theoretical and empirical approach. More precisely, the research consists in six chapters: **1)** *Introduction*, **2)** *Literature Review*, **3)** *Research Questions and Relative Hypotheses*, **4)** *Methodology*, **5)** *Analysis and Discussion*, and **6)** *Conclusions and Limitations*. *Figure 1* below provides a graphical representation of the structure of the thesis.

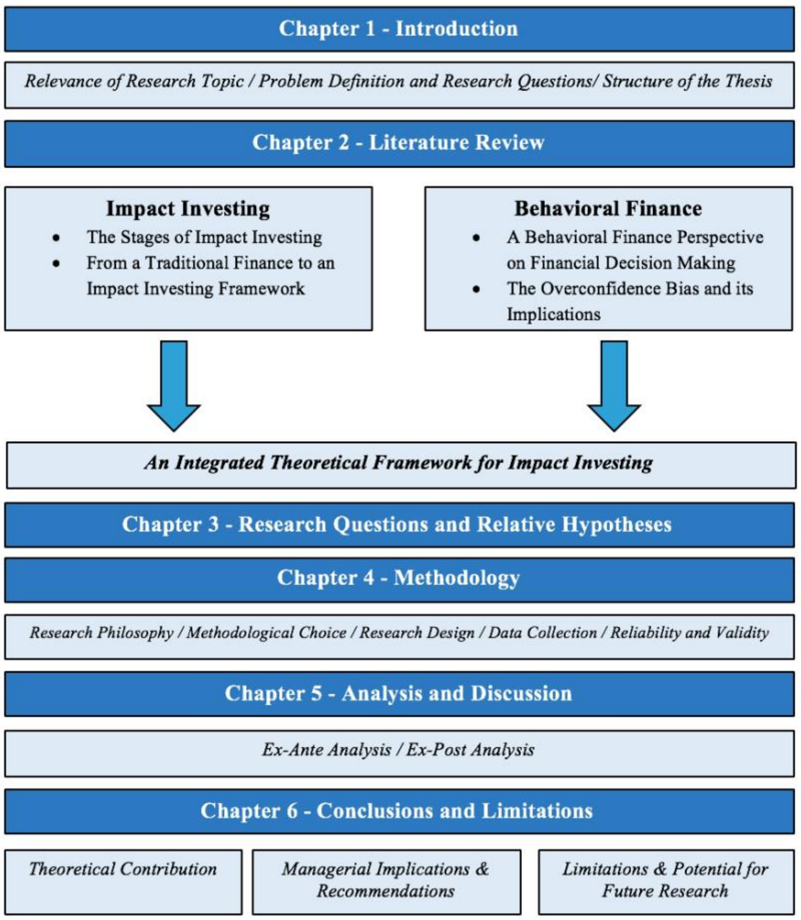

Figure 1 – Research Structure

In the *Introduction* chapter previously discussed, a brief explanation of the new stream of impact investing and its critical role in achieving the Climate Action goal has been presented with a particular focus on Italy. Thereafter, the researchers pointed out the need to address whether Impact Risk - proposed within the Impact Investing Framework of Hornsby & Blumberg (2013) - is considered as a new and significant parameter separated from Financial Risk. Additionally, the researchers addressed the need to integrate the Impact Investing Framework with the behavioral finance perspective. In this regard, the researchers discussed how the presence of the overconfidence bias within impact investors could be examined to gain insights on their risk preferences.

In the second chapter, namely the *Literature Review,* the theoretical contributions of the two main academic fields addressed by this research project will be explained and critically discussed. In the first part, the impact investing literature is presented. By starting from the general perspective of Sustainable Finance, the researchers will outline how the impact investing strategy differs from other sustainable investment approaches. Thereafter, the researchers will focus on the Impact Investing Framework formulated by Hornsby & Blumberg (2013). In the second part, the behavioral finance literature is outlined. By introducing the behavioral finance perspective on financial decision-making, the researchers will then focus on the behavioral bias of overconfidence and its managerial implications. Lastly, a comprehensive theoretical framework integrating insights from the impact investing and the behavioral finance literature will be presented.

Consequently, in the third chapter, after having conducted and critically discussed a Literature Review on the two main research areas, the *Research Questions and Relative Hypotheses* will be formulated.

In the fourth chapter, the *Methodology* necessary to address the research questions will be described and critically evaluated. More specifically, the researchers use a Choice-Based Conjoint Analysis and a Calibration Test. On the one hand, the Choice-Based Conjoint Analysis will be used as a preference elicitation method to gain insights on impact investors' preferences for the risk parameters identified within the Impact Investing Framework. On the other hand, the Calibration Test will be used to find a numerical expression for the overconfidence bias affecting impact investors, namely the Bias Score. Consequently, the Bias Score variable will be used as an interaction term within the estimation method of the Choice-Based Conjoint Analysis to explain impact investors' risk preferences. Moreover, this chapter will explain the research philosophy, the research design and the data collection approaches. Lastly, the reliability and validity of the methods will be discussed.

In the fifth chapter, named *Analysis and Discussion,* the researchers will present and critically discuss the findings of the research. More precisely, in the Ex-Ante Analysis, the researchers will answer the three research questions. While, in the Ex-Post analysis, researchers will look retrospectively at the results and make further considerations.

Finally, in the last chapter, named *Conclusions and Limitations,* the researchers will present the general summary of the thesis, its theoretical contribution, its managerial implications and relative recommendations, its limitations and insights for future research.

CHAPTER 2 - LITERATURE REVIEW

The *Literature Review* chapter is structured in three parts. Firstly, the researchers will outline the theoretical foundation of the impact investing strategy. Secondly, the behavioral theory of financial decision-making will be presented. Lastly, in the conclusive part, the researchers will integrate these two theoretical contributions to provide the comprehensive financial decision-making framework for impact investing at the core of the thesis.

2.1 IMPACT INVESTING PERSPECTIVE ON INVESTMENT DECISION-MAKING

2.1.1 Investment Approaches within Sustainable Finance: ESG, SRI and Impact Investing

The broad area of *Sustainable Finance* considers how finance interacts with sustainable development, which is an integrated concept including economic, social and environmental concerns (Schoenmaker, 2017). The European Commission (2020) defines Sustainable Finance as *"the provision of finance to investments taking into account environmental, social and governance (ESG) considerations"*. According to the Toronto Centre (2019), Sustainable Finance is characterized by three investment approaches: **1)** *Environmental, Social, and Governance* (ESG) *Investing*, **2)** *Socially Responsible Investing* (SRI), and **3)** *Impact Investing*. As previously mentioned in the *Introduction* chapter (*see page 5*), Impact Investing has been selected as the focus of this thesis as it plays a key role in unlocking private capital to fund projects within the cleantech sector to reduce carbon emissions and tackle climate change. However, as the names of these investment approaches are used interchangeably (Höchstädter & Scheck, 2015), it is relevant to briefly explain the key characteristics of each investment approach to provide definitional clarity and point out the key similarities and differences among them.

ESG Investing

ESG Investing is an investment activity systematically including environmental, social and governance considerations, in terms of risks and opportunities, on a company's operations to enhance the traditional investment analysis (Grim & Berkowitz, 2018). Despite including ESG considerations within the investment approach, the key target of this investment strategy remains to achieve a financial performance and it does not formally prevent investing into companies because of undesirable ESG practices (Grim & Berkowitz, 2018).

SRI

SRI takes one step further compared to ESG Investing as it goes beyond financial performance considerations by integrating non-financial factors (e.g. social, ethical, environmental) during the investment decision process (Budde, 2008). SRI is delivered through three strategies: **1)** *social screening*, **2)** *proactive investing* and **3)** *shareholder activism* (Budde, 2008). Firstly, social screening, which represents the most prominent strategy among the three, includes negative as well as positive screening and focuses on either excluding specific securities (sin stocks) or including securities on the basis of their compliance with ESG criteria. (Budde, 2008). Secondly, proactive investing aims at directing funds towards public companies developing projects with a social or environmental impact (Budde, 2008). Lastly, shareholder activism implies that social investors owning shares within a company have the power to influence corporate behavior by asking for an improvement of the company's ESG compliance and by enforcing their desired level of ethical attitude (Budde, 2008).

Impact Investing

The term *Impact Investing* was first adopted in 2007 during a meeting held by The Rockefeller Foundation in Bellagio (Italy), where practitioners discussed the urgency for creating a comprehensive industry with the global goal of *"using profit-seeking investments to generate social and environmental good"* (Harji & Jackson, 2012). Due to the absence of a clear globally accepted definition and an ongoing debate among leaders in the field, there has been a continuous effort to achieve a definitional clarity regarding impact investing (Harji & Jackson, 2012). The Global Impact Investing Network (GIIN, 2020) provides the most recent and precise definition of this investing strategy by describing impact investments as: *"Investments made into companies, organizations and funds with the intention to generate positive, measurable social and environmental impact alongside a financial return"*. To do so, impact investors target many investment opportunities, both in developed and emerging economies, across all asset classes with different levels of financial risk and return, with the main goal of providing capital to address global challenges within various sectors (GIIN, 2020). Moreover, to be qualified as an impact investment, the prioritization of the non-financial return over the financial return is not required (Evenett & Richter, 2011). In fact, impact investors can choose freely which criteria is more relevant for their investment strategy (Evenett & Richter, 2011). Accordingly, impact investors are identified as "*Impact-First*", if they optimize impact and are willing to give up some financial return, or "*Finance-First*", if they follow the opposite strategy

(Höchstädter & Scheck, 2015). Nevertheless, investors may also decide to pursue a mixed strategy and make both financial first and impact first investments (Godeke & Pomares, 2009).

From the definition given by the GIIN (2020), the three major characteristics of impact investing can be pointed out:

- The *intentionality* of the investor in generating a positive non-financial impact (GIIN, 2020), meaning that social or environmental impact must be planned as a goal in advance and cannot be an incidental side-effect of a commercial deal (Brown & Swersky, 2012);
- A *financial return* must be earned from the investment, which can vary from below-market-rate to market-rate (GIIN, 2020) or in some cases even above-market rate (Best & Harji, 2013);
- A *measure* of the impact generated must be provided by the investors to ensure a transparent and accountable system (GIIN, 2020) and to enable industry-wide performance assessment (Jackson & Harji, 2014).

This latter characteristic has been enhanced by the initiative managed by the GIIN in developing the Impact Reporting and Investment Standards (IRIS), a set of standardized impact metrics indicators regarding both social and environmental performances (Narain *et al.*, 2012).

2.1.2 Impact Investing: A Different Take on Sustainable Finance

The characteristics outlined above play a key role in enabling the researchers to deal with the lack of conceptual clarity, which arises when comparing impact investing with related concepts (Höchstädter & Scheck, 2015).

On the one hand, SRI differs from impact investing as the latter uses *"market-based solutions to create social change"* (Laing *et al.*, 2012), meaning that impact investors seek to invest in enterprises where "achieving the good" is a fully rooted goal within their business model. Therefore, impact investing goes beyond applying the key strategies of negative or positive screening of traditional investment characterizing SRI. In fact, impact investors are driven by *"the ultimate impact an investment can create"* and target impact investees whose existence is based on delivering a positive social or environmental impact (Höchstädter & Scheck, 2015). Hence, while SRI is directed towards large publicly listed companies selected based on their ESG compliance, impact investors direct capital towards privately held small enterprises providing innovative solutions to solve social or environmental problems within different sectors, according to their preferences (Höchstädter & Scheck, 2015).

On the other hand, the ESG investing approach offers a more accurate investment analysis, but it differs from impact investing. In fact, although impact investors target companies with good ESG criteria, they take a step further and also look at whether the company offers products and services that will have a measurable social or environmental impact (Cruz, 2018).

2.1.3 The Stages of Impact Investing

The impact investment strategy follows a structured investment process, which is composed of five essential stages outlined in *Figure 2* below (Hornsby & Blumberg, 2013; Allman & Escobar de Nogales, 2015). In the following paragraphs, the researchers will present the key points relevant to define each stage within the impact investing process.

Figure 2 - Stages of Impact Investing

Sourcing & Screening

The first stage of the impact investing process involves identifying potential investments (Allman & Escobar de Nogales, 2015). However, given that impact investors are presented with a variety of potential investment opportunities, they must screen investments to ensure that they are both *eligible* and *suitable* (Hornsby & Blumberg, 2013). The first critical aspect, eligibility, is essential to ensure that the proposed investment can be validly considered as an impact investment (*see page 14*), meaning that the investment truly aims at generating positive impact (Hornsby & Blumberg, 2013). The second critical aspect, suitability, refers to how well the proposed impact investments' characteristics fit with the investor's strategy (Hornsby & Blumberg, 2013). Therefore, by screening investments according to these two critical aspects, impact investors can ensure better investment choices.

Investment Analysis (Due Diligence)

The sourcing & screening process just outlined provides investors with a refined number of investment opportunities (Allman & Escobar de Nogales, 2015). Consequently, the second stage consists in conducting an in-depth due diligence, which will help impact investors determine whether each investment is solid from the financial and impact generation perspectives (Hornsby & Blumberg, 2013). In fact, impact investors are concerned with the financial risk/return profile as well as with the impact risk/return profile of the investment. Therefore, the due diligence process will provide impact investors with relevant information regarding the risk and return parameters characterizing impact investments. Thereafter, impact investors will integrate these results into the investment decision-making process (Hornsby & Blumberg, 2013).

Investment Decision

In the third stage, which represents the focus of this thesis, impact investors evaluate the information regarding the key investment parameters collected during the due diligence process. Consequently, to make an investment decision that closely aligns with their preferences, impact investors are required to make various trade-offs among such parameters (Hornsby & Blumberg, 2013).

Monitoring & Evaluation

The fourth stage corresponds to the post-investment activity of monitoring and evaluating that the investment made is actually having the intended effects, both from a financial and impact generation perspectives (Hornsby & Blumberg, 2013). Therefore, impact investors must continuously monitor and evaluate the soundness of their investment choice.

Reporting

Finally, within the fifth stage, impact investors are required to prepare their impact reports to the general public by applying the same standards of transparency and accountability that they expect from their investees (Hornsby & Blumberg, 2013). This final step is critical both from an investor and investee perspective because investors' impact results are based on the impact reports provided by their investees (Hornsby & Blumberg, 2013).

After having summarized the key points characterizing each stage of the impact investing process, it can be concluded that impact investing clearly takes a step further when compared to the traditional financial decision-making process (Hornsby & Blumberg, 2013). In fact, impact investors, during the *Investment Analysis* stage, are provided with relevant information not only regarding the financial risk/return profile of the investment, but also regarding the impact risk/return profile (Hornsby & Blumberg, 2013). Therefore, impact investors, during the *Investment Decision* stage, are required to integrate both financial and impact related dimensions within their investment-decision making process. For this reason, in the following sections, the researchers will firstly briefly introduce the traditional theory of financial decision-making. In this context, since a detailed analysis of the traditional financial decision-making model is beyond the scope of this thesis, the researchers will just focus on the most significant assumptions and key concepts. Secondly, the researchers will discuss how the traditional theory of financial decision-making is challenged through the lens of impact investing. Thirdly, the *Impact Investing Framework* formulated by Hornsby & Blumberg (2013) will be presented as the central frame of reference adopted within this study. Finally, since the thesis focuses on the *Investment Decision* stage of impact investing, the trade-offs among the four key parameters provided by the Impact Investing Framework adopted (i.e. Financial Return, Financial Risk, Impact Return and Impact Risk) will be analyzed.

2.1.4 The Traditional Risk-Return Framework of Financial Decision-Making

The traditional framework of financial decision-making is based on models and theories which describe, through a normative approach, how individual investors make investment choices (Baker & Ricciardi, 2014). In particular, the Traditional Finance theory has a normative rather than positive approach to the description of real-life decision-making processes. This means that such theory discusses how individual agents are supposed to make investment decisions, rather than describing how individuals actually make investments decisions (Baker & Ricciardi, 2014). In fact, according to Markowitz (1952), rational and self-interested investors should always maximize their utility by aiming for the highest possible risk-adjusted financial return. Thus, the two fundamental parameters to take into account during an investment decision are Financial Risk and Financial Return. The Traditional Finance theory also assumes that rational investors are risk-averse, meaning that although they dislike risk, they are willing to take it if they are adequately compensated (Booth *et al.*, 2016). However, Markowitz (1952) does not take into consideration the potential impact that an investment might have on the society and on the environment (Cosack & Bach, 2019). Thus, the Traditional Finance theory is focused purely on maximizing the Financial Return at a given level of Financial Risk without taking the impact dimension into account (Cosack & Bach, 2019). For this reason, the following paragraph will concentrate on the Impact Investing critique to the traditional financial decision-making framework.

2.1.5 The Impact Investing Critique to The Traditional Theory of Financial Decision-Making

The traditional (also known as "*neoclassical*") theory of financial decision-making is based on the assumption that individual decision-makers within the economies are self-interested individuals that act rationally (Ingersoll, 1987). However, two main critiques to this traditional framework have been developed: the Behavioral Finance critique and the Impact Investing critique. The former was developed during the 1980s (Illiashenko, 2017), whereas the latter, as previously mentioned (*see page 13*), was adopted during the 2000s (Harji & Jackson, 2012). For clarity reasons, while the Impact Investing critique to the Traditional Finance Framework will be analyzed in the following section, the Behavioral Finance critique will be further discussed within the *Behavioral Finance* part of this chapter (*see page 28*).

Impact investing, by supporting the duality of *"doing good while doing well"*, poses a challenge to the traditional finance assumptions. As more private investors are showing higher interest in allocating capital into investment opportunities that have a purpose or impact (Toronto Centre, 2019), there is additional evidence that the traditional finance view of a self-interested and unemotional investor is unrealistic (Godeke & Pomares, 2009). By choosing an investment option that allows them to simultaneously achieve a financial return while addressing a social or environmental challenge, the impact investing view shows that individuals present other traits, such as altruism (Godeke & Pomares, 2009). Consequently, considering the new assumption of altruism, which directs investors to generate not only financial profits but also social and environmental impact, a variety of new frameworks for financial decision-making have been developed. However, due to the limited scope of this thesis, the researchers will focus on the Impact Investing Framework formulated by Hornsby & Blumberg (2013). Thus, in the following sections, the researchers will outline the key components of such framework and, simultaneously, describe how it differs from other impact investing frameworks.

2.1.6 The Impact Investing Framework of Financial Decision-Making

As previously explained within the paragraph *The Stages of Impact Investing* (*see page 15*), during the impact investing financial decision-making process, both the impact and the financial side of the investment should be taken into account. Therefore, when considering impact investing, the traditional framework of financial decision-making, involving only the two parameters of Financial Risk and Financial Return, is no longer appropriate. The reason is that impact investors must consider two additional important parameters related to the positive impact they intend to generate in the world, namely Impact Return and Impact Risk (Hornsby & Blumberg, 2013). While the former indicates the "*impact that stands to be generated*", the latter refers to the "*risk that the impact will in fact not materialize*" (Hornsby & Blumberg, 2013). Therefore, while making an investment choice, impact investors consider the investment's financial risk/return profile as well as the impact risk/return one. For this reason, Hornsby & Blumberg (2013) formulated a theoretical *Impact Investing Framework* of financial decision-making, where impact investors have to consider four key parameters: *Financial Return, Financial Risk, Impact Return and Impact Risk*. Due to their novel nature, the two impact related parameters will be explained and critically discussed in the following sections. However, since both of these parameters are highly dependent on the *Impact Plan* of the enterprise that programmed the investment, the researchers will firstly focus on defining the key characteristics of this concept and, secondly, they will proceed to examine the notions of Impact Return and Impact Risk. By doing so, a more comprehensive and thorough understanding of the Impact Investing Framework selected can be attained. For clarity reasons, *Figure 3* below displays a brief graphical representation of the focus of this thesis.

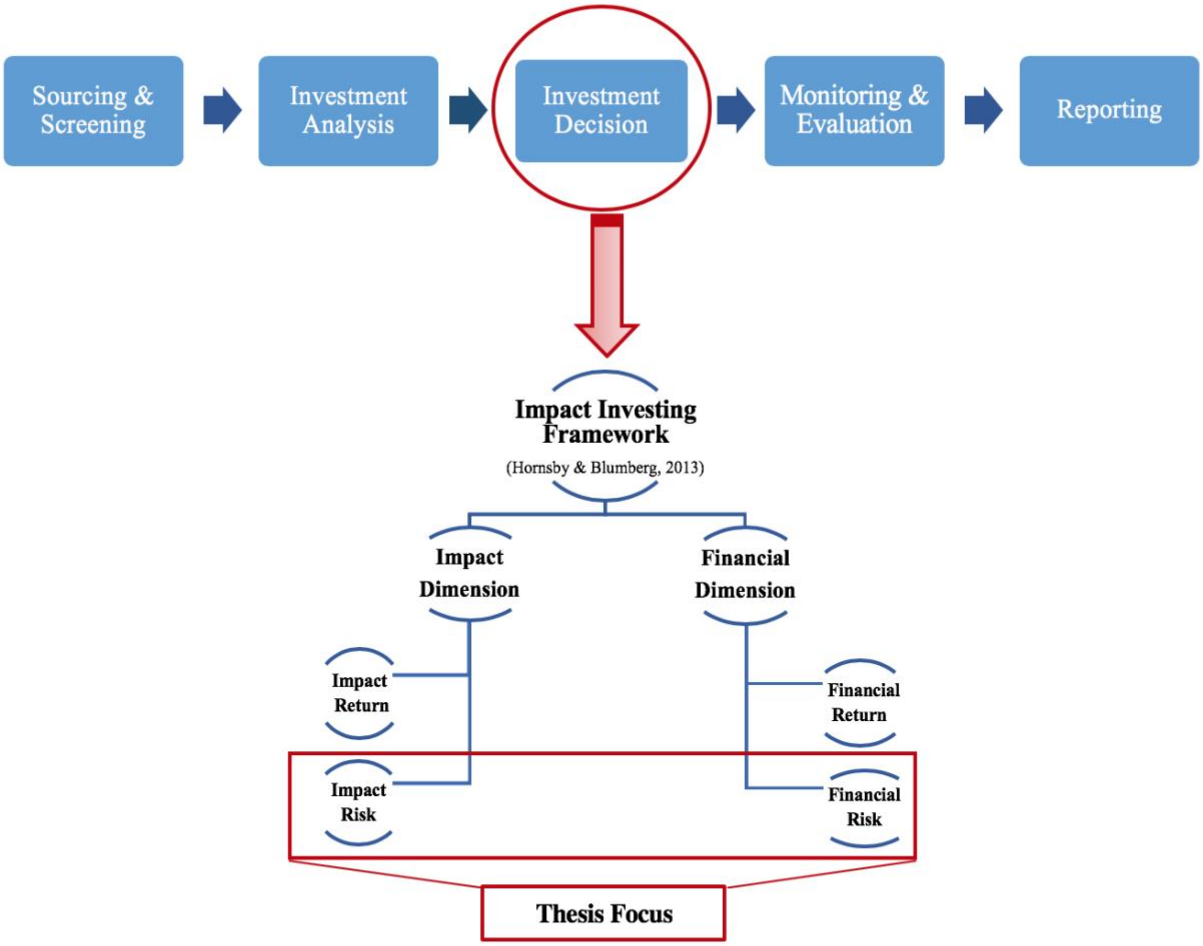

Figure 3 - The Focus of the Thesis

The Impact Plan

The *Impact Plan* is defined as *"a standardized form used to document an enterprise's intentionality in generating social or environmental benefits"* (Sirull & Thornley, 2013). In other words, the impact plan proposes a theory of change, meaning that it sets out the prospective impact that the investment intends to create in the future and how it will be generated (Hornsby & Blumberg, 2013). The impact plan includes three key components: **1)** the impact goals that the investment is seeking to achieve, **2)** a description of how the investment will generate the intended impact, and **3)** a discussion of the risks that may hinder the realization of the positive impact, or even lead to negative social or environmental consequences (Sirull & Thornley, 2013). Moreover, according to Hornsby & Blumberg (2013), the impact plan's validity depends on how effectively it has been designed. *Table 3* below describes the key qualities that an impact plan must display in order to be considered effective.

The Impact Plan	
Explicit	It involves ensuring that the impact plan displays: • Clarity • Concreteness • Completeness
Reasoned	It involves ensuring that the impact plan presents a compelling and well-reasoned theory of change.
Integral	It involves ensuring that the impact plan is integral to the organisation's business strategy. Therefore, potential tensions between impact-generating and revenue-generating activities are avoided.
Feasible	It involves ensuring that the organisation has the resources, capacity, skills and relevant experience to execute the plan.
Evidenced	It involves ensuring that there is evidence supporting the impact plan's approach to impact generation. Evidence may include: • Track record • Precedents • Research • Control group
Evidenceable	It involves ensuring that a robust impact measurement system is in place to produce evidence and demonstrate the impact generated by carrying out the impact plan.

Table 3 - The Key Qualities of the Impact Plan

The role of the impact plan within the impact investment process is essential because it influences the two key parameters of Impact Return and Impact Risk (Hornsby & Blumberg, 2013). In fact, on the one hand, the impact plan, by including precise impact goals, will delineate the type of Impact Return an investment will deliver in the future. On the other hand, the validity of the impact plan, which depends on how effectively it has been designed, influences Impact Risk (Hornsby & Blumberg, 2013). In the following paragraphs, each impact parameter is individually explained and critically analyzed.

Impact Return

Impact Return (also known as "*Impact Generation*") represents the potential for real change that the investment opportunity presents, or, in other words, "*the volume of impact that the investment proposes to generate*" (Hornsby & Blumberg, 2013). In principle, this theoretical definition can be translated into a more practical concept that connects to the notion of impact plan previously defined. Impact Return addresses the quantity of impact to be generated as a result of an impact investment, if the impact plan proves to be successful (Hornsby & Blumberg, 2013). In this sense, Impact Return can be associated to the impact equivalent of the Financial Return of an investment (Hornsby & Blumberg, 2013). However, while the Financial Return of an investment can be measured in monetary terms, Impact Return cannot be measured in a common fungible currency because, for example, social impact is conceptually and practically different from environmental impact (Addy *et al.*, 2019*)*. Therefore, it is virtually impossible to use a measure representing a common denominator for such a variety of effects (Hornsby & Blumberg, 2013). However, within the context of cleantech investments (focus of this thesis), although Impact Return cannot be calculated using a uniform and universally accepted fungible means, some general measurement standards can be applied. As explained at *page 14*, the most popular ones are the IRIS measurement standards, a set of standardized impact metrics indicators regarding both social and environmental performances, which allows the aggregation and comparison of data across investments (Narain *et al.*, 2012). Thus, for example, in the case of impact investing in carbon reduction technologies, Impact Return is the environmental impact that could be expressed as the *"amount of greenhouse gas emissions reduced"* (IRIS, 2020).

Furthermore, according to Hornsby & Blumberg (2013), while defining Impact Return, one should also distinguish the direct from the indirect nature of the impact generated by the investment. In this sense, three types of impact generation have been identified: **1)** *direct impact*, meaning the impact perceived by the beneficiaries mentioned in the impact plan and their immediate circle; **2)** *wider impact*, meaning the impact received by the community, the sector and the society at large; and **3)** *investor impact*, meaning the impact that investors and their capital have on the organization operationalizing the investment (Hornsby & Blumberg, 2013). Comparing these three types of impact, one can conclude that *direct impact* has a direct nature (as the name itself shows), whereas *wider impact* and *investor impact* have a more indirect nature and are generally too complex to be accurately measured (Hornsby & Blumberg, 2013). For this reason, the researchers will refer to Impact Return in its *direct* form.

Moreover, although the researchers have considered just one definition of Impact Return until now (Hornsby & Blumberg, 2013), the entirety of the streams of impact investing literature supports, with adequate limitations, such broad definition. Puttick & Ludlow (2012) describe Impact Return as the outcome of an investment that presents the potential for real change. Similarly, So & Staskevicius (2015), define it as the *"positive change in the society and environment generated by the investment"*. On another note, Allman & Escobar de Nogales (2015) indirectly formulate Impact Return as the positive consequences on society and environment at large ingrained in the business operations, products or services considered within the investment project. Lastly, Brest & Born (2013) divide the Impact Return parameter into three further parameters: *enterprise impact*, *investment impact*, and *non-monetary impact*. The enterprise impact, similar to the *direct impact* defined by Hornsby & Blumberg (2013), is the social value provided by the enterprise through the impact investment project. The investment impact, similar to the *wider impact* formulated by Hornsby & Blumberg (2013), is the investors financial contribution to the social value created by the project. Finally, the non-monetary impact, similarly to the *investor impact* designated by Hornsby & Blumberg (2013), is represented by the various contributions, besides cash, that the investors make to the project.

Concluding, although the impact investing literature cited in this paragraph represents a valuable contribution to the definition of Impact Return, one can observe that the definitions provided are not placed within a more general framework of financial decision-making. In other words, the definition of Impact Return formulated by Hornsby & Blumberg (2013) is the only example where the Impact Return parameter is recognized within a comprehensive framework for decision-making among impact investments. For this reason and for the sake of cohesiveness, the researchers will consider such definition as the most appropriate for the scope of the thesis.

Impact Risk

According to Hornsby & Blumberg (2013), the overall effectiveness of the impact plan will influence the *Impact Risk*, which represents the "*likelihood that the potential impact to be created fails and does not materialize*". Thus, if the Impact Return is the volume of impact that the investment proposes to generate, Impact Risk is the risk that such impact will not be achieved (Hornsby & Blumberg, 2013). In this sense, the impact plan represents a particularly important concept to define the Impact Risk of an investment. In fact, Impact Risk is the measure of the certainty (probability) that an investment *"will deliver on its proposed impact, as detailed in the impact plan"* (Hornsby & Blumberg, 2013). Hence, Impact Risk depends on the validity and effectiveness of the impact plan: the more effectively the impact plan is defined, the lower the Impact Risk will be. More precisely, as explained in the paragraph *Impact Plan* (*see Table 3*), the impact plan is valid only if it is explicit, reasoned, integral, feasible, evidenced and evidenceable (Hornsby & Blumberg, 2013). Therefore, if the impact plan of the investment taken into account satisfies all these characteristics, then the Impact Risk of such investment will be minimal. On the contrary, if the impact plan of the investment does not satisfy all these characteristics, the vice versa is true. For this reason, Impact Risk should be considered as a separate notion from Financial Risk (Hornsby & Blumberg, 2013). In fact, an investment may be sound financially and have a low Financial Risk but present a weak impact plan (due to e.g. weak mission, uncertain theory of change, low levels of evidence etc.) leading to a high Impact Risk. Conversely, an investment may present a very effective impact plan implying a low level of Impact Risk but exhibit financial weaknesses, thus leading to a high Financial Risk.

Although the conceptual separation between Impact Risk and Financial Risk formulated by Hornsby & Blumberg (2013) is largely accepted by the academic literature on impact investing, two main theoretical issues regarding the notion of Impact Risk can be recognized. The first problem is related to the definitional heterogeneity of such parameter. The second problem is associated to the academic debate over the idea that Impact Risk and Financial Risk should be considered as two conceptually and empirically different parameters.

The Definitional Heterogeneity of the Impact Risk Parameter

Although the concept of Impact Risk is relatively recent, the definitional landscape for this parameter is diverse and not cohesive due to its unquantifiable nature (Brandstatter & Lehner, 2016). In fact, within the impact investing literature, some definitions of Impact Risk present clear similarities with each other, while other authors propose very different interpretations. For example, similarly to Hornsby & Blumberg (2013), Godeke & Pomares (2009) define Impact Risk as the "*uncertainty of generating the intended impact*". Equivalently, Puttick & Ludlow (2013) delineate the term as the innovative concept that gives an "*indication of the certainty that an investment will lead to the stated impact*". Nicholls *et al.* (2015) provides a comparable definition, where the parameter is elaborated as "*the likelihood that a given allocation of capital will generate the expected social outcomes irrespective of any financial returns or losses*". However, unlike Godeke & Pomares (2009) and Puttick & Ludlow (2013), Nicholls *et al.* (2015) clearly state the uncorrelated nature of the financial dimensions of an investment from the impact ones. As explained above, this precise observation was formally and explicitly introduced by Hornsby & Blumberg (2013), who affirmed the independence between the parameters of Impact Risk and Financial Risk.

On another note, a different stream of impact investing literature presents a slightly divergent definition of such parameter. In fact, Geobey *et al.* (2012) delineate Impact Risk as the risk that *"interventions and investment practices might have negative social returns*". Similarly, Lehner (2016) explains that this parameter has not been fully conceptualized at present and that its definition ranges from the risk of obtaining "*negative societal impacts despite the well-intended investment motives*" to the uncertainty that the impact project "*fails to deliver*". Likewise, Laing *et al*. (2012) summarize Impact Risk as the risk that impact investments might alienate key stakeholders and compromise its impact plan. Thus, such risk can be considered as *"uncompensated"* as there is "*no increased expected return when exposed to this type of risk*" (Laing *et al*., 2012).

Overall, taking into account all these definitional elements, one can conclude that the definition stated by Hornsby & Blumberg (2013) should be taken as a frame of reference as it integrates the majority of the characteristics pointed out by the cited authors within the impact investing literature.

Impact Risk and Financial Risk as Separated Parameters

As mentioned in the paragraph above, Impact Risk and Financial Risk are considered as two separate parameters within the framework proposed by Hornsby & Blumberg (2013). However, while publications quoted in the previous paragraph see Impact and Financial Risk as two independent parameters (Puttick & Ludlow, 2013; Godeke & Pomares, 2009; Nicholls *et al.*, 2015), three other publications describe only one aggregate measure of risk. More precisely, both Emerson (2012) and Saltuk & El Idrissi (2012) propose a three-dimensional framework consisting of *Risk, Return, and Impact*. The approach adopted by these two academic publications is very similar.

