Louvain School of Management

Biases in investment decision making: a study on differences in herding behavior between sustainable and traditional investments.

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ABSTRACT

This master thesis aims to measure the herding behavior differences between sustainable investments and traditional investments for mixed investors. Mixed investors are individuals whose portfolio is composed of both investments aimed at financial returns and at sustainability contributions. As the community of mixed investors has been steadily increasing over time, it is therefore key to understand their decision process better.

After a literature review on both sustainable investing and behavioral finance (with a focus on investment decision making) we tested different hypotheses for variations in herding behavior. The main hypothesis was the relationship between investment type and herding behavior. We also looked at the relationship between socio-demographic factors and investment habit characteristics on herding behavior as well as the interaction effect these two relationships could have. The different hypotheses were tested with the help of a quantitative study on data collected through an online survey circulated between November and December 2021. The sample obtained was of 175 respondents, of which 101 were usable responses and among these 87 qualified as mixed investors.

We found that the herding behavior of mixed investors depends on the type of investment. Mixed investors seem to be more subject to herding for their traditional investments than for their sustainable investments. Socio-demographic traits such as income, education and gender appeared to not have an influence on herding behavior. Younger investors (under 26) tend to be more subject to herding than older investors but only in the case of traditional investments. Investment habit traits such investment size impact the herding behavior irrespective of the type of investment. Investors investing a significant portion of their wealth (>75%) were less subject to herding. Passive investor seem to be more subject to herding than active investors in the case of sustainable investments. There seems to be a learning effect, as after three years of investment experience, investors become less subject to herding. This effect is found for both sustainable and traditional investments but is stronger for the latter category.

Finally, our findings in Exploratory Factor Analyses suggest that the herding bias is better represented by sub-factors rather than one composite variable.

We also found that pure traditional investors are less subject to herding than mixed investors.

Finally, we propose paths for future research on the analysis of the investment decision making process of mixed investors.

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Introduction

Over the past two decades, incorporating environmental, social and ethical components in all aspects of our lives has increased in prevalence. Today, most people try to address these issues with the tools and power at their disposal. In the case of wealth management and financial investments, this translates into the development and popularity of sustainable investments (also designated as Socially Responsible Investments). A lot of effort is put in understanding what qualifies an investment as sustainable, what motivates investors to opt increasingly for such investments and on the socio-demographic and psychological factors that influence the chance of investing sustainably.

In parallel, the realization that humans do not act in a pure rational way, as traditional economic models indicated, is being more and more documented in the literature as well. The studies developed in this context fall under the field of behavioral finance. In this field, the decision making process of humans is believed to be subject to shortcuts: biases and heuristics. These shortcuts are used when humans use their intuitive system (System 1) rather than their reasoning system (System 2) to facilitate a decision (Kahneman, 2011). Financial investments are no exception to this rule, numerous authors have found that humans use these shortcuts even for supposedly rational investment decisions.

Until now, the literature bringing these two fields of finance together has been mainly focused on understanding why individuals chose sustainable investments over traditional investments (understand "with pure financial motives"). Recently, this dichotomous segmentation has been further refined to include a broader community of investors i.e. investors picking both traditional and sustainable investments in their portfolio (or "mixed" investors). The rationale behind the initial investment decision of opting for one investment rather than the other and in which proportions is well documented in the literature.

We believe that little attention has been given to the investment allocation decisions, *after* an individual has decided on his portfolio segmentation (i.e. sustainable vs. traditional investments). Does an individual follow the same decision process when choosing the financial products for his traditional or sustainable investments? As we know that biases and heuristics impact the investment decision process of an individual, we can rephrase our question as: is an investor subject to the same decision shortcuts and biases depending on the type of investment he is looking at (sustainable vs. traditional)?

Research objective and scope

In the case of our study we will explore this question by looking at one bias in particular: the herding bias (i.e. the tendency to mimic others). Herding is a frequently discussed bias in investment decisions as it is believed to lead to market inefficiencies in the form of bubbles and crashes. Moreover, the tendency to follow others is particularly relevant in the case of sustainable investments as the initial decision to opt for sustainable investments is often influenced by peers (see literature review).

We do not limit ourselves to some financial products (e.g. only stocks) nor to particular sustainable investment classes (e.g. only impact investing). We leave the definitions of investment in financial products and sustainable investments relatively broad.

Furthermore, we focus on the investment decision making variations for mixed investors, i.e. going for both sustainable and traditional investments. We do not interest ourselves at the reasons originally pushing an investor to go for both sustainable and traditional investments or the motivations behind an increase in sustainable investment. We believe this is a topic already extensively covered in the literature.

Finally, we limit the scope of the population we would like to analyze. As we are interested in individual behavior, we concentrate on retail investors taking investment decisions themselves.

Methodology

In order to perform our study and answer our research question we will first produce a literature review on the topics of sustainable investing and behavioral finance to get an overview on both subjects as well as understand how they are linked to each other. We will also query the factors that influence behavioral finance biases and sustainable investment choices as they might have a mitigating effect on the relationship between investment type and herding behavior. We will then gather primary data through the form of a closed-ended questionnaire. Finally, we will adopt a deductive approach and test our hypotheses through a within-subject design, observing differences in herding for each investor depending on the type of investment.

PART I : LITERATURE REVIEW

CHAPTER I : Sustainable investing

In this chapter we will cover the field of sustainable investing. We will first analyze sustainable investments (or Socially Responsible Investments), what they cover, what drives their popularity and what hinders their implementation. Then we will turn to sustainable investors, describe who they are and understand which individuals tend to belong more to that category.

I. Sustainable investments

1. Sustainable finance

Sustainable finance stems from the realization that welfare is not maximized if companies focus solely on profits and that it is key to incorporate externalities (e.g. environmental) in the value maximization process (Dumas & Louche, 2016). Sustainable finance encompasses concepts as various as social business, green bonds etc. Under the broader umbrella of sustainable finance, we find Socially Responsible Investments (hereafter SRI), also called sustainable investments.