Each decision-maker uses the three parameters just outlined to map a profile for each investment. All the three parameters are assessed within the due diligence process and the Risk parameter comprises several risk factors analyzed from a traditional finance and impact perspectives. Similarly, Laing *et al.* (2012) propose a financial decision-making framework with combined risks and combined returns. Thus, although the authors recognize that Impact Risk should be thought as separate concept (*see paragraph above*), they still propose a framework integrating the financial and impact returns in one combined return parameter and consolidating the financial and impact risks in one blended risk parameter (Laing *et al.,* 2012).
Concluding, although the majority of the impact investing literature considers Impact Risk and Financial Risk as stand-alone parameters, limited set of scholars still considers them as one unique parameter. However, the overall perception of practitioners is that impact investors should examine these two parameters separately when making an investment decision, but little effort has been deployed in empirically and quantitatively testing such idea (Brandstetter & Lehner, 2016). For this reason, the researchers selected this particular issue as a central topic within this thesis.

Concluding, the researchers decided to adopt the Hornsby & Blumberg (2013) Impact Investing Framework for financial decision-making due to three main motives:

- It offers a general definition of Impact Return, which is largely used among other impact investing practitioners and it places such parameter within a comprehensive financial decision-making framework;
- It provides a precise and integrated definition of Impact Risk;
- It considers the Impact Risk and Financial Risk parameters separately, allowing the researchers to conduct an empirical and quantitative test on these two essential concepts within impact investing.

To summarize, by adopting the Impact Investing Framework (Hornsby & Blumberg, 2013) when making an investment decision, impact investors have to consider four key parameters: the first two arising from the traditional framework of financial decision-making, and the other two from the impact investing field. They respectively are: **1)** Financial Return, **2)** Financial Risk, **3)** Impact Return, and **4)** Impact Risk. The final investment decision depends on impact investors looking at performance across these four parameters and finding the right balance among them, according to their personal investment preferences and attitudes towards risk (Hornsby & Blumberg, 2013). For this reason, in the following section the researchers will describe the most important trade-offs that impact investors have to consider during the *Investment Decision* stage of the impact investing process (*see page 16*).

2.1.7 Considerations on Parameters’ Trade-offs

Financial Return and Impact Return Trade-off

The most discussed trade-off is the one between Financial and Impact Return. In fact, regarding the well-know *“financial and impact return trade-off”,* two main streams of literature can be recognized. The first one is long-established and supports the idea that Financial Return comes at the expense of Impact Return and vice-versa (Brest & Born, 2013). The second one is more recent and promotes the opinion that a satisfactory Financial Return and Impact Return can be attained simultaneously, meaning that with true impact investing, no actual trade-off between these two kinds of returns should be made (Grabenwarter & Liechtenstein, 2011).

According to the first stream of impact investing literature, if the impact investor is not willing to sacrifice Financial Return, no significant social and environmental impact can be generated (Brest & Born, 2013). In fact, as demonstrated by Godeke and Pomares (2009), this statement is supported by the structural characteristics of sustainable investment projects themselves, whereby investments with a large return on the impact side cannot have a considerable financial return. As a consequence, the impact investing sector is “*stuck in a limbo*” (Evans, 2013) because impact investors need to decide on the trade-off between the financial and impact objectives when making an investment decision (Mitchell *et al.*, 2008). In other words, claiming a profit-maximizing behavior inevitably leads impact investors to drift away from Impact Return and concentrate on Financial Return (Bennick *et al.*, 2017).

In total discordance with the first stream of literature, other impact investing practitioners and scholars argue that there is no such thing as a trade-off between Impact Return and Financial Return (Grabenwarter & Liechtenstein, 2011). As empirically demonstrated by Grabenwarter & Liechtenstein (2011), investment projects that create an environmental and social impact do not imply the absence of healthy cash flows and thus, of significant financial returns (Bugg-Levine & Emerson, 2011). In this sense, the “*financial and impact return trade-off*” represents a “*myth*” in the investment space because it goes against the true definition of impact investing, which is the one of creating Financial Return along with Impact Return, not considering the generation of one at the expense of the other (Pandit & Tamhane, 2018). On this note, the clean technologies sector paved the way for this new way of communicating *“between what used to be two strictly segregated worlds”* (Grabenwarter & Liechtenstein, 2011). In fact, in the cleantech sector, the benefits for the environment and financial profitability can co-exist and be achieved simultaneously within the business model (Grabenwarter & Liechtenstein, 2011). As a result, Financial Return does not come at the expense of Impact Return and vice-versa. However, the main flaw in these arguments is that impact investors’ mindsets is not considered, meaning that their cognitive decision-making process and their preferences are not taken into account. As a consequence, although some impact investments (such as the ones in the cleantech sector) are actually structured in a way that could guarantee both a range of satisfying financial returns and valuable impact returns, investors' mindsets could still be wired with the old trade-off paradigm. Hence, this can represent an obstacle to the development of the impact investing sector, which cannot evolve if the individuals working in the sector itself still reason within this categorical mental trade-off between the Impact and the Financial Returns of investments (Grabenwarter & Liechtenstein, 2011). For these reasons, in this thesis, the researchers will consider that the investments' return will be placed somewhere within the area depicted in the graph on *Figure 4* below.

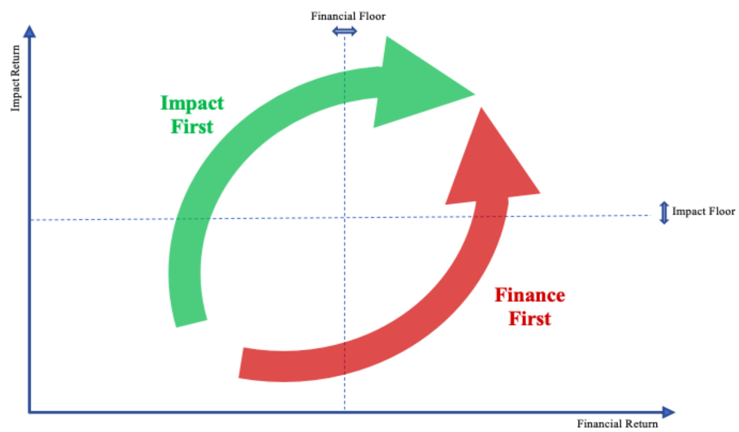

Figure 4 - Financial and Impact Returns Trade-Off

According to their preferences, impact investors can either have a "*financial floor*" or an "*impact floor*" by setting a required minimum level of respectively Financial Return or Impact Return (Hornsby & Blumberg, 2013). As previously noted, "Impact-First" investors will make more socially motivated investments which fall in the upper left area of the graph, while "Finance-First" investors will make more financially motivated investments which fall in the lower right area of the graph. Finally, the upper right area allows for a high Impact Return and high Financial Return combination, representing the best investment option (Hornsby & Blumberg, 2013).

Financial Risk/Return Trade-off and Impact Risk/Return Trade-off

Another largely discussed trade-off is the one between Financial Risk and Financial Return. As previously mentioned, the discussion about this trade-off belongs to the traditional risk and return framework of financial decision-making (*see page 17*). However, when considering impact investing, an additional trade-off must be considered, namely the one between Impact Risk and Impact Return generated. Thus, within the Impact Investing Framework, impact investors need to consider these two trade-offs simultaneously (Hornsby & Blumberg, 2013). Due to this added complexity, impact investing literature has documented that impact investors' show a more tolerant risk-attitude compared to traditional investors and that they are more willing to forego their compensation for the risk they are taking, which means that they tend to "*over-forgive*" risks (Lane, 2014; Emerson, 2012). Therefore, the researchers expect that impact investors show a more tolerant behavior towards risks. However, due to the limited empirical testing around the practical separation of Impact Risk from Financial Risk, no evidence has been reported for the existence of such risk-taking behavior in the context of the Financial Risk/Return trade-off and Impact Risk/Return trade-off, separately. Thus, by having a better understanding of the Impact Risk parameter, which represents a critical factor within impact investing, the researchers can contribute to the impact investing literature by shedding new light on impact investors' behavior towards this new dimension of risk and consequently provide a more comprehensive argument regarding these two trade-offs (Emerson, 2016).

Financial Risk and Impact Risk Trade-off

The last relevant trade-off that impact investors face during the *Investment Decision* stage is the one between Financial Risk and Impact Risk. What one can expect is that an investor will try to compensate a high level of Financial Risk with a low level of Impact Risk, and vice versa (Hornsby & Blumberg, 2013). However, given the relatively young concept of impact investing and the novel nature of Impact Risk, this trade-off has not been discussed within the literature. For this reason, by gaining knowledge about Impact Risk and Financial Risk within the Impact Investing Framework (Hornsby & Blumberg, 2013), the researchers can empirically test and further investigate whether a trade-off among the two dimensions of risk exist in reality and how impact investors balance them when making an investment decision.

To sum up, throughout this section of the *Literature Review* regarding impact investing, the researchers have identified two main areas needing further research. The first area is connected to the issue that scholars within impact investing have theorized around the conceptual separation between Impact Risk and Financial Risk, but no academic publication has empirically and quantitatively tested such conceptual division. For this reason, the researchers have adopted the theoretical framework of Hornsby & Blumberg (2013) as it will allow them to use the clear definitions of the four key parameters used by impact investors within their financial decision-making process: Financial Return, Financial Risk, Impact Return and Impact Risk. Consequently, the second area, which is connected to the first one, is associated to the trade-offs within the four parameters just mentioned. In this context, a better understanding of Impact Risk will shed more light on how impact investors balance their preferences between Impact Risk and Impact Return, as well as between Impact Risk and Financial Risk, during the investment decision-making stage.

In conclusion, impact investors are faced with complex investing decisions, where they are required to balance four key parameters simultaneously (i.e. Financial Return, Financial Risk, Impact Return, Impact Risk) and make trade-offs according to their personal preferences (Hornsby & Blumberg, 2013). More specifically, since investment decision-making within impact investing is characterized by such a complex framework, it is more appropriate to approach impact investing with a behavioral finance perspective, which takes into consideration human psychology and the *"not-so rational"* behavior of investors (*see page 8*). In fact, human psychology is considered to have a key role on decisions related to impact investing (Duiker *et al.*, 2016). In particular, the presence of the so-called *"cognitive biases"* within an individual's psychology, is relevant to the decision-making in the field of finance (Duiker *et al.*, 2016). While extensive research investigates how cognitive biases influence the preferences of regular investors, little research has been conducted to investigate how these mental processes influence impact investors (Duiker *et al*., 2016). Therefore, in the second part of this chapter, the researchers will outline the foundations of the Behavioral Finance theory. The focus will be directed to the overconfidence bias as scholars within Behavioral Finance identified such cognitive bias as the most relevant to explain investors' preferences and attitudes towards risk. For this reason, the researchers will use overconfidence to explain impact investors' behavior towards Financial Risk and, most importantly, towards the new risk dimension of Impact Risk.

2.2 A BEHAVIORAL FINANCE PERSPECTIVE ON INVESTMENT DECISION-MAKING

2.2.1 The Behavioral Critique to the Traditional Theory of Financial Decision-Making

As introduced in the previous part of this chapter, the Traditional Finance theory is based on four fundamental assumptions about agents facing an investment choice: **1)** economic agents are self-interested individuals; **2)** economic agents have rational preferences across possible outcomes or states of the world; **3)** economic agents maximize their utility in the face of their budget constraints and, **4)** economic agents make independent decisions based on all the relevant information (Ackert & Deaves, 2018). In other words, each individual agent acts as a *homo economicus* (Doucouliagos, 1994), who makes decisions in a rational way by maximizing his/her expected utility while having access to all the relevant information provided in the market. Moreover, in this "perfect world", there is no *uncertainty* about the future and agents should maximize their happiness given their degree of risk aversion, meaning the extent to which agents actually dislike *risk* (Ackert & Deaves, 2018). Despite the elegance of this framework, future decisions in real-life involve both *uncertainty* and *risk*. Uncertainty refers to a situation where investors are unaware of all the possible outcomes and they cannot assess their probabilities in advance (Wells, 1976), whereas risk refers to a situation where the decision-maker can evaluate all the outcomes and also associate probabilities to each one in advance (Wells, 1976). In other words, agents need to ponder both the *"known unknown"*, namely the risky outcomes, and the *"unknown unknown"*, namely the uncertain outcomes (Shiller, 2003). As a consequence, *rational choices* within this context may be difficult (Schettkat, 2018). In fact, according to Simon (1986), there are external and internal constraints when making a rational choice in an uncertain environment because rationality is, to some extent, bounded. This means that agents are not capable of gathering all the relevant information on all the alternative choices and, even in the case they were able to do so, they would not be capable of processing the large amount of information collected (Simon, 1986). That is why economic agents not only use *"cold calculations but also a mixed game of skill and chance*" (Keynes, 1937) when making an investment decision. In fact, to overcome complex and time-consuming investment decisions, investors frequently use mixed heuristics methods to simplify these processes (Kahneman, 2011). Thus, precisely because agents act using this mixed approach, it can be inferred that cognitive processes and psychology play an important role in the investment decision-making process. In particular, Kahneman (2011) defines the cognitive process including "*skill and chance*" as *System 1* and the cognitive process including "*cold calculations"* as *System 2*. More specifically, the author defines human behavior and human thinking as described by a dichotomy where System 1 represents traits of intuition, impulsive reactions, effortless heuristics as well as automatic responses, and System 2 represents deliberate reasoning, slow and controlled thinking as well as effortful cognitive processes. Due to the nature of the two systems, the automatic System 1 is more prone to judgment mistakes than the reflective System 2 (Kahneman, 2011). These systematic errors that System 1 experiences usually go under the more popular name of "*behavioral biases"*, which represent the study subjects of the relatively young field of Behavioral Finance. Developed in 1980s, Behavioral Finance incorporated the study of psychology into the analysis of financial decision-making (Illiashenko, 2017). Unlike the Neoclassical theories in which decision-making is based only on cold-headed logic, Behavioral Finance allows for agents' "*not-so rational*" behavior during the investment process. In this sense, the introduction of the behavioral critique to the traditional Finance Theory is revolutionary because it depicts financial decision-making under uncertainty through a descriptive/positive lens rather than through a normative one (Ackert & Deaves, 2018).

Concluding, Behavioral Finance provides insights into investor behavior where such behavior cannot be placed within traditional frameworks (Ackert & Deaves, 2018). Thus, as the intention of this thesis is to study impact investors' preferences throughout the complex process of investment decision-making, findings from behavioral finance appear to be the most appropriate to support this empirical research. In fact, on the one hand, the impact investing framework is based on the relaxation of the traditional assumption that investors are self-interested. On the other hand, the behavioral finance framework of investment decision-making is based on the relaxation to the traditional assumption that investors are rational. As a result, the researchers can conclude that integrating the former approach with the latter may provide a more realistic examination of the financial decision-making process in the context of impact investments.

2.2.2 Behavioral Biases in the Investment Decision-Making Process

As mentioned in the previous section, Behavioral Finance studies the individual process of investment decision through the lenses of human psychology (Baker & Ricciardi, 2014). More precisely, this field examines the mental processes and emotional issues that individuals, financial experts and traders reveal during the financial planning and the investment management process (Baker & Ricciardi, 2014). In other words, Behavioral Finance studies the so-called investor behavior when investors' decisions move away from the traditional definition of rationality. In fact, investors establish short-cuts and heuristics that, on the one hand, save time but, on the other hand, lead them away from rational long-term thinking (Baker & Ricciardi, 2014). Given the large number of behavioral biases present in the literature of Behavioral Finance, the researchers will provide a concise overview only over the most relevant ones in *Table 4* below. Thereafter, to better address the scope of this thesis (*see page 8*), the researchers will briefly introduce the overconfidence bias, which will be further discussed in the next section.

Behavioural Biases	Source	Description
Representativeness	Bar-Hillel (1984); Kahneman & Tversky (1972); Baker & Ricciardi (2014)	Investors display a representativeness bias when they judge the probability of a sample by how well it represents certain salient features of the population from which it was drawn. This bias is exemplified when investors expect samples to be highly representative of their parent population.
Loss Aversion	Kahneman & Tversky (1972); McGarvey (2018)	The bias of loss aversion is highly documented in the Behavioural Finance literature and it was first introduced by Kahneman & Tversky's Prospect Theory in 1972. This bias is displayed when investors have a tendency to be more sensitive to reductions in their levels of wellbeing than to relative increases.
Herding Behaviour	Grinblatt *et al.* (1995); Lakonishok *et al.* (1992); Warmers (1999)	The bias is displayed when investors follow the decision of a large group of noise traders rather than making decisions based on their personal analysis. The main implication of this bias is connected to a reduction in the dispersion and a simultaneous increase in the mean of the distribution of project earnings forecasts designed by investors. This ultimately leads to high inaccuracy in published earnings estimates. As a consequence, investors will mistake the reduced dispersion of the project returns for reduced project risk and, thus, they will be more optimistic towards the future returns of the project itself.
Home Bias	Kumar & Goyal (2014); Trautmann *et al.* (2008); Dimmock *et al.*, (2016)	The home bias is displayed when investors prefer to invest in domestic projects rather than foreign ones. The bias is mainly caused by investors generally showing aversion to ambiguity. In principle, in decisions made under uncertainty, investors prefer assets involving clear probabilities (risk) to assets involving vague probabilities (ambiguity). Thus, investors invest in local rather than foreign projects because investing in projects located in the country where the investor belongs is experienced by them as a displaying lower ambiguity. The home bias can have harmful consequences as it causes a decline in risk diversification in projects and financial portfolios of investors.

Table 4 - Behavioral Biases Overview

The Overconfidence Bias

Overconfidence is a well-established bias that makes investors being too confident about their knowledge and skills and more willing to take risks associated to investments, even when they are not accordingly compensated for it (Kumar & Goyal, 2015). As a consequence, overconfidence leads investors to display excessive trading tendencies and risk-taking behavior (Odean, 1998), which usually leads to underperformance and realized gains that do not cover transaction costs of the investment deals (Barber & Odean, 2000; Barber & Odean, 2001).

Summing up, although the researchers presented the most relevant behavioral biases affecting investors during the investment decision-making process, in reality, a much larger and diverse set of biases exists (Ackert & Deaves, 2018). However, due to the limited scope of the research project and due to the focus of the thesis on impact investors' preferences for Impact Risk and Financial Risk, the researchers will concentrate only on the overconfidence bias as it plays an important role in influencing risk preferences. Hence, the next section will discuss in detail the nature of such bias and the implications of this heuristic on the investment decision-making process.

2.2.3 Overconfidence Bias and its Implications

Differences Between Overconfidence and Optimism

Before diving into the details regarding the effects of overconfidence on investors' decisions, it is important to understand what overconfidence formally is and how it can be distinguished from the related concept optimism (Ackert & Deaves, 2018). For clarity reasons, an example is presented. If a *rational*, *optimistic* and *overconfident* investors are asked the following question: *"what will be the return of a green bond in the next month?"*, their answer will respectively be related to *Figures 5, 6* and *7* below:

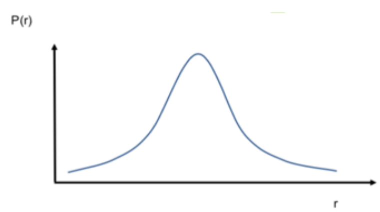

Figure 7 – Rational Investor

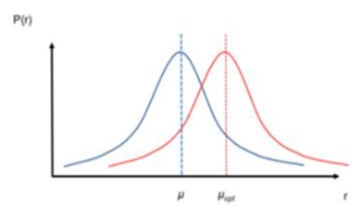

Figure 5 – Optimistic Investor

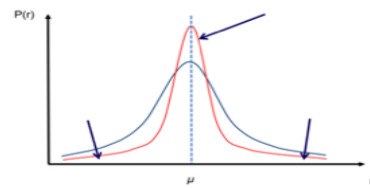

Figure 6 - Overconfident Investor

Figure 5, 6 and *7* represent the subjective probability distributions of the three investors over a probability space continuous in r, which is the return of the green bond over the next month. In principle, the investors attach a subjective probability to the different potential returns of the green bond. In *Figure 5*, since the investor is rational, the subjective probability distribution coincides with the objective probability distribution of the returns. Differently, in *Figure 6*, the red subjective probability distribution of the optimistic investor, compared to the objective probability distribution of the rational investor (blue curve), is shifted to the right. As a result, the mean return of the distribution μ_{opt} of the optimistic investor is higher than the mean μ of the rational investor. Thus, the subjective probability of each return happening in the world of the optimistic investor is higher compared to the subjective probability felt by the rational investor (Ackert & Deaves, 2018). Lastly, in *Figure 7*, the red subjective probability distribution of the overconfident agent, compared to the objective probability distribution of the rational investor (blue curve), is flatter at the extremes, but higher in correspondence to the mean of the distribution. Hence, overconfidence consists in the intuition that obtaining the average is more likely than it actually is, although the mean expected value does not change (Ackert & Deaves, 2018). The reason is that an overconfident agent shows a tendency to overestimate the probability of achieving the average outcome as a result of a presumptuous belief in his/her abilities to bring about that particular outcome (Fabre & Heude, 2009).

In conclusion, on the one hand, optimism is the tendency to perceive an event as more likely to result in a favorable outcome, irrespective of the objective probability of that outcome actually occurring. On the other hand, overconfidence is the tendency to overestimate the probability of achieving one's objectives as a result of a presumptuous belief in one's abilities to bring about a particular outcome. In other words, an optimistic investor will have an unrealistic expectation of the probability of obtaining a positive result, whereas an overconfident investor believes that he/she has a better judgment ability than what is actually true.

The Three Types of Overconfidence

Literature about overconfidence defines this behavioral bias in diverse ways. In fact, according to empirical tests over agents, overconfidence can take three different shapes (*Figure 8* below), which are empirically and conceptually different (Moore & Healy, 2008).

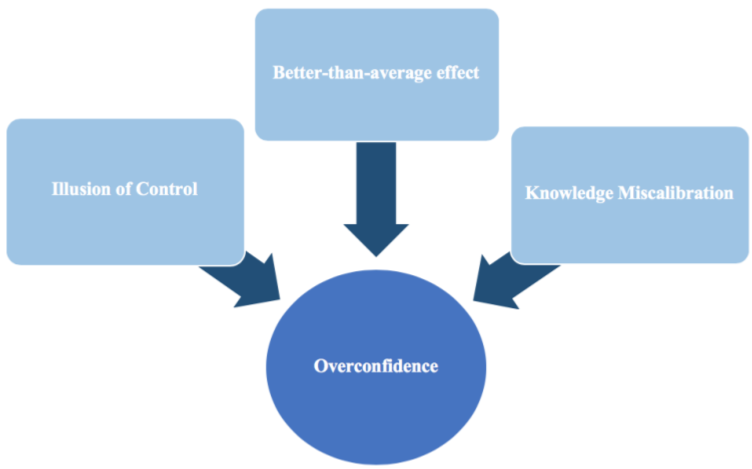

Figure 8 - The Three Types of Overconfidence

The first type of overconfidence can be defined as the overestimation of one's actual performance, abilities, level of control, or chances of success (Moore & Healy, 2008). This kind of overconfidence derives from the *illusion of control* that agents tend to have over events (Langer, 1975). In general, agents believe they have more control over events than objectively can be true. For example, a manager can influence the performance and the stock returns of his/her own company through his/her decisions. Thus, when asked about the range of return of its company stocks, he/she will give a very smaller range of possible future returns compared to an outsider analyst. The reason is that he/she is likely to be overconfident over his abilities to predict the returns and influence them through his/her own decisions (Ackert & Deaves, 2018).

The second type of overconfidence can be defined as the overplacement of one's performance relative to others (Moore & Healy, 2008). In principle, agents believe that they are better than others, such as when people rate themselves better than the median. This kind of overconfidence is called *better-than-average effect* (Svenson, 1981; Taylor & Brown, 1988), whereby agents have the tendency to think that their abilities and knowledge are superior compared to the average (Ackert & Deaves, 2018).

The third type of overconfidence is *miscalibration*. This type of overconfidence occurs when agents overestimate the precision of their knowledge and their abilities (Moore & Healy, 2008). Because of the nature of this bias, overconfidence expressed in the form of miscalibration has a negative impact on the cognitive ability to make a financial decision because the investor is basing his/her own decisions on a mistaken perception of the precision of his own knowledge regarding the investment material (Mandell, 2004).

Concluding, overconfidence can take different forms and due to its diverse nature, it is very situation-specific. Because of this, there are several factors that affect the overconfidence displayed by investors. In the following paragraph, external factors that influence the intensity of overconfidence are outlined and connected to the behavior of investors.

Exogenous Factors Affecting the Intensity of Overconfidence

There are several factors affecting the intensity of the overconfidence bias on the decision-making process of investors, namely **1)** the hard/easy nature of the decision that needs to be taken; **2)** the extent of control over the future events; **3)** the level of expertise and the age of the agent; **4)** the amount of feedback received during and after the decision-making process; and **5)** the gender of the individual decision-maker.

The Effect of Hard Versus Easy Tasks

According to Moore & Healy (2008) and Lichtenstein *et al.* (1981), overconfidence increases with the increase in the difficulty of the decision task presented to the investor. The reason is that, when an agent is asked to make a decision over tasks that are presented as difficult, he/she will tend to display a higher intensity of overconfidence precisely because of the hard nature of the decision that has to be made. Thus, the opposite happens when tasks are easy. However, Moore & Healy (2008) also showed that within difficult tasks, agents tend to overestimate their actual knowledge but also mistakenly believe that they are worse than others, meaning that there is a less intense better-than-average effect. Simultaneously, within easy tasks, agents and investors underestimate their actual knowledge but mistakenly believe that they are better than others, meaning that there is a more intense better-than-average effect.

Control Over Events

According to what it was concluded in the section *Types of overconfidence*, the more the agents believe that they might have partial - if not total - control over events, the higher will be the intensity of the overconfidence bias displayed by those agents. In other words, the larger the illusion of control, the more intense the overconfidence (Ackert & Deaves, 2018).

The Effect of the Years of Expertise and Age

Several studies have examined how the level of expertise, in terms of number of years of experience or practice, influences decision making (Newell & Simon, 1972; Shanteau, 1992; Anderson, 2004). In particular, evidence confirmed that experts in the financial sector seldom outperform novices with less expertise in the same sector (Bedard *et al.*, 1993). In parallel, studies relating to overconfidence used this previous research to show that experts, when compared to novices, are more prone to overconfidence in their decision-making process within the financial markets (Lambert *et al.*, 2012). Thus, Lambert *et al.* (2012) define the variable "years of experience" as a good proxy for overconfidence. Connecting the two streams of findings, research from Lambert *et al.* (2012) shows that the higher the level of expertise, the more individuals tend to be overconfident, leading to underperformance. The reason is that overconfident experts show a higher risk-seeking attitude compared to novices in the financial sector, leading them to take unjustified risks without being accordingly compensated (Mishra & Metilda, 2015). Thus, according to Mishra & Metilda (2015), this chain of events will lead experts to seldom overperform the novices in the long run. Furthermore, linked to the academic research that combines the effect of the years of expertise to experts' overconfidence, Bruine de Bruin *et al.* (2012) suggest that in demanding jobs, such as being an investor, older adults are more overconfident than younger adults. This finding was previously affirmed by Crawford & Stankov (1996) and further confirmed by the empirical proof of Ho *et al*. (2016), who also used the variable "age" as a proxy for overconfidence. Concluding, the older the investor and the more years of experience he/she accumulates, the more overconfident he/she should be.

The Effect of Receiving Feedback

Literature about overconfidence has shown evidence that as the level of feedback given on individual performance increases, the intensity of individuals' overconfidence decreases (Pulford & Colman, 1997). More precisely, Lichtenstein *et al.* (1981) tested that the miscalibration effect, and thus overconfidence, was reduced by giving the individual agents very detailed instructions regarding the accuracy of their answers and by providing subjects extensive feedback on these factors. On the same note, Arkes *et al.* (1987) proved that, by giving feedback on the correctness of the answers rather than their accuracy, the intensity of overconfidence of the individuals receiving feedback was lower than the control group, which did not receive any.

The Effect of Gender

Demographic research around overconfidence showed that males seem to be more overconfident than females (Prasad & Mohta, 2012; Bhandari & Deaves, 2006; Mishra & Metilda, 2015). More specifically, account data collected from brokerage firms showed that due to higher overconfidence levels associated to male gender individuals, men trade 45% more than women (Barber & Odean, 2001). As a consequence, this behavior reduces male portfolio performance in the financial markets by 2.65% per year as opposed to a reduction of 1.72% per year for women (Barber & Odean, 2001). Thus, overall not only men are more overconfident than women, but also they trade more excessively because of their risk-loving attitude (Barber & Odean, 2001). For this reason, Barber & Odean (2001) used the variable "male gender" as a proxy for overconfidence.

A brief graphical overview of the factors affecting the intensity of overconfidence can be observed in *Figure 9* below.

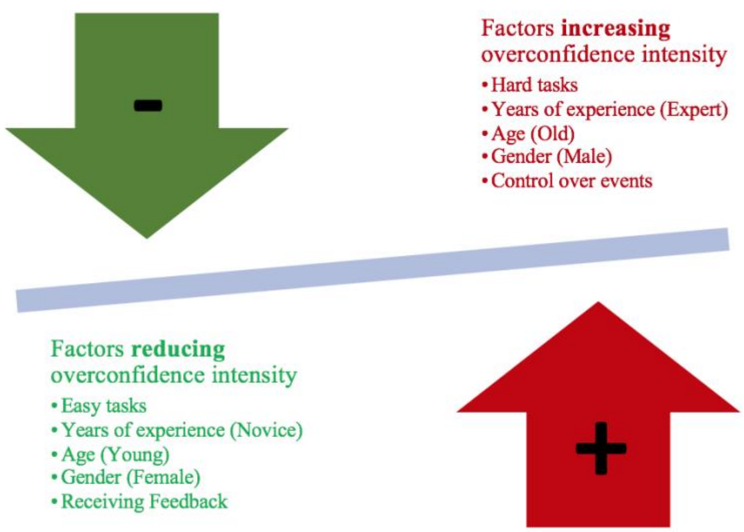

Figure 9 - Factors Affecting Overconfidence Intensity

After having determined the factors that affect the intensity of investors' overconfidence, research shows a lack of insights regarding how this behavioral bias could be connected to and affect impact investors (Duiker *et al.*, 2016). In fact, the overconfidence bias and its effects are particularly relevant in impact investing because, as opposite to traditional investing:

- Impact investors face *harder investment tasks* due to the additional impact parameters (i.e. Impact Return and Risk) to be taken into consideration while facing the process of financial decision-making (Duiker *et al.*, 2016);
- Impact investors can exercise a *high degree of control* and oversight over the deployment of capital to cleantech projects (Ministry of Foreign Affairs of Denmark, 2018);
- Impact investors are provided with *little precise feedback* on their financial and impact performance due to the novelty and mostly untested nature of investment criteria (O' Flynn & Barnett, 2017);
- Impact investors have to develop *high levels of expertise* not only in the financial sector but also in the impact specific sector they intend to invest in (Clavier & Malhotra, 2017);
- The impact investing sector, in similarity with the traditional finance sector, is mostly *dominated by the male gender* (Simon, 2018).

Considering all these factors, analyzing the overconfidence bias among impact investors is deemed to be particularly relevant. In order to explain the relevance of overconfidence among impact investors even further, in the next paragraph, the researchers will explain the reasons why this bias is so common and why it perpetuates overtime through the actions of the investor.

The Widespread Nature of Overconfidence

Among all the behavioral biases affecting investors, overconfidence is documented as the most common cognitive bias (Gervais & Odean, 2015). It is believed that investors possess three main behavioral traits that contribute to the longevity of overconfidence: the *self-attribution bias*, the *hindsight bias* and the *confirmation bias* (Bradley, 1978; Roese & Vohs, 2012; Nickerson, 1998). Firstly, the self-attribution bias is a cognitive phenomenon whereby agents tend to attribute success to innate aspects (e.g. talent or foresight) and attribute failures to situational factors (Bradley, 1978). Through the self-attribution bias, investors "learn" to be overconfident (Gervais & Odean, 2001) because agents learn asymmetrically from good and bad events: if the event is positive then agents will think that the positivity of the event was stirred by their ability, whereas, if the event is negative, then agents will think that it was because of bad luck (Kuhnen, 2015). For this reason, self-attribution causes individuals to learn to be overconfident, leading the intensity of the overconfidence bias to increase, rather than converge to an accurate knowledge self-assessment (Mishra & Metilda, 2015). Secondly, Granhag *et al.* (2000) affirm that another behavioral trait related to overconfidence is the hindsight bias. In fact, according to the authors, the hindsight bias occurs when people feel that they "knew it all along", meaning they believe that an event is more predictable after it becomes known than it was before it became known. This bias leads to agents' overconfidence because it affects one's ability to make sound judgments (Roese & Vohs, 2012). Thus, the larger the hindsight effect, the more the investor is going to be overconfident of his/her own abilities in retrospect. Lastly, the third behavioral bias contributing to the longevity of overconfidence is the confirmation bias occurring when the agent presents the tendency to interpret new evidence as confirmation of his/her own existing beliefs or theories (Nickerson, 1998). Precisely because the confirmation bias affects the interpretation of information by creating an "*illusion of knowledge*" (Park *et al.*, 2010; Barber & Odean, 2001), this bias is a key factor driving investors' overconfidence (Park *et al.*, 2010; Daniel *et al.*, 1998). In practice, as investors reinforce their prior beliefs through the confirmation bias, they will ultimately believe that they are more knowledgeable than they actually are, thus being more overconfident.

After having explained the nature of the three behavioral traits contributing to the longevity of the overconfidence bias, the final paragraph of this section will focus on the practical implications of overconfidence on the investment strategy. It is also worth underlining that, in previous paragraphs, the researchers already briefly identified some of the documented effects of overconfidence on investors' behavior. However, in the following paragraph, such effects will be described from a holistic perspective.