2. Socially Responsible Investments

SRI is not officially defined (Capelle-Blancard and Monjon, 2012; Sandberg et al., 2009). We find references to terms as broad as ethical investment, ESG (Environment Social and Governance) investing or green funds (Sandberg et al., 2009) as well as the gaining popularity of impact investing (Dumas & Louche, 2016). This broadness of definition of SRI and hence investment styles complicates research on the matter (Dumas & Louche, 2016; Sandberg et al., 2009)

The understanding of SRI has considerably evolved over time, reflecting the evolution of collective beliefs on SRI in our society. Moving from a heavily ethics centered perspective and underperformance belief in the 1980's to a more neutral and professional view nowadays, as it is now believed to be more materially relevant (von Wallis & Klein, 2015).

The common understanding of the term is that it is based on two different dimensions: ethical (ESG: environmental, social, and corporate governance) and financial (Widyawati, 2020). These two dimensions are being worked on simultaneously when deciding for an investment strategy (Breedt et al., 2019) with varying degrees of concerns regarding the integration of one in the other (Paetzold & Busch, 2014; von Wallis & Klein, 2015). The ethical objectives are typically measured by the impact on ESG issues (Pender & Brocchetto, 2011) whereas the financial objectives are, as in the tradition, measured by superior risk-adjusted returns (Pender

& Brocchetto, 2011). SRI is seen as both a way to pressure companies on sustainability and as a new financial service for a given demand (Widyawati, 2020).
In general, it is accepted that SRI contributes to sustainable development (Widyawati, 2020). The diversity in definition on one hand increases the popularity of SRI due to an appeal to a potentially broader set of investors and on the other hand makes a general understanding more complicated and hence hinders its implementation (Dumas & Louche, 2016; Widyawati, 2020)

As its definition is left broad, there are various ways of applying sustainable investment strategies whose popularity and use vary depending on expected returns (Amel-Zadeh & Serafeim, 2018; von Wallis & Klein, 2015) as well as geographic location (Pender & Brocchetto, 2011).
Among the different sustainable investment possibilities, we find shareholder advocacy (engagement), integration of ESG factors in analysis of stocks, screening with inclusionary and exclusionary strategies and best-in-class strategy relative to industry peers (Pender & Brocchetto, 2011), less commonly cited strategies are portfolio tilt changing the aggregate ESG characteristics of a portfolio, thematic investment and risk-premium investing (smart beta). (Amel-Zadeh & Serafeim, 2018).
Screening is based on the application of arbitrary ethical or moral criteria to restrict the investment universe (Dumas & Louche, 2016), exclusionary screening means leaving out some companies (Pender & Brocchetto, 2011). This is perceived to be the least effective strategy as it does not truly change the unethical practices (Dumas & Louche, 2016) but is simultaneously the most common used strategy (Amel-Zadeh & Serafeim, 2018). Thanks to the increasing access to data and standardization initiatives such as the UN global compact, recently inclusionary screening strategies have gained on popularity (Amel-Zadeh & Serafeim, 2018; Unruh et al., 2016) although the most adequate way of integrating ESG factors quantitatively is still uncertain (Widyawati, 2020).

The majority of SRI literature uses ESG metrics as a proxy (Widyawati, 2020) for sustainability. The reliability and transparency of these metrics is problematic (Widyawati, 2020). These ESG metrics are provided by different organization and initiatives who provide conflicting results on ESG scores (Breedt et al., 2019). These differences typically stem from the self-reported aspect of sustainability data and the lack of accuracy check (Unruh et al., 2016) as well as on data collection methods, varying data formats (Widyawati, 2020) and methodologies (Widyawati, 2020). This makes indices aggregations and benchmarking cumbersome (Amel-

Zadeh & Serafeim, 2018; Breedt et al., 2019; Friede, 2019). Another argument for the precarious aspect of these ESG metrics is its inconsistency over time and lack of accountability.

High ESG scores are typically not held over the long run by fund managers due to allocation decisions (Dumas & Louche, 2016; Wimmer 2013). Moreover, hardly anywhere are executives liable for their ESG reporting, contrary to financial reporting.

This pushes investors to treat ESG information with care and little confidence, discounting it (Friede, 2019). To palliate this lack of standardization, it is of uttermost importance to have universal and reliable ESG standards, in order to speed up the SRI adoption (Breedt et al., 2019; Busch et al., 2016).

3. Drivers SRI

In recent years, sustainable investment has risen steadily and is expected to continue on this path (Amel-Zadeh & Serafeim, 2018; Breedt et al., 2019; Paetzold & Busch, 2014; Pender & Brocchetto, 2011). This is attested by the increasing SRI literature and mainstream media presence (Breedt et al., 2019; Capelle-Blancard and Monjon, 2012), the growth of such assets (von Wallis & Klein, 2015) as well as the increased use of tools to connect ESG and corporate performance (Unruh et al., 2016). What are the drivers explaining this rise in popularity? We will focus on demand factors considered to be the main drivers (Amel-Zadeh & Serafeim, 2018; Breedt et al., 2019; Pilaj, 2017; Paetzold & Busch, 2014; Williams, 2007).

3.1. Desire to achieve return

According to traditional finance theory, the increase in demand for sustainable investments should be explained by an increase in return for the investor (Amel-Zadeh & Serafeim, 2018; Beal et al., 2005; Hafenstein & Bassen, 2016; Nilsson, 2008; Unruh et al., 2016). This increase can come from a growth in the value of the firm or from an improvement of its financial performance due to sustainability integration. If we look at growth in value, the focus on social awareness increases the attractiveness of a firm, this drives the share price upwards and hence as well the value of the firm (Pasewark & Riley, 2010). If we turn to financial performance, sustainability integration contributes to the management of ESG-related risks (Diouf et al., 2016) and decreases the firms cost of capital due to a higher regulation conformity (Amel-Zadeh & Serafeim, 2018).

Nonetheless, the consensus in the literature on this potential link between SRI and financial performance is that it is inconclusive (Dumas & Louche, 2016; Friede et al., 2015; von Wallis

& Klein, 2015; Widyawati, 2020). The topic is heavily documented and the disagreements numerous (Capelle-Blanchard & Monjon, 2012; Friede et al., 2015; Williams, 2007), sustainability integration has found to have both a positive and negative relationship with market performance (Breedt et al., 2019). It seems that other factors influence that relationship. Breedt et al. (2019) document the effect of a large-cap bias and Friede et al. (2015) find that the geography of the firm is determinant. Developed Europe exhibits a much smaller share of positive results (26.1%) compared to emerging markets (65.4%) for instance (Friede et al., 2015). Moreover, the heterogeneity of SRI approaches, identified previously (Derwall et al., 2011; Dumas & Louche, 2016; Widyawati, 2020) and the choice of methodology to measure the performance (Dumas & Louche, 2016) creates discrepancies between studies.