The Implications of Overconfidence on the Financial Decision-Making Process

Overconfidence is a common bias among different categories of professional investors including fund managers, analysts and investment advisors/consultants (Moore & Healy, 2008; Menkhoff *et al.*, 2006; Torngren & Montgomery, 2004). Due to the longevity and diffused nature of this bias, many empirical studies have been focusing on the financial performance implications of overconfidence within the investment sector. Overconfidence not only leads to excessive trading (Odean, 1999; Barber & Odean, 2001; Glaser & Weber, 2007; Deaves *et al.*, 2006), but also to a higher risk-taking behavior (Broihanne *et al.*, 2014) leading to underperformance and realized gains that do not cover transaction costs of the investment deals (Barber & Odean, 2000; Barber & Odean, 2001). As a result, the more overconfident the investor, the more likely he/she will choose high-risk investment prospects, even when not being accordingly compensated for it (Barber & Odean, 2001). Similarly, according to Nosić & Weber (2010), overconfidence and risk perception have a positive effect on the risk-taking behavior of individual investors. Aside from excessive trading activity, additional consequences of overconfidence

that have been extensively documented are an excessive volatility in markets (Daniel *et al.*, 1998; Gervais & Odean, 2001) and a combined phenomenon of underreaction and overreaction to information (Daniel & Titman, 1999; Daniel *et al.*, 1998; Glaser & Weber, 2007; Lee & Swaminathan, 2000).
By combining this large set of theoretical models that explain the effects of the overconfidence bias on the financial decision-making process of investors, it can be concluded that not only behavioral finance literature on overconfidence agrees on defining overconfident investors as more likely to possess risky portfolios than rational ones, but also it agrees that this risk-taking behavior results in under-diversified portfolios and investment decisions (Lambert *et al.*, 2012). Additionally, this kind of under-diversified investment decisions will lead to a lower performance level compared to the one of rational investors (Lambert *et al.*, 2012).

Concluding, since investors displaying overconfidence about their abilities to evaluate potential investment projects also display an increased risk-taking behavior, it can be deduced that impact investors will display the same biased pattern when making an investment decision. In other words, in the context of impact investing, it can be assumed that overconfident impact investors will prefer riskier investment prospects, compared to rational impact investors.

2.2.4 A Concluding Remark: The Choice of Miscalibration

Before moving to the third and last part of the *Literature Review* chapter, it is worthwhile mentioning that although the behavioral finance literature identifies three types of overconfidence, namely illusion of control, better-than-average effect and knowledge miscalibration (*see page 33*), this research project will concentrate only on *knowledge miscalibration*. The fundamental reason behind such choice is that the illusion of control and better-than-average effect are very ethereal concepts and are difficult to operationalize in terms of precise proxies (Ackert & Deaves, 2018). Therefore, as explained by Michailova *et al.*, (2017), concentrating only on the miscalibration bias will allow the researchers to avoid the reliance on such imperfect measurements for overconfidence. The *Methodology* chapter will discuss more about the technical nature of the miscalibration bias and how it can be measured through the Calibration Test.

To sum up, throughout this section of the *Literature Review* regarding behavioral finance, the researchers have firstly explained the main assumptions behind the behavioral critique to traditional theory of financial decision-making. Secondly, by focusing on the most relevant cognitive biases that might be encountered during the investment decision, the researchers aimed their attention at the overconfidence bias. Consequently, the researchers proceeded with defining the overconfidence bias as formally separated from the related concept of the optimism bias. Thereafter, although the researchers will concentrate on overconfidence as approximated by miscalibration, the three types of overconfidence were outlined. Additionally, the researchers focused on the factors affecting the intensity of the overconfidence bias and its widespread nature. Lastly, the implications of the overconfidence bias on the investors' financial decision-making process were presented.

In the next final section, the researchers will integrate the insights gathered from the impact investing and behavioral finance literature previously discussed to present the comprehensive theoretical framework that will be adopted throughout the thesis.

2.3 AN INTEGRATED THEORETICAL FRAMEWORK FOR IMPACT INVESTING

Given the scope of this thesis, the researchers have opted for a comprehensive theoretical framework integrating insights from the impact investing literature and the behavioral finance perspective. The motive behind such choice is twofold. On the one hand, the researchers will be able to adopt the Impact Investing Framework formulated by Hornsby & Blumberg (2013) to empirically test the conceptual separation between Impact Risk and Financial Risk (*see page 23*). On the other hand, the researchers will be able to explore the impact investors' risk-tolerant attitude documented by the literature (*see page 26*). In fact, given the complex cognitive nature of the impact investing financial decision-making process, where investors need to balance the impact and financial side of risks and returns, behavioral considerations will provide a more appropriate representation of the investment decision-making reality (Duiker *et al.*, 2016). For this reason, among all the heuristics used by impact investors to facilitate their complex investment decision-making processes, the overconfidence bias can be considered as the most relevant to explain their risk-taking attitude (Ackert & Deaves, 2018). This reasoning is supported by the main assumption, provided by the behavioral finance literature, that overconfident traditional investors will be more willing to take higher Financial Risk (Barber & Odean, 2001). Therefore, the researchers expect that a similar reasoning can be applied to impact investors. However, given that impact investors have to consider an additional dimension of risk, i.e. Impact Risk, the researchers expect that overconfident impact investors will be more willing to take up not only higher Financial Risk but also higher Impact Risk. Therefore, by interacting the risk parameters of the Impact Investing Framework formulated by Hornsby & Blumberg (2013) with the new behavioral variable of the overconfidence bias, the researchers will be able to:

1. Address the need for an empirical test confirming the conceptual separation between the parameters of Impact Risk and Financial Risk within the context of impact investing;
2. Investigate whether impact investors show the overconfidence bias while facing the investment decision-making process;
3. Examine whether the overconfidence bias explains the impact investors tolerance for not only for Financial Risk but also for the new parameter of Impact Risk.

A graphical representation of the integrated theoretical framework adopted by the researchers can be observed in *Figure 10* below:

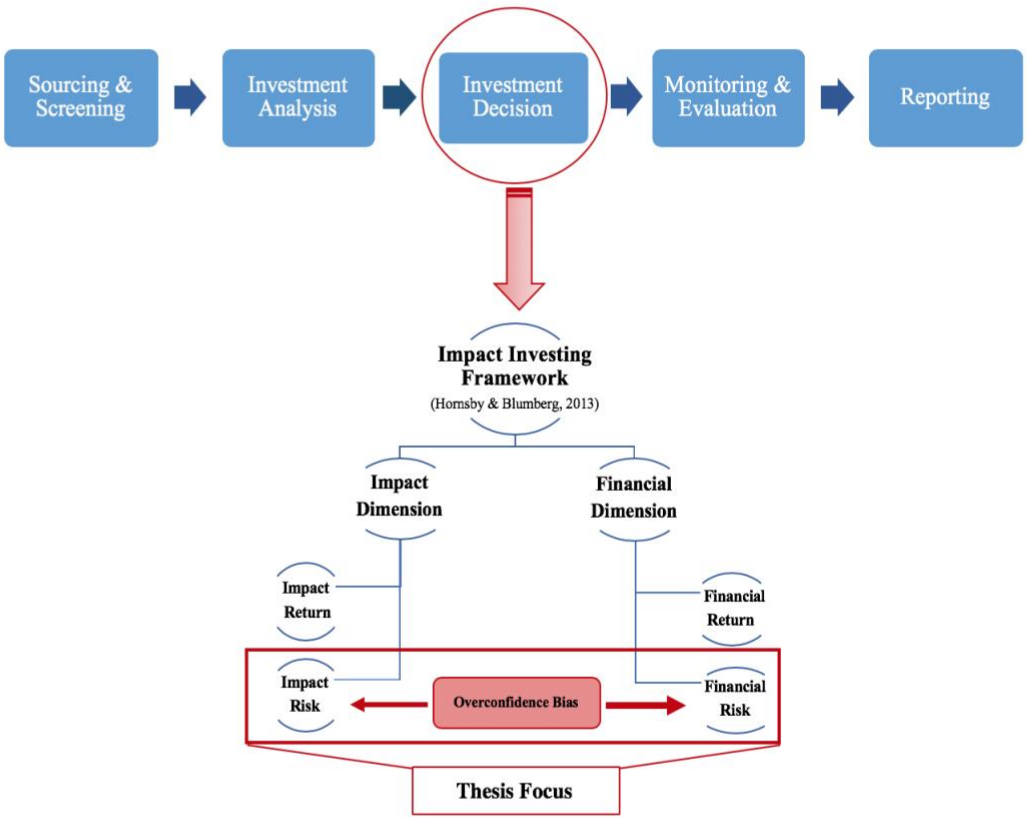

Figure 10 - Integrated Theoretical Impact Investing Framework

Concluding, by empirically applying the integrated theoretical framework for impact investing just presented, the researcher will be able to address the research questions formulated in the next chapter.

CHAPTER 3 - RESEARCH QUESTIONS AND RELATIVE HYPOTHESES

Following the theoretical background provided in the *Literature Review*, the purpose of this chapter is to outline the research questions and the relative hypotheses addressed within this study.

Throughout the first part of the *Literature Review* chapter on impact investing, by adopting the Impact Investing Framework proposed by Hornsby and Blumberg (2013), the researchers identified four key parameters characterizing impact investments: Financial Return, Financial Risk, Impact Return and Impact Risk. Although the impact investing literature defined Impact Risk as a conceptually different parameter from Financial Risk, this separation has never been empirically tested. As a result, the first research question addresses whether Impact Risk is considered as an important factor within the investment decision-making process, meaning that it is perceived as a separated concept from the traditional Financial Risk. The researchers expect that Impact Risk represents a relevant factor for impact investors during the investment decision-making process, underlying the fact that it is actually considered separately from Financial Risk. More precisely, the researchers expect that impact investors' choices will be negatively affected by Impact Risk within the investment decision-making process. As a result, the first research question and its relative hypothesis are formulated as follows:

Research Question 1 (Q1): ***Do impact investors consider Impact Risk as an important factor within the investment decision-making process?***

Hypothesis 1 (H1): *Higher Impact Risk negatively influences impact investors' choices within the investment decision-making process.*

The second research question introduces the behavioral finance perspective and tries to detect whether impact investors are overestimating the precision of their knowledge, hence are overconfident in terms of miscalibration. The overconfidence bias has been investigated thoroughly and it is considered one of the most common bias among traditional investors. Given the common nature of the bias, the researchers expect that impact investors are not considered an exception when it comes to overconfidence. However, no empirical research has been conducted to confirm whether this cognitive bias is actually present among impact investors. As a result, the second research question and its relative hypothesis are formulated as follows:

Research Question 2 (RQ2): ***Are impact investors overestimating the precision of their knowledge? In other words, are impact investors on average overconfident?***
Hypothesis 2 (H2): *Impact investors, on average, overestimate the precision of their knowledge.*

The third research question investigates whether the presence of the overconfidence bias within impact investors influences their tolerant risk attitude and, in turn, their investment choices. In particular, according to the theoretical background provided within the *Literature Review* chapter, overconfident traditional investors prefer investment prospects with a higher Financial Risk. Given that impact investors have to consider an additional dimension of risk related to the impact they generate (i.e. Impact Risk), the researchers expect that overconfident impact investors will be more willing to choose investments displaying a high Impact and Financial Risk, compared to non-overconfident impact investors. As a result, the third research question and its relative hypothesis are formulated as follows:

Research Questions 3 (RQ3): **Are impact investors' preferences for risk affected by the overconfidence bias?**
Hypothesis 3a (H3a): *Overconfident impact investors are more willing to choose investments displaying a high Impact Risk, compared to non-overconfident impact investors.*
Hypothesis 3b (H3b): *Overconfident impact investors are more willing to choose investments displaying a high Financial Risk, compared to non-overconfident impact investors.*

To sum up, *Figure 11* below represents the *conceptual model* of the research, which provides a clear image on how the research questions will be answered. The four parameters derived from the Impact Investing Framework formulated by Hornsby & Blumberg (2013) represent the independent variables that influence impact investors' choice of impact investment profiles, which represent the dependent variable. Moreover, the overconfidence bias is analyzed to detect how it affects impact investors' preferences towards the two risk parameters (i.e. Impact Risk and Financial Risk).

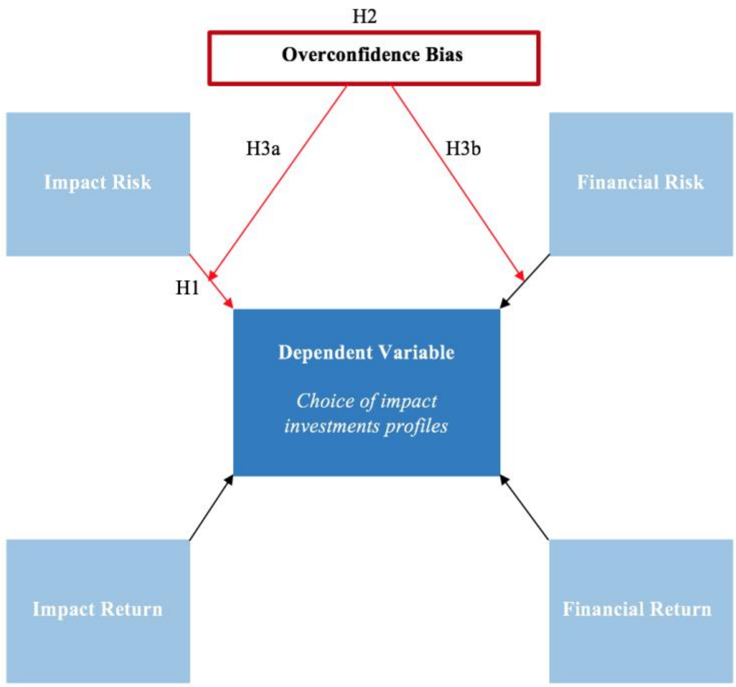

Figure 11 - The Conceptual Model

In the next chapter, the researchers will explain how they operationalize such research intends using a coherent methodological framework.

CHAPTER 4 - METHODOLOGY

In order to provide a more detailed description of the stages involved in the research process, the researchers refer to *Figure 12* below showing the *"Research Onion"* proposed by Saunders *et al.* (2016). In the following sections, by starting from the outer layer and proceeding towards the inner one, the researchers will outline the research methodology that has been adopted to address the research questions. Lastly, the researchers will address the reliability and validity of the selected methodology.

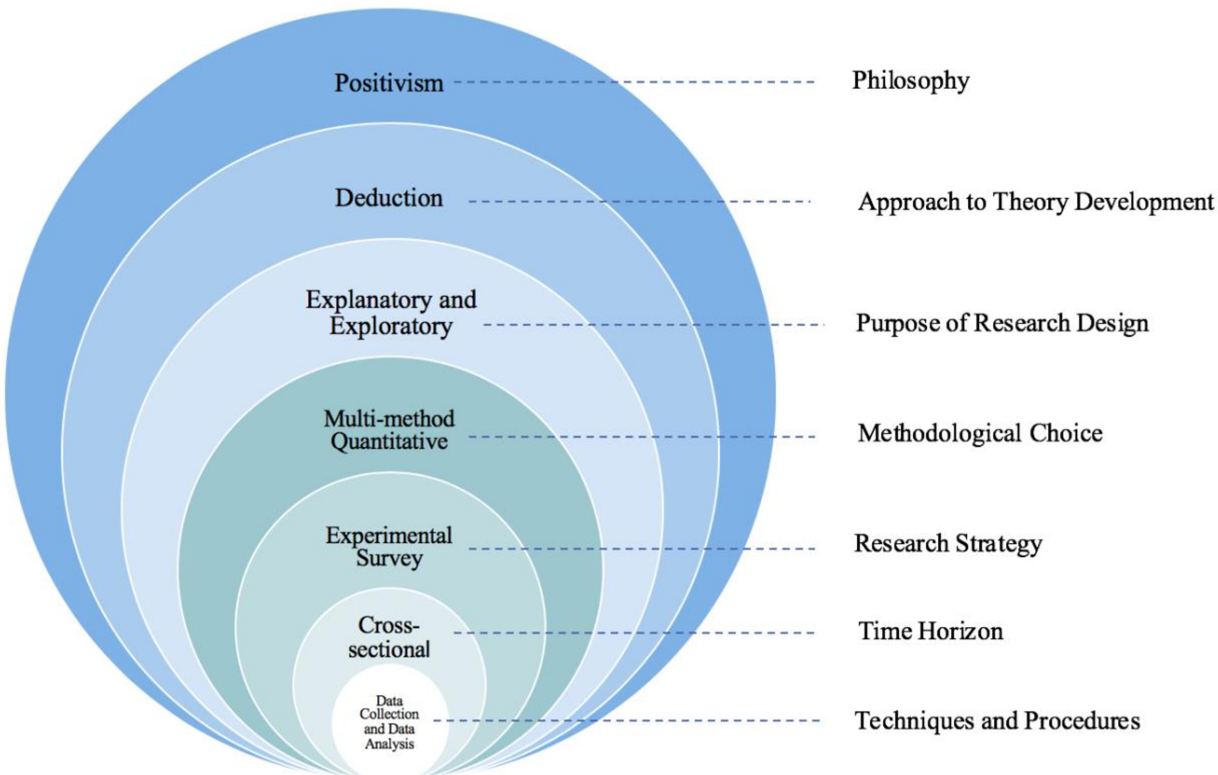

Figure 12 - The Research Onion

4.1 THE RESEARCH PHILOSOPHY

The *research philosophy* addresses the system of beliefs and assumptions about the development of knowledge used within a research project (Saunders *et al.*, 2016). More precisely, the research philosophy is based upon three main components: *epistemology*, *ontology* and *axiology*. Firstly, epistemology refers to the assumptions about knowledge, what is considered acceptable, valid and legitimate, and how one communicates knowledge to others (Saunders *et al.*, 2016). Secondly, ontology relates to the assumptions about the nature of reality, meaning how one views and studies research objects (Saunders *et al.*, 2016). Lastly, axiology refers to the values and ethics within the research process, meaning how the researchers collaborating on this project view both their own values and those of the research participants (Saunders *et al.*, 2016).

Taking into account this threefold framework, the research philosophy of this thesis corresponds to the one of *Positivism* (Saunders *et al.*, 2016). The reasons behind this choice are two. The first reason is that finance, thus impact investing, is a quantitative and objective science (Van Der Wijst, 2013). The second reason is that behavioral finance studies are defined as belonging to a positivist rather than normative view of the world, describing finance investors' behavior as it really is and not as it should be (Ackert & Deaves, 2018). To sum up, the main ontological, epistemological and axiological assumptions regarding the positivist research philosophy adopted within this thesis, are outlined in *Table 5* below (Saunders *et al.*, 2016):

Positivism		
Ontology	**Epistemology**	**Axiology**
• Real, external and independent; • One true reality (universalism); • Granular (things); • Ordered.	• Scientific method; • Observable and measurable facts; • Law-like generalization; • Numbers; • Causal explanation and prediction as contribution.	• Value-free research; • Researcher is detached, neutral and independent of what is researched; • Researcher maintains objective stance.

Table 5 - Ontological, Epistemological and Axiological Assumptions

Overall, to critically analyze the positivist approach adopted, it can be argued that it is the most difficult one to achieve from an axiological point of view because excluding researcher's own values is rather difficult (Saunders *et al.*, 2016). Despite this, given the two reasons previously provided regarding the topic delimitation of this project, it can be argued that the positivist approach is the one that is best suited for the scope of this thesis.

4.2 THE APPROACH TO THEORY DEVELOPMENT

Every research project involves the use of theory, which may be implicit or explicit in the design of the research (Saunders *et al.*, 2016). The extent to which one is clear regarding the theory used at the beginning of the research defines the reasoning approach one will adopt through the study. Saunders *et al.* (2016) propose three approaches to theory development: deductive, inductive and abductive. Firstly, by adopting a deductive approach, the researcher starts with using the existing theory to develop hypotheses and concludes with testing those hypotheses. Secondly, by adopting an inductive approach, the researcher starts by collecting data to explore a phenomenon and concludes with generating a theoretical framework. Lastly, by adopting an abductive approach, the researcher starts by collecting data to explore a phenomenon, he/she identifies patterns/themes to generate/modify a pre-existent theory and concludes with testing it with the new data collected.

Among these three theory development approaches, the researchers adopted a deductive reasoning as it represents the most suitable approach given the positivist research philosophy selected for this thesis (Saunders *et al.*, 2016). Therefore, by initially using existing literature belonging to impact investing and behavioral finance, the researchers specified the conditions under which the theory was expected to hold and later deduced four main testable hypotheses. Thereafter, the hypotheses made will be tested by collecting the appropriate primary data. Consequently, if the hypotheses will test positive, then the theory will be confirmed. Conversely, if the hypotheses will test negative, then the theory will be rejected.

4.3 THE PURPOSE OF THE RESEARCH DESIGN

According to Saunders *et al.* (2016), research can be designed to fulfill either a descriptive, explanatory, exploratory or evaluative purpose, or a combination of these. Firstly, a descriptive research describes the accurate profile of events, persons or situations. Secondly, an explanatory study focuses on studying a situation in order to explain causal relationships between variables. Thirdly, an exploratory research discovers new insights about a phenomenon. Lastly, an evaluative study finds how effective something works (e.g. process, program, policy, strategy etc.). The way in which the research questions are formulated will guide the researchers towards one, or more, of these research purposes (Saunders *et al.*, 2016). According to the research questions previously formulated (*see page 42*), the purpose of this thesis can be considered explanatory because the researchers will analyze the relationship that exists between the four key parameters of the Impact Investing Framework formulated by Hornsby & Blumberg (2013) and examine how the overconfidence bias explains the impact investors tolerance for risk.

4.4 THE METHODOLOGICAL CHOICE

4.4.1 A Brief Terminological Distinction and the Quantitative Nature of the Research

Before diving into the explanation of the next stages of the research design, for clarity reasons, the researchers will outline a terminological distinction between what is defined as *research strategy*, namely the strategy used to collect data, and the *methodological choice*, namely the method used to analyze the data collected (Saunders *et al.*, 2016). However, despite this distinction, both the research strategy and methodological choice adopted within this thesis can be defined as *quantitative* (Saunders *et al.*, 2016). In fact, the difference between a quantitative and a qualitative research is that the former uses numeric data, whereas the latter uses non-numeric data like words, images and video clips (Saunders *et al.*, 2016). Moreover, quantitative research is associated with a positivist philosophy and a deductive reasoning approach, where highly structured data is collected in order to test theory (Saunders *et al.*, 2016). Thus, since a quantitative approach is suitable to examine the relationship between variables (Saunders *et al.*, 2016), it can be concluded that it is the most appropriate to test the four proposed hypotheses (*see page 42*).
Concluding, while a more detailed explanation of the methodological choice will be discussed in the following paragraphs, the research strategy will be discussed in the next section (*see page 63*).

4.4.2 Method Selection: An Explanation

In order to address the research questions previously reported and gain insights within the impact investing decision-making process through the lens of behavioral finance, it is necessary to use a method which allows the researchers to:

- Reveal and analyze impact investors' preferences towards the four key parameters of the Impact Investing Framework used within the investment decision-making process;
- Find a numerical measure for the overconfidence bias affecting impact investors;
- Investigate how the overconfidence bias within impact investors explains their preferences for risks.

In order to obtain insights about impact investors' investment choices, different methods of analysis could have been taken into consideration. For instance, impact investors could have been either observed during the investment process or asked to provide a description on how they make an investment decision during an interview (Saunders *et al.*, 2016). Nevertheless, a direct observation approach would not be the best method because it is time consuming given that behavior must be observed many times in order for the data to be reliable. Moreover, since the research is focusing on how the overconfidence bias affects investors' preferences it would be difficult to observe such behavioral phenomenon and the consequences it has on their choices (Brown L., 2019). Similarly, asking impact investors to provide individual descriptions on how they make an investment decision could be misleading since, due to their bounded rationality, they do not have a clear understanding of their decision-making process (Zacharakis & Meyer, 1998). Furthermore, it would be difficult for investors to recognize whether their behavior is influenced by an unconscious bias (Zacharakis & Meyer, 1998). Furthermore, the methods previously described are *preference exploration methods*, meaning that not only these methods are qualitative in nature but also, they base the analysis on collected descriptive and unstructured data (Soekhai *et al.*, 2019). However, for the purpose of this thesis it is essential to identify two quantitative research methods rather than qualitative. Thus, the most appropriate quantitative methods have been identified as a Choice-Based Conjoint Analysis (CBCA), in the form of a Discrete Choice Analysis, and as a Calibration Test. Firstly, the *preference elicitation method* of CBCA will allow the researchers to collect quantifiable and structured data to gain insights about attitudes and preferences of impact investors towards the parameters characterizing each investment. Secondly, the Calibration Test will allow the researchers to quantify the level of overconfidence bias characterizing each respondent. As result, according to the distinction made by Saunders *et al.* (2016), to address the research questions a *multi-method quantitative study* has been adopted as the methodological choice. On the one hand, this thesis can be defined quantitative because it uses the mathematical and statistical methods of Choice-Based Conjoint Analysis (Hensher *et al.*, 2005; Rao, 2014) and Calibration Test (Lichtenstein *et al.*, 1981) to analyze data. On the other hand, it can be defined through a multi-method approach because the researchers use two different methods both displaying a quantitative nature. Therefore, the following section describes the method of CBCA, while in the next section the Calibration Test will be outlined (*see page 59*).

4.4.3 The Choice-Based Conjoint Analysis

Throughout this section, firstly the researchers will briefly lay out the foundation of Conjoint Analysis and identify different types of conjoint methods. Thereafter, the researchers will concentrate on the Choice-Based Conjoint Analysis (CBCA) as it represents the selected method within this research.

The Foundations of Conjoint Analysis

Conjoint Analysis lays its foundation back to the 1920s within the academic contribution by Luce & Tukey (1964). Today it is considered one of the most widely used quantitative tools in marketing research as it allows to gain knowledge into the targeted consumers' preferences influencing their decision-making process (Orme, 2009).

According to Rao (2014), Conjoint Analysis refers to a quantitative method that estimates the structure of a consumer's preferences for a product profile defined in its attributes and levels. Therefore, when referring to Conjoint Analysis, it is essential to specify the difference between the two key terms: *Attributes* and *Levels*. Attributes represent the objectively measured descriptive characteristics of a product (e.g. color), which are composed of different levels, representing the subjective assessments of the characteristics of that product (e.g. green, blue) (Orme, 2002). Therefore, Conjoint Analysis refers to a technique that requires respondents to make a choice on a number of product profiles, which are described on a set of common attributes and levels. From this series of choices made by the respondents, it is possible to investigate the underlying structure of respondents' preferences within their decision-making process (Shepherd & Zacharakis, 1999).

Conjoint Analysis in the Academic Literature

Although, this method has its origins within the marketing research field, today it is used extensively in other different academic fields, as it allows to measure preferences for a product on the basis of quasi-realistic decision-making situations (Orme, 2009). Conjoint Analysis has been used also within the finance field, it was firstly introduced through the research made by Zinkhan & Zinkhan (1990), which used this method to determine customers' preferences when considering financial services. More recently, through the work of Block *et al.* (2019), an experimental Conjoint Analysis has been used to investigate the investment criteria of private equity investors.

The Three Types of Conjoint Analysis Methods

As indicated by Orme (2009), three types of conjoint methods can be identified: **1)** *Ratings-Based Methods* (RBM), **2)** *Choice-Based Conjoint Analysis* (CBCA), and **3)** *Adaptive Conjoint Analysis* (ACA). These three methods follow a *decompositional approach*, meaning that respondents' stated preferences or choices are decomposed to obtain utility coefficients (Orme, 2009). One of the first method adopted was the RBM, which was introduced by Paul Green in the early 1970s (Orme, 2009). This method involves asking respondents to rate or rank a series of products, where each product is composed of different attributes characterized by different levels (Orme, 2009). However, the popularity of this method declined when, in the early 1990s, CBCA, also known as *Discrete-Choice Modeling*, started to become popular evolving into the most popular conjoint technique worldwide (Orme, 2009). Instead of rating or ranking product profiles, within CBCA respondents are shown a set of products - characterized by a set of attributes and levels - among which respondents must choose the one they would purchase (Orme, 2009). Lastly, ACA has been developed in 1985 when Sawtooth Software released a new conjoint analysis software, which provides a more updated approach compared to the traditional CBCA and RBM. In fact, ACA proposes an online survey where respondents are asked to choose among or give a rating to a set of products (Orme, 2009). Each section of the survey adapts to the respondents' previous answers through a systematic investigation that allows the survey to focus on those attributes and levels that have the most influence on individuals' preferences (Orme, 2009). As mentioned above, very few researchers use the RBM while the majority of scholars are favoring CBCA or ACA as they closely mimic the reality of the purchasing process (Orme, 2009). However, due to the unavailability of Sawtooth Software within Copenhagen Business School departments, the researchers could not consider ACA as an available option. Therefore, CBCA has been selected as the final method to analyze the data collected.

The Choice-Based Conjoint Analysis

CBCA has its roots in Discrete Choice Analysis (or Discrete Choice Experiment) and it is also known as a *"stated"* choice method because it examines the intended choices of respondents among other hypothetical choice possibilities (Rao, 2014). More precisely, stated or discrete choice methods simulate choices similar to the ones people face in the actual marketplace through experiments designed in a way consistent with random utility theory, which form the basis to analyze stated choice data (Rao, 2014). Thus, the basic assumption in this context is that individuals make a choice from a finite set of alternatives such that their utility is maximized (Rao, 2014). In the practical case of this research, to provide a quasi-realistic investment decision-making situation, the respondents will face a series of choice tasks, where in each task, they will be required to state their preferred profile among a set of hypothetical impact investments alternatives, each characterized by a different combination of attributes' levels (Louviere and Woodworth, 1983). Therefore, to provide a more precise and clear understanding of how the researchers will make use of the CBCA to analyze the data collected, it is essential to describe its three main steps, namely **1)** the design of the choice tasks, **2)** the estimation model to determine the probability of choices and **3)** the estimation method (Rao, 2014) (*Figure 13*).

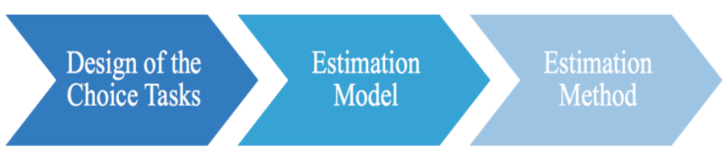

Figure 13 **-** *The Three Steps of CBCA*

The Design of the Choice Tasks

As mentioned above, CBCA requires individuals to face a finite number of choice tasks, where in each task, they will be required to state their preferred profile among a set of product alternatives, each characterized by a different combination of attributes' levels. Therefore, the first step of CBCA consists in identifying the product of interest and in designing profile alternatives described by different attributes' levels. As previously introduced, an attribute is a characteristic of a product (e.g. color), made up of various levels (e.g. green, red, blue) (Orme, 2002). Thus, since this thesis focuses on impact investors' investment choices within the cleantech sector, the product of interest has been identified as carbon reduction investment specializing in a new unproven clean technology. As a result, each investment profile is characterized by a set of investment attributes. To identify the relevant attributes, the researchers adopted the four key parameters outlined within the Impact Investing Framework illustrated in the *Literature Review* chapter (*see page 18*), which respectively are: *1) Financial Return, 2) Financial Risk, 3) Impact Return and 4) Impact Risk* (Hornsby & Blumberg, 2013). Moreover, to simplify the respondents' tasks, only two levels for each attribute have been identified, namely High and Low. A more practical description of the attributes and levels used within the discrete choice experiment will be provided within the *Survey Design* section (*see page 65*). Moreover, to keep the choice experiment as realistic as possible, a full profile approach, rather than a two-factors-at-a-time approach[1], has been chosen. This approach consists in showing respondents different profiles, all characterized by the given attributes (Green & Srinivasan, 1978). Nevertheless, the major limitation of such approach is the possibility of information overload, whereby respondents may be tempted to simplify the experimental task by basing their preference just on few attributes, ignoring other important ones. Therefore, to ensure that respondents make a choice based on all the shown attributes, it is recommended to include six or fewer attributes, each described on about two to five levels (Green & Srinivasan, 1978). For this reason, the researchers' decision to adopt the four key parameters of Financial Return, Financial Risk, Impact Return and Impact Risk, each described on two levels (i.e. High and Low), further ensures the avoidance of the information overload problem.

After having identified the attributes and their respective levels, researchers must decide on the design of choice tasks, where each consists of a subset of the investment profiles previously identified. Within this process, it is important to determine the size of choice task and the total number of choice tasks in the experiment (Rao, 2014). To further reduce the problem of information overload, this choice experiment provides two carbon reduction

[1] The *two-factors-at-a-time-approach* considers attributes on a two-at-a-time basis. The respondent is asked to rank the various combinations of each attributes' levels from most preferred to least preferred. Although the simplicity of this approach which avoids the problem of information overload, it is not considered a very realistic approach (Green & Srinivasan, 1978).

investments within each choice task. Therefore, respondents are presented with a paired comparison and are forced to choose one of the two carbon reduction investments.

Regarding the number of choice tasks in the experiment, rather than using a full factorial design or an orthogonal design, through the use of *Ngene Software* an efficient design has been generated (Ngene, 2018). In particular, while the full factorial design considers each possible choice situation and the orthogonal design reduces the number of profiles to minimize the correlation between attributes' levels, the efficient design reduces the number of profiles to minimize the parameters' standard errors (Ngene, 2018). Thus, by using the Ngene Software, the design of the experiment is efficient, meaning that each level appears equally often within an attribute, and it is orthogonal, meaning that each pair of levels appear equally often across all the four attributes within the design. In this way, efficient experimental designs maximize the precision of the model (Johnson *et al.*, 2013). Concluding, the efficient design generated six choice tasks, each containing two investment profiles. Each experimental choice task will be thoroughly described in the *Survey Design* section of this chapter (*see page 65*) and in *Appendix 1* (*at page 129*).