In conclusion, the performance differences between SRI and non-SRI is inconclusive and we can hence not assume with certainty that sustainability integration allows for higher return generation. If financial performance alone cannot explain the rising attraction of investors to SRI, what motivates them then?

We have identified two non-financial commonly cited reasons for SRI motivation in the literature: desire for personal satisfaction and social pressure.

3.2. Personal satisfaction

The desire for personal satisfaction (Pasewark & Riley, 2010) is pushed by ethical motives (Amel-Zadeh & Serafeim, 2018; Beal et al., 2005; Dumas & Louche, 2016), the belief system (Hafenstein & Bassen, 2016; Widyawati, 2020) and individual values of investors (Bauer & Smeets, 2015; Diouf et al., 2016; Dorfleitner & Nguyen, 2016; Dumas & Louche 2016; Friede, 2019; Hafenstein & Bassen, 2016; Pasewark & Riley, 2010; Widyawati, 2020). Investors are looking more and more for investments in line with their personal values (Diouf et al., 2016; Dumas & Louche, 2016; Statman 2004). Integrating personal values in investment decisions generates emotional benefits for the investor (Hafenstein & Bassen, 2016; Lewis 2001), what Beal et al. (2005) call a “psychic return”. They “put their money where their morality is” (Diouf et al., 2016, p.47).

The sensitivity of each investor to sustainable issues impacts the amount he is willing to invest responsibly (Diouf et al., 2016) but generally not the intensity of the psychic return (Beal et al., 2005; Dorfleitner & Nguyen, 2016; Hafenstein & Bassen, 2016). A minority genuinely want to achieve social change with their investment activities (Beal et al., 2005; Cullis, Lewis and Winnett 1992), their psychic return is then dependent fully on the actual outcome. The varying motivations of investors on this doing good scale explains the wide variety of financial services available (Beal et al., 2005; Pasewark & Riley, 2010).

3.3. Social Factors

The collective beliefs and social factors of our society (Dumas and Louche, 2016; von Wallis & Klein, 2015) can push investors as well. A society's interpretation of how financial markets will evolve (defined as "collective belief") drives them away from the quantitative measures of finance (von Wallis & Klein, 2015) and shapes how investors make decisions. This collective belief is heavily influenced by the access to information which is where the media and peers play a big role (Diouf et al., 2016) as people are afraid of searching for contradicting evidence (Friede, 2019). First, the media coverage of an issue strongly influences collective beliefs. This is the case for SRI, with a strong traditional and social media coverage, partially explaining the growing demand (Diouf et al., 2016; von Wallis & Klein, 2015). Second, investment decisions are especially impacted by socio-cultural aspects (Hofstede and Hofstede, 2005 as cited in Williams, 2007) with a strong influence of the peer group (Beal et al., 2005), particularly relatives and friends (East 1993; Paetzold & Busch, 2014; Rosen et al., 1991; Statman, 2005). Some authors believe that this results in some sort of social pressure on individuals for their investments, although this opinion is not shared by all (see Paetzold & Busch, 2014).

3.4. Balance

Ultimately, both financial and non-financial motivations impact SRI decision (Beal, Goyen, & Phillips, 2005; Mackenzie & Lewis, 1999). The degree of impact of one or the other is heterogeneous (Dorfleitner & Nguyen, 2016; Paetzold & Busch, 2014; Widyawati, 2020). The balance between the two motives varies with the intensity of ethical concerns (Beal et al., 2005; Pasewark & Riley, 2010). It is believed that investors may be ready to waive return to increase their sustainability exposure (Hafenstein & Bassen, 2016) but with contradictory discussions and findings (Dorfleitner and Utz 2014; Hafenstein & Bassen, 2016; Mackenzie and Lewis 1999; Lewis 200; Lewis & Mackenzie 2000; Rosen et al., 1991). This trade-off between both can be theoretically explained in different ways. One way to see it is as some sort of ethical penalty (Pasewark & Riley, 2010) or positive psychic return. Another way is the prospect theory from Kahneman and Tversky (1979) adapted to this situation as the perception of a win or a loss depends on an aspirational level (Hafenstein & Bassen, 2016).

4. Barriers SRI

SRI, although gaining on importance, is still not fully developed and part of mainstream financing, hindering its potential contribution to the progression of societal goals (Friede, 2019). There seems to be a gap between the interest in SRI and actual participation (Friede, 2019; Paetzold & Busch, 2014). What is slowing down its adoption? There is no consensus on the dominant barriers (Friede, 2019; Paetzold & Busch, 2014). According to Paetzold & Busch (2014) the barriers arise primarily between the intention to invest in SI and the actual investing.

First, the investor will be faced with a lack of adequate and standardized information (Friede, 2019; von Wallis & Klein, 2015), hindering the comparability among firms (Amel-Zadeh & Serafeim, 2018; Friede, 2019). Internal organizational inefficiencies causes firms and advisors to communicate little on sustainability issues (Friede, 2019; Paetzold & Busch, 2014). Moreover, it is complex to incorporate it in valuation models (Friede, 2019), which is why most investors do not factor it (Unruh et al., 2016). That is even the case for professional investors where only 10% incorporate ESG criteria in investment analysis (Friede, 2019).
Then, the sustainable financial product supply is not sufficient (Friede, 2019; Paetzold & Busch, 2014; von Wallis & Klein, 2015) as investors have the impression that these products do not correspond to ethical expectations (Paetzold & Busch, 2014). This creates a form of inertia among investors(von Wallis & Klein, 2015).

We have now a better understanding of what sustainable investments are, what are the drivers of their rising popularity and why they are not universally adopted yet. We will now address the category of the population who opts for these investments: so-called sustainable investors.

II. Sustainable investors

1. Socially Responsible investors

Due to the numerous investment styles and the lack of unified definition described previously, the way investors integrate sustainability criteria in their investment strategies is heterogeneous (Amel-Zadeh & Serafeim, 2018; Friede, 2019; Widyawati, 2020) with varying motivation, interest, perception of SRI (Paetzold & Busch, 2014) and intensity (Pasewark & Riley, 2010). The term "sustainable investor" hence covers a large spectrum of possibilities.

In SRI studies, the definition of SRI is left open to the participants of the study to avoid too restricting criteria and framing effects (Paetzold & Busch, 2014) as participants themselves consider their sustainability implication independently from the way they invest (Dorfleitner & Nguyen, 2016). The differences in the multiple understandings of SRI are hence neglected (Pasewark & Riley, 2010). There is a tendency to define responsible investors quite broadly and homogenize investors with varying interest and implication degrees (Diouf et al., 2016; Paetzold & Busch, 2014; Pasewark & Riley, 2010). This is understandable when we consider that a sustainable asset is truly defined as such by values of a single investor, hence with a high dose of subjectivity (Dumas & Louche, 2016).

In the realm of consumer products, so called “ethical consumers” are a rising category (McGoldrick & Freestone, 2008) with a strong willingness to pay for products in line with their morals. Similarly, in the case of investments, ethical investors are growing (von Wallis & Klein, 2015). They are pushing evermore the demand for sustainable investment products and contribute strongly to its popularity (Amel-Zadeh & Serafeim, 2018; Breedt et al., 2019; Paetzold & Busch, 2014; Pilaj, 2017).

These ethical investors are almost exclusively retail investors. They have more leverage into how they want to express their responsible investment strategy than institutional investors who have to answer to different legal requirements (Pender & Brocchetto, 2011).

1.1. Dichotomy sustainable vs. Traditional

“Sustainable investors” as opposed to “conventional investors” or “traditional investors” have been compared frequently in the past (Widyawati, 2020). Both groups are believed to use different variables in investment decision making (Diouf et al., 2016). This view requires to be nuanced. They share similar concerns such as financial performance (Diouf et al., 2016; Dorfleitner & Nguyen, 2016; Dumas & Louche, 2016). These can be more important than ethical criteria for some SR investors (Dorfleitner & Nguyen, 2016; McLachlan and Gardner, 2004). More generally, the trade-off between financial and sustainable criteria varies from investor to investor (Beal et al., 2005).

In fact, the limitation to pure traditional investors and pure sustainable investors is extremely restrictive (Pasewark & Riley, 2010; Statman 2000), it is common to find investors invested in both unethical and ethical funds (Diouf et al., 2016; Dumas & Louche, 2016) and very few investors invest their entire portfolio socially (Pasewark & Riley, 2010). Hence the SRI investment level should be measured on a continuous scale rather than in a binary form (Pasewark & Riley, 2010). We can consider that there exists a unique ideal mixture for each individual investor to optimize its portfolio (Dumas & Louche, 2016). Lewis and Mackenzie

(2000a) for example find that SR investors have on average approximately a third of their portfolio invested sustainably, this share decreases with higher investment volumes (Dorfleitner & Nguyen, 2016). To achieve their ethical and social goals, investors give more importance to the amount of capital invested rather than the proportion of total wealth (Bauer and Smeets, 2015; Dorfleitner & Nguyen, 2016; Nilsson, 2008).

2. Variations

The motivations and impediments of investing sustainably as developed previously are not exactly similar among all categories of the population (Diouf et al., 2016). In the literature, we find numerous studies on the factors that alter these considerations. We can divide them in two categories: individual and macro factors.

On an individual basis, we find variations mainly depending on demographic factors and sustainable orientation. On a macro level, geography is a common variation factor.

2.1. Socio-demographic

With personal consumption, the likelihood of going for the ethical alternative and the willingness to pay varies with demographics, although weakly (McGoldrick & Freestone, 2008). We could expect a similar relationship with demographics in the case of personal investment. This is indeed extensively researched in the literature (Dorfleitner & Nguyen, 2016; Hafenstein & Bassen, 2016; Junkus and Berry 2010; Lewis & Mackenzie, 2000; McLachlan&Gardner, 2004; Nilsson, 2009; Rosen et al.,1991; Tippet, 2001; Tippet & Leung, 2001; Widyawati, 2020; Williams, 2007) where scholars find characteristics such as gender, education and income to have an impact (Beal et al., 2005; Diouf et al., 2016; Williams, 2007). Their findings converge on factors such as gender, with a positive effect of women (Beal et al., 2005; Dorfleitner & Nguyen, 2016; Williams, 2007) and on education, with the higher educated investing more sustainably (Beal et al., 2005; Dorfleitner & Nguyen, 2016; Dumas & Louche, 2016; Rosen et al., 1991; Williams, 2007). However, they diverge on age and wealth, both considered significant. Most find that younger investors choose more for SRI (Beal et al., 2005; Dorfleitner & Nguyen, 2016; Dumas & Louche, 2016; Rosen et al., 1991; Williams, 2007), whereas Hafenstein and Bassen (2016) find that it is the case for older investors. On wealth, Paetzold and Busch (2014) and Williams (2007) believe that wealthier investors opt more for SRI due to their longer-term perspective though Beal et al. (2005) and Dorfleitner and Nguyen (2016) support that lower salaried opt for sustainability in investments.

Nonetheless some authors (such as Diouf et al., 2016; Hafenstein & Bassen, 2016; McLachlan and Gardner, 2004; Widyawati, 2020; Williams, 2007) find weak or no influence of demographic factors on sustainable investment choice variations.

2.2. Sustainable orientation

Another factor influencing the motivations and impediments is seemingly the degree of personal ethics and orientation toward sustainability (Hafenstein & Bassen, 2016; von Wallis & Klein, 2015; Widyawati, 2020; Williams, 2007). The personal ethical values of a single investor will impact the need for "ethical coherence" in his investments. All investors do not need the same mix of ethical and unethical assets in a portfolio to feel happy, hence the ideal allocation varies (Dumas & Louche, 2016). "As the opportunity cost of investing in accordance with ones values grows, the strength of those values take on added importance" (Pasewark & Riley, 2010,p.247). This is usually the case if in their consumer behavior they already take sustainability into account, then what matters most to them is the general sustainability impression rather than specific ESG categories (Hafenstein & Bassen, 2016).