The Estimation Model to Determine the Probability of Choices

The second step of CBCA consists in identifying the estimation model to determine the probability of choices. To allow for the estimation model to match the realistic nature of the choice experiment the researchers will conduct, the *Mixed-Logit Model* [2] is the chosen estimation model to implement the analysis (Hensher *et al.*, 2005). During the last twenty years, the Mixed-Logit Model has become one of the most prominent statistical models within the field of *Choice-Based Conjoint Analysis* (Hauber *et al.*, 2016). The model finds its roots within the theoretical contribution of McFadden and Train (2000), who applied the LOGIT model to choice behavior so that it was coherent with the Random Utility Theory (Hensher *et al.*, 2005). In principle, the Mixed-Logit Model (MXL) consists in a regression model that relates *choices* to the *characteristics/attributes* of the alternatives available to decision-makers (Hauber *et al.*, 2016) and to unobserved *individual-specific factors* that influence the respondents' different preferences in choice decision (Audibert *et al.*, 2013). In order to explain the innovative nature of the MXL, one should start by assuming that each individual facing a choice between two (or more) alternatives will always choose the alternative that maximizes his/her own utility. Thus, when a person n faces a choice among J alternatives, the utility derived from a j alternative is specified as follows (Train, 2009):

[2] The Mixed-Logit Model also called Random-Parameter Logit Model, Mixed Multinomial Logit or Hybrid Logit Model

$$U_{nj} = \beta'_n X_{nj} + \varepsilon_{nj}$$

whereby:

- X_{nj} is a vector of observed variables that represents the characteristics of the alternative (i.e. *attributes*) and the characteristics of the decision-maker (i.e. *individual-specific factors*);
- β'_n is a vector of estimated coefficients representing the person n's tastes for the variables in X_{nj};
- ε_{nj} is the random error term following an independently and identically type 1 extreme-value distribution, which indicates the inability of the researcher to accurately measure the respondents' utility (Hauber *et al.*, 2016).

As a consequence, it can be deduced that the individual n choses alternative i among all the J alternatives, if and only if $U_{ni} > U_{nj}\ \forall\ j \neq i$. Thus, for a person n, the probability of choosing i among all the J alternatives can be defined as follows (Train, 2009):

$$\Pr(choice = i) = \frac{e^{\beta'_{n'} x_{ni}}}{\sum_J e^{\beta'_{n'} x_{nj}}}$$

In written terms, the formula above states that the odds of choosing alternative i is the ratio between the probability of choosing alternative i and the sum of the probability of choosing all the other alternatives presented in the same choice task. The innovative notion introduced by the MXL is that the vector β'_n, which describes the estimated coefficients representing the person's tastes, is composed of β parameters that are normally distributed with mean $\beta_{attribute}$ and standard deviation $\sigma_{attribute}$. In particular:

- Each $\beta_{attribute}$ represents a *mean estimate of the preference score (or utility score*) for a specific attribute and consists in the "*relative contribution of that attribute to the total utility that individuals assign to the chosen alternative, ceteris paribus*" (Hauber *et al.*, 2016);
- Each $\sigma_{attribute}$ describes the variability (or heterogeneity) of the specific preference score for an attribute. This means that the larger σ is, the larger variability in preferences, which in turn means that individuals have different preferences over that specific attribute (Train, 2009; Hensher *et al.*, 2005).

Consequently, by applying the MXL to the researchers' impact investing experiment where the respondents were administered a two-alternatives choice task, J would equal 2 and the probability of choosing one investment profile i would be 1 minus the probability of choosing the other profile (j) in that choice task. Thus, the underlying utility function for an individual n choosing alternative i over alternative j to a choice task within this experiment would be:

$$U_i = \beta_{Impact\ Return} * (Impact\ Return) + \beta_{Impact\ Risk} * (Impact\ Risk) + \beta_{Financial\ Return} * (Financial\ Return) + \beta_{Financial\ Risk} * (Financial\ Return) + \varepsilon_i$$

Hence, for individual n, the connected choice probability function of choosing i over j within a specific choice task would be:

$$\Pr(choice = i) = \frac{e^{\beta\prime, x_i}}{\sum_2 e^{\beta\prime, x_j}}$$

As a result, when running the MXL on the collected dataset within *R* (statistical computing tool) and using dummy variables to explain the attributes' levels (i.e. 1 for high levels of the attribute and 0 for low levels of the attribute), the results of the estimation of the coefficients, which are normally distributed with mean $\beta_{attribute}$ and standard deviation $\sigma_{attribute}$, will be presented as in *Table 6* below:

	Estimate	**P-value**
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	…	…
Impact Return ($\boldsymbol{\beta_{iret}}$)	…	…
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	…	…
Financial Return ($\boldsymbol{\beta_{fret}}$)	…	…
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	…	…
Standard Deviation		
SD. Impact Return ($\boldsymbol{\sigma_{iret}}$)	…	…
SD. Impact Risk ($\boldsymbol{\sigma_{irisk}}$)	…	…
SD. Financial Return ($\boldsymbol{\sigma_{fret}}$)	…	…
SD. Financial Risk ($\boldsymbol{\sigma_{frisk}}$)	…	…

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1

McFadden R^2: xxx

Table 6 - Representation of the Estimated Parameters

Before introducing the different interpretations of coefficients, one should always consider the goodness of fit. In these regards, the researchers will focus on the McFadden R_2, which always spaces from 0, indicating no predictive value of the model, to 1, indicating perfect fit (Hensher *et al.*, 2005). This coefficient, similar to the R_2 in linear regression, expresses how well the MXL model explains the data collected. A McFadden R_2 measuring a relatively good fit of the model ranges from 0.15 to 0.4 (Hensher *et al.*, 2005).

The Interpretation of the Coefficients

In *Table 6*, the *significance of an attribute's mean estimate* β corresponds to the conclusion that the attribute is considered by respondents as a relevant parameter within the choice tasks (Train, 2009; Hensher *et al.*, 2005). Thus, the opposite is true if the attribute's mean estimate is not significant. Similarly, the *significance of an attribute's* σ relates to the finding that the preferences of respondents for that attribute are heterogenous, meaning that those preferences vary across respondents due to individual-specific traits. Hence, the absence of an attribute's σ significance corresponds to the *"fixed"* nature of an attribute's β parameter, which means that preferences for that attribute do not vary across respondents[3] (Train, 2009; Hensher *et al.*, 2005).

Moreover, one may notice that in *Table 6* there is only one β and one σ estimates for each attribute rather than one β and one σ estimates for each attribute's level. The reason is related to the dummy variable coding chosen for the experimental and survey design. In fact, each respondent will face forced choice between two profiles that were described as a combination of high or low levels for each of the four chosen attributes. As a result, the parameters in the MXL refer to the high level of each attribute with the low level being the reference category (Train, 2009). In particular, by considering the mean estimates of the βs in the model, the interpretation of the coefficient is straight forward. The mean estimate of $\beta_{attribute}$ is the *logit of the increase (decrease) in utility for a project with high level of that attribute compared to a similar project with a low level of the same attribute, ceteris paribus* (Train, 2009). In other words:

- If the mean estimate of $\beta_{attribute}$ is positive, it means that respondents like that attribute. Thus, a project characterized by a high level of that attribute is more likely to be chosen compared to one characterized by a low level of such attribute, ceteris paribus;

3 An attribute is considered as having a fixed effect on the utility of the choice if respondent 1 derives the same level of utility from that attribute's levels as respondent 2.

- If the mean estimate of $\beta_{attribute}$ is negative, it means that respondents dislike that attribute. Thus, a project characterized by a high level of that attribute is less likely to be chosen compared to one characterized by a low level of such attribute, ceteris paribus.

For example, the mean estimate of β_{iret} coefficient is the *logit of the increase in utility for a project with high level of Impact Return compared to a similar project with a low level of Impact Return, ceteris paribus*. In other words, if the mean estimate of β_{iret} is + 1.5, it means that respondents like Impact Return. Thus, a project characterized by a high level of Impact Return is more likely to be chosen compared to one characterized by a low level of Impact Return, ceteris paribus. Given that the mean estimate of β_{iret} for the high level of Impact Return is + 1.5, the β_{iret} for the low level of Impact Return is simply mirrored and it corresponds to - 1.5. More precisely, moving from a low level to a high level of Impact Return, increases the utility (in logit terms) of the individual by 1.5. Conversely, moving from a high level to a low level of Impact Return, decreases the utility (in logit terms) of the individual by 1.5.

Furthermore, it is also worthwhile specifying that the value of the β and σ coefficients that will be estimated depends on the two levels that the researchers will identify for each attribute. Had the researchers chosen another description for high and low levels of the four attributes, the coefficients would have been different as the MXL is applied to precise experimental data. Thus, the results that will be analyzed in the chapter *Analysis and Discussion* are experiment-specific and should be generalized only with adequate limitations.
Concluding, the MXL provides a flexible model that does not focus only on the mean impact of observed attributes, but it also allows to incorporate unobserved individual-specific factors that influence the respondents' heterogeneity in choice decision (Audibert et. al, 2013). Thanks to this blended approach, through the introduction of overconfidence as an interaction term, the MXL allows to explain whether the heterogeneity in respondents' preferences is explained by overconfidence, which represents an individual-specific trait. Therefore, through the MXL model the researchers are able to determine whether heterogeneity exists among impact investors' preferences for Impact Risk as well as Financial Risk. Hence, through the introduction of an interaction term, the MXL model allows to explain whether such heterogeneity in preferences is explained by overconfidence. A more detailed explanation of how the researchers operationalize the interaction analysis will be presented in the section *Overconfidence as an Interaction Term* (*see page 61*).

The Estimation Method

The research uses the maximum likelihood estimation method, which represents the most common method for estimating the parameters within the MXL model. The maximum likelihood estimation method implies selecting as estimates the model's coefficients that maximize the likelihood (probability) function (Montopoli & Anderson, 2007).

Advantages and Disadvantages of Choice-Based Conjoint Analysis

Using the CBCA to gain insights into individuals' preferences has both advantages and disadvantages. The key advantage is that providing a set of choices, from which individuals have to choose the most preferred option, closely mimics what people would face in a real decision-making scenario. Generally, this is considered a simple and natural task that every individual performs in its daily life (Sawtooth Software, 2020). However, to simplify respondents' tasks and avoid the problem of information overload, Green & Srinivasan (1978) suggested that CBCA provides more precise results when there are relatively few attributes and levels. This represents a key disadvantage, especially when the research deals with a complex decision-making situation, which requires a larger number of attributes in order to be described realistically. In fact, this research does not focus on a regular buyer choosing among simple products, but the respondents represent impact investors who, among the choice tasks provided, will have to make an investment decision regarding carbon reduction investment profiles. Therefore, due to the higher complexities that characterize the investment decision, in reality it would not be sufficient to define an investment just on four attributes (i.e. Financial Risk, Financial Return, Impact Risk and Impact Return), as impact investors will consider many more factors during the investment decision-making process (Hornsby & Blumberg, 2013). Moreover, although each attribute has been described only on two levels (e.g. high and low), in real-life it would not be appropriate to consider risks and returns described in such a discrete way. However, in order to implement the discrete-choice experiment and present respondents relatively simplified tasks, the researchers had to make the assumption that risk and return follow a discrete nature rather than a continuous one.

4.4.4 The Calibration Test

As previously explained in the *Literature Review* chapter (*see page 34*), *miscalibration* is the cognitive bias represented by the tendency of agents to overestimate the precision of their knowledge or their abilities (Ackert & Deaves, 2018). Within the literature documenting experiments on individuals' knowledge calibration, the *Calibration Test* is the most accurate method to measure such bias (Ackert & Deaves, 2018). This method consists in participants answering a series of general knowledge questions and subsequently stating what their confidence level is regarding their chances of being correct in each answer (Ackert & Deaves, 2018).

The Calibration Test in the Academic Literature

A common method of measuring miscalibration is through the Calibration Test. This test was initially developed in the 1960s to measure the precision of meteorological forecasts (Atlas & Mossop, 1960). Later, it was used in the psychology field to measure the precision of perception and related areas (Attneave, 1962). During the 1970s, the method was applied to what is nowadays called Behavioral Economics and Finance. In particular, the first scholars applying the Calibration Test to measure the overconfidence bias were Lichtenstein *et al. (*1981), who reviewed the literature of miscalibration across the fields and consolidated the calibration method on a theoretical basis. On more recent times, the method has been used widely within the Behavioral Finance field in order to test how overconfident investors forecast future returns (Deaves *et al.*, 2010) and how overconfidence changes across genders (Deaves *et al.*, 2009).

To measure miscalibration, the literature identifies two types of calibration assessment techniques. The first consists in measuring the probability judgement of the agent through *discrete proportions tasks (*Lichtenstein *et al.*, 1981), whereas the second consists in measuring the probability judgement of the agent through *continuous proportions tasks* using the so-called *fractile method*[4] (Lichtenstein *et al.*, 1981). However, since the latter method requires extensive effort from the respondents to complete the experimental tasks, the researchers relied on the measurement of miscalibration through discrete proportion tasks. In this way, the mental effort demanded from the respondents was kept to a minimum and the chances of the respondents completing the miscalibration experiment were maximized.

[4] The Fractile Method is used to measure miscalibration with continuous quantities. Miscalibration is measured by asking subjects to estimate for a number of questions - with unknown numerical answers – an upper and lower limit such that the respondent is X% sure that the true answer will fall into that interval (Lichtenstein *et al*., 1981).

Measuring Miscalibration through Discrete Proportion Tasks

In order to measure miscalibration with discrete proportion tasks, respondents of the survey are required to answer a series of multiple-choice questions and estimate how confident they are that the answers given were the correct ones. In this sense, discrete proportions can be characterized according to the number of alternatives the question offers (Lichtenstein *et al.*, 1981). In the question, there can be **1)** *no alternatives* (e.g. Of the 208 countries in the world, how many have defined renewable energy targets?), meaning that the respondent needs to provide an answer him/herself; **2)** *one alternative* (e.g. Of the 208 countries in the world, 144 have defined renewable energy targets. What is the probability that this statement is true?), meaning that the respondent needs to provide a relevant range of probability scale from 0 to 1; or **3)** *two or more alternatives* (e.g. Of the 208 countries in the world, how many have defined renewable energy targets? (a) 86, (b) 94, (c) 102, (d) 144), meaning that the respondent selects the single most likely alternative and subsequently states the probability that their answer is correct (Lichtenstein *et al.*, 1981). In the practical case of this thesis, the researchers have decided to administer respondents a Calibration Test where the individual had to choose among four alternatives. In this way, the researchers minimized the cognitive choice effort that would have been experienced by respondents without guiding their choice towards the right answer.

In this instance, miscalibration is tested by comparing the percentage of questions that a respondent has answered to correctly with the respondent's average confidence level stated regarding the answers to these questions (Lichtenstein *et al.*, 1981). Thus, miscalibration is numerically expressed through the *Bias Score* (Lichtenstein *et al.*, 1981). According to Pulford (1996), the Bias Score is calculated as the difference between the average confidence level across all questions and the average of correct answers. A positive Bias Score represents overconfidence, whereas a negative Bias Score represents underconfidence (Lichtenstein *et al.*, 1981). As a result, a Bias Score of 0 represents a well-calibrated person (Lichtenstein *et al.*, 1981). The general formula is as follows (Lichtenstein *et al.*, 1981):

$$\textit{Bias Score} = \textit{average confidence score} - \textit{average correct score}$$

According to Lichtenstein *et al.* (1981), the Bias Score ranges from -1 to 1, whereby the more the score is close to -1 the more the agent can be considered under-confident. If the score is close to 1, the vice versa is true, whereas if the score is 0, the individual is well calibrated. As a consequence, using the Bias Score to measure overconfidence practically enables this bias to be used as an interaction term within the MXL model selected. In this way, the researchers can assess how the overconfidence bias affects the preference scores of the risk attributes, namely Financial and Impact Risk, included in the choice-based experiment.

Before explaining what the advantages and the disadvantages of using the Calibration Test to measure overconfidence are, it is fundamental to describe how an interaction term is defined and operationalized in statistical terms.

Overconfidence as an Interaction Term

According to Hayes (2007), the effect of X on some variable Y is moderated by W if its size, sign, or strength depends on or can be predicted by W. In this sense, W is said to be to be an *interaction term* of X's effect on Y, or that W and X *interact* in their influence on Y. A graphical explanation of how interaction works can be found in *Figure 14* below:

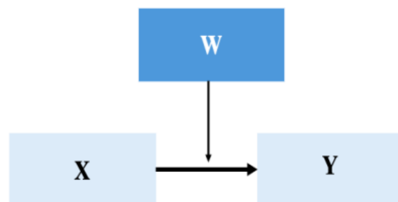

Figure 14 - The Interaction Effect

According to Hensher *et al.* (2005), introducing an interaction in the MXL model between the mean estimate of a preference score for an attribute and an individual-specific trait is not equivalent to revealing the presence or absence of preference heterogeneity around the preference score of that attribute, if any heterogeneity is present (*see page 56*). In fact, it is fundamental to mention that an interaction analysis can be executed only for an attribute that shows preference heterogeneity across respondents (i.e. the standard deviation of the preference score for the attribute is statistically significant) (*see page 56*) (Hensher *et al.*, 2005). Essentially, the core intuition is that if the preferences for an attribute do not change across individuals (i.e. no preference heterogeneity or statistically insignificant standard deviation of the preference score), it is illogical to test for interaction where the interaction term cannot explain the variability in the respondents preferences by definition (Hensher *et al.*, 2005). Moreover, if the interaction between a new introduced individual-specific variable (interaction term W) and a specific attribute is not statistically significant, then one can conclude that the interaction term W does not explain the preference heterogeneity of the respondents over the attribute (Hensher *et al.*, 2005). However, this does not imply that there is not preference heterogeneity around the attribute, but simply that the researchers cannot explain such heterogeneity with that individual specific variable (Hensher *et al.*, 2005).

By applying the statistical concept of the interaction term to this project, the researchers will use overconfidence, measured by the Bias Score, as the interaction term. Thus, through an interaction analysis the researchers will understand whether overconfidence increases the tolerance in the preferences of respondents not only towards the

Financial Risk attribute but also towards the Impact Risk attribute when making a specific investment choice. If the interaction effect between the Bias Score and each of the before-mentioned attributes is statistically significant, then the researchers can conclude that the overconfidence bias explains respondents' preference heterogeneity over Impact and Financial Risk. In other words, as mentioned in the chapter *Research Questions* (*see page 42*), the researchers will test if overconfident respondents are more willing to choose investment displaying a high Impact Risk/Financial Risk compared to non-overconfident respondents (see *Figure 15* and *16* below).

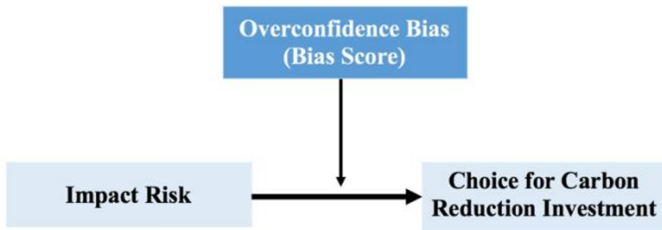

Figure 15 - Overconfidence Interaction with Impact Risk

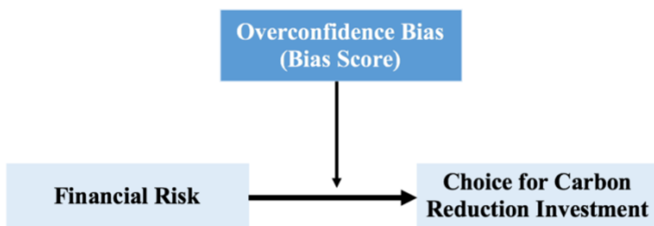

Figure 16 - Overconfidence Interaction with Financial Risk

Advantages and Disadvantages of the Calibration Test

Using the Calibration Test as the main method to measure knowledge miscalibration has both advantages and disadvantages.

On the one hand, it is worth noticing that although the project regards the financial field, where variables as risk and return are continuous in nature, in this thesis the researchers use discrete tasks to measure respondents' overconfidence. Despite using continuous tasks would have been more appropriate given the continuous nature of the variables analyzed, the choice of using discrete rather than continuous tasks is motivated by the fact that reasoning within continuous tasks is more cognitive demanding for respondents discouraging them from completing the survey (De Vaus, 2013).

On the other hand, the researchers' approach to measure overconfidence presents one main flaw. In fact, the researchers are measuring only one type of overconfidence, i.e. miscalibration, rather than all the three types mentioned in the academic literature (*see page 33*). However, by choosing just one of the three types of overconfidence, the researchers overcame the problem of finding a proxy for such ethereal concept (Ackert & Deaves, 2018).

4.5 THE RESEARCH STRATEGY

Saunders *et al.* (2016) define research strategy as the methodological link between the research philosophy and the choice of methods to analyze data. Given the characteristics of the Choice-Based Conjoint Analysis and the Calibration Test, the research strategy adopted is a *survey experiment* (Saunders *et al.*, 2016). In the following paragraphs, firstly, the two different components of the research strategy - i.e. experimental and survey components - will be explained and, secondly, the mixed approach between these two research tools will be discussed.

4.5.1 The Experimental Component

Although experiments are a form of research that derives from natural sciences, they are also largely used in social sciences research (Saunders *et al.*, 2016). The aim of an experiment is to study causal links (Saunders *et al.*, 2016). More precisely, experiments study whether a variation in independent variables produces a change in a dependent variable (Saunders *et al.*, 2016). In this thesis, the method of data collection can be defined experimental because the researchers are observing how the change in one of the four variables - i.e. Impact Risk, Impact Return, Financial Risk, Financial Return - affects the dependent variable, i.e. choice for impact investment profile. In addition, an important characteristic of experimental approaches in economic and financial studies is that researchers can observe the behavior of investors in an abstract environment that they can control. Thus, by exposing the participants to different scenarios, one should be able to identify a causality (Charness *et al.*, 2012). As a consequence, there are two ways to control these environments: through a *within-subject design* or through a *between-subject design* (Charness *et al.*, 2012). In the former, the participants are exposed to more than one treatment and causal estimates are calculated by comparing the behavior of each individual within each treatment (Charness *et al.*, 2012). Conversely, in the latter, each individual is exposed to only one treatment and causal estimates are calculated by comparing the behavior of those receiving the treatment with the behavior of those not receiving it (Charness *et al.*, 2012). In the case of this thesis, the researchers did not have a valid and reliable control group at disposal. Thus, the experimental design can be defined as *within-subjects*. According to Charness *et al.* (2012), within-subjects experiments have two advantages: **1)** the internal validity does not depend on the assignment received and, **2)** it offers a boost of statistical power.

Moreover, due to the choice-based nature of the CBCA, the method of data collection can be defined as a *discrete-choice experiment (*Mangham *et al.*, 2008). In this way, the researchers use a quantitative technique to elicit preference that could be used in the absence of revealed preference data. As previously mentioned, the experiment involves asking individuals to state their preference over hypothetical alternative investment scenarios (*see page 51*). Each alternative is described by several attributes and the responses are then used to determine if preferences are significantly affected by the attributes (Mangham *et al.*, 2008).

4.5.2 The Survey Component

The survey strategy is usually connected to a deductive approach (Saunders *et al.*, 2016). The research strategy adopted within this thesis can be described as a survey because, although the nature of the data collection is mostly experimental, the platform where the researchers administered the choice-experiment and the Calibration Test was Qualtrics. In fact, surveys are popular tools to collect a large amount of data from a wide population in an economical way (Saunders *et al.*, 2016). In the case of this project, the researchers administered an online questionnaire to a sample consisting of professionals within the impact investing field in Italy, namely impact fund managers, impact fund analysts, impact investing consultants and academics researching or teaching impact investing related subjects. In this way, the researchers could collect primary quantitative data and then analyze it through descriptive and inferential statistics.

4.5.3 The Survey Experiment

Bringing the two perspectives together, the research strategy adopted through this project can be defined as a *survey experiment* (Lavrakas *et al.*, 2019). On the one hand, the researchers used the platform of Qualtrics to administer the online survey. On the other hand, the survey was used to conduct the choice-based experiment within-subjects to test specific hypotheses about causal relationships between the variables considered (Saunders *et al.*, 2016).

4.6 THE TIME HORIZON

Given the time constraint of the research project, a *cross-sectional approach* has been adopted, whereby data from a representative sample has been collected at a specific point in time (Saunders *et al.*, 2016). More precisely, the data collection process lasted for approximately 3 weeks.

4.7 THE DATA COLLECTION

This study is based on primary data that has been collected using an online survey designed on Qualtrics. The survey has been sent via e-mail to approximately 120 Italian respondents using an anonymous link and responses have been collected from March 16th, 2020 to April 5th, 2020. The respondents were contacted through Kai Hockerts' network in Italy in collaboration with the Cottino Social Impact Campus in Turin (*see page 6*). Moreover, to obtain the largest possible sample, the researchers also utilized their LinkedIn network. In the following paragraphs, firstly, the researchers will focus on the design of the survey administered and, secondly, they will describe the sample used within this research project. Lastly, the limitations of the data collection method will be outlined.

4.7.1 The Survey Design

As previously stated, to address the research questions, the researchers are adopting: **1)** a discrete-choice experiment to understand respondents' preferences, and **2)** a Calibration Test to provide a measure regarding respondents' overconfidence. Therefore, the survey consists of 24 questions divided into three main sections, which were compiled using the Italian language given the research focus on Italian impact investors.

The first section consists of six brief questions regarding demographics. More precisely, respondents were asked to indicate their age, gender, nationality, educational background, current job industry and years of experience within such industry. A summary of this demographic data will be presented in the following section describing the sample (*see page 69*).

The second section outlines the questions needed to implement the choice-based experiment. Firstly, respondents were provided with a brief hypothetical scenario, which outlines their tasks for the following six questions. Within the scenario, respondents were asked to imagine they were being offered a series of choice tasks, each containing two products, from which they had to make a choice depending on their personal preferences. Given the purpose of the research, the chosen product is an impact investment within the cleantech sector specializing in new unproven technologies aiming at carbon reduction. The scenario also provides a clear description of attributes and levels characterizing each impact investment project. As previously mentioned in the section *The Design of the Choice Tasks* (*see page 52*), each carbon reduction investment is identified by four parameters (or attributes) and each parameter is described by a different level. The researchers defined the attributes and the relative levels as follows (*Table 7* below):

- *Financial Return* refers to the monetary amount earned or lost on an investment over a time horizon (Hornsby & Blumberg, 2013). The Internal Rate of Return (IRR) over the next year has been used as a metric to indicate the Financial Return of the carbon reduction investment. Mathematically, it represents the discount rate which makes the Net Present Value (NPV) of a project equal to zero (Booth *et al., 2016)*. Although it is a simple financial performance measure, it can be easily compared to the benchmark IRR for cleantech investments which amounts to 6% (Cambridge Associates, 2018). Therefore, in this case, two levels have been identified, a carbon reduction investment with an IRR of 8% has a *High Financial Return* because it outperforms the benchmark IRR, while an investment with IRR of 4% has a *Low Financial Return*.
- *Financial Risk* refers to the potential risk that an investment will not reach its targeted rate of financial return (Hornsby & Blumberg, 2013). Since it is a very broad term, to provide more clarity within the survey and simplify the respondents' tasks, it has been defined as the likelihood that, after ending, the project has only reached the break-even point, or worse. Therefore, a *Low Financial Risk* is the 5% probability of only breaking even, while a *High Financial Risk* is the 50% probability of not creating any profit.
- *Impact Return* refers to the volume of impact the investment proposes to generate (Hornsby & Blumberg, 2013). Since the product of interest is a carbon reduction investment, Impact Return will be measured in terms of environmental impact as the expected amount of CO2 that the new carbon-reduction technology investment will reduce in the next year (IRIS, 2020). To give a more consistent benchmark to respondents, the Impact Return is also expressed as car equivalent of CO2 emissions avoided (AWEA, 2020). According to statistics (see *Appendix 2 at page 130)*, the *Impact Return* achieved by the project can be either *Low* corresponding to 10 million tons of CO2 reduced (2.5 million cars per year), or *High* corresponding to 20 million tons of CO2 reduced (5 million cars per year).
- *Impact Risk* refers to the likelihood that the potential impact to be created fails and does not materialize (Hornsby & Blumberg, 2013). Within the survey, two levels of Impact Risk have been identified: a *Low Impact Risk* is the 5% probability that the planned CO2 reduction is not realized and a *High Impact Risk* is the 50% probability that the targeted Impact Return is not realized.

Attributes	*Impact Return*	*Impact Risk*	*Financial Return*	*Financial Risk*
Low Level	10 million tons of CO2 reduced (2.5 million cars per year)	5% probability that the planned CO2 reduction is not realized	IRR of 4%	5% probability of only breaking even, or worse
High Level	20 million tons of CO2 reduced (5 million cars per year)	50% probability that the planned CO2 reduction is not realized	IRR of 8%	50% probability of only breaking even, or worse

Table 7 - Attributes and Levels

As one may observe, the researchers have defined the attributes selected in a way that minimizes correlation among them. In fact:

- Financial Return and Financial Risk are defined in a way that higher-risk investments are not always priced to offer higher expected financial returns than lower-risk options, allowing for the irrational trait of respondents' overconfidence to be observed[5].
- Impact Return and Impact Risk are defined in a way that higher-risk investments are not always priced to offer higher expected impact returns than lower-risk options, allowing for the irrational trait of respondents' overconfidence to be observed[5].
- Financial Risk and Impact Risk are defined as two uncorrelated concepts due to the connection of the Impact Risk definition to the concept of impact plan (Hornsby & Blumberg, 2013). In fact, an investment may be sound financially and present low Financial Risk but present a weak impact plan (due to e.g. weak mission, uncertain theory of change, low levels of evidence etc.) leading to a high Impact Risk. Conversely, an investment may present a very satisfactory impact plan implying a low level of Impact Risk but exhibit financial weaknesses, thus leading to a high Financial Risk.
- Financial Return and Impact Return are defined as two uncorrelated concepts due to the connection of the Impact Return definition to the concept of impact plan. In fact, Impact Return addresses the quantity of impact to be generated, if the impact plan proves to be successful. Thus, an investment may display a bad impact performance due the impact plan being only partially successful but still show a good financial performance.

[5] Literature on overconfidence documented that overconfident investors are willing to take riskier prospects without being accordingly compensated (Barber & Odean, 2001).

It is also worthwhile reminding that the effects resulting from the choice-based experiment, that will be discussed later in the *Analysis and Discussion* chapter, are specific to the attributes' level chosen within the experiment. Therefore, if the attributes' levels were formulated differently, the choice-experiment could have led the researchers to a different result (Hensher *et al.*, 2012). However, to ensure that the attributes and levels selected within this research project were relevant, realistic and understandable (Orme, 2002), these criteria were reviewed by experts in the finance and clean technology sectors through a face validity test.

To implement the choice-based experiment, respondents were presented six choice tasks, each composed of two impact investment alternatives, where each alternative was characterized by a unique combination of attributes' levels. *Appendix 1* *(at page 129)* shows the twelve impact investments profiles generated and how they were combined in order to create six choice tasks. This configuration has been reached through the use of Ngene Software which ensured an efficient design (Ngene, 2018).

Lastly, the third part of the survey consists of six general knowledge questions regarding the impact investing field. After each question, respondents were asked to select how confident they were that the previous answer given was the correct one[6]. In fact, as previously stated in the *Calibration Test* section of this chapter (*see page 59*), from the data collected from these two types of questions, the researchers were able to obtain a *Bias Score* for each respondent (Lichtenstein *et al.*, 1981), using this formula:

Bias Score = average confidence score - average correct score

The Bias Score represents how overconfident respondents are in terms of miscalibration, which indicates how much they overestimate the precision of their knowledge (Ackert & Deaves, 2018).

Additionally, the last page of the survey allowed respondents to leave additional comments or feedback. This step was created by the researchers to reflect on the limitations regarding the research project and also to receive new suggestions for future research. Concluding, the complete version of the survey administered to respondents, both in Italian and in English, can be found in the *Appendix 3* (*at page 131*).

6 Respondents could select a confidence percentage level between 25%, 50%, 75% and 100% (Lichtenstein *et al.*, 1981)

4.7.2 The Sample

The sample selected for this study has been chosen to be closely representative of the impact investing field in Italy. Given that the methodology of the CBCA requires a relatively large sample, professionals were selected based on accessibility of respondents by the researchers. Therefore, the sample consists of professionals within the impact investing field in Italy, namely impact fund managers, impact fund analysts, impact investing consultants and academics researching or teaching impact investing related subjects. Thus, more in general, experts knowledgeable about the impact investing sector, meaning that overall the sample represents a good proxy for Italian impact investors (Müller, 2013). As previously explained in the *Introduction* chapter (*see page 6*), Italy has been chosen as a representative country because the impact investing field is considered an important recent trend. Moreover, given the nationality of the researchers, they could exploit the absence of language barriers to study this recent phenomenon that is becoming more popular in Italy by having access to the Cottino Social Impact Campus' network.

The survey has been sent to approximately 120 individuals, whereby each individual was asked to share it with their network of impact investing professionals. Thus, although the researchers could not estimate the total number of individuals that received the survey due to its anonymous nature, they estimated a rough number of 240 individuals reached (assuming that each individual sent the survey to at least 1 colleague). Overall, the researchers collected a total of 103 responses. However, the final sample consisted of 89 responses. In fact, 14 responses had to be excluded either because they were incomplete or because the respondent took less than 8 minutes to complete the survey. In fact, after collecting the data, the estimated average time to complete the survey was 8 minutes. Thus, all the respondents who spent less than the average time to complete the survey were excluded from the sample to ensure the accuracy of results.

As stated in the *Survey Design* section (*see page 65*), in the first part of the survey, researchers collected data regarding respondents' demographics, which are summarized in *Table 8* below.

Description of the Sample: Demographics	
Sample size	
n	89
Nationality	
Italy	100%
Gender	
Female	31%
Male	69%
Age	
20-30	23%
31-40	32%
41-50	24%
51-60	17%
60+	3%
Educational Background	
Finance	38%
Business	37%
Humanities	11%
Engineering	7%
Natural Sciences	4%
Other	3%
Current Job Sector	
Finance	47%
Consulting	24%
Academia	19%
Other	10%
Years of Experience	
0	2%
1-5	29%
6-10	21%
11-15	19%
16-20	12%
20+	17%

Table 8 - Sample Demographics

Given that the study is conducted in Italy, all the respondents have an Italian nationality. The final sample is composed by 69% of male respondents, and 31% of female respondents (*Figure 17*). Therefore, the sample reflects the fact that the impact investing sector, in similarity with the traditional finance sector, is male dominated (Simon, 2018).

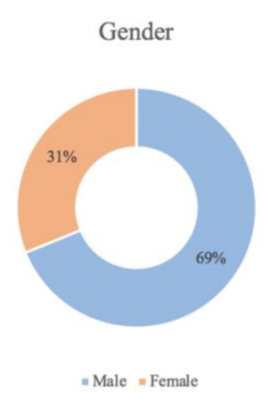

Figure 17 - Gender Demographics

The majority of the sample, 32%, belongs to the 31 - 40 age bracket, followed by 24%, 23% and 17% belonging respectively to the 41 - 50, 20 - 30 and 51 - 60 age brackets. Only 3% belonged to the 60+ age class, which is reasonable given that impact investing in Italy represents a recent trend *(Figure 18)*.

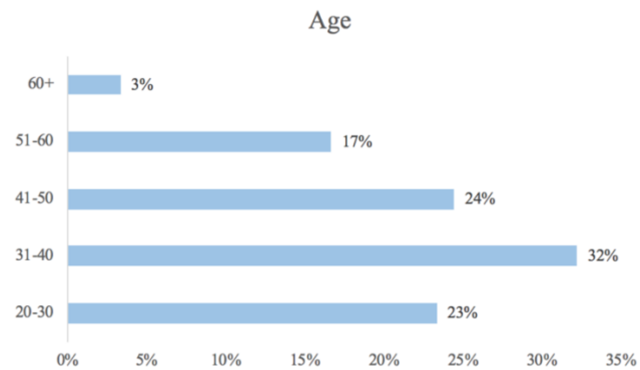

Figure 18 - Age Demographics

Regarding the educational background, 38% of respondents have a finance background, 37% have a business background, while the rest has a more heterogeneous background (*Figure 19*). Given that the majority has either a finance or business background, it can be ensured that the respondents were generally familiar with the notions provided within the survey.

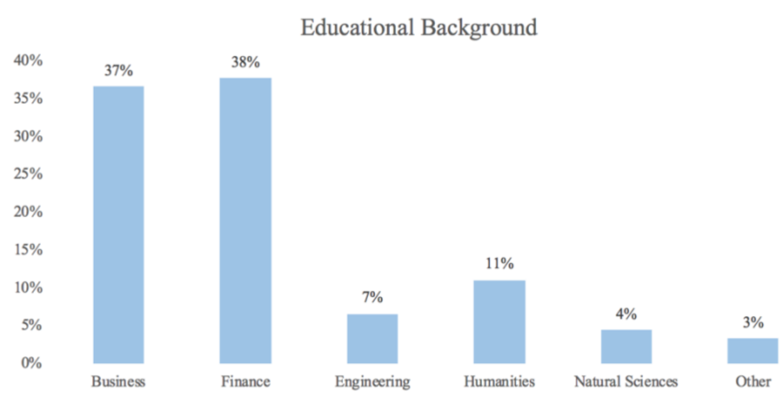

Figure 19 - Educational Background Demographics

Another important demographic element is represented by the sector in which the respondents are currently working. As *Figure 20* shows, 47% of respondents are currently working within the finance sector, this means that the majority of respondents is familiar with the investment decision-making process. Moreover, since the sample is composed of people with knowledge and experience within the impact investing sector, the researchers expect them to be also familiar with investment decisions considering impact related dimensions. The second most relevant sector is Consulting (24%), followed by Academia (19%) and Other (10%).

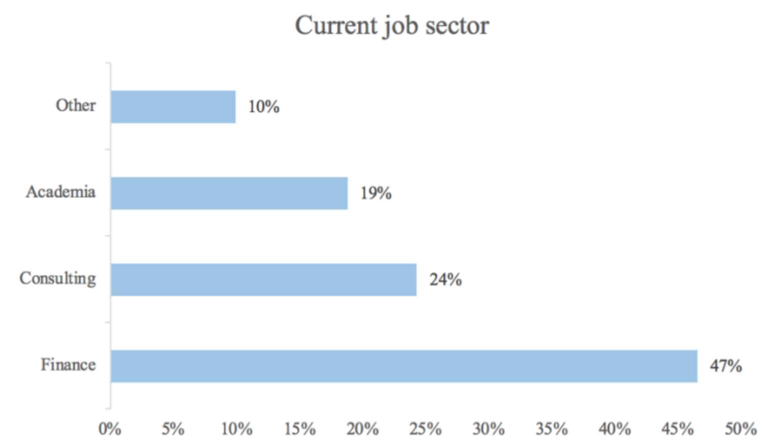

Figure 20 - Current Job Sector Demographics

Lastly, respondents were asked about the years of experience within their current job industry. The majority of respondents, 29%, has 1 - 5 years of experience. However, a good percentage of the sample, 21%, 19% and 17% has respectively 6 - 10, 11 - 15 and 20+ years of experience. Therefore, it can be deduced that in general the sample is composed of professionals with relevant years of experience in their current industry (*Figure 21*).

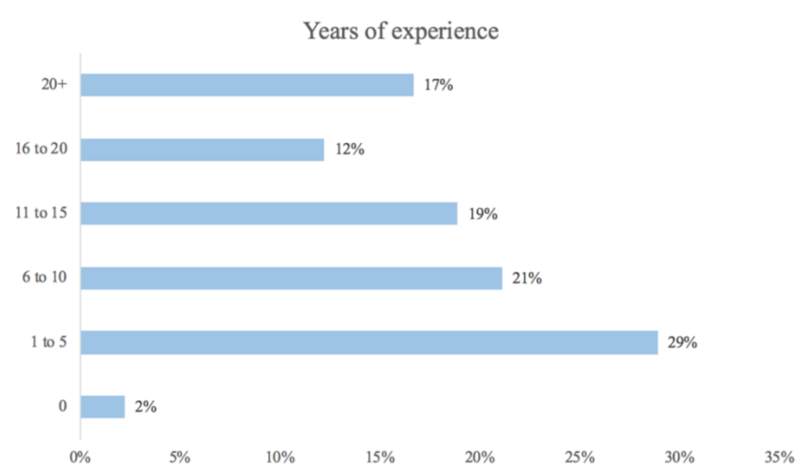

Figure 21 - Years of Experience Demographics

4.7.3 Limitations of Data Collection

Within this section the main limitations of the data collection method are presented. Firstly, since the research is conducted among impact investing professionals in Italy, the nationality of the sample is homogeneous. Therefore, by considering a more heterogeneous sample the researchers could have increased the reliability of the research project. Secondly, the final sample was limited to 89 respondents. In fact, given that out of 103 total respondents 14 responses could not be considered valid, it can be deduced that the dropout rate is approximately 13.5%. The reason might have been that the survey can be considered quite demanding, especially when respondents are presented six choice tasks from which they have to choose the most preferred impact investment profile. However, given the nature of this study, it was necessary to present respondents with an impact investment product. Thus, the researchers tried to minimize the information overflow risk by simplifying the respondents' tasks and offering them a simplistic version, based on fewer attributes and levels, compared to what would happen in reality. Despite the researchers' effort to minimize the cognitive burden placed on respondents, the sample size is still relatively smaller than what CBCA requires (i.e. roughly 200 respondents) to provide more accurate results (Rao, 2014). However, given **1)** the recent nature of the impact investing trend in Italy; **2)** the time constraints of the thesis project and **3)** the adverse circumstances of Italy in the period of data collection due to COVID19 outbreak, the final sample can be considered satisfactory to obtain significant results.

4.8 RELIABILITY AND VALIDITY

Reliability and validity are central concepts for making judgements about the quality of the quantitative research executed within this thesis (Saunders *et al.*, 2016).

4.8.1 Reliability

Reliability refers to replication and consistency of the research project. More precisely, a distinction between *internal* and *external reliability* can be made (Saunders *et al.*, 2016).

Internal reliability refers to ensuring consistency within a research project, which may be achieved by having more than one researcher responsible for analyzing the data within the research project. This will ensure that they both agree about the data analysis and its interpretation (Saunders *et al.*, 2016). In this regard, the presence of two researchers, responsible for the data interpretation and analysis, improved the internal reliability of the project.

External reliability refers to whether the data collection techniques and the methodologies chosen to conduct the analysis would produce consistent findings if the study was replicated by the same researchers, or different ones, in another occasion (Saunders *et al.*, 2016). Within this research project it is relevant to separately discuss the external reliability of the two methodologies used, namely: the CBCA (or discrete-choice analysis) and the Calibration Test.

On the one hand, there are different ways to check for external reliability regarding CBCA. For instance, a "test-retest approach" using the same survey at different points in time for the same respondents (within-subject approach), or testing between two samples how small changes in the background scenario or in the formulation of attributes and levels affects the results (between-subject approach) (Rakotonarivo *et al.*, 2016). However, none of these approaches were feasible. In fact, due to the anonymity of respondents, the researchers were not able to replicate the study addressing the same respondents in different points in time. Moreover, due to the limited scope of this thesis, the researchers did not collect a reference sample deriving from a more European - rather than just Italian - sample population. This could have further improved the external reliability of the methodology as the researchers could have ensured that similar results were obtained in the Italian and the European sample. However, due to adverse circumstances during data collection caused by the COVID19 outbreak, the researchers were not able to perform such extended external reliability analysis.

On the other hand, to improve the external reliability of the Calibration Test, the researchers conducted a pilot analysis on a sample composed of 40 finance students. The pilot study showed that, when replicating the Calibration Test on a different sample, similar findings regarding the average Bias Score were obtained.

Moreover, given that reliability of the results and relative conclusions is often hindered by various threats (*Table 9* below), the research has been designed in a way to avoid encountering such threats (Saunders *et al.*, 2016).

Threat	Definition	Explanation
Participant Error	Any factor which adversely alters the way in which a participant performs.	For example, asking a participant to complete a survey just before a lunch break may affect the way they respond compared to choosing the less sensitive time. For instance, they may not take care and hurry to complete it.
Participant Bias	Any factor which induces a false response.	For example, conducting an interview in an open space may lead participants to provide falsely positive answers where they fear they are being overheard, rather than retaining their anonymity.
Researcher Error	Any factor which alters the researcher's interpretation.	For example, a researcher may be tired or not sufficiently prepared and misunderstand some of the more subtle meaning of his/her interviewees.
Researcher Bias	Any factor which induces bias in the researcher's recording of responses.	For example, a researcher may allow her/his own subjective view or disposition to get in the way of fairly and accurately recording and interpreting participants' responses.

Table 9 - Reliability Threats

The researchers tried to avoid these reliability threats in several ways. Firstly, by providing an online self-administered survey, the researchers maintained a detached position and did not interfere with respondents' completion of the survey. This is also coherent with the positivist philosophy characterizing this research project (*see page 46*). Therefore, the participant error and the participant bias threat were minimized. In fact, respondents were able to decide when it was the most appropriate time to complete the survey and they had no incentive in providing false responses because the survey could have been completed individually on a smartphone or computer and it was completely anonymous. Moreover, the researcher error and the researcher bias threats were minimized as well. In fact, according to the positivist approach adopted, the researchers based the interpretation of results on observable and measurable facts by following an objective view.

Concluding, on the one hand, the presence of two researchers, responsible for the data interpretation and analysis, improved the internal reliability of the project. On the other hand, in terms of improving external reliability, a more extended analysis could have been conducted including both a within-subject and a between-subject tests. Finally, the research has been designed in a way to avoid encountering threats in reliability of findings and conclusions.

4.8.2 Validity

Validity refers to the appropriateness of the measures used and the accuracy of the results (Saunders *et al.*, 2016). To ensure that the variables chosen within the research were meaningful for respondents, these criteria were selected based on literature findings, and reviewed by experts in the finance and clean technology sectors through a face validity test. Similarly to reliability concerns, it is relevant to discuss the validity of the two methodologies used, namely: the CBCA (discrete-choice analysis) and the Calibration Test.

On the one hand, CBCA is considered one of the best preference elicitation methods in terms of validity. In fact, the discrete-choice experiment provided to respondents closely mimics what investors would face in a real impact investing decision-making scenario (Sawtooth Software, 2020). Therefore, this procedure, by resembling the way decisions are made in the real world, increases the likelihood that the behavior observed within this discrete-choice experiment actually corresponds to the true behavior of impact investors.

On the other hand, the Calibration Test formulated within the research, following Lichtenstein *et al.* (1981) approach, can be considered valid in the sense that by following a structured approach, the researchers provide a representative measure that truly indicates the extent of respondents' miscalibration. In fact, Lichtenstein *et al.* (1981) assume that the Bias Score (obtained through the Calibration Test) highly approximates the miscalibrated and overconfident traits of respondents. However, as explained in the *Literature Review* chapter (*see page 33*), overconfidence includes two additional phenomena other than miscalibration: the better-than-average effect and the illusion of control. Thus, the validity of the Calibration Test could be improved by adopting a measure that comprehensively represents respondents' overconfidence, rather than focusing just on miscalibration.

CHAPTER 5 - ANALYSIS AND DISCUSSION

In order to thoroughly analyze the data collected, illustrate the results and discuss any relevant pattern within impact investors' preferences, the researchers divided this chapter into three parts, according to the analytical research approach suggested by Myrdal (1939). The first part is titled *Ex-Ante Analysis* and includes the analysis of the results using a prospective approach. In this part, the researchers will test and discuss the four hypotheses stated in the chapter *Research Questions and Relative Hypotheses* (*see page 42*). The second part is titled *Ex-Post Analysis* and includes the analysis and discussion of the results using a retrospective approach. In this part, the researchers will use the demographics and other individual-specific traits to outline further considerations on the results. Lastly, the third part will address a summary of the findings and their relative discussion.

Concluding, the data analysis has been carried out using R as the chosen econometric analysis software. Moreover, as mentioned in the chapter *Methodology* (*see page 57*), it is worthwhile mentioning that the effects the researchers will be discussing are valid just for the attributes' levels that were chosen and tested. Thus, the reader should take the conclusions that the researchers will draw in the next sections as case-specific and sample-specific and should generalize the results to a more general population of impact investors with adequate limitations.

5.1 THE EX-ANTE ANALYSIS

This section has the purpose of analyzing and interpreting the results of the survey experiment administered to a sample of 89 respondents. To investigate such results the methodology of Choice-Based Conjoint Analysis (or Discrete Choice Analysis) was applied. More precisely, the *Ex-Ante Analysis* will be further divided into two sections. In the first section, the researchers will estimate the Mixed-Logit Model without the use of the overconfidence bias, measured by the Bias Score, as interaction term and will respond to RQ1 by testing H1. In the second section, the researchers will firstly respond to RQ2 by testing whether the respondents are on average overconfident (H2). Secondly, the researchers will estimate the Mixed-Logit Model with the use of the overconfidence bias as the interaction term to test H3a and H3b, which will allow them to address RQ3.

5.1.1 The Model without Overconfidence as an Interaction Term

The first step in the analysis is the estimation of a general Mixed-Logit Model (M1). By using a Mixed-Logit Regression (*see page 53*), the researchers regressed the utilities of the four dummy-coded attributes (independent variables) of Impact Return, Impact Risk, Financial Return and Financial Risk on the total utility of the dummy-coded dependent variable, which is the choice for a specific carbon reduction investment project among two potential alternatives (*see page 55*). In this preliminary approach, the researchers assumed that the preferences for all the four attributes were normally distributed with mean $\beta_{attribute}$ and standard deviation $\sigma_{attribute}$. The parameters' estimates computed through R are summarized by *Table 10* below:

	Estimate	p-value
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.050	0.8572
Impact Return ($\boldsymbol{\beta_{iret}}$)	0.892	0.0002 ***
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-2.115	1.590e-05 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	0.749	0.0079 **
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-1.948	0.0003 ***
Standard Deviation		
SD. Impact Return ($\boldsymbol{\sigma_{iret}}$)	1.557	3.835e-06 ***
SD. Impact Risk ($\boldsymbol{\sigma_{irisk}}$)	-0.288	0.8039
SD. Financial Return ($\boldsymbol{\sigma_{fret}}$)	1.002	0.0097 **
SD. Financial Risk ($\boldsymbol{\sigma_{frisk}}$)	1.652	0.0001 ***

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.149

Table 10 - Summary Results (M1)

In *Table 10*, by considering only the goodness of fit of the model and the significance of the independent variables of such model, two main observations can be made. On the one hand, the McFadden R_2 is equal to 0.149, meaning that the model explains the data collected relatively well (Hensher *et al.*, 2005). On the other hand, only three out of four attributes show both their mean preference score and the relative standard deviation as significant, meaning that the model just estimated is not correctly describing the choices made by the respondents (Hensher *et al.*, 2005). In fact, although the attribute Impact Risk shows a mean preference score β_{irisk} significant at the 1% level, it presents a non-significant standard deviation σ_{irisk} of - 0.288 (p-value = 0.8039). This means that, despite Impact Risk being considered as an important factor during the financial decision-making process of impact investors, it does not show preference heterogeneity across the respondents. Thus, Impact Risk should be thought as a *fixed* *term*[7], meaning that preferences for such attribute do not vary across respondents (Hensher *et al.,* 2005). For this reason, a more precise estimation model M2 had to be performed to adjust this preliminary estimation model (M1) to the fixed effect of the respondents' preferences towards Impact Risk (Hensher *et al.,* 2005).

The researchers estimated M2, similarly to M1, by regressing the utility of the four dummy-coded attributes of Impact Return, Impact Risk, Financial Return and Financial Risk on the total utility of the dummy-coded dependent variable, which is the choice for a specific carbon reduction investment project among two potential alternatives. However, in this model, only Impact Return, Financial Return and Financial Risk are assumed to be normally distributed, whereas Impact Risk is assumed to be a fixed term. Thus, the estimated coefficients of M2 have been summarized in *Table 11* below:

	Estimate	**p-value**
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.052	0.846
Impact Return ($\boldsymbol{\beta_{iret}}$)	0.888	0.0002 ***
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-2.045	7.283e-06 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	0.738	0.0066 **
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-1.883	0.0002 ***
Standard Deviation		
SD. Impact Return ($\boldsymbol{\sigma_{iret}}$)	1.440	4.451e-06 ***
SD. Financial Return ($\boldsymbol{\sigma_{fret}}$)	0.935	0.015 *
SD. Financial Risk ($\boldsymbol{\sigma_{frisk}}$)	1.618	8.382e-05 ***

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.142

Table 11 - Summary Results (M2)

As one can observe in *Table 11*, when comparing M1 with M2, the term *SD. Impact Risk* (σ_{irisk}) disappeared because the attribute Impact Risk does not show preference heterogeneity, hence displaying a "*fixed effect on the model*" (Hensher *et al.,* 2005). On another note, by considering the model fit coefficient of McFadden R_2, one fundamental consideration should be made. By comparing this score to the one obtained in M1, they seem to reveal that M1 displays a slightly better model fit relative to M2, meaning that the McFadden R_2 of M1 is slightly larger

[7]As previously mentioned, if Impact Risk is a fixed term, then respondent 1 derives the same level of utility from the high level of Impact Risk as respondent 2. Similarly, respondent 1 derives the same level of utility from the low level of Impact Risk as respondent 2.

than the one of M2 (0.149 > 0.142). In fact, as theorized by Hauber *et al.* (2016), this score improves with the addition of specifications regarding the explanatory variables. Thus, since the researchers reduced the number of normally distributed parameters within the model, a deterioration of the model fit scores was expected. However, one can deduce that in M2, a deterioration of model fit score should not be a cause of concern as M1 and M2 should not be directly compared (Hensher *et al.*, 2005). The reason is that M1 and M2 represent two completely different models, where only the latter holistically describes the preferences of the sample correctly (Hensher *et al.*, 2005). To conclude, the researchers will use M2 as the appropriate estimation model describing respondents' preferences. On this account, the following paragraphs will focus firstly on testing H1 and, secondly, on a further discussion of the results.

Testing Hypothesis 1

By testing H1, the researchers will be able to answer RQ1, which consists in the following question: "*Do impact investors consider Impact Risk as an important factor within the investment decision-making process?"*. Thus, H1 was stated as follows (*see page 42*):

"*Higher Impact Risk negatively influences impact investors' choices within the investment decision-making process"*

Table 11 above shows that the mean estimate of the preference for Impact Risk (β_{irisk}) is significant at the 0.1% level. Thus, this concludes that Impact Risk is considered as an important factor by respondents when making a decision regarding carbon reduction investments (Hensher *et al.*, 2005). After having tested that this attribute is actually relevant in the financial decision-making process of respondents, the researchers focused on the size and the sign of the effect that Impact Risk had in their choice behavior. In fact, *Table 11* displays that Impact Risk had by far the greatest effect on the respondents' investment preferences. In fact, β_{irisk} is - 2.045, which represents the largest coefficient in absolute terms. Additionally, β_{irisk} presents a negative sign, which means that respondents heavily disliked Impact Risk. However, because of the dummy-coded design in M2, one can apply a more precise interpretation of β_{irisk}, which consists in considering - 2.045 as the logit of the decrease in utility for an investment with a high level of Impact Risk compared to a similar investment with a low level of Impact Risk, ceteris paribus. Thus, the mean estimate for the high level of Impact Risk (compared to the low level) is - 2.045. Conversely, the mean estimate for the low level of Impact Risk (compared to the high level) is equal to + 2.045. In other words, moving from a low level of Impact Risk to a high level of the same attribute decreased the utility (in logit terms) of the respondents by 2.045, ceteris paribus. Therefore, the probability of choosing a project with a High level of Impact Risk is lower compared to the probability of choosing a project with a Low level of Impact Risk, ceteris paribus. Hence, this concludes that higher Impact Risk negatively influences respondents' choices within the investment decision-making process. Concluding, this result leads the researchers to accept H1.

Discussing Hypothesis 1

All in all, the acceptance of H1 can be inserted within the impact investing literature on the conceptual separation between Financial and Impact Risk. More precisely, the significance of the large negative effect of Impact Risk supports the stream of academic literature that theorizes that Impact Risk and Financial Risk should be conceived as two conceptually and practically different parameters (Hornsby & Blumberg, 2013; Puttick & Ludlow, 2013; Godeke & Pomares, 2009; Nicholls *et al.*, 2015). In fact, choosing an investment project with a high Impact Risk does not necessarily imply that the project involves high Financial Risk (Hornsby & Blumberg, 2013). In principle, an impact project may have a good financial prospect with Low Financial Risk, but it could have a poor impact plan, which in turn will lead to a High Impact Risk (Hornsby & Blumberg, 2013). As explained within the *Literature Review* chapter (*see page 23*) this fundamental distinction has been only theorized by relevant academic literature but no scholar has tried to empirically test it. Additionally, the methodology that the researchers used to test such distinction is innovative and has been used very limitedly to analyze impact investors' preferences (Hsu *et al.*, 2014). Concluding, by considering Financial Risk and Impact Risk as two separate parameters, new insights regarding respondents' preferences for these two types of risk will be provided in the next paragraph by placing Financial Risk and Impact Risk within the Impact Investing Framework (Hornsby & Blumberg, 2013).

Further considerations on Hypothesis 1: The Impact Investing Framework

After having determined that Impact Risk had the greatest negative effect on respondents' preferences, it is worthwhile positioning this parameter within the Impact Investing Framework to perform a critical analysis of the conclusions for RQ1. For this reason, in the following paragraphs the researchers will discuss:

- The mean estimates of preference scores and the relative standard deviations for each of the three remaining attributes, i.e. Impact Return, Financial Return and Financial Risk (*see page 82*);
- The trade-off between Financial Return and Impact Return (*see page 83*);
- The trade-off between Financial Risk and Impact Risk (*see page 85*);
- The trade-off between the Financial Risk and Financial Return as well as between Impact Risk and Impact Return (*see page 86*);
- The combination of attributes' levels within the Impact Investing Framework that maximizes the utility of the respondents (*see page 87*).

Preference Scores and Standard Deviations of the Remaining Attributes

Financial Risk

According to *Table 11*, the second largest effect on respondents' choices - after Impact Risk - is Financial Risk, which shows a β_{frisk} equal to - 1.883, significant at the 0.1% level, and a σ_{frisk} of 1.618, significant at the 0.1% level. If one focuses on the mean estimate of the preference score (β_{frisk}), it can be concluded that, as expected, not only Financial Risk was an important variable within impact investing decisions but also that respondents disliked Financial Risk. Therefore, switching from a carbon reduction project with a Low level of Financial Risk to a project with a High level of Financial Risk decreased (in logit terms) the utility of respondents by 1.883, ceteris paribus. In other words, the probability of choosing a project with a High level of Financial Risk is lower compared to the probability of choosing a project with a Low level of Financial Risk, ceteris paribus. Additionally, given the significance of σ_{frisk}, one can conclude that respondents' preferences over this attribute are heterogeneous (Hensher *et al.*, 2005). Furthermore, by comparing this variable with the Impact Risk attribute, it can be concluded that respondents disliked Impact Risk (β_{irisk} = - 2.045) more than Financial Risk (β_{frisk} = - 1.883), confirming that Impact Risk is perceived as a separate parameter than Financial Risk.

Impact Return

According to *Table 11*, the third largest effect on respondents' preferences is related to Impact Return, which shows a β_{iret} equal to 0.888, significant at the 0.1% level, and a σ_{iret} of 1.440, significant at the 0.1% level. By focusing on the mean estimate of the preference score (β_{iret}), one can conclude that, as expected, not only Impact Return was an important variable within impact investing decisions but also that respondents largely liked Impact Return. Therefore, switching from a carbon reduction project with a Low level of Impact Return to a project with a High level of Impact Return increased (in logit terms) the utility of respondents by 0.888, ceteris paribus. In other words, the probability of choosing a project with a High level of Impact Return is higher compared to the probability of choosing a project with a Low level of Impact Return, ceteris paribus. Moreover, given the significance of σ_{iret}, one can conclude that respondents' preferences over Impact Return are heterogeneous (Hensher *et al.*, 2005). Furthermore, comparing this variable with the Impact Risk attribute, one can conclude that respondents disliked Impact Risk more than they liked Impact Return because, in absolute terms, - 2.045 (β_{irisk}) is larger than 0.888 (β_{iret}).

Financial Return

According to *Table 11*, the smallest effect on impact investors' preferences is connected to Financial Return, which shows a β_{fret} equal to 0.738, significant at the 1% level, and a σ_{fret} of 1.618, significant at the 0.1% level. By focusing on the mean estimate of the preference score (β_{fret}), one can conclude that, as expected, not only Financial Return was an important variable within impact investing decisions, but also that respondents liked Financial Return. Therefore, switching from a carbon reduction project with a Low level of Financial Return to a project with a High level of Financial Return increased (in logit terms) the utility of respondents by 0.738, ceteris paribus. In other words, the probability of choosing a project with a High level of Financial Return is higher compared to the probability of choosing a project with a Low level of Financial Return, ceteris paribus. Furthermore, given the significance of σ_{fret}, one can conclude that respondents' preferences over Financial Return are heterogeneous (Hensher *et al.,* 2005). Moreover, comparing this variable to Financial Risk and to Impact Return, one can conclude that respondents:

- Disliked Financial Risk more than they liked Financial Return because, in absolute terms, - 1.883 (β_{frisk}) is larger than 0.738 (β_{fret});
- Liked Impact Return more than Financial Return, because 0.888 (β_{iret}) is larger than 0.738 (β_{fret}).

The Financial Return and Impact Return Trade-off

To completely understand the nature of return preferences within respondents, a focus on the trade-off between Impact Return and Financial Return is necessary. As the researchers outlined in the previous paragraph, respondents liked Impact Return more than Financial Return as the preference score of the former is larger than the latter. Thus, it can be deduced that, according to the definition adopted within the chapter *Literature Review* (*see page 25*), respondents can be described as mainly *"Impact-First"* rather than *"Finance-First"* (Brest & Born, 2013; Mitchell *et al.*, 2008; Hornsby & Blumberg, 2013). Additionally, thanks to the methodology used it was also possible to identify a numerical expression for the trade-off between Financial and Impact Return. In other words, the researchers computed the Marginal Rate of Substitution (MRS) for the return attributes (R Cran, 2020).

The Marginal Rate of Substitution of Financial Return for Impact Return

The MRS coefficient explaining the respondents' trade-off between returns is computed as follows (R Cran, 2020):

$$MRS\ of\ Financial\ Return\ for\ Impact\ Return = \frac{\beta_{Impact\ Return}}{\beta_{Financial\ Return}} = \frac{0.888}{0.738} = 1.2$$

However, given the dummy-coded nature of the variables within the experimental design, to interpret this coefficient in realistic terms, the researchers needed to take an additional assumption, which consists in considering that the attributes Financial Return and Impact Return have a linear (rather than logarithmic) effect on the utility that the respondents derive from the investment choice (R Cran, 2020). This critical assumption allows for the MRS of Financial Return for Impact Return to be interpreted as follows: in order for a respondent to increase the level of Impact Return from 10 to 20 million tons of CO_2 reduction, the respondent would be willing to sacrifice Financial Return moving from IRR of 8% to one of 3.2%. Thus, respondents are more willing to give up a better financial performance than to give up a better impact performance of a project, meaning once again that respondents in the sample can be recognized as *"Impact-First"*. A more detailed explanation of the MRS coefficient can be found in *Appendix 4 (at page 155)*.

These results can be inserted in the discussion denominated as "*financial return and impact return trade-off*" (Evans, 2013). In fact, according to Hornsby & Blumberg (2013) and Höchstädter & Scheck (2015), impact investors defined as *"Impact-First"* sacrifice Financial Return for an increase in Impact Return, at the same level of risk. This definition applies to the sample because the calculated trade-off shows that for respondents Impact Return and Financial Return do not have the same weight (i.e. preference score) and that, somehow, they still have a very categorical understanding of impact investing (Evans, 2013). This means that, in the sample, respondents' decision-making approach to impact investing assumes that one cannot reach a high Financial Return and, at the same time, obtain a high Impact Return. However, according to more recent literature on impact investing, more savvy impact investors have been gradually moving beyond this trade-off debate and have been developing more sophisticated approaches that can guarantee a high risk-adjusted return with substantial social and environmental impact (Grabenwarter & Liechtenstein, 2011). Hence, nowadays the well-known "*financial and impact return trade-off*" has been transforming into what has been defined as a "*myth*" (Pandit & Tamhane, 2018). Nevertheless, in discordance with this stream of impact investing literature, the obtained results confirm that, although impact investors are developing new investment frameworks where both high Impact Return and high Financial Return can be attained, the fundamental *"financial and impact returns trade-off"* is still present in their mental framework used while making an investing decision. Thus, as explained in the *Literature Review* chapter (*see page 25*), the trade-off within these two types of return can hinder the development of the impact investing sector in the long run (Grabenwarter & Liechtenstein, 2011). A further discussion on the managerial implication of the just tested phenomenon will be executed in the *Conclusions and Limitations* chapter (*see page 108*).

The Financial Risk and Impact Risk Trade-off

To correctly understand the Impact Investing Framework, one should not only observe the returns' side of the investment, but also take the risks side into account. As explained in previous paragraphs of this section (*see Table 11*), Impact Risk and Financial Risk represent the two attributes with the largest (negative) effect on respondents' preferences. Moreover, the results described that respondents disliked Impact Risk more than Financial Risk (*see page 82*). Thus, these observations seem to describe that, in the same way in which literature outlines the presence of an "*financial return and impact return trade-off*", within the minds of respondents, a so-called "*financial risk and impact risk trade-off*" is also present. To thoroughly depict and analyze this new observed trade-off, the researchers computed a MRS coefficient for the risks.

<u>*The Marginal Rate of Substitution of Financial Risk for Impact Risk*</u>

The MRS coefficient explaining the respondents' trade-off between risks is calculated in the following manner (R Cran, 2020):

$$MRS\ of\ Financial\ Risk\ for\ Impact\ Risk = \frac{\beta_{Impact\ Risk}}{\beta_{Financial\ Risk}} = \frac{-2.045}{-1.883} = 1.09$$

Nevertheless, given the dummy-coded nature of the variables within the experimental design, to interpret this coefficient in realistic terms, the researchers needed to take a linearity assumption, similar to the one taken while computing the MRS between the returns' coefficients (*see page 83*). This critical assumption allows for the MRS of Financial Risk for Impact Risk to be interpreted as follows: in order for a respondent to decrease the level of Impact Risk from a 50% to a 5% percentage probability of not delivering the impact as planned, the respondent would be willing to take up Financial Risk moving from a 5% probability to a 54% probability of only breaking even or worse. Hence, generally respondents are more willing to take up a high Financial Risk than to face a high Impact Risk. A more detailed explanation of the MRS coefficient can be found in *Appendix 5* (*at page 156*).

Overall, this result further empirically confirms the view considering Impact and Financial Risks separately, which is only theoretically introduced within the literature of impact investing (Hornsby & Blumberg, 2013; Puttick & Ludlow, 2013; Godeke & Pomares, 2009; Nicholls *et al.*, 2015; Brandstetter & Lehner, 2016). In this regard, the analyzed results' can be understood as original and innovative. In fact, on the one hand, Impact Risk and Financial Risk have been empirically tested as two separate, rather than overlapping, variables within the impact investing decision-making process. On the other hand, Impact Risk seems to have a larger importance in the investment choices of respondents. This phenomenon can have two main potential explanations. The first one is that the savvy impact investor is actually concerned with each of these aspects of risk and with how these various aspects play out within the context of impact investing (Hornsby & Blumberg, 2013). The second one has a more practical nature and it is related to the formulation used to define the attribute Impact Risk. In fact, the researchers defined Impact Risk as the risk that the potential impact to be created by the project fails and does not materialize due to the overall ineffective formulation of the so-called impact plan (Hornby & Blumberg, 2013). Although the decision to define the attribute in this way was determined by the general and inclusive nature of the definition, as explained in the *Literature Review* chapter, different definitions of Impact Risk can be associated with the term (*see page 22*). Thus, by considering a different definition of Impact Risk, the researchers could have concluded different insights and results. Due to the limited scope of this research project, further research could explore how impact investors' risk preferences change depending on the different definitions assigned to Impact Risk.