2.3. Geography

We have seen that the performance of SRI compared to conventional investments varies depending on the geography of the financial market, with more positive results in North America than in developed Europe for example (Friede et al., 2015). On a more macro level, we would expect the motivations and impediments of investors to also vary geographically. This is indeed documented in the literature, Amel-Zadeh and Serafeim (2018) find that the ethical motive (cf. supra) plays a much larger role in Europe than in North America. European investors believe strongly in the change they can bring with their engagement with companies. Political and financial traditions in countries, such as state intervention in social issues, also have an impact (Dumas & Louche, 2016; Pender & Brocchetto, 2011; Williams, 2007). In countries with social security (e.g. Germany) older investors are ready to invest sustainably (Hafenstein & Bassen, 2016).

CHAPTER 2: Behavioral Finance

We now turn to the overview of behavioral finance. In the first part of the chapter we will focus on what defines behavioral finance and why its study is appropriate in the case of investment decision making. We will then make an in-depth analysis of the herding bias, the focal point of our thesis. In the second part we will look in more detail at the investment decision making process and we will cover the individual characteristics and context factors that can influence the biases observed in an investment decision process.

I. Behavioral finance

1. Definition

In traditional finance and economic theory, actors are assumed to be rational. This entails that they have complete information which they act upon without any emotion or bias, maximizing their utility (Yakuban et al., 2015). This is the case for example in the efficient market hypothesis (EMH), where all information is integrated in prices of assets (Kumar & Goyal, 2015).

Nonetheless over time anomalies have risen concerning the theoretical market reactions (Taffler, 2018), requiring an alternative theory to efficient markets (Kumar & Goyal, 2015). This alternative theory took the shape of a new field of study in finance: behavioral finance.

Behavioral finance emerged in the 1980 as the study of psychology in financial decision making (Kumar & Goyal, 2015). Since its founding fathers (we can mention, among others: Kahneman, Tversky, Shiller, Thaler, Shefrin, Barber and Odean) the popularity of the field has kept on increasing, as attested by the amount of studies and theories developed over time. Behavioral finance moves away from neoclassical economic theory and the theory of rational choice. In the theory of rational choice people have unlimited cognitive capabilities to process information before making a choice (Kumar & Goyal, 2016; Madaan & Singh, 2019). However, humans have limited cognitive capabilities and are hence considered to be subject to “bounded rationality” (Simon, 1956). They are not able to obtain sufficient information to take decisions and are subject to errors which pushed them to make “irrational” decisions (Jaiyeoba et al., 2019; Kumar & Goyal, 2015; Kumar & Goyal, 2016; Yakuban et al., 2015). To palliate their limited cognitive abilities, they follow their feelings and intuitions (Chhapra et al., 2018) and incorporate biases, emotions and rules of thumb to facilitate decision making(Bilgehan, 2014; Jaiyeoba et al., 2019; Kumar & Goyal, 2015; Madaan & Singh, 2019).Originally, behavioral finance was believed to explain the irrational behavior of people as opposed to the rational, the latter was considered as still an ideal to strive for (Taffler, 2018). Modern behavioral finance considers people as normal as opposed to "rational" (Kumar & Goyal, 2016; Taffler, 2018).

Behavioral finance can be analyzed from both a macro (BFMA) and micro (BFMI) perspective. The former targets markets and their anomalies whereas the latter concentrates on individual investors (Yakuban et al., 2015). As retail investors are small units but together carry a lot of weight, their study is particularly important (Jaiyeoba et al., 2019).

As any field, some gaps still remain in the study of behavioral finance. Among the limitations frequently mentioned in the literature, we find: extensive focus on investor behavior as opposed to other actors such as managers (Bilgehan, 2014), studies conducted in laboratory environments, limiting their real world replicability (Taffler, 2018; Zahera & Bansal, 2018), predominance of individual biases neglecting social interactions (Taffler, 2018), little importance given to feelings and emotions in decision making (Taffler, 2018), focus on single countries overlooking potential geographical variations (Kumar & Goyal, 2015; Zahera & Bansal, 2018); few primary data collected (Kumar & Goyal, 2015), analysis conducted often on one bias at the time (Jaiyeoba et al., 2019).

2. Debate on optimality

Behavioral finance is strongly gaining on popularity and we have seen that it still has some room of improvement, but why has it become so popular? Why is it so important to know that people do not make purely rational decisions and suffer from some biases?

Individuals are subject to emotional responses and psychological biases, reactions that distort their reality (Lubis et al., 2015; Taffler, 2018) and affect their decision, away from traditional rational behavior (Beal et al., 2005; Shefrin and Statman, 1985). Scholars disagree whether these emotional responses drive away investors from their optimal solution, and are hence costly (no maximization of net present value (Madaan & Singh, 2019) to the investor, or if it helps them achieve the same conclusion in an easier way (Lubis et al., 2015; Yakuban et al., 2015; Zahera & Bansal, 2018).

A larger consensus seems to believe that they are costly. Not only are they costly, but they are evermore present, as most people, including professionals develop behavioral biases and are limited in their cognitive processes (Bilgehan, 2014; Kumar & Goyal, 2016). Retail investors use more public information and are more influenced by sensational events (noise) and market sentiment when taking decisions (Jaiyeoba et al., 2019). But even institutional investors, although believed to be better informed and with a longer investment horizon, are also subject to these issues (Jaiyeoba et al., 2019). It is hence of uttermost importance to integrate this unconscious in financial behavior (Taffler, 2018). In short, these biases could help explain the gaps between what was expected following finance theories and what we observe empirically (Zahera & Bansal, 2018).

3. Heuristics, frame dependence and biases

In investment decision making we find heuristics, frame dependence and biases. Heuristics can be considered as rules of thumb for decision making (Yakuban et al., 2015). Frame dependence indicates that people make decisions depending on how the information is presented and perceived by them depending on circumstances (Yakuban et al., 2015). Biases that impact the decision making of investors can be of two sorts: cognitive and emotional. Cognitive biases are "misinterpretation of data, faulty reckoning, statistical inaccuracy, or memory error" (Yakuban et al., 2015,p.887) and emotional biases are based on "feelings, intuition, or impulsive thinking" (Yakuban et al., 2015, p.887).

In the literature, it is not common to examine different biases in a single study, they are usually tested one by one (Kumar & Goyal, 2015). However, there is no consensus on the results for each of them (Kumar & Goyal, 2016).

4. Herding

Among the topics frequently discussed in the behavioral finance literature, we can mention the topic of herding. Herding can broadly be understood as the tendency of an individual to follow the crowd when taking a decision.

Herding is the result of a shortcut taken in human brains (in the limbic system) where people consider that the right behavior to adopt in a situation is the one adopted by everybody else (Prechter, 2001). Herding has found to be extremely useful in a certain number of life threatening situations faced by humans in history, which is why evolution has made going against the crowd physically painful for individuals (Prechter, 2001) and humans intuitively believe they are safer when they join the crowd (Aharon, 2021). Over time this has led to the persistence of herding in numerous non-life-threatening decisions taken in human societies. These range from the number of children we wish to have to who we vote for (Banerjee, 1992).

The herding behavior is particularly present in situations where rigorous reasoning is required and most actors lack knowledge (Prechter, 2001), which is the case for financial investment decisions. However, it is commonly believed that adopting a herding behavior in financial markets can lead to sub-optimal solutions (Prechter, 2001) as such a behavior results in bubbles and crashes (Banerjee, 1992).

There is no unified definition of herding behavior in financial markets, but we can summarize it as the deliberate imitation of other's investment decisions (Merli & Roger, 2013). Scholars appear to classify the herding behavior of investors depending on the intent of the individual. When herding is the result of homogeneous market-wide reactions to public information (Stavroyiannis & Babalos, 2017) it is considered to be driven by information (Hsieh et al., 2020) and is qualified as spurious herding. In that case there is no intent to herd, but the behavior observed is the result of a specific context. The other possibility is that an investor replicates the actions of others despite one's own information (Sabir et al., 2019; Škrinjarić, 2018; Stavroyiannis & Babalos, 2017). The decision is then considered to be driven by the behavior of others (Hsieh et al., 2020) and this type of herding is qualified as intentional herding.

The latter form of herding is the one of interest to behavioral finance scholars. Intentional herding can be rational or non-rational depending on the reasoning behind the decision (Bekiros et al., 2017; Dewan & Dharni, 2019; Scharfstein & Stein, 1990,). When a herding decision is driven by fundamentals, it is defined as rational as it protects the interests of the investor (Dewan & Dharni, 2019; Stavroyiannis & Babalos, 2017). There are three reasons that can qualify herding as rational according to some scholars: payoff externalities, reputational concerns and informational differences among participants (Merli & Roger, 2013; Škrinjarić, 2018). Nonetheless most scholars argue that herding is non-rational as it decreases market efficiency (Bekiros et al., 2017). Herding is considered non-rational if one follows others blindly despite having information themselves and without knowing for sure if the other is right (Banerjee, 1992; Dewan & Dharni, 2019), it is purely driven by imitation. The explanation for these non-rational herding behaviors can be found through the psychology of investors.

Some common psychological biases are found to trigger non-rational intentional herding behavior (Merli & Roger, 2013) such as overconfidence (Sabir et al., 2019) or the representativeness heuristic (Hsieh et al., 2020). Common non-rational explanations for herding are social conventions (Keynes, 1936), a desire for conformity and consensus (Lakonishok et al., 1994; Devenow & Welch, 1996), a sense of security (Goldbaum, 2008) and the belief in the continuation of past behavior (Lakonishok et al., 1994).

In the literature the words "herding bias" (also called herd mentality bias or bandwagon effect) and "herding behavior" appear to be used without a clear distinction between both.

Herding behavior can be measured both quantitatively and qualitatively. Qualitative methods take the form of surveys, allowing for a direction interaction with investors. The latter method is the best option to measure the inner motivation and intention of an investor (Dewan & Dharni, 2019). Quantitative methods measure herding behavior through the analysis of transaction or return data (Stavroyiannis & Babalos, 2017). The most commonly used transaction-based method is the LSV developed by Lakonishok et al. (1992). It measures the buying pressure for a given asset (Merli & Roger, 2013). The most popular return-based method is the one proposed by Christie and Huang (1995) which looks at deviations from the CAPM. The deviations can be measures in absolute terms (CSAD) or by standard deviation (CSSD) (Hsieh et al., 2020). A common criticism of quantitative herding measures is their inability to measure the drivers of herding behavior (Merli & Roger, 2013). Dewan and Dharni (2019) recommend an increase in studies on the personality traits causing herding.

Herding behavior can be found for both individual and institutional investors. Studies on individual investors are less common although they find a stronger tendency for herding (Hsieh et al., 2020; Merli & Roger, 2013; Škrinjarić, 2018).

Now that we have seen the importance of biases in the cognitive processes of humans and the clear presence of herding in our lives, we can move on the investment decision making process and the variations observed between individuals.

II. Investment Decision Making

1. The process

There are two systems that define our decision-making process: intuition (System 1) and reasoning (System 2) (Kahneman, 2011). In System 2, people search for information and evaluate the alternatives based on this procedure. This requires a lot of time and cognitive capacity. As an alternative, people can use predictable rules and rely on their intuition (System 1) to choose between different investments (Monti et al., 2012). In investment decision making we could expect both models to be followed depending on the context and/or the individual preferences of an investor (Kumar & Goyal, 2016).

Traditional theory only admits the financial considerations as maximization of returns depending on risk aversion and liquidity preferences as the deciding factor in investment decision (Beal et al., 2005; Dorfleitner & Nguyen, 2016; Kumar & Goyal, 2016; Pasewark & Riley, 2010). When being asked to rank variables in order of importance to decision making, investors mostly chose "traditional wealth maximization" variables aka. risk, diversification and return (Beal et al., 2005; Dorfleitner & Nguyen, 2016; Nilsson, 2008).
In investment decision making, investors factor in information that the standard economic theory would expect them to do, they use fundamental and technical analysis (Lathif & Aktharsha, 2016). In this they use significant factors such as dividends, past performance of the company, accounting, ownership structure, bonus payments and expected corporate earnings (Yakuban et al., 2015; Zahera & Bansal, 2018). These are the arguments pushed forward by the rationalists, that do not believe in the existence of expressive benefits (Beal et al., 2005).
In the case of an important decision investors tend to take a traditional decision process based on rational financial information (Kahneman, 2003; Thaler, 1999)

However, due to the great number of participants in investment decisions, there is no unique way of decision making. The complexity of all processes depends on individual emotions and behaviors (Zahera & Bansal, 2018). When individuals have to take a decision regarding their investment they can be influenced by a multitude on factors (Hillenbrand et al., 2020; Kumar & Goyal, 2015), they use diverse criteria: attitudes, behavioral biases as well as emotions, habits and social interaction (Chhapra et al., 2018). Attitude encompasses emotions, moods, weather and availability of information (Hillenbrand et al., 2020; Jaiyeoba et al., 2019; Zahera & Bansal, 2018), or anticipation of future regret (Barberis, Huang and Thaler, 2006).