Financial Risk/Return Trade-off and Impact Risk/Return Trade-off

Finally, by integrating the earlier conclusions on the Impact Investing Framework, the researchers can outline a holistic interpretation of the results. As explained in the previous paragraphs, on the *impact side* of the framework, respondents disliked Impact Risk more than they liked Impact Return (*see page 82*). Similarly, on the *financial side* of the framework, respondents disliked Financial Risk more than they liked Financial Return (*see page 83*). Thus, in both the impact and financial sides of the Impact Investing Framework, respondents showed a considerable *risk-averse behavior*, meaning that they disliked risk, but they were willing to assume it if they were accordingly compensated (Booth *et al.*, 2016). This result is in contrast with the theoretical contribution by Lane (2014) and Emerson (2012), which theorized that impact investors show a risk-tolerant attitude and display a tendency to over-forgive risks, meaning that they tend to forgo their compensation for the risk they are taking. Indeed, the mean estimates of the preference scores clearly indicated that the two risk parameters had a much larger influence on the probability that a cleantech project was chosen, compared to the two return parameters. Thus, in other words, the risk dimension of the investment had more influence than the return dimension of the investment itself during the investment decision-making process. For clarity reasons, the researchers placed a further numerical proof of respondents' rational risk-averse behavior on a choice-by-choice basis in *Appendix 6* (*at page 157*). Furthermore, in *Appendix 6*, it can be observed that not only respondents were risk-averse but that they also chose their preferred impact investing projects with an *"Impact-First"* approach, favoring the impact risk-adjusted performance of the investment over the financial risk-adjusted performance. However, it can also be observed that in three (out of six) choice tasks - where individuals had to make a choice between one investment profile with a higher risk-adjusted impact return and one with a higher risk-adjusted financial return - respondents displayed almost a 50-50 distribution among the two alternatives proposed in each of the choice tasks. Thus, this result demonstrates that, although the sample can overall be considered *"Impact-First",* the dominance of this investment approach over the *"Finance-First"* approach was not completely outstanding. Therefore, this indicates that impact investors' decision strategy is virtually moving beyond the "*financial and impact returns trade-off*" towards a more comprehensive view of impact investing where Financial and Impact Return can be achieved simultaneously (Grabenwarter & Liechtenstein, 2011). This reasoning is further confirmed by the MRS of Financial Return for Impact Return and the MRS of Financial Risk for Impact Risk previously computed. The former was equal to 1.2, whereas the latter was equal to 1.09, meaning that in both cases the Impact and Financial preference scores used were not extensively different from each other because the MRSs scores were close to 1. This reflects the fact that the Impact Return preference score was not very different from the one of Financial Return. Similarly, the Impact Risk score was not very different from the one of Financial Risk.

To sum up, by enlarging the focus of the analysis over the entire Impact Investing Framework, the researchers concluded that the sample had an *"Impact-First"* and risk-averse nature. Thus, given this two-folded nature of the sample, the researchers will examine what would be the best investment profiles that would maximize the respondents' utility.

Utility-Maximizing Investment Profiles

In order to explain which combination of the attribute's levels would maximize the utility of respondents, the researchers need to consider a broader focus than the one adopted in the previous paragraph. This means that, as outlined in *Appendix 7* (*at page 163*), the researchers will examine the overall set of choices described within the full factorial design (i.e. 16 investment profiles) rather than the efficient design used in the survey experiment (i.e. 12 investment profiles).

According to the mean preference score outlined in *Table 11*, the most preferred (first-best) investment profile would be a project displaying High Impact and Financial Returns and Low Impact and Financial risks, meaning the profile showing the most preferred level for each of the four attributes. This investment profile provides an average total utility of 5.554 to respondents in the sample (*see Appendix 7 at page 163*), and it is defined as a dominant choice as every respondent would maximize returns and minimize risks (Hurtado, 2016). Thus, considering such investment alternative as the most preferred is predictable because, if presented in a choice task, each single respondent would choose a high returns-low risks investment. For this reason, the researchers focused their attention on the second-best investment profile, which provides an average total utility of 4.078 to respondents in the sample (*see Appendix 7 at page 163*), and was composed by the following attribute' levels: *High Impact Return, Low Impact Risk, Low Financial Return and Low Financial Risk*. This result further confirms that, on the one hand, respondents used a *"Impact-First"* investment approach sacrificing a financial risk-adjusted performance for a high impact risk-adjusted performance. On the other hand, it confirms that respondents were risk-averse because the investment profile considered displayed low levels of Impact and Financial Risk.

5.1.2 The Model with Overconfidence as an Interaction Term

After having addressed RQ1 and confirmed H1 by using M2, the researchers will now address RQ2 and RQ3, by testing respectively H2, H3a and H3b. Firstly, H2 introduces the behavioral finance perspective to test whether respondents show the overconfidence bias. Consequently, after H2 is confirmed, the researchers will test H3a and H3b by complementing M2 using an interaction term, namely the overconfidence trait previously tested in H2.

Testing Hypothesis 2

To address RQ2 and test the presence of the overconfidence bias among impact investors, the researchers adopted the methodology of the Calibration Test proposed by Lichtenstein *et al.* (1981). The Calibration Test is used to measure respondents' miscalibration, one type of overconfidence occurring when impact investors overestimate the precision of their knowledge (Ackert & Deaves, 2018). Therefore, respondents were asked to answer six general knowledge questions within the impact investing field and after each question they had to select how confident they were that the answer given was the correct one. Consequently, across all six questions, the researchers calculated the average of correct answers and the average of the confidence level expressed by every respondent. By adopting this approach, the researchers calculated a Bias Score for each respondent, whereby:

Bias Score = average confidence score – average correct score

The Bias Score numerically expresses the miscalibration concept. More precisely, a respondent displaying a positive Bias Score shows that he/she is overconfident, whereas a negative Bias Score represents under-confidence. Therefore, a Bias Score of 0 represents a well-calibrated person (Lichtenstein *et al.*, 1981). After having briefly summarized the method used to address RQ2, H2 will be tested. Hypothesis 2 was stated as follows:

"Impact investors, on average, overestimate the precision of their knowledge."

To accept or reject H2, it is necessary to test whether the average Bias Score across the sample is significantly higher than zero, where zero represents the score of a well-calibrated individual. This shows the fact that, on average, respondents are overestimating the precision of their knowledge, and hence are overconfident.

The researchers calculated the *average confidence score* and the *average correct score* across the sample, which respectively corresponded to 0.460 and 0.195. Thus, by applying the formula just presented, the average Bias Score characterizing the sample was calculated as 0.265 (= 0.460 - 0.195). *Table 12* below summarizes the descriptive statistics of the Bias Score variable across the sample:

Descriptive Statistics: Bias Score	
Mean	0.265
Standard Error	0.019
Standard Deviation	0.181
Sample Variance	0.033
Skewness	-0.287
Minimum	-0.250
Maximum	0.667
Confidence Level (95%)	0.038

Table 12 - Bias Score Descriptive Statistics

According to *Table 12*, the smallest Bias Score obtained was - 0.25, this reflects that the sample selected also contained some respondents who were under-confident. The largest Bias Score characterizing the sample was 0.667, reflecting that respondents showed varying degrees of Bias Score. *Figure 18* below shows that the Bias Score variable approximately followed a normal distribution. In fact, the majority of respondents had a Bias Score between 0.17 - 0.31 and the others were distributed fairly symmetrically around this range. This is further confirmed by the skewness of - 0.287 (Hensher *et al.*, 2005).

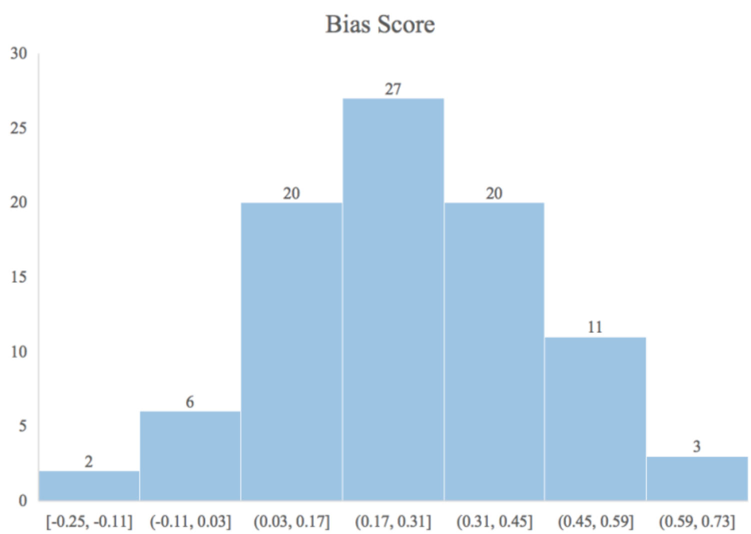

Figure 22 - Distribution of the Bias Score

As mentioned in the section *Reliability* of the *Methodology* chapter (*see page 73*), to assess the reliability of the average Bias Score obtained from the sample, the researchers also calculated the average Bias Score for a pilot sample composed of 40 respondents. The average Bias Score for the pilot sample was 0.28, which reflects that the mean Bias Score of 0.265 obtained for the final sample is a reliable measure.

To determine whether the sample is representative of the population, the 95% confidence interval for the mean has been calculated by using the formula:

$$mean(x) \pm z\frac{s}{\sqrt{n}}$$

whereby *mean(x)* is the sample mean (0.265), *z* corresponds to the z-value (1.96 for 95% confidence level), *s* is the sample standard deviation (0.181) and *n* is the number of observations (89) (Hensher *et al.*, 2012). Therefore, by subtracting (adding) the value 0.04 from (to) the mean, the 95% confidence interval corresponds approximately to the range of [0.23 - 0.31]. This further reflects that the sample mean of 0.265 is representative of the population mean (Hensher *et al.*, 2012).
Although *Table 12* shows that the average Bias Score is higher than zero and equal to 0.265, it is necessary to test the significance of the mean Bias Score derived from the sample. Therefore, the one-sample t-test was performed. Since the researchers are interested in testing that the mean overconfidence (in terms of Bias Score) is significantly larger than zero, two hypotheses were formulated:

H_0*: mean Bias Score = 0*

H_1*: mean Bias Score > 0*

By running the t-test on the statistical software R, a p-value of 2.2e-16 has been found. Since the p-value is lower than the 0.05 significance level, there is evidence to reject the null hypothesis (H_0) in favor of the alternative hypothesis (H_1). Therefore, the mean Bias Score of 0.265 can be considered statistically significant (Hensher *et al.*, 2012). Since, within the sample, the average Bias Score has been tested as significantly positive and different from zero, it can be concluded that on average respondents were miscalibrated and overestimated the precision of their knowledge. Given that within this research project a positive Bias Score is used as a measure for overconfidence, the statement shows the presence of the overconfidence bias among respondents and allows the researchers to accept H2. Thus, the analysis can proceed to address RQ3.

Testing Hypothesis 3

To address RQ3, which focuses on whether overconfidence among respondents affects their preferences for risk, the researchers complemented the previously introduced M2 (*see page 79*) with the interaction term of the Bias Score variable, representing the overconfidence bias. This new model allows the researchers to detect whether the heterogeneity of respondents' preferences for risk is explained by this interaction term (*see Figure 15 and Figure 16*).

Testing Hypothesis 3a

Hypothesis 3a was stated as follows:

"Overconfident impact investors are more willing to choose investments displaying a high Impact Risk, compared to non-overconfident impact investors."

As previously mentioned (*see Table 11*), the attribute Impact Risk has been tested as a significantly relevant parameter having a negative effect on respondents' preferences during the investment decision-making process. However, the attribute Impact Risk presented a non-significant standard deviation, meaning that the attribute had a fixed effect and that respondents' preferences for this attribute did not vary. Given the fixed nature of Impact Risk, estimating the new model M3a with the addition of the interaction term is not feasible. In fact, the model cannot test whether overconfidence among respondents influences their preferences for Impact Risk, given that the sample does not present sufficient preference heterogeneity with regards to this attribute (*see page 61*). Given these considerations, H3a could not be tested.

Testing Hypothesis 3b

H3b was stated as follows:

"Overconfident impact investors are more willing to choose investments displaying a high Financial Risk, compared to non-overconfident impact investors."

As previously mentioned (*see page 82*), the attribute Financial Risk has been tested as a significantly relevant parameter having the second greatest (negative) effect on respondents' preferences during the investment decision-making process. Moreover, the attribute is characterized by a standard deviation (σ_{frisk}) equal to 1.618 significant at the 0.1% level, showing that Financial Risk displayed the highest preference variability across respondents (*see*

Table 11). In contrast with the attribute Impact Risk previously discussed, a significant standard deviation represents that the preferences regarding Financial Risk are heterogeneous, meaning that the preferences for this attribute vary across respondents due to individual-specific traits. Therefore, in this case, it was feasible to estimate a new Mixed-Logit Model with the Bias Score as interaction term (M3b). In fact, the model estimates whether the heterogeneity of preferences regarding Financial Risk is explained by the overconfidence trait characterizing respondents. The researchers estimated M3b, similarly to the other models, by regressing the utility of the four dummy-coded attributes of Impact Return, Impact Risk, Financial Return and Financial Risk on the total utility of the dummy-coded dependent variable represented by the respondents' choices within each choice task. Additionally, the interaction term Bias Score was introduced within the Mixed-Logit Regression on the attribute Financial Risk. The estimated coefficients resulting from M3b are summarized in *Table 13* below:

	Estimate	p-value
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.052	0.846
Impact Return ($\boldsymbol{\beta_{iret}}$)	0.883	0.0002 ***
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-2.044	6.975e-06 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	0.737	0.0065 **
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-2.160	0.0002 ***
Financial Risk : Bias Score ($\boldsymbol{\beta_{frisk:bias}}$)	1.044	0.2458
Standard Deviation		
SD. Impact Return ($\boldsymbol{\sigma_{iret}}$)	1.436	4.452e-06 ***
SD. Financial Return ($\boldsymbol{\sigma_{fret}}$)	0.930	0.0152 *
SD. Financial Risk ($\boldsymbol{\sigma_{frisk}}$)	1.604	0.0001 ***

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.143

Table 13 - Summary Results (M3b)

By looking at the coefficient of model fit, M3b is characterized by a McFadden R_2 of 0.143, showing that the model explains the respondents' preferences relatively well (Hensher *et al.*, 2005). What is new within M3b is the mean preference score for Financial Risk (β_{frisk}) and the mean preference score called "*Financial Risk : Bias Score*" ($\beta_{frisk:bias}$). The former coefficient equals to - 2.160 and corresponds to the preference score that the respondents with the lowest Bias Score assign to a high level of Financial Risk compared to a low level of the same attribute. Since within the sample, the lowest Bias Score corresponds to - 0.25 (*see Table 12*), the coefficient

β_{frisk} represents the preference score that an under-confident respondent has for the high level of Financial Risk compared to the low level. The latter mean preference score ($\beta_{frisk:bias}$) equals to 1.044 and represents the interaction effect existing between respondents' preferences for Financial Risk and the overconfidence bias, which is an individual-specific trait. In other words, $\beta_{frisk:bias}$ corresponds to the preference score that the respondents with the highest Bias Score assign to a high level of Financial Risk relative to a low level of Financial Risk. However, *Table 13* shows that $\beta_{frisk:bias}$ is not significant (p-value = 0.2458). Therefore, H3b has to be rejected. This means that, although there is prominent heterogeneity in respondents' preferences regarding Financial Risk, in this case such heterogeneity is not explained by their level of overconfidence (Hensher *et al.*, 2012). Alternatively, if $\beta_{frisk:bias}$ was to be found significant, the researchers would have expected that the interaction coefficient $\beta_{frisk:bias}$ would have been positive, showing that overconfident respondents were willing to take up a higher Financial Risk (Barber & Odean, 2001; Broihanne et al., 2014). However, given that the sample used within research project has been found to be considerably risk-averse a more realistic expectation would have corresponded to the interaction coefficient $\beta_{frisk:bias}$ to be still negative but closer to zero, meaning that overconfident respondents would have been less reluctant to take risk than non-overconfident respondents.

Overall, by having rejected both H3a and H3b, no evidence has been found on overconfidence trait influencing respondents' preferences towards Impact Risk and Financial Risk. The former hypothesis could not be tested because the model was not feasible, given the absence of heterogeneity in respondents' preferences regarding Impact Risk. The latter one had to be rejected because the coefficient representing the interaction effect was not significant, meaning that overconfidence does not explain respondents' preferences for Financial Risk.

Discussing Hypothesis 3b

Overall, the estimation of M3b allowed the researchers to conclude that overconfidence bias does not influence respondents' preferences for Financial Risk. This result may have four potential explanations. The first explanation could be that the sample used consisted only of 89 respondents. This may represent a problem as CBCA requires a very large number of respondents to provide more accurate estimates (roughly around 200) (Rao, 2014). Hence, by doubling the sample size the analysis could have reached better coefficients' significance. Secondly, another potential explanation may be that, although the average Bias Score for the sample is 0.265, showing that respondents on average are overconfident, it can be argued that the average Bias Score is relatively low (Lichtenstein *et al.*, 1981). In fact, given that the maximum Bias Score obtained in the sample is 0.667 (*Table 12*), by having access to a larger sample the researchers could have observed whether the average Bias Score would have increased. Thirdly, through the Calibration Test, the researchers focused only on one type of overconfidence, namely miscalibration. Therefore, by finding a way to complement in a numerical expression all the three types of overconfidence (i.e. miscalibration, better-than-average effect and illusion of control), the interaction term could have represented more comprehensively the overconfidence bias and provided more accurate results. However, due to the limited scope of this thesis, this task could be further explored in future research. Lastly, as previously discussed (*see page 86*), the sample displayed a clear risk-averse attitude, meaning that respondents were willing to take Financial Risk only if adequately compensated. Hence, this result is in contrast with the main behavioral finance assumption behind overconfidence bias, whereby overconfident investors behave irrationally by taking excessive Financial Risk without being accordingly compensated (Barber & Odean, 2011).

5.2 THE EX-POST ANALYSIS

After having concluded the Ex-Ante Analysis and addressed the three Research Questions at the heart of this research project, by implementing an Ex-Post Analysis, the researchers will look retrospectively at the results obtained and make some further considerations. In the Ex-Ante Analysis, the researchers analyzed and further discussed the mean estimates of the preference scores for the four attributes in the Impact Investing Framework (Hornsby & Blumberg, 2013). However, less attention was aimed at their respective standard deviations, indicating respondents' preference heterogeneity around each attribute. For this reason, this part will focus on gaining more insights around the preference heterogeneity over Financial Risk, Financial Return and Impact Return. In this context, considerations about Impact Risk could not be made because the model was not feasible since the attribute did not show sufficient heterogeneity among respondents' preferences (i.e. standard deviation of Impact Risk was not significant).

5.2.1 Further Considerations About the Heterogeneity of Financial Risk

The Ex-Ante Analysis showed that respondents displayed preference heterogeneity with regards to Financial Risk (*see page 82*). For this reason, the researchers tried to explain such heterogeneity with the individual-specific trait of overconfidence, as measured by the Bias Score. However, the Bias Score resulted as not significant in explaining the heterogeneity regarding respondents' preferences for Financial Risk (*see page 91*). Therefore, it is relevant to test whether by operationalizing overconfidence differently, an evidence explaining the presence of heterogeneity in impact investors preferences for Financial Risk could be found. This can be obtained by complementing the model M2 with an interaction term described by other individual-specific traits that are close proxies for overconfidence. As mentioned in the *Literature Review* chapter (*see page 34*), demographics such as *Gender*, *Age* and *Years of Experience* serve this purpose. In fact, as supported by Barber & Odean (2001), men are more prone to overconfidence than women, particularly in the realm of finance. Moreover, Ho *et al.* (2016) state that in demanding jobs, such as being an impact investor, older adults are more overconfident than younger ones. Lastly, Deaves *et al.* (2010) support the idea that greater years of experience are associated with higher levels of overconfidence. Therefore, the researchers estimated three Mixed-Logit Models, whereby each model introduced a different interaction term, described by one of the overconfidence proxies previously noted. The models tested whether each of these proxies for overconfidence could explain impact investors' preference heterogeneity for Financial Risk. Given that overconfident impact investors are prone to take up more risks (Barber & Odean, 2001), the researchers expect that:

- Male respondents are more willing to choose investments displaying a high Financial Risk, compared to female respondents;
- Older respondents are more willing to choose investments displaying a high Financial Risk, compared to younger respondents;
- More experienced respondents are more willing to choose investments displaying a high Financial Risk, compared to less experienced respondents.

However, for the three estimated models, each interaction effect with the attribute Financial Risk resulted as non-significant (*see Appendix 8 at page 164*). Therefore, by using the other proxies for overconfidence the researchers still did not obtain any evidence on whether the overconfidence characterizing respondents explains the heterogeneity in their preferences for Financial Risk.

5.2.2 Further Considerations About the Heterogeneity of Financial and Impact Return

As previously mentioned, it is relevant to observe whether the demographic data collected about respondents explains the heterogeneity in their preferences for Impact Return and Financial Return. Given that the sample appeared to follow an *"Impact-First"* approach (*see page 83*), the researchers executed an interaction analysis to understand whether the *"Impact-First"* nature of the respondents could be explained by demographics regarding their impact investing knowledge, educational background and current job industry.

Knowledge Within the Impact Investing Field and Impact Return: An Interaction Analysis

As previously mentioned in the *Survey Design* section (*see page 65*), one part of the survey consisted in the Calibration Test, whereby respondents answered six general knowledge questions about the impact investing field. In this context, the average number of correct answers was calculated for each respondent and was named *Average Correct Score*. Due to its nature, this score approximated respondents' actual knowledge within the impact investing sector. Respondents could score from a range of 0 to 1, where 0 corresponded to giving the wrong answer to all of the six questions, and 1 corresponded to responding correctly to all of them. By using the Average Correct Score as an interaction term, the new model M4 estimated the following preference scores *(Table 14)*:

	Estimate	**p-value**
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.085	0.7523
Impact Return ($\boldsymbol{\beta_{iret}}$)	0.599	0.0341 *
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-1.977	8.806e-06 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	0.716	0.0092 **
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-1.876	0.0003 ***
Impact Return : Average Correct ($\boldsymbol{\beta_{iret:correct}}$)	1.803	0.0482 *

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.144

Table 14 - Summary Results (M4)

By looking at the coefficient of model fit, this model is characterized by a McFadden R_2 of 0.144, meaning that the model explains the respondents' preferences relatively well (Hensher *et al.*, 2005). *Table 14* shows that, on the one hand, less knowledgeable respondents have a β_{iret} of 0.599, significant at the 5% level. On the other hand, more knowledgeable respondents have a preference score for Impact Return of 1.803 ($\beta_{iret:correct}$), significant at the 5% level. This means that more knowledgeable respondents have a higher preference score for Impact Return, with respect to the less knowledgeable respondents ($\beta_{iret:correct} > \beta_{iret}$). However, a similar reasoning could not be made on the effect that impact investing knowledge has towards respondents' preferences regarding Financial Return because the interaction effect was not significant (*see Appendix 9 at page 167*). These results are subject to some limitations. In fact, given that across the sample the average of correct answers was 0.19 (corresponding on average to 1 correct answer out of 6), it might not be correct to consider these results as particularly relevant. Moreover, this low Correct Average Score is due to the fact that the purpose of this thesis was not to test the actual knowledge of respondents, but rather testing how much they overestimated the precision of such knowledge. Therefore, it is not entirely appropriate to consider the Average Correct Score as a valid approximation for their knowledge. Further research could provide a more comprehensive set of questions to accurately test respondents' knowledge and provide more valid results. On another note, observing that more knowledgeable respondents prefer higher Impact Return supports the view that greater knowledge regarding impact investing is essential for the growth of this sector because investors will make their decisions by having a greater awareness of the positive impact they can create on the environment (Woodland, 2019).

Experience Within the Finance Industry and Financial Return: An Interaction Analysis

The demographic data collected showed that the majority of the sample (47%) is currently working within the finance industry. Therefore, the researchers estimated the Mixed-Logit Model M5 including an interaction term expressed as a dummy, namely 1 if the respondent was working in finance and 0 otherwise. M5 estimated an interaction effect to observe whether having experience within the Finance industry affects respondents' preferences for Financial Return. By using the variable *Industry Finance* as an interaction term, the new model M5 estimated the following preference scores *(Table 15)*:

	Estimate	**p-value**
Mean Preference Score		
Intercept ($\boldsymbol{\beta}_0$)	-0.086	0.7484
Impact Return ($\boldsymbol{\beta}_{iret}$)	0.960	8.165e-05 ***
Impact Risk ($\boldsymbol{\beta}_{irisk}$)	-1.963	8.806e-06 ***
Financial Return ($\boldsymbol{\beta}_{fret}$)	0.375	0.2214
Financial Risk ($\boldsymbol{\beta}_{frisk}$)	-1.870	0.0003 ***
Financial Return : Industry Finance ($\boldsymbol{\beta}_{fret:industy\_fin}$)	0.680	0.0320 *

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.146

Table 15 - Summary Results (M5)

By looking at the coefficient of model fit, this model is characterized by a McFadden R_2 of 0.146, showing that the model explains the respondents' preferences relatively well (Hensher *et al.*, 2005). As *Table 15* shows, respondents who are currently working in finance have a higher preference score towards Financial Return compared to the ones who are not working in finance, as $\beta_{fret:industry\_fin}$ is greater than β_{fret} (0.680 > 0.375). However, the researchers could not make a similar observation regarding Impact Return, because the interaction effect was not significant (*see Appendix 10 at page 168167*). Finally, although the researchers have previously concluded that the sample showed an *"Impact-First"* trend (*see page 83*), it can be noticed that the trend is moderated by the respondents' experience within the finance sector.

Finance Educational Background, Impact Return and Financial Return: An Interaction Analysis

Finally, demographic data collected within the survey displayed that the majority of the sample belonged to either a financial (38%) or a business (37%) background. Although the two backgrounds were shown separately in the survey, the researchers decided to merge these two demographic variables and consider them as a single element denominated as Finance Background. The reason is that both graduates from a business and from a purely finance backgrounds are more likely to eventually find a job in the finance sector. Therefore, the researchers estimated M6a and M6b including an interaction term expressed as a dummy, namely 1 if the respondent had a background in finance and 0 otherwise. The models estimated an interaction effect between the respondents' background in finance and their preference for Impact Return (M6a) and Financial Return (M6b). More precisely, the two interaction analyses have been executed separately and the results were then compared. The new models M6a and M6b estimated the following preference scores *(Table 16 and 17)*:

	Estimate	**p-value**
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.095	0.724
Impact Return ($\boldsymbol{\beta_{iret}}$)	1.617	9.212e-06 ***
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-1.994	1.001e-05 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	0.736	0.0077 **
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-1.906	0.0002 ***
Impact Return : Finance Background ($\boldsymbol{\beta_{iret:finbackground}}$)	-0.943	0.0060 **

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.150

Table 16 - Summary Results (M6a)

	Estimate	p-value
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.098	0.718
Impact Return ($\boldsymbol{\beta_{iret}}$)	0.961	0.0001 ***
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-2.015	8.095e-06 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	-0.045	0.909
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-1.909	0.0002 ***
Financial Return : Finance Background ($\boldsymbol{\beta_{fret:finbackground}}$)	1.014	0.0119656 *

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.151

Table 17 - Summary Results (M6b)

By looking at the coefficients of model fit, one can observe that M6a is characterized by a McFadden R_2 of 0.150, whereas M6b is characterized by a McFadden R_2 of 0.151. This means that both models explain the respondents' preferences relatively well, in particular, the second model explains the data collected slightly better than the first one (Hensher *et al.*, 2005). Additionally, one can conclude that the two models displayed in *Table 16* and *Table 17* above better explain the data collected, when compared to M2 (*see Table 11*). Furthermore, *Table 16* and *Table 17* above show two important results. On the one hand, by looking at *Table 16*, individuals who have a finance background have a negative preference score towards Impact Return ($\beta_{iret:finbackground}$ = - 0.943). This means that respondents who have a background in finance dislike Impact Return. By focusing instead on the individuals who do not have a finance background, one can find a positive preference score towards Impact Return. This means that respondents who do not have a finance background like Impact Return (β_{iret} = 1.617). Overall, individuals who have a finance background prefer low levels of Impact Return, whereas respondents who do not have such background prefer high levels of such attribute.

On the other hand, by looking at *Table 17* individuals who have a finance background have a positive preference score towards Financial Return ($\beta_{fret:finbackground}$ = 1.014). This means that respondents who have a background in finance like Financial Return. By focusing instead on the individuals who do not have a finance background, one can find a negative preference score towards Financial Return (β_{fret} = - 0.045). This means that respondents who do not have a finance background Financial Return. Overall, individuals who have a finance background prefer high levels of Financial Return, whereas respondents who do not have such background prefer low levels of this attribute.

Integrating the insights from the two models, respondents who have a finance background prefer high levels of Financial Return and low levels of Impact Return (*"Finance-First"* approach), whereas respondents who do not have such background prefer high levels of Impact Return and low levels of Financial Return (*"Impact-First"* approach). This result confirms the primary insights proposed by Delsen & Lehr (2019) regarding the importance of the educational background on impact investors' preferences for sustainable projects. Moreover, the discussed outcome contributes to the literature on financial literacy. In fact, individuals with higher financial literacy tend to like Financial Return more than Impact Return, because - due to their deeper knowledge about financial products and services - they can secure higher financial returns (Bajo *et al*., 2015).

To sum up, through M6a and M6b, the researchers can deduce that impact investors' educational background explains the heterogeneity in their preferences for returns. More specifically, individuals belonging to a finance background display a higher propensity to choose projects with high financial returns, whereas respondents belonging to a non-finance background (e.g. humanities or natural sciences) show a larger propensity to choose projects with high impact returns. Moreover, if one focuses on the influence of the educational background on the preference for Financial Return, a further consideration can be made. In fact, in the sample, 67 respondents had a background in finance and, among these, 37 were both financially trained and worked within the finance industry. For this reason, a more thorough analysis would consist in understanding whether for these 37 individuals, the preference for Financial Return is even more accentuated. However, given that this thesis does not focus on the effect of demographics over the returns' preferences, the researchers will leave this analysis as a potential starting point for future research.

Concluding, although the *"Impact-First"* trend within the sample appears relevant, it can be observed that the trend is moderated by respondents' educational background in finance. In other words, for respondents who are trained in finance, the dominance of the impact performance over the financial performance is abated. Moreover, this discussion connects once again to the inference previously depicted on the presence of a "*financial and impact returns trade-off*" within the minds of impact investors. In fact, since respondents still reason within this paradigm, a more thorough analysis of the connection between investors' preferences and their educational background is fundamental. However, due to the limited scope of the thesis project, the empirical testing and a more accurate analysis of such relation is left to future research.

5.3 CONCLUSIVE SUMMARY

Throughout this chapter, the researchers have reported and discussed the results of the data collected by the experimental survey. Since, such analysis has been divided into an *Ex-Ante* and an *Ex-Post Analysis*, a similar approach will be applied to summarize the findings of the research.

5.3.1 Ex-Ante Analysis

Initially, the researchers have estimated M2 as the MXL model representing respondents' preferences and have afterwards responded to RQ1 by testing H1. Subsequently, the researchers addressed RQ2 by calculating the sample average Bias Score and tested H2. Lastly, M3b was estimated and RQ3 was answered by testing H3a and H3b. *Table 22* below presents a summary of the hypotheses tested:

Research Question	Hypothesis	Confirmed/ Rejected
RQ1: Do impact investors consider Impact Risk as an important factor within the investment decision-making process?	***H1**: Higher Impact Risk negatively influences impact investors' choices within the investment decision-making process.*	**Confirmed**
RQ2: Are impact investors overestimating the precision of their knowledge? In other words, are impact investors on average overconfident?	***H2**: Impact Investors, on average, overestimate the precision of their knowledge.*	**Confirmed**
RQ3: Are impact investors' preferences for risk affected by the overconfidence bias?	***H3a**: Overconfident impact investors are more willing to choose investments displaying a high Impact Risk, compared to non-overconfident impact investors.*	Not Applicable
	***H3b**: Overconfident impact investors are more willing to choose investments displaying a high Financial Risk, compared to non-overconfident impact investors.*	**Rejected**

Table 18 - Summary of Hypotheses Tested

Table 18 displays three main conclusions. Firstly, the answer to RQ1 consists in confirming that Impact Risk is considered as conceptually different from the notion of Financial Risk and, more precisely, that such attribute has the largest negative effect on respondents' preferences. Secondly, the answer to RQ2 corresponds instead to the confirmation of the presence of the overconfidence bias among respondents. Finally, the answer to RQ3 consists in rejecting the idea that overconfidence affects respondents' preferences for Impact and Financial Risk during the investment decision-making process. Additionally, the researchers discussed further considerations related to the Impact Investing Framework. They outlined that the largest effect in absolute terms on respondents' preferences is associated to Impact Risk, followed by Financial Risk, Impact Return and finally by Financial Return. Due to the order of the effects just specified, the researchers concluded that respondents in the sample display a risk-averse attitude and use an *"Impact-First"* approach while considering the Financial and Impact Return trade-off. Moreover, while making investment decisions regarding cleantech investments, respondents also ponder a Financial and Impact Risk trade-off, where the impact dimension matters the most. Consequently, the researchers outlined the second-best investment[8] profile that would maximize the utility of respondents, which corresponds to the combination of High Impact Return, Low Impact Risk, Low Financial Return, Low Financial Risk. This outcome further confirmed the conclusion that **1)** respondents are risk-averse as the profile that maximizes their utility has low levels of Impact and Financial Risks, and **2)** respondents are *"Impact-First"* as they favor the impact risk-adjusted performance over the financial risk-adjusted performance of the investment. Moreover, although the researchers argued that respondents show an aversion to risk, they also display the overconfidence bias. However, since the overconfidence bias did not explain the respondents' preference for both Impact and Financial Risk, the researchers identified three potential explanations for such result. The first is the relatively small sample size (Rao, 2014). The second lies in the way in which the researchers operationalized overconfidence. In fact, although the Bias Score is highly representative of the respondents' knowledge miscalibration, it is not a comprehensive measure for overconfidence due to the threefold nature of this bias (Ackert & Deaves, 2018). The third is related to the documented risk-averse behavior of the sample. Concluding, the researchers decided to proceed to the Ex-Post Analysis and look at these results retrospectively.