But other factors than emotions and attitudes also play a role: information conveyed by media and broker (Zahera & Bansal, 2018), desire to get rich, tolerance to risk and influence of peers opinion (Zahera & Bansal, 2018) and social norms (Pilaj, 2017) or perceived fairness of an investment (Ullah et al., 2020). Retail investors rely mainly on public information, conveyed by attention grabbing events (Jaiyeoba et al., 2019).

2. Biases

It is more and more documented that investment decisions are affected by behavioral biases (Agnew, 2006; Bilgehan, 2014; Chhapra et al., 2018; Kumar & Goyal, 2016; Zahera & Bansal, 2018). Investors behave irrationally when they neglect fundamental value, fall for peer examples, retain losses and trade excessively among other things.

Among the biases that have found to have a significant impact on decision making we have: overconfidence (Chhapra et al., 2018; Gunay and Demirel, 2011; Jaiyeoba et al., 2019; Madaan & Singh, 2019; ; Ullah et al., 2020; Yakuban et al., 2015), hindsight (Chhapra et al., 2018), herding (Chhapra et al., 2018; Gunay and Demirel, 2011; Madaan & Singh, 2019; Ullah et al., 2020; Yakuban et al., 2015), anchoring (Jaiyeoba et al., 2019), representativeness (Jaiyeoba et al., 2019), availability (Jaiyeoba et al., 2019), disposition effect (Ullah et al., 2020).

3. Variation

Although we find numerous studies on the impact of biases on decision making, we find little information on what drives these biases and what increases the propensity of an individual to be subject to a bias (Hillenbrand et al., 2020; Ullah et al., 2020). According to Zahera & Bansal (2018) more research should be conducted on the factors that cause an increase in the biases as well as demographical variations which could then help categorize biases better and find ways to mitigate their effects. These findings can help financial advisors to tailor better their measures and suggestions of investments (Hillenbrand et al., 2020).

We have seen that individuals use a great range of factors in their investment decision making and that due to the complexity of that population, each individual is different in his or her own decision process (Beal et al., 2005). As investors are different in their decision process, they also differ to which extent they are subject to specific biases. There are different factors that can explain a variation in biases, these variations can be between different individuals (individual factors) or for a same individual at different decision points (context factors).

3.1. Individual characteristics

Regarding individual characteristics that impact the propensity to be subject to a specific bias we find mainly investor typology and socio-demographic factors.

We see some variation in these biases depending on the type of investor (Ullah et al., 2020; Zahera & Bansal, 2018). The first distinction is between individual and institutional investor. Dhar and Zhu (2006) find that non-professionals are more subject to biases. Lee et al. (2004) finds that this is especially the case for herd behavior, it is however not found for other biases such as overconfidence, anchoring and representative heuristic (Jaiyeoba et al., 2019). The second distinction is between active and passive investors. Active investors are more prone to biases than passive investors (Ullah et al., 2020; Zahera & Bansal, 2018). We can also mention the impact of investor size (Ekholm and Pasternack, 2008). Ackert et al. (2010, as cited in Ullah et al., 2020) find that the use of heuristics is more used by small investors. The third variable is the investment horizon, the shorter the more subject to biases (Ullah et al., 2020). Finally, higher level of investment experience attenuates the presence of biases (Jaiyeoba et al., 2019; Kumar & Goyal, 2016; Ullah et al., 2020).

The most commonly used demographic factors are gender, age, income, education (Agnew, 2006; Cesarini et al., 2010; Kumar & Goyal, 2016; Ullah et al., 2020; Yakuban et al., 2015). For gender, women are usually considered to make better choices and be subject to less biases than men (Agnew, 2006; Barber and Odean, 2001; Da Costa et al., 2008; Kumar & Goyal, 2015) which is not found by Lin (2012), who in the case of herding find the opposite. For age, young people are considered to be more subject to biases (Lin, 2012) although Zaidi and Tauni (2012) find no significant impact of age. In the case of income, Dhar and Zhu (2006) find that low income people are more subject to biases this is confirmed by Agnew (2006), Calvet et al. (2009) and Kumar and Goyal (2015), who find that better salaried people make better choices. Finally, in the case of education, as we could expect, higher levels of education attenuate the presence of biases (Calvet et al. 2009; Jaiyeoba et al., 2019), this is however not shared by Zaidi and Tauni (2012). There also less widely spread factors that have found to be significant such as family composition and lifestyle impact (Mathuraswamy and Rajendran, 2015 as cited in Kumar & Goyal, 2016).

3.2. Context

We have previously focused on the individual characteristics that impact decision making, a field extensively documented in the literature. We would like now to look at the context variations, and the little scope of studies that have addressed this problem. The propensity of falling for biases can also depend on the circumstances and context of the decision such as the way financial information is portrayed (Hillenbrand et al., 2020; Zahera & Bansal, 2018). The type of financial product that is considered in the decision can also impact the heuristics followed by investors (Benartzi and Thaler, 2001, as cited in Agnew, 2006).

CHAPTER 3: Behavioral explanations to SRI

This chapter aims at bringing together the fields of behavioral finance and sustainable investing and look at what is currently discussed in the literature. We will cover the information overload observed in sustainable investments as well behavioral explanations to the barriers and motivations for SRI.

I. Information overload

Sustainable investments suppose the integration of additional non-financial information in the decision making process. This increases the total amount of information available to the investor and can reach a point where it exceeds the capacity available to process it. The latter situation, defined as information overload (cf. supra), is hence frequent in sustainable investments (Hafenstein & Bassen, 2016). In the case of information overload, investors use shortcuts to facilitate decision making. For SRI this translates into the mimicking of one's own consumer habit, the use of affect heuristics or basing one's decision only on non-financial information as it is easier to understand (Hafenstein & Bassen, 2016).