5.3.2 Ex-Post Analysis

After concluding the Ex-Ante Analysis, the researchers focused on drawing further considerations on the preference heterogeneity around Financial Risk - since Impact Risk appeared as a fixed term - using as interaction variables the demographic data used by the literature as proxies for overconfidence, i.e. Age, Gender and Years of Experience. However, none of these relations was found significant, thus, no further deductions could be gathered on Financial Risk. Subsequently, to further clarify the *"Impact-First"* nature of the respondents, the researchers re-directed their attention on variables explaining the heterogeneity of preferences for Impact and Financial Returns. As a result, it has been concluded that:

- More knowledgeable respondents prefer investment profiles with higher Impact Return compared to the ones displaying a poorer knowledge in impact investing;

[8] The researchers focused on the second-best investment profile as the first-best resulted the dominant profile because it included high returns and low risks.

- Respondents currently working in finance prefer investment alternatives including higher Financial Return compared to the ones not working in such sector;
- Respondents with a financial educational background prefer investment projects entailing higher Financial Return and lower Impact Return, whereas respondents without such background preferred profiles including higher Impact Return and lower Financial Return.

Thus, although the *"Impact-First"* trend within the sample appears as still relevant, it can be observed that the trend is moderated by the respondents' educational background in finance and by their experience within the finance sector. Additionally, for respondents who have a finance background, the dominance of the impact performance over the financial performance is abated.

After having summarized the results and discussion, in the next chapter the researchers will focus on the literature contribution, the managerial implications as well as the limitations and the future research potential of this thesis project.

CHAPTER 6 - CONCLUSIONS AND LIMITATIONS

The findings discussed in the previous chapter analyzed investors' preferences for cleantech investments and the overconfident behavior of Italian impact investing professionals. To provide a concluding remark on the findings, on the theoretical and practical contributions of this academic thesis, as well as on its limitations and potential for future research, the researchers will divide this chapter in four parts. The first part will briefly summarize the overall research approach starting from the theoretical background of this thesis, continuing with the methodology and finishing with the results and the relative critical analysis. The second part will outline the theoretical contribution made by the researchers to the Impact Investing and Behavioral Finance academic literature illustrated in the chapter *Literature Review*. The third part will compile the practical managerial implications and additional recommendations connected to the results obtained by the researchers. The fourth part will outline the limitations of the thesis associated with the delimitation of the research topic, the methodology and the analysis of the results. Additionally, by considering such limitations, potential scenarios for future research are presented.

6.1 RESEARCH SUMMARY

The present research analyzed investors' preferences for cleantech investments and the overconfident attitude of Italian impact investors, impact investing professionals and experts. The researchers commenced the study by clarifying the different investment approaches within sustainable finance and then focused the attention on the impact investing strategy. The Impact Investing Framework formulated by Hornsby & Blumberg (2013) was explained and later used to identify the four main parameters that impact investors evaluate during the investment decision-making process: Financial Return, Financial Risk, Impact Return and Impact Risk. Thereafter, the researchers concentrated on Impact Risk as, unlike the remaining three attributes, it has not received a large empirical attention from the academic literature of impact investing, and it has been considered as a concept implicitly included in the notion of Financial Risk. Moreover, given the complexity of the investment decision-making process, the researchers decided to integrate the Impact Investing Framework with the theoretical background of Behavioral Finance. Also, precisely because this thesis focuses on the concepts of Impact and Financial Risks and given the documented risk-tolerant attitude of impact investors, among the numerous biases identified by the Behavioral Finance literature, overconfidence was the most relevant cognitive bias explaining risk preferences of investors. More specifically, the researchers decided to aim their attention at knowledge miscalibration as the appropriate way to operationalize such bias.

After having outlined the main theoretical background, the researchers selected the Choice-Based Conjoint Analysis (CBCA) and the Calibration Test as the designed methods to analyze the survey data collected from a sample of impact investing experts in Italy. In fact, on the one hand, through the CBCA, the researchers were able to administer the respondents six investment scenarios that resembled the way investment decisions are made in the real world and to decompose respondents' preferences for each single parameter within the Impact Investing Framework. On the other hand, through the Calibration Test, the researchers were able to find a numerical expression for the overconfidence bias by observing their knowledge overestimation while answering six general knowledge questions.

Finally, the analysis and the discussion of the results generated three main conclusions. Firstly, it was concluded that Impact Risk is considered as conceptually different from the notion of Financial Risk and, more precisely, that such attribute has the largest (negative) effect on respondents' preferences. Secondly, the presence of the overconfidence bias among respondents was confirmed. Lastly, it was established that the overconfidence trait of the respondents did not explain the risk preferences of the sample. Additionally, the researchers discussed further considerations on the Impact Investing Framework and concluded that the sample showed a considerable risk-averse attitude and used an *"Impact-First"* investment approach while considering the Financial and Impact Return trade-off. Moreover, while making investment decisions regarding cleantech investments, respondents also pondered a Financial and Impact Risk trade-off, where the impact dimension mattered the most. Furthermore, despite the *"Impact-First"* trend within the sample, it was observed that this trend was moderated by respondents' educational background in finance and by their experience within the finance sector. Additionally, for respondents who were trained in finance, the *"Finance-First"* investment approach was prevalent.

After having thoroughly summarized the content and conclusions of this research project, the attention will concentrate on the theoretical contribution that such project advances towards the academic literature of Impact Investing and Behavioral Finance.

6.2 THEORETICAL CONTRIBUTION

Due to the two-fold nature of the theoretical background employed in the chapter *Literature Review*, it is fundamental to divide the theoretical contribution generated by this thesis in two sections: the former will outline the theoretical contribution made to the stream of academic literature of *Impact Investing*, while the latter will discuss the theoretical contribution made to the academic literature of *Behavioral Finance*.

6.2.1 Theoretical Contribution to the Impact Investing Literature

As previously mentioned, the researchers utilized the Impact Investing Framework (Hornsby & Blumberg, 2013) - including the four parameters of Impact Return, Impact Risk, Financial Return and Financial Risk – adopted in the financial decision-making process by impact investors as a starting point for the investigation. The attention was thereafter focused on one of the parameters of this framework, namely Impact Risk, due to the existence of an academic gap in providing an empirical evidence on its conceptual division from the well-established concept of Financial Risk. Moreover, due to the novel nature of Impact Risk, the literature has expressed an interest in understanding how it influences impact investors' choices (Horsby and Blumberg, 2013; Brandstetter & Lehner, 2016; Puttick & Ludlow, 2013; Godeke & Pomares, 2009; Nicholls *et al.* 2015). Thus, through the use of the method of CBCA, the researchers were able to empirically test the material applicability of the Impact Investing Framework above mentioned and, as consequence, the theoretical separation between Impact Risk and Financial Risk. As a result, the insights obtained after the analysis of the data collected contribute to the impact investing literature in two important ways.

On the returns side of the framework, the researchers confirmed that, although recent impact investing literature supports the idea that the "*Financial and Impact Return trade-off*" represents a myth (Grabenwarter & Liechtenstein, 2011), the sample still has a very categorical understanding of impact investing, where a good impact performance is only achievable if investors are willing to give up some Financial Return (Evans, 2013). In fact, it was observed that the sample acted with an *"Impact-First"* investment approach in mind (Hornsby & Blumberg, 2013). However, the researchers also observed that the preference for an *"Impact-First"* or *"Finance-First"* approach is heavily influenced by the educational background and the job industry of the respondents, where the probability of choosing projects with a better financial - compared to impact - performance increases if the decision-maker works in finance or has an educational finance background.

On the risks side of the framework, the researchers identified that not only Impact Risk is indeed considered a conceptually and practically different concept from Financial Risk, but also that Impact Risk is the factor that matters the most while making an investment decision. In fact, a cleantech project displaying a high Impact Risk heavily decreased the utility of respondents and hence decreased also the likelihood of that project being chosen. Consequently, the researchers introduced the idea that a *"Financial and Impact Risk trade-off"* may be present in the minds of respondents. Moreover, despite the risk-tolerant attitude of impact investors documented in the literature (Lane, 2014; Emerson, 2012), the results clearly indicated a risk-averse attitude of the sample both on the financial and on the impact side. This could clearly affect the development of the impact investing sector as investors are not willing to finance projects with high financial and impact risk, thus forgoing profitable projects that may have large positive effects on the environment.

6.2.2 Theoretical Contribution to the Behavioral Finance Literature

At the beginning of this study, the researchers integrated the impact investing viewpoint with the new perspective of behavioral finance to better explain the risk preferences of impact investors. Consequently, overconfidence was identified as one of the most common cognitive biases affecting investors' preferences for risk (Ackert & Deaves, 2018). More specifically, behavioral finance literature on overconfidence formulates that overconfident investors show a higher propensity to take up riskier investment prospects (Barber & Odean, 2001). As a result, the researchers' expectation was that overconfident impact investors would be more willing (i.e. less reluctant) to take up both Financial Risk and Impact Risk. Hence, overconfidence, approximated by knowledge miscalibration, was used to explain the heterogeneous preferences of impact investors towards Financial Risk and Impact Risk. However, the outcome of the hypotheses testing process was not as expected. In principle, although the respondents' in the sample showed on average a tendency of overestimating their knowledge, the overconfidence bias did not explain their risk preferences. Concluding, this research can be useful to behavioral finance scholars because it displays that conclusions on the risk preferences of traditional investors may not always be material for the impact investing sector. In fact, there may be exceptions, as the one of impact investing outlined in this thesis, where, although investors display irrational traits of overconfidence, they still show a risk-averse attitude.

6.3 MANAGERIAL IMPLICATIONS AND RECOMMENDATIONS

Behavioral finance and impact investing represent two theoretical frameworks that combine finance with psychology and philanthropy, respectively. As a result, by integrating insights from behavioral finance to the Impact Investing Framework (Hornsby & Blumberg, 2013), the researchers believe that practitioners in the impact investing field can better manage their investment decision-making process by thoroughly understanding their own preferences for Impact and Financial Return as well as for Impact and Financial Risk. In this regard, the results outlined in the chapter *Analysis and Discussion* can be translated into three main consequences for impact investing practitioners. In the next three paragraphs, the researchers will also outline potential recommendations to be directed at impact investing professionals operating within the Italian territory.

6.3.1 Managerial Implication (1): Risk Aversion and Impact-First Investment Approach

A primary managerial implication of the results may be that Italian impact investors may use the researchers' conclusions to:

1. Revise their categorial way of thinking about the impact and financial performance and move towards a more comprehensive view of simultaneously achieving a satisfactory impact and financial performance;
2. Critically analyze their risk-averse attitudes both on the impact and on the financial side of their investment decision-making process.

In fact, the results displayed that respondents still reason within the mental framework where one should give up good financial performance to have a better impact performance of the investment (Impact-First investment approach). Moreover, the researchers demonstrated that respondents' in the sample heavily disliked both Impact and Financial Risk and illustrated that this behavior may hinder the development of the impact investing sector because opportunities with increased risks are forgone. Thus, measures like improving the *training* of impact investors and *co-investments* should be preferred solutions for investors displaying the characteristics explained in **1)** and **2)** above, respectively. More specifically, through a more balanced training increasing both their financial and sustainability knowledge, impact investors may better comprehensively understand that within their decision-making process they may be able to achieve both financial and impact objectives rather than pursuing only the former or the latter (GIIN, 2020). On another note, co-investments within cleantech projects may also be effective because they will leverage the risk-attitudes of different impact investors. In fact, through joint deals, not only the supply of capital for cleantech project will increase but also more risk-averse impact investors can collaborate with other investors having a more progressive preference on risk. This solution would balance any under or overestimation of risks and contribute to the development of the cleantech sector (Mitchell *et al.*, 2008). Through these two actions, risk overestimation of impact investors would be reduced, and a better impact and financial performance can be attained simultaneously.

6.3.2 Managerial Implication (2): Reducing Impact and Financial Risk

The second managerial implication consists in the identification of the ideal cleantech project for Italian impact investors. As explained in the section *Utility-Maximizing Profiles* (*see page 87*), the ideal investment corresponds to a cleantech project entailing a high risk-adjusted impact performance, meaning that investors would obtain 20 million metric tons of CO2 reduced with a 5% risk of not achieving such CO2 reduction, and a low risk-adjusted financial performance, meaning that they would obtain an IRR of 4% with a 5% risk of not breaking even. This combination of the four parameters of the Impact Investing Framework (Hornsby & Blumberg, 2013) would maximize the utility of the representative sample of Italian respondents. Moreover, as explained in *Managerial Implication 1*, respondents show a significant risk-averse attitude toward Impact Risk and Financial Risk. Regarding Impact Risk, the results confirmed that this parameter has the largest (negative) effect on respondents' choices. For this reason, the first priority of cleantech practitioners, who are currently working on a strategy to attract more capital and investors, should be to find a solution to reduce Impact Risk to a minimum. As previously mentioned in the *Impact Plan* section (*see Table 3*), a way to reduce Impact Risk is addressing the effectiveness of the impact plan (Hornsby & Blumberg, 2013). Therefore, cleantech practitioners should ensure to provide impact investors with an impact plan that is *explicit, reasoned, integral, feasible, evidenced and evidenceable* (Hornsby & Blumberg, 2013). By designing the impact plan in such way, Impact Risk will be minimized. Regarding Financial Risk, the results confirmed that this parameter has the second largest (negative) effect on respondents' choices. Therefore, the second priority of cleantech practitioners should be to find a solution to reduce Financial Risk to a minimum. This means that they should propose investment prospects with the lowest risk-adjusted financial return, meaning a prospect having low financial risk but also low financial return. In other words, the targeted asset class that best fits these characteristics is the fixed-income (bonds) class (GIIN, 2020).

Concluding, this information can be useful for practitioners as, by marketing an investment project fitting the current preferences of investors, they can raise the probability that such cleantech projects will be funded.

6.3.3 Managerial Implication (3): Addressing Overconfidence

The last managerial implication is related to the overconfidence bias displayed by the sample. The "diagnosis" of such bias, consisting in the overestimation of impact investors' knowledge, can help respondents affected by it to be aware of such personal trait and search for practical measures to decrease the effect such bias. According to behavioral finance literature regarding overconfidence, receiving feedback generally reduces the effect of the overconfidence bias. Evidence shows that as the level of feedback given on the performance of individuals increases, the intensity of the overconfidence of such individuals decreases (Pulford & Colman, 1997; Lichtenstein *et al.*, 1981). More precisely, by decreasing the overconfidence bias among impact investors, the likelihood of displaying a higher unjustified risk-taking behavior can be reduced, ensuring a better portfolio diversification and improved investment choices (Lambert *et al.*, 2012).

6.4 LIMITATIONS AND POTENTIAL FOR FUTURE RESEARCH

As the reader may already have observed through the thesis, the results and conclusions drawn by the researchers present multiple limitations. Thus, in this section, the attention will be aimed at such limitations and how future research could overcome them. For clarity reasons, this part is divided into three sections: the focus of the research, the sample and the methodology.

6.4.1 The Focus of The Research

The first most important limitation is connected to the focus of this thesis project. On the one hand, due to practical reasons related to the experimental survey, the researchers found necessary to concentrate on just one sector among the many where the Impact Investing Framework is applied (Hornsby & Blumberg, 2013). Hence, by selecting the cleantech sector, the researchers were able to define the four parameters (i.e. Financial Return, Financial Risk, Impact Return, Impact Risk) in realistic terms within the survey administered to respondents. However, if this distinction was not operated by the researchers, the results outlined in this thesis could have had the potential to be generalized to the impact investing sector overall. Moreover, by choosing a carbon reduction investment as the product of interest within the experimental design, the researchers limited the analysis of investors' preferences just for the environmental impact return and not for the social impact return. This latter would have been calculated if the researchers were to choose another theme of the investment, such as a project employing individuals living in developing countries at a fair wage.

On the other hand, another relevant problem that could be identified within the scenario proposed to respondents is that impact investors only had to consider stand-alone investments that were not inserted in a general investment portfolio. In fact, in most cases, impact investors make investment decisions based on the principle of risk diversification. Thus, for example, they are willing to finance a project that displays higher financial and impact risk only if, in the same portfolio, they have a project that displays lower financial and impact risk (Hornby & Blumberg, 2013). All in all, although this limitation decreases the realistic nature of the experimental survey, it also largely reduced the risk of data overflow that the respondents might have experienced during the choice tasks.

Potential for Future Research

As explained in the previous paragraph, due to practicalities in the experimental survey design, the researchers had to limit their focus on the environmental sphere of the impact investing sector. Thus, investigating whether the obtained conclusions would be confirmed with projects focusing on the more social sphere of impact investing would allow for a more comprehensive understanding of impact investors' investment decision-making process and risk-behavior. Moreover, future research could also examine how this behavior changes when impact investors are required to insert such projects within an impact investing portfolio. In this way, scholars would be able to grasp the entirety of the investment decision-making process and further analyze whether investors present cognitive biases or incoherent preferences when moving from a more granular to a more generalized investment choice.

6.4.2 The Sample

The second limitation is related to the *nature* and the *size* of the sample constituting the dataset used to apply the selected methodology.

The sample nature can be defined as homogeneous in terms of nationality of respondents. At the same time, the sample can also be described as too heterogeneous because the researchers did not make two fundamental distinctions within the survey design, which may have partly affected the results. Firstly, no distinction was made between fund managers (institutional impact investors) and private investors. While the former operate investment decisions according to an investing mandate, the latter operate investment decisions based on their personal preferences. Secondly, no distinction was made between venture (or angel) investors and other impact investors. While the former are generally more eager to take up riskier projects (Ruhnka & Young, 1991), the latter normally focus on working with less risky projects. Concluding, by making these two main distinctions the researchers might have obtained more specific results.

The sample size, constituted by 89 respondents, can be defined as limited. In fact, as explained in the chapter *Methodology* (*see page 73*), a sample of roughly 200 would have been ideal given the nature of the method the researchers later applied. However, despite the sample size being very narrow, the researchers still obtained significant results. All in all, it can be concluded that the results obtained by the researchers can be considered acceptable, given: **1)** the recent nature of the cleantech trend in Italy, and **2)** the time constraints under the adverse economic and health circumstances that Italy was experiencing due to the COVID19 outbreak emergency.

Potential for Future Research

According to the limitation outlined in the previous paragraph, the researchers were able to identify three suggestions for future research. Firstly, to overcome the heterogeneity of the sample, future research should apply the methodology used within this thesis project to a more specific sample, dividing impact fund managers from impact private investors. In this way, by – for example – focusing only on impact private investors, scholars can deeply understand the personal preferences of investors who do not act following a mandate or legal restrictions. Similarly, to further overcome the heterogeneous nature of the sample, future research should apply the methodology to two different samples, one including angel investors and the other including impact investors. By comparing the findings of the former sample with the ones of latter, scholars could gain more insights about the risk-taking behavior of impact investors in Italy and understand whether the general risk-averse nature detected in this research is limited to one group of investors or can be generalized to the totality of Italian impact investors. Lastly, to overcome the problems related to the size and the homogeneous nationality of the sample, future research should address a more European (rather than only Italian) sample. On this note, scholars would not only reach a larger set of respondents, but they would also understand the risk-preferences of European impact investors for projects in the cleantech sector.

6.4.3 The Methodology

The Choice-Based Conjoint Analysis

The third limitation is connected to the methodology used, namely CBCA in the form of Discrete Choice Analysis. In fact, the value of the parameters estimated depends on the way in which attributes and levels are identified. Had the researchers chosen a different description for the two levels and the four attributes, the coefficients would have been different as the method relied on specific experimental data. Thus, the results analyzed are experiment-specific and should be generalized only with the adequate limitations. For example, the attribute Financial Return has been defined in percentage terms (namely an IRR of 4% and 8%, compared to a benchmark of 6%) rather than in absolute monetary terms (e.g. streams of cash flows). Although using percentage terms could appear more effective, it would have probably been more intuitive for those investors not having a financial educational background to receive financial return information in the form of material amounts of cash in EUR terms.

The Calibration Test and the Proxies for Overconfidence

The last limitation is associated with how the researchers operationalized the variable of overconfidence, which was later used as an interaction term within the estimation model. A primary consideration may be that, as explained in the chapter *Literature Review* (*see page 33*), overconfidence may be translated in three main effects: better-than-average effect, illusion of control and knowledge miscalibration (Ackert & Deaves, 2018). Given this distinction, the researchers decided to use knowledge miscalibration as the selected effect that better approximated the overconfidence bias because, unlike the other two effects, knowledge miscalibration could be measured following a documented methodology, namely the Calibration Test. In this way, the researchers did not have to rely on proxies previously used in the literature for the overconfidence bias, which are generally considered too broad and prone to be subject to poor generalizations. However, although the researchers could rely on a structured methodology to measure knowledge miscalibration through a scalar variable defined as Bias Score, the results suggested that a more effective measure for overconfidence should have been selected. In fact, in testing H3a and H3b (*see page 91*), the researchers invalidated the expectation that overconfidence explained the heterogeneous risk preferences of respondents. For this reason, it can be inferred that measuring the overconfidence bias by only focusing on one effect rather than leveraging on its three-fold nature might have partly limited the results obtained.

Potential for Future Research

Based on the limitations outlined in the previous paragraphs, researchers could identify two main potential schemes for future research. A primary scheme may be to apply the methodology of CBCA by defining the four main parameters of the Impact Investing Framework differently compared to the ones selected. Thus, scholars would empirically test if impact investors preferences would adjust or transform to the way in which investment projects risks and returns are formulated and presented to them. This aspect would be particularly relevant for marketing reasons. In fact, if professionals working to attract investors to fund sustainable projects would be aware of the best way of framing such investment prospects, they could use this information to make such projects more appealing to impact investors in the market. A secondary scheme would entail the overcoming of the limitation connected to the three-fold nature of overconfidence bias. In principle, to obtain a more comprehensive understanding of the overconfidence bias effect on the risk preferences of impact investors, future research could complement the findings of this research project by using a proxy which integrates all the three effects of overconfidence within one numerical expression.

In conclusion, this thesis contributes to the impact investing field by adopting a behavioral finance perspective. The researchers addressed the recent finance trends of impact investing and behavioral finance with a strategic perspective in mind. In fact, through an innovative methodology, combining the Choice-Based Conjoint Analysis and the Calibration Test, the researchers were able to study impact investors' financial decision-making process and risk preferences for cleantech investments with a particular focus on how the overconfidence bias explains such preferences. Although the researchers identified various limitations within their research, they outlined relevant strategic implications for impact investing practitioners in Italy. For this reason, they believe that this project can represent a relevant starting point for future research, given the global importance of impact investing and climate action.

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APPENDIX

Appendix 1- The Six Choice Tasks

	Impact Return	*Impact Risk*	*Financial Return*	*Financial Risk*	
1	**High** 20 million tons of CO2 reduced	**Low** 5% probability that the planned CO2 reduction is not realized	**High** IRR of 8%	**High** 50% probability of only breaking even	**Choice task 1**
2	**Low** 10 million tons of CO2 reduced	**High** 50% probability that the impact return is not realized	**High** IRR of 8%	**Low** 5% probability of only breaking even	
3	**Low** 10 million tons of CO2 reduced	**Low** 5% probability that the planned CO2 reduction is not realized	**Low** IRR of 4%	**High** 50% probability of only breaking even	**Choice task 2**
4	**High** 20 million tons of CO2 reduced	**High** 50% probability that the impact return is not realized	**High** IRR of 8%	**Low** 5% probability of only breaking even	
5	**Low** 10 million tons of CO2 reduced	**Low** 5% probability that the planned CO2 reduction is not realized	**High** IRR of 8%	**High** 50% probability of only breaking even	**Choice task 3**
6	**High** 20 million tons of CO2 reduced	**High** 50% probability that the impact return is not realized	**Low** IRR of 4%	**Low** 5% probability of only breaking even	
7	**Low** 10 million tons of CO2 reduced	**High** 50% probability that the impact return is not realized	**High** IRR of 8%	**High** 50% probability of only breaking even	**Choice task 4**
8	**High** 20 million tons of CO2 reduced	**High** 50% probability that the impact return is not realized	**Low** IRR of 4%	**High** 50% probability of only breaking even	
9	**Low** 10 million tons of CO2 reduced	**High** 50% probability that the impact return is not realized	**High** IRR of 8%	**Low** 5% probability of only breaking even	**Choice task 5**
10	**High** 20 million tons of CO2 reduced	**Low** 5% probability that the planned CO2 reduction is not realized	**Low** IRR of 4%	**High** 50% probability of only breaking even	
11	**Low** 10 million tons of CO2 reduced	**Low** 5% probability that the planned CO2 reduction is not realized	**High** IRR of 8%	**High** 50% probability of only breaking even	**Choice task 6**
12	**High** 20 million tons of CO2 reduced	**High** 50% probability that the impact return is not realized	**Low** IRR of 4%	**High** 50% probability of only breaking even	

Appendix 1 - The Six Choice Tasks

Appendix 2 - Impact Return Calculations

To find an approximate measure for the largest impact return in terms of CO2 reduction that a cleantech project could have, the researchers performed the following calculations based on US numbers because these statistics were not available for Italy. Firstly, the average number of wind turbines installed in the US since 2015 was used. According to USGS (2020), on average 3000 turbines have been built in the US each year since 2005. Therefore, to calculate on average how many wind turbines were present in 2017, the researchers multiplied 3000 x 12 (where 12 represents the number of years from 2005 to 2017). As a result, in 2017 an approximate total number of 36000 wind turbines in the US is present. Given that the amount of CO2 reduced in 2017 equals 190 million metric tons (AWEA, 2020), by dividing this number (190 million) with the number of total wind turbines in 2017 (36000), the amount of CO2 reduced by one turbine has been calculated as approximately 5277. Thereafter, to calculate how much CO2 would be reduced by the largest project, the amount of CO2 reduced by one turbine (5277) was multiplied by the number of turbines that make up the largest windfarm in the US (4000) (AWEA, 2020), which equals to 21.2 million metric tons of CO2 reduced (corresponding to 5000 cars equivalent) (AWEA, 2020). Therefore, this number justifies the choice of the researchers to select 20 million metric tons of CO2 reduction as the highest impact in terms of CO2 reduction.

Appendix 3 - English and Italian Surveys

English Version: Impact Investing Survey

Dear respondents,
thank you very much for taking the time to dedicate to our joint research project between Copenhagen Business School and the Cottino Social Impact Campus!
The survey concerns preferences of investors in the cleantech sector.
The survey will just take 10 minutes of your time and we will be grateful for any input you will be willing to help us with!

Kai Hockerts (Project Director)
Martina Grilli and Michela Cocco (Project Leaders)

How old are you? Please choose your age bracket.

- ◯ 20-30
- ◯ 31-40
- ◯ 41-50
- ◯ 51-60
- ◯ 60+

Please select your gender.

- ◯ Male
- ◯ Female
- ◯ Prefer not to say

Please state your nationality.

- ◯ Insert your nationality

What is your educational background? Please choose your degree major.

- ◯ Business
- ◯ Finance
- ◯ Engineering
- ◯ Humanities
- ◯ Natural Sciences
- ◯ Other ______________________________

In which field would you position your current job?

- ◯ Finance
- ◯ Consulting
- ◯ Academia
- ◯ Other ______________________________

How long have you worked in the industry? Please select the appropriate experience bracket.

- ◯ 0
- ◯ 1-5
- ◯ 6-10
- ◯ 11-15
- ◯ 16-20
- ◯ 20+

The European Union defines sustainable finance as *"the provision of finance to investments taking into account environmental, social and governance considerations".* Please imagine you are being offered **a number of investment alternatives within the clean tech-sector** specializing in **new unproven technologies** aiming at carbon reduction. You are asked to make a choice between the different alternatives presented. Whether you prefer sustainable impact or financial returns depends on your personal preferences. Before choosing in which alternative to invest, a due diligence has been conducted by an independent consultant. The analysis provided you with investment profiles presenting the following four characteristics regarding risks and returns of the individual projects:

1. Impact return: refers to the expected **amount of CO_2 reduced** by the investment in the next year (also expressed as car equivalent of CO_2 emissions avoided). The impact return can be:

a) Low = **10** million metric tonnes of CO_2 reduced **-** equivalent of 2.5 million cars per year
b) High = **20** million metric tonnes of CO_2 reduced **-** equivalent of 5 million cars per year

2. Impact risk: due to uncertainty about the impact plan, each investment is characterized by an impact risk which describes the **likelihood** that, after the project has ended, it turns out that there was actually **little to no CO_2 reduction**. The impact risk can be:

a) Low = **5%** chance that planned CO_2 reduction is not realized
b) High = **50%** chance that planned CO_2 reduction is not realized

3. Financial return: refers to the **IRR** for the carbon reduction investment project considering that the benchmark IRR for these types of investments is 6%. The financial return can be:

a) Low = investment's IRR equal to **4%**
b) High = investment's IRR equal to **8%**

4. Financial risk: due to uncertainty about the future costs related to the project there is a financial risk which describes the **likelihood** that after the project has ended it turns out that it has **only broken even** or worse. The financial risk can be:

a) Low = **5%** probability of only breaking even
b) High = **50%** probability of only breaking even

[Note that according to the definition of impact risk and financial risk, the two dimensions are formally independent of each other, meaning that high impact risk does not imply high financial risk and vice versa. The same reasoning is true for low impact risk and low financial risk]

Please find below two investment prospects:

	PROJECT A	PROJECT B
Impact Return	**High** (20 million metric tons of CO2 reduced (high)	**Low** (10 million metric tons of CO2 reduced)
Impact Risk	**Low** (5% probability that the planned CO2 reduction is not realized)	**High** (50% probability that the planned CO2 reduction is not realized)
Financial Return	**High** (IRR= 8%)	**High** (IRR= 8%)
Financial Risk	**High** (50% probability of only breaking even)	**Low** (5% probability of only breaking even)

Please click on the alternative you would invest in

◯ Project A

◯ Project B

Please find below two investment prospects:

	PROJECT A	PROJECT B
Impact Return	**Low** (10 million metric tons of CO2 reduced)	**High** (20 million metric tons of CO2 reduced)
Impact Risk	**Low** (5% probability that the planned CO2 reduction is not realized)	**High** (50% probability that the planned CO2 reduction is not realized)
Financial Return	**Low** (IRR= 4%)	**High** (IRR= 8%)
Financial Risk	**High** (50% probability of only breaking even)	**Low** (5% probability of only breaking even)

Please click on the alternative you would invest in

◯ Project A

◯ Project B

Please find below two investment prospects:

	PROJECT A	PROJECT B
Impact Return	**Low** (10 million metric tons of CO_2 reduced)	**High** (20 million metric tons of CO_2 reduced)
Impact Risk	**Low** (5% probability that the planned CO_2 reduction is not realized)	**High** (50% probability that the planned CO_2 reduction is not realized)
Financial Return	**High** (IRR= 8%)	**Low** (IRR= 4%)
Financial Risk	**High** (50% probability of only breaking even)	**Low** (5% probability of only breaking even)

Please click on the alternative you would invest in

- ◯ Project A
- ◯ Project B

Please find below two investment prospects:

	PROJECT A	PROJECT B
Impact Return	**Low** (10 million metric tons of CO_2 reduced)	**High** (20 million metric tons of CO_2 reduced)
Impact Risk	**High** (50% probability that the planned CO_2 reduction is not realized)	**High** (50% probability that the planned CO_2 reduction is not realized)
Financial Return	**High** (IRR= 8%)	**Low** (IRR= 4%)
Financial Risk	**High** (50% probability of only breaking even)	**High** (50% probability of only breaking even)

Please click on the alternative you would invest in

- ◯ Project A
- ◯ Project B

Please find below two investment prospects:

	PROJECT A	PROJECT B
Impact Return	**Low** (10 million metric tons of CO_2 reduced)	**High** (20 million metric tons of CO_2 reduced)
Impact Risk	**High** (50% probability that the planned CO_2 reduction is not realized)	**Low** (5% probability that the planned CO_2 reduction is not realized)
Financial Return	**High** (IRR= 8%)	**Low** (IRR= 4%)
Financial Risk	**Low** (5% probability of only breaking even)	**High** (50% probability of only breaking even)

Please click on the alternative you would invest in

○ Project A

○ Project B

Please find below two investment prospects:

	PROJECT A	PROJECT B
Impact Return	**Low** (10 million metric tons of CO_2 reduced)	**High** (20 million metric tons of CO_2 reduced)
Impact Risk	**Low** (5% probability that the planned CO_2 reduction is not realized)	**High** (50% probability that the planned CO_2 reduction is not realized)
Financial Return	**High** (IRR= 8%)	**Low** (IRR= 4%)
Financial Risk	**High** (50% probability of only breaking even)	**High** (50% probability of only breaking even)

Please click on the alternative you would invest in

○ Project A

○ Project B

One last step: please answer a few general knowledge questions regarding sustainability. Please, for the purpose of the survey **do not use any external or online resources.**

The number of wind turbine service technician jobs is expected to increase by __ percent by 2026

- 36%
- 66%
- 75%
- 96%

How confident are you that your answer is the correct one?

- 25%
- 50%
- 75%
- 100%

In 2015 the Country with the highest renewable energy consumption (% of total final energy consumption) was:

- Iceland
- Congo
- Sweden
- Germany

How confident are you that your answer is the correct one?

- 25%
- 50%
- 75%
- 100%

Of the 208 countries in the world, how many have defined renewable energy targets?

- 86
- 94
- 102
- 144

How confident are you that your answer is the correct one?

- 25%
- 50%
- 75%
- 100%

When was the first green bond issued?

- 2006
- 2008
- 2010
- 2012

How confident are you that your answer is the correct one?

- 25%
- 50%
- 75%
- 100%

What is total amount of global green bonds issued during the first half of 2019?

- ◯ 23 USD billion
- ◯ 54 USD billion
- ◯ 67 USD billion
- ◯ 86 USD billion

How confident are you that your answer is the correct one?

- ◯ 25%
- ◯ 50%
- ◯ 75%
- ◯ 100%

Which of these four banks have issued the largest USD amount of green bonds in 2018?

- ◯ Bank of America
- ◯ Fannie Mae
- ◯ Industrial Bank of China
- ◯ Citi Bank

How confident are you that your answer is the correct one?

- ◯ 25%
- ◯ 50%
- ◯ 75%
- ◯ 100%

Thank you very much for completing the survey! Your answers are very much appreciated.

Please, feel free to add any additional comments you would have about our survey in the text box below.

____

END OF THE QUESTIONNAIRE

Italian version: Impact Investing Survey

Gentili rispondenti,

Vi ringraziamo in anticipo per aver dedicato il vostro tempo al nostro progetto di ricerca congiunto tra la Copenaghen Business School e il Cottino Social Impact Campus di Torino!
Il questionario riguarda le preferenze degli investitori nel settore cleantech.
Il questionario impiegherà solo 10 minuti del vostro tempo e vi saremo grati per ogni risposta riceveremo dalla vostra organizzazione.

Kai Hockerts (Project Director)
Martina Grilli e Michela Cocco (Project Leaders)

Indichi la sua età.

- ○ 20-30
- ○ 31-40
- ○ 41-50
- ○ 51-60
- ○ 60+

Selezioni il suo sesso.

- ○ Uomo
- ○ Donna
- ○ Preferisco non esprimerlo

Indichi la sua nazionalità.

- ○ Inserisca la sua nazionalità

Selezioni il suo background educativo.

- ◯ Gestione aziendale
- ◯ Finanza
- ◯ Ingegneria
- ◯ Materie umanistiche
- ◯ Scienze Naturali
- ◯ Altro ____________________________

In quale campo collocherebbe il suo attuale lavoro?

- ◯ Finanza
- ◯ Consulenza
- ◯ Accademia
- ◯ Altro ___________________________

Selezioni la lunghezza (in anni) della sua esperienza nel settore in cui attualmente lavora.

- ◯ 0
- ◯ 1-5
- ◯ 6-10
- ◯ 11-15
- ◯ 16-20
- ◯ 20+

L'Unione Europea definisce la finanza sostenibile come *"una strategia d'investimento che, oltre a perseguire logiche finanziarie, integra fattori ambientali, sociali e di governance nel suo processo"*. Seguendo questa logica, immagini le venga offerta una **serie di investimenti** nel **settore del cleantech**, i quali si specializzano in **nuove tecnologie sperimentali** che mirano alla riduzione di CO_2 nell'atmosfera. Qui di seguito, le viene chiesto di fare una scelta tra le diverse alternative di investimento. La sua scelta può essere guidata dai rendimenti finanziari o da quelli relativi all'impatto ambientale e questo dipende dalle sue preferenze personali. Prima di scegliere in quale alternativa investire, un consulente ha condotto un processo di due diligence sui potenziali progetti. L'analisi ha fornito profili di investimento che presentandole seguenti caratteristiche relative ai rischi e ai rendimenti dei singoli progetti:

1. Impatto ambientale: si riferisce alla **quantità di CO_2** che il progetto di investimento prevede di **ridurre** nel prossimo anno (anche espresso come quantità di CO_2 ridotta in termini di auto). Il rendimento ambientale può essere:
a) Basso = **10** milioni di tonnellate di CO_2 ridotta **-** equivalente di 2.5 milioni di auto per anno
b) Alto = **20** milioni di tonnellate di CO_2 ridotta **-** equivalente di 5 milioni di auto per anno

2. Rischio ambientale: Data l'incertezza riguardante l'impact plan (piano d'impatto), ogni investimento è caratterizzato da un rischio ambientale, il quale descrive la **probabilità** che, una volta terminato, il progetto abbia portato ad una **scarsa o nulla riduzione di CO_2** rispetto a quella pianificata. Il rischio ambientale può essere:
a) Basso = **5%** di probabilità che la riduzione di CO_2 pianificata non venga realizzata
b) Alto = **50%** di probabilità che la riduzione di CO_2 pianificata non venga realizzata

3. Rendimento finanziario: si riferisce al **tasso interno di rendimento (TIR)** del progetto di investimento, considerando che il benchmark TIR per questo tipo di investimenti (cleantech con focus riduzione CO_2) è 6%. Il rendimento finanziario può essere:
a) Basso = TIR dell'investimento pari al **4%**
b) Alto = TIR dell'investimento pari all' **8%**

4. Rischio finanziario: A causa dell'incertezza sui futuri costi legati al progetto, esiste un rischio finanziario, il quale descrive la **probabilità** che, una volta terminato, abbia **raggiunto** solamente il **break-even point** (punto di pareggio) o abbia addirittura **generato perdite** finanziarie. Il rischio finanziario può essere:
a) Basso = **5%** di probabilità di raggiungere solamente il break-even point
b) Alto = **50%** di probabilità di raggiungere solamente il break-even point

[N.B. Si noti che data la loro definizione, il rischio finanziario e il rischio ambientale sono formalmente indipendenti. Questo significa che un alto rischio ambientale non implica un alto rischio finanziario e viceversa. Lo stesso ragionamento risulta valido anche con un basso rischio finanziario e un basso rischio ambientale]

Qui di seguito può trovare due prospetti di investimento:

	PROGETTO A	PROGETTO B
Impatto Ambientale	**Alto** (20 milioni di tonnellate CO_2 ridotta)	**Basso** (10 milioni di tonnellate CO_2 ridotta)
Rischio Ambientale	**Basso** (5% probabilità riduzione di CO_2 pianificata non venga realizzata)	**Alto** (50% probabilità riduzione di CO_2 pianificata non venga realizzata)
Rendimento Finanziario	**Alto** (TIR = 8%)	**Alto** (TIR = 8%)
Rischio Finanziario	**Alto** (50% probabilità di raggiungere solo il breakeven point)	**Basso** (5% probabilità di raggiungere solo il breakeven point)

Clicchi sul progetto da lei preferito:

○ Progetto A

○ Progetto B

Qui di seguito può trovare due prospetti di investimento:

	PROGETTO A	PROGETTO B
Impatto Ambientale	**Basso** (10 milioni di tonnellate CO_2 ridotta)	**Alto** (20 milioni di tonnellate CO_2 ridotta)
Rischio Ambientale	**Basso** (5% probabilità riduzione di CO_2 pianificata non venga realizzata)	**Alto** 50% probabilità riduzione di CO_2 pianificata non venga realizzata
Rendimento Finanziario	**Basso** (TIR = 4%)	**Alto** (TIR = 8%)
Rischio Finanziario	**Alto** (50% probabilità di raggiungere solo il breakeven point)	**Basso** (5% probabilità di raggiungere solo il breakeven point)

Clicchi sul progetto da lei preferito:

○ Progetto A

○ Progetto B

Qui di seguito può trovare due prospetti di investimento:

	PROGETTO A	PROGETTO B
Impatto Ambientale	**Basso** (10 milioni di tonnellate CO2 ridotta)	**Alto** (20 milioni di tonnellate CO2 ridotta)
Rischio Ambientale	**Basso** (5% probabilità riduzione di CO2 pianificata non venga realizzata)	**Alto** (50% probabilità riduzione di CO2 pianificata non venga realizzata)
Rendimento Finanziario	**Alto** (TIR = 8%)	**Basso** (TIR = 4%)
Rischio Finanziario	**Alto** (50% probabilità di raggiungere solo il breakeven point)	**Basso** (5% probabilità di raggiungere solo il breakeven point)

Clicchi sul progetto da lei preferito:

◯ Progetto A

◯ Progetto B

Qui di seguito può trovare due prospetti di investimento:

	PROGETTO A	PROGETTO B
Impatto Ambientale	**Basso** (10 milioni di tonnellate CO2 ridotta)	**Alto** (20 milioni di tonnellate CO2 ridotta)
Rischio Ambientale	**Alto** (50% probabilità riduzione di CO2 pianificata non venga realizzata)	**Alto** (50% probabilità riduzione di CO2 pianificata non venga realizzata)
Rendimento Finanziario	**Alto** (TIR = 8%)	**Basso** (TIR = 4%)
Rischio Finanziario	**Alto** (50% probabilità di raggiungere solo il breakeven point)	**Alto** (50% probabilità di raggiungere solo il breakeven point)

Clicchi sul progetto da lei preferito:

◯ Progetto A

◯ Progetto B

Qui di seguito può trovare due prospetti di investimento:

	PROGETTO A	PROGETTO B
Impatto Ambientale	**Basso** (10 milioni di tonnellate CO_2 ridotta)	**Alto** (20 milioni di tonnellate CO_2 ridotta)
Rischio Ambientale	**Alto** (50% probabilità riduzione di CO_2 pianificata non venga realizzata)	**Basso** (5% probabilità riduzione di CO_2 pianificata non venga realizzata)
Rendimento Finanziario	**Alto** (TIR = 8%)	**Basso** (TIR = 4%)
Rischio Finanziario	**Basso** (5% probabilità di raggiungere solo il breakeven point)	**Alto** (50% probabilità di raggiungere solo il breakeven point)

Clicchi sul progetto da lei preferito:

- ◯ Progetto A
- ◯ Progetto B

Qui di seguito può trovare due prospetti di investimento:

	PROGETTO A	PROGETTO B
Impatto Ambientale	**Basso** (10 milioni di tonnellate CO_2 ridotta)	**Alto** (20 milioni di tonnellate CO_2 ridotta)
Rischio Ambientale	**Basso** (5% probabilità riduzione di CO_2 pianificata non venga realizzata)	**Alto** (50% probabilità riduzione di CO_2 pianificata non venga realizzata)
Rendimento Finanziario	**Alto** (TIR = 8%)	**Basso** (TIR = 4%)
Rischio Finanziario	**Alto** (50% probabilità di raggiungere solo il breakeven point)	**Alto** (50% probabilità di raggiungere solo il breakeven point)

Clicchi sul progetto da lei preferito:

- ◯ Progetto A
- ◯ Progetto B

Un ultimo step: compili gentilmente le seguenti domande di cultura generale riguardanti la sostenibilità. Per la buona riuscita di questo esperimento, la preghiamo cortesemente di **non usare risorse online esterne a questo questionario**.

Il numero di posti di lavoro come tecnico addetto alla manutenzione di turbine eoliche dovrebbe aumentare di __ % entro il 2026.

- 36%
- 66%
- 75%
- 96%

Quanto è sicuro/a che la risposta precedentemente data è quella corretta?

- 25%
- 50%
- 75%
- 100%

Nel 2015 il paese con il più alto consumo di energia rinnovabile (come % del consumo energetico totale) è stato:

- ◯ Islanda
- ◯ Congo
- ◯ Svezia
- ◯ Germania

Quanto è sicuro/a che la risposta precedentemente data è quella corretta?

- ◯ 25%
- ◯ 50%
- ◯ 75%
- ◯ 100%

Dei 208 paesi presenti al mondo, quanti hanno definito obiettivi formali per le energie rinnovabili?

- 86
- 94
- 102
- 144

Quanto è sicuro/a che la risposta precedentemente data è quella corretta?

- 25%
- 50%
- 75%
- 100%

Quando è stato emanato il primo green bond?

- ○ 2006
- ○ 2008
- ○ 2010
- ○ 2012

Quanto è sicuro/a che la risposta precedentemente data è quella corretta?

- ○ 25%
- ○ 50%
- ○ 75%
- ○ 100%

Qual è l'ammontare totale di green bonds emanati durante la prima metà del 2019?

- 23 USD-miliardi
- 54 USD-miliardi
- 67 USD-miliardi
- 86 USD-miliardi

Quanto è sicuro/a che la risposta precedentemente data è quella corretta?

- 25%
- 50%
- 75%
- 100%

Quale di queste quattro banche ha emanato il più grande ammontare (in USD dollari) di green bonds durante il 2018?

- Bank of America
- Fannie Mae
- Industrial Bank of China
- Citi Bank

Quanto è sicuro/a che la risposta precedentemente data è quella corretta?

- 25%
- 50%
- 75%
- 100%

Vi ringraziamo ancora una volta per aver completato il questionario.

Qui di seguito troverà uno spazio per inserire eventuali commenti riguardanti il questionario appena completato. Qualsiasi feedback è fortemente apprezzato.

____

FINE DEL QUESTIONARIO

Appendix 4 – Marginal Rate of Substitution of Financial and Impact Returns

The MRS coefficient explaining the respondents' trade-off between returns is computed as follows:

$$MRS\ of\ Financial\ Return\ for\ Impact\ Return = \frac{\beta_{Impact\ Return}}{\beta_{Financial\ Return}} = \frac{0.888}{0.738} = 1.2$$

However, given the dummy-coded nature of the variables within the experimental design, to interpret this coefficient in realistic terms, the researchers needed to take an additional assumption, which consists in considering that the attributes *Financial Return* and *Impact Return* have a linear (rather than logarithmic) effect on the utility that the respondents derive from the investment choice (R Cran, 2020). This critical assumption allows for the MRS of *Financial Return* for *Impact Return* to be interpreted as follows: in order for a respondent to increase the level of *Impact Return* from 10 to 20 million tons of CO2 reduction, the respondent would be willing to sacrifice *Financial Return* moving from IRR of 8% to one of 3.2%. As the reader may observe, although the Impact Return attribute is allowed to move from its low to high level, the *Financial Return* attribute is now moving from 8% (high level) to 3.2%, which does not coincide with the low level of 4% identified for the experiment design. The reason why this occurs is due to the "linear effect" assumption the researchers previously outlined. In fact, since an increase in *Financial Return* from 4% to 8% represents 1 unit (low to high level), 1-unit upward movement equals 4%. A 1.2 (MRS) increase is thus 1.2 x 4%, which equals 4.8%. So, an increase in *Financial Return* from 4% to 8.8% (4% + 4.8%) provides the same utility as an increase in *Impact Return* from 10 to 20 million tons of CO2 reduction. Therefore, one can conclude that the respondent would be willing to sacrifice *Financial Return* moving from 8% to 3.2% (8% - 4,8%) in order to receive a boost in *Impact Return* and move from an impact of 10 to an impact of 20 million tons of C02 reduced. Hence, in utility terms, this trade-off will allow them to stay on the same indifference curve.

Appendix 5 – Marginal Rate of Substitution of Financial and Impact Risks

The MRS coefficient explaining the respondents' trade-off between risks is calculated in the following manner (R Cran, 2020):

$$MRS\ of\ Financial\ Risk\ for\ Impact\ Risk = \frac{\beta_{Impact\ Risk}}{\beta_{Financial\ Risk}} = \frac{-2.045}{-1.883} = 1.09$$

Nevertheless, given the dummy-coded nature of the variables within the experimental design, to interpret this coefficient in realistic terms, the researchers needed to take a similar assumption to the one taken while computing the MRS between the returns' coefficients. This consists in contemplating that the attributes *Financial Risk* and *Impact Risk* have a linear (rather than logarithmic) effect on the utility that the respondents derive from the investment choice. This critical assumption allows for the MRS of *Financial Risk* for *Impact Risk* to be interpreted as follows: in order for a respondent to decrease the level of *Impact Risk* from a 50% to a 5% percentage probability of not delivering the impact as planned, the respondent would be willing to take up *Financial Risk* moving from a 5% probability to a 54% probability of only breaking even or worse. As the reader can observe, although the Impact Risk attribute is allowed to move from its high to low level, the *Financial Risk* attribute is now moving from 5% (low level) probability to 54%, which does not coincide with the high level of 50% risk identified within the experiment design. The reason why this occurs is due to the "linear effect" assumption the researchers previously outlined. In fact, since an increase in *Financial Risk* from 5% to 50% represents 1 unit (low to high level), 1-unit upward movement equals 45%. A 1.09 (MRS) increase is thus 1.09 x 45%, which equals 49%. So, a decrease in *Financial Risk* from 54% (5% + 49%) to 5% provides the same utility as a decrease in *Impact Risk* from 50% to 5% probability of not delivering the impact as planned. Therefore, one can conclude that the respondent would be willing to take up more *Financial Risk* moving from 5% to 54% in order to receive a reduction in *Impact Risk* and move from the risk of not delivering the impact as planned of 50% to a risk of 5%. Hence, in utility terms, this trade-off will allow them to stay on the same indifference curve.

Appendix 6 - Risk Averse Behavior

Since *Impact Risk* is explained in negative terms (i.e. the risk probability of not reaching the CO2 reduction planned), in order to compute the expected returns, the researchers compiled the complementary probability of reaching the CO2 reduction planned as *100% - Impact Risk.* In the same way, since *Financial Risk* is explained in negative terms (i.e. the risk probability of only breaking even or worse), in order to compute the expected returns, the researchers compiled the complementary probability of performing better than just breaking even as *100% - Financial Risk*. Thus, the *Expected Return* columns in the tables below corresponds to the *Risk-adjusted Return* computed as *(1-Risk) * Return.*

CHOICE TASK 1

Project A		
Attributes	**Levels**	**Expected return**
Impact Return	20 million metric tons of CO2 reduced (high)	19 million metric tons of CO2 reduced
Impact Risk	5% probability that the planned CO2 reduction is not realized (low)	
Financial Return	IRR= 8% (high)	IRR = 4%
Financial Risk	50% probability of only breaking even (high)	
66% of respondents chose this alternative		

Project B		
Attributes	**Levels**	**Expected return**
Impact Return	10 million metric tons of CO2 reduced (low)	5 million metric tons of CO2 reduced
Impact Risk	50% probability that the planned CO2 reduction is not realized (high)	
Financial Return	IRR= 8% (high)	IRR = 7.6%
Financial Risk	5% probability of only breaking even (low)	
34% of respondents chose this alternative		

In choice task 1, project A showed a higher expected return on the impact side (19 mio of CO2 reduced > 5 mio CO2 reduced), whereas project B showed the higher expected return on the financial side (IRR = 7.6% > IRR = 4%). Thus, in this case there is not one general rational choice and the decision was mainly driven by their impact-first or finance-first approach. However, one can observe that, for respondents choosing A because of the largest expected impact return, the impact risk is the lowest and the impact return the highest. So, from the impact side perspective, A can be defined as the rational choice (Booth *et al.*, 2016). On another note, if one instead focuses on respondents choosing B because of the largest expected financial return, here the financial risk is the lowest and financial return the highest. So, from the financial side perspective, B can be defined as the rational choice (Booth *et al.*, 2016). Overall, in this choice task, since 66% of individuals have chosen project A, which is superior to B from an impact perspective, the sample made a choice with an impact-first approach in mind. More precisely, the respondents can be identified as risk-averse because they maximize their impact returns while minimizing the impact risk (Booth *et al.*, 2016).

CHOICE TASK 2

Project A		
Attributes	**Levels**	**Expected return**
Impact Return	10 million metric tons of CO2 reduced (low)	9.5 million metric tons of CO2 reduced
Impact Risk	5% probability that the planned CO2 reduction is not realized (low)	
Financial Return	IRR = 4% (low)	IRR = 2%
Financial Risk	50% probability of only breaking even (high)	
31% of respondents chose this alternative		

Project B		
Attributes	**Levels**	**Expected return**
Impact Return	20 million metric tons of CO2 reduced (high)	10 million metric tons of CO2 reduced
Impact Risk	50% probability that the planned CO2 reduction is not realized (high)	
Financial Return	IRR = 8% (high)	IRR = 7.6%
Financial Risk	5% probability of only breaking even (low)	
69% of respondents chose this alternative		

In choice task 2, the project showed a slightly higher expected return both on the impact and on the financial side is project B (10 mio of CO2 reduced > 9.5 mio CO2 reduced; IRR = 7.6% > IRR = 2%), Thus, alternative B can be defined as the rational choice. In this scenario, the majority of respondents (69%) chose project B, which is also the rational choice. Moreover, one can observe that on the impact side, project B shows the highest impact return with the highest impact risk, whereas on the financial side, the project shows the largest financial return with the smallest financial risk. Hence, in choice task 2 respondents were risk-averse because, although they dislike risk, they are still willing to assume it if they are adequately compensated (Booth *et al.*, 2016).

CHOICE TASK 3

Project A		
Attributes	**Levels**	**Expected return**
Impact Return	10 million metric tons of CO2 reduced (low)	9.5 million metric tons of CO2 reduced
Impact Risk	5% probability that the planned CO2 reduction is not realized (low)	
Financial Return	IRR = 8% (high)	IRR = 4%
Financial Risk	50% probability of only breaking even (high)	
51% of respondents chose this alternative		

Project B		
Attributes	**Levels**	**Expected return**
Impact Return	20 million metric tons of CO2 reduced (high)	10 million metric tons of CO2 reduced
Impact Risk	50% probability that the planned CO2 reduction is not realized (high)	
Financial Return	IRR= 4% (low)	IRR = 3.8%
Financial Risk	5% probability of only breaking even (low)	
49% of respondents chose this alternative		

In choice task 3, project A showed a slightly higher expected financial return (IRR = 4% > IRR = 3.8%), whereas project B showed a slightly higher expected impact return (10 mio of CO2 reduced > 9.5 mio CO2 reduced). Thus, in this case there is not one general rational choice. In fact, this can be seen in the % scores of respondents choosing project A or B, which almost be approximated to a 50-50 scenario and the decision was mainly driven by their impact-first or finance-first approach. In this choice task, since 51% of individuals have chosen project A, which is superior to B from a financial perspective, the sample made a choice with a finance-first approach in mind. However, one can observe that, for respondents choosing A due to the largest expected financial return, the financial risk is the highest and the financial return is the highest. So, from the financial perspective, A can be defined as the rational choice and respondents can be defined as risk-averse because although they dislike financial risk, they are still willing to assume it if they are adequately compensated (Booth *et al.*, 2016). On another note, if one instead focuses on respondents choosing B because of the largest expected impact return, the impact risk is the highest and the impact return is the highest. So, from the impact perspective, B can be defined as the rational choice and respondents can be outlined as risk-averse because although they dislike impact risk, they are still willing to assume it if they are adequately compensated (Booth *et al.*, 2016).

CHOICE TASK 4

Project A		
Attributes	**Levels**	**Expected return**
Impact Return	10 million metric tons of CO2 reduced (low)	5 million metric tons of CO2 reduced
Impact Risk	50% probability that the planned CO2 reduction is not realized (high)	
Financial Return	IRR= 8% (high)	IRR = 4%
Financial Risk	50% probability of only breaking even (high)	
47% of respondents chose this alternative		

Project B		
Attributes	**Levels**	**Expected return**
Impact Return	20 million metric tons of CO2 reduced (high)	10 million metric tons of CO2 reduced
Impact Risk	50% probability that the planned CO2 reduction is not realized (high)	
Financial Return	IRR= 4% (low)	IRR = 2%
Financial Risk	50% probability of only breaking even (high)	
53% of respondents chose this alternative		

In choice task 4, project A showed the higher expected return on the financial side (IRR = 4% > IRR = 2%), whereas project B showed a higher expected return on the impact side (10 mio of CO2 reduced > 5 mio CO2 reduced). Thus, also in this case there is not one general rational choice. In fact, this can be seen in the % scores of respondents choosing project A or B, which can almost be approximated to a 50-50 scenario and the decision was mainly driven by their impact-first or finance-first approach. In this choice task, since 53% of individuals have chosen project B, which is superior to A from an impact perspective, the sample made a choice with an impact-first approach in mind. However, one can observe that, for respondents choosing A because of the largest expected financial return, the financial risk was 50% as project B but the financial return was higher compared to B. So, from the financial perspective, A can be defined as the rational choice and respondents can be defined as rational because they choose the option with the highest expected financial return (Booth *et al.*, 2016). On another note, if one instead focuses on respondents choosing B because of the largest expected impact return, the impact risk was 50% as project A but the impact return was higher compared to A. So, from the impact perspective, B can be defined as the rational choice and respondents can be described as rational because they choose the option with the highest expected impact return (Booth *et al.*, 2016). Overall, the respondents can be identified as risk-averse because they are willing to accept a high level of risk if they are adequately compensated for it (Booth *et al.*, 2016), either on the impact or financial side.

CHOICE TASK 5

Project A		
Attributes	**Levels**	**Expected return**
Impact Return	10 million metric tons of CO2 reduced (low)	5 million metric tons of CO2 reduced
Impact Risk	50% probability that the planned CO2 reduction is not realized (high)	
Financial Return	IRR = 8% (high)	IRR = 7.6%
Financial Risk	5% probability of only breaking even (low)	
48% of respondents chose this alternative		

Project B		
Attributes	**Levels**	**Expected return**
Impact Return	20 million metric tons of CO2 reduced (high)	19 million metric tons of CO2 reduced
Impact Risk	5% probability that the planned CO2 reduction is not realized (low)	
Financial Return	IRR = 4% (low)	IRR = 2%
Financial Risk	50% probability of only breaking even (high)	
52% of respondents chose this alternative		

In choice task 5, project A showed the higher expected financial return (IRR = 7.6% > IRR = 2%), whereas project B showed a higher expected impact return (19 mio of CO2 reduced > 10 mio CO2 reduced). Thus, in this case there is not one general rational choice. In fact, this can be seen in the % scores of respondents choosing project A or B, which can almost be approximated to a 50-50 scenario and the decision was mainly driven by their impact-first or finance-first approach. In fact, in this choice task, since 52% of individuals have chosen project B, which is superior to A from an impact perspective, the sample made a choice with an impact-first approach in mind. However, one can observe that for respondents choosing A because of the largest expected financial return, the financial risk is the lowest and the financial return the highest. So, from the financial perspective, A can be defined as the rational choice (Booth *et al.*, 2016). On another note, if one instead focuses on respondents choosing B because of the largest expected impact return, the impact risk is the lowest and impact return the highest. So, from the impact perspective, B can be defined as the rational choice (Booth *et al.*, 2016). Overall, the respondents can be identified as risk-averse because they maximise their returns while minimizing the risk (Booth *et al.*, 2016) either on the impact or financial side.

CHOICE TASK 6

Project A		
Attributes	**Levels**	**Expected return**
Impact Return	10 million metric tons of CO2 reduced (low)	9.5 million metric tons of CO2 reduced
Impact Risk	5% probability that the planned CO2 reduction is not realized (low)	
Financial Return	IRR = 8% (high)	IRR = 4%
Financial Risk	50% probability of only breaking even (high)	
78% of respondents chose this alternative		

Project B		
Attributes	**Levels**	**Expected return**
Impact Return	20 million metric tons of CO2 reduced (high)	19 million metric tons of CO2 reduced
Impact Risk	50% probability that the planned CO2 reduction is not realized (high)	
Financial Return	IRR = 4% (low)	IRR = 2%
Financial Risk	50% probability of only breaking even (high)	
22% of respondents chose this alternative		

In choice task 6, project A showed the higher expected financial return (IRR = 4% > IRR = 2%), whereas project B showed a higher expected impact return (19 mio of CO2 reduced > 9.5 mio CO2 reduced). Thus, in this case there is not one general rational choice. However, in this choice task the % of respondents choosing project A is way higher than % of respondents choosing project B. Therefore, since 78% of individuals have chosen project A, which is superior to B from a financial perspective, the sample made a choice with a finance-first approach in mind. However, one can observe that, for respondents choosing A because of the largest expected financial return, the financial risk is the highest and the financial return is the highest. So, from the financial side of the choice, A can be defined as the rational choice and respondents can be defined as risk-averse because although they dislike financial risk, they are still willing to assume it if they are adequately compensated (Booth *et al.*, 2016). On another note, if one instead focuses on respondents choosing B because of the largest expected impact return, the impact risk is the highest and impact return is the highest. So, from the impact side of the choice, B can be defined as the rational choice and respondents can be outlined as risk-averse because although they dislike impact risk, they are still willing to assume it if they are adequately compensated (Booth *et al.*, 2016).

*Appendix 7 - Utility-Maximizing Investment Profiles**

	Impact Return		Impact Risk		Financial Return		Financial Risk		
Investment Profile	Level	Coefficient	Level	Coefficient	Level	Coefficient	Level	Coefficient	Total Utility
1	0	-0,888	1	-2,045	1	0,738	0	1,883	-0,312
2	1	0,888	1	-2,045	0	-0,738	0	1,883	-0,012
3	1	0,888	0	2,045	0	-0,738	0	1,883	4,078
4	0	-0,888	0	2,045	1	0,738	0	1,883	3,778
5	1	0,888	0	2,045	1	0,738	1	-1,883	1,788
6	0	-0,888	1	-2,045	0	-0,738	0	1,883	-1,788
7	0	-0,888	0	2,045	0	-0,738	1	-1,883	-1,464
8	1	0,888	1	-2,045	0	-0,738	1	-1,883	-3,778
9	1	0,888	1	-2,045	1	0,738	0	1,883	1,464
10	1	0,888	0	2,045	1	0,738	0	1,883	5,554
11	0	-0,888	0	2,045	0	-0,738	0	1,883	2,302
12	0	-0,888	1	-2,045	1	0,738	1	-1,883	-4,078
13	1	0,888	1	-2,045	1	0,738	1	-1,883	-2,302
14	0	-0,888	1	-2,045	0	-0,738	1	-1,883	-5,554
15	0	-0,888	0	2,045	1	0,738	1	-1,883	0,012
16	1	0,888	0	2,045	0	-0,738	1	-1,883	0,312

* ”1” = high level | “0” = low level

In the table above, the researchers outlined the 16 investment profiles included in the full factorial design. Firstly, each investment profile was partitioned in the levels constituting the alternative. Secondly, each level was associated with the relative preference score obtained in *Table 11*. Thirdly, the total preference score was computed for each investment profile. Finally, in order to understand the first and second-best investment profiles maximizing the utility of the respondents’ sample the researchers ranked the utilities from largest to lowest. The ranking can be observed in the table below:

Ranking	Investment Profile	Total Utility
1st	**10**	**5,554**
2nd	**3**	**4,078**
3rd	4	3,778
4th	11	2,302
5th	5	1,788
6th	9	1,464
7th	16	0,312
8th	15	0,012
9th	2	-0,012
10th	1	-0,312
11th	7	-1,464
12th	6	-1,788
13th	13	-2,302
14th	8	-3,778
15th	12	-4,078
16th	14	-5,554

The first-best option corresponds to Investment Profile 10, which shows a high level for both impact and financial returns as well as a low level for both impact and financial risk. The second-best option corresponds to Investment Profile 3. The profile displays high impact return and low impact risk, on the impact side, whereas it displays low financial return and low financial risk on the financial side.

Appendix 8 - Interaction Effects on Financial Risk

INTERACTION EFFECT OF GENDER ON FINANCIAL RISK

	Estimate	**p-value**
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.088	0.7476
Impact Return ($\boldsymbol{\beta_{iret}}$)	0.928	0.0002 ***
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-2.017	9.014e-06 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	0.764	0.0071 **
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-1.763	0.0144 *
Financial Risk : Gender ($\boldsymbol{\beta_{frisk:gender}}$)	-0.133	0.7438

Significance codes: '***' p-value < 0.001 \| '**' p-value < 0.01 \| '*' p-value < 0.05 \| '.' p-value < 0.1
McFadden R^2: 0.144

INTERACTION EFFECT OF AGE ON FINANCIAL RISK

	Estimate	**p-value**
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.088	0.7477
Impact Return ($\boldsymbol{\beta_{iret}}$)	0.928	0.0001651 ***
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-2.018	9.502e-06 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	0.765	0.0071**
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-1.890	0.0021 **
Financial Risk : Age ($\boldsymbol{\beta_{frisk:age}}$)	-0.0005	0.997

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.144

INTERACTION EFFECT OF YEARS OF EXPERIENCE ON FINANCIAL RISK

	Estimate	p-value
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.088	0.7454
Impact Return ($\boldsymbol{\beta_{iret}}$)	0.960	8.480e-05 ***
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-1.975	9.546e-06 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	0.715	0.0094 **
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-1.890	0.0018 **
Financial Risk : Years of Experience($\boldsymbol{\beta_{frisk:years}}$)	0.004	0.9687

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.141

Appendix 9 - Interaction effect of Knowledge on Financial Return

	Estimate	**p-value**
Mean Preference Score		
Intercept ($\boldsymbol{\beta_0}$)	-0.089	0.7405
Impact Return ($\boldsymbol{\beta_{iret}}$)	0.957	8.359e-05 ***
Impact Risk ($\boldsymbol{\beta_{irisk}}$)	-1.971	9.393e-06 ***
Financial Return ($\boldsymbol{\beta_{fret}}$)	0.837	0.0125 *
Financial Risk ($\boldsymbol{\beta_{frisk}}$)	-1.873	0.0003 ***
Financial Return : Average Correct ($\boldsymbol{\beta_{fret:correct}}$)	-0.639	0.5020

Significance codes: '***' p-value < 0.001 \| '**' p-value < 0.01 \| '*' p-value < 0.05 \| '.' p-value < 0.1
McFadden R^2: 0.142

Appendix 10 - Interaction effect of Industry Finance on Impact Return

	Estimate	p-value
Mean Preference Score		
Intercept ($\boldsymbol{\beta}_0$)	-0.088	0.7436
Impact Return ($\boldsymbol{\beta}_{iret}$)	0.997	0.0003 ***
Impact Risk ($\boldsymbol{\beta}_{irisk}$)	-1.973	9.528e-06 ***
Financial Return ($\boldsymbol{\beta}_{fret}$)	0.713	0.0096 **
Financial Risk ($\boldsymbol{\beta}_{frisk}$)	-1.875	0.0003 ***
Impact Return : Industry Finance ($\boldsymbol{\beta}_{iret:industy\_fin}$)	-0.077	0.7832

Significance codes: '***' p-value < 0.001 | '**' p-value < 0.01 | '*' p-value < 0.05 | '.' p-value < 0.1
McFadden R^2: 0.141