II. Behavioral explanations

1. Behavioral explanations to barriers of SRI

Individual based barriers to sustainable investment can have a behavioral explanation that can take the form of short-time horizon bias, inertia or herding (Friede, 2019). In the case of short-time horizon bias, investors tend to invest less sustainably (Friede, 2019; Hafenstein & Bassen, 2016; Paetzold & Busch, 2014). The time orientation of individuals affects their environmental sensitivity and behavior which is a common cognitive barrier (Paetzold & Busch, 2014). As SI may be seen as more volatile, the financial losses associated with a shorter time orientation discourage people from investing more (Paetzold & Busch, 2014). We can also think of inertia, the higher levels of uncertainty and information push people to invest less sustainably (Friede, 2019). Furthermore, when faced with uncertainty, individuals will focus on conventional approaches and will mimic peer behavior (Friede, 2019). These behavioral failures can be an explanation to the low share of SRI in the market. Some authors believe that investors can be "nudged" to improve this share (Pilaj, 2017).

2. Behavioral explanations to motivations for SRI

It is key for humans to feel like their behavior respects the unspoken moral rules and their values (Beal et al., 2005; Jaiyeoba et al., 2019; Statman, 2017; Ullah et al., 2020).

In the case of sustainable investment, we have seen that one of the motivations is the possibilities it offers to generate emotional benefits, a psychic return, by investing for good and using money in line with their values (Beal et al., 2005). This is sometimes referred to as "warm glow", the pleasant feeling we feel when we do good without especially creating an impact as it is rather based on the intention than the outcome. In the case of retail investors, it is easier to act on their beliefs, values and knowledge compared to institutional investors (Friede, 2019; Jaiyeoba et al., 2019; Ullah et al., 2020). These individual investors are especially subject to belief perseverance and to search for compelling evidence that confirms their views (Barberis & Thaler, 2003; Friede, 2019) which is particularly important in the case of SRI. Investors respond to the mental representation they create for objective information (Pilaj, 2017). As investors have limited awareness of alternatives and capacity to take decisions, SRI investment decision is dependent on these beliefs, values and hence biases.

Literature review conclusion

Socially responsible investments (SRI) are a rising category of financial investments combining ethical and financial dimensions. SRI are not uniquely defined and there are myriad ways to implement an SRI strategy (the most common being the use of ESG metrics). As the way one can integrate sustainability criteria in his strategy can vary tremendously and as the balance between financial and non-financial reasons varies from investor to investor, the qualification of "sustainable investor" covers a large spectrum of possibilities. The segmentation often made between sustainable investors on one side and conventional investors on the other does not reflect the reality. Today, the vast majority of investors is interested in *both* sustainable *and* financial (or traditional) investments. There are also factors influencing the motivation to invest sustainably. These are socio-demographic factors (e.g. gender, education, age and income) and one's sustainable orientation.

According to traditional finance theory, the goal to achieve return should be the main criteria in explaining the choice for a specific investment. In the case of SRI, there is no consensus in the literature on the sustainability integration's positive impact on financial performance. The reasons explaining the gaining popularity of SRI hence need to be found elsewhere: the pressure of the peer group and influence of media presence and the desire for personal satisfaction by investing in accordance with the values of the investor.

Humans often face a large amount of information in order to make a decision and have limited cognitive capabilities to treat all that information (information overload). They can rely on two different systems to treat all information when making a decision: an intuitive system (System 1) and a reasoning system (System 2). When they use their intuitive system, they rely on mental shortcuts (biases and heuristics) to help them in their decision process. Whether the use of such heuristics and biases deviates people from their optimal solution or not is heavily debated.

Investment decisions do not escape the rule of choice between system 1 and system 2.

Indeed, numerous biases have been found to impact the investment decision of investors. One of these biases frequently documented in the literature is the herding bias (or herding behavior). Herding is the tendency of an individual to follow the crowd. Herding can be sub-divided between spurious herding (without intention to imitate) and intentional herding (with intention to imitate). The latter form is the one associated to the herding bias. Intentional herding can be both rational and non-rational depending on the reasoning, most scholars agree it is non-rational. Herding can be measured through individual-based methods (survey) and macro methods (LSV and CAPM deviations).

The use of biases in investment decision making varies with the socio-demographic profile and the investor type (trait characteristics). The presence of a bias in an investment decision can also depend on how the information available is portrayed to the investor and on the context of the decision (state characteristics). Trait variations will result in biases differences between investors (different individuals) whereas state variations can cause biases differences within an investor (the same individual).

In the case of sustainable investments, the use of behavioral explanations for the decision making process is particularly indicated as both financial and non-financial information have to be integrated. This increases the amount of available information an investor needs to process and hence may increase the use mental shortcuts to reach a decision. Current research on behavioral explanations to SRI have focused on the barriers and motivations to invest in sustainable investments or not, they restrict themselves to the *why*. Little study has been performed on the understanding and the measuring of the decision process of investors in the case of a sustainable investment, the *how*, i.e. after they have decided to allocate a portion of their wealth to SRI.

Our study aims at addressing the part of the population interested in both financial and sustainable investments (hereafter defined as “mixed” investors). With the help of behavioral finance literature findings, we will look at *how* these investors implement their investment decisions. The implementation of such an investment decision can be done with the help of mental shortcuts (biases and heuristics) and especially the herding bias (hereafter referred to as “herding”). As mixed investors face two types of investment decisions: traditional and sustainable investments, we will look at herding differences between the two types of investment for a same individual. This contributes to the strand in the literature looking at the impact of state variations (context and portrayal of information) on the biases of an investor. As socio-demographic and investor traits have previously been found to significantly impact biases in investment decision making, their effect will also be analyzed depending on the type of investment.

PART II: EMPIRICAL STUDY

Introduction

At the end of the previous part we have synthesized what we will analyze in this empirical part: the herding behavior differences between the sustainable and traditional investments for mixed investors (i.e. investors with both sustainable and traditional investments in their portfolio).

In the first chapter, we will go over our methodology: the target population, data collection and the hypotheses we will test further on. We also describe the survey we have built in order to collect data. This survey is composed of three parts: the first to understand the socio-demographic and investor profile of the respondent, the second part to classify investors and the last one to measure the herding bias for both sustainable and traditional investments. In this last part we construct two multi-item scales (one framed as sustainable and one framed as traditional) in order to measure the non-directly observable psychological construct: the herding bias.

In the second chapter we will move on to the analysis of results. First, we will describe the sample obtained through our data collection. We will then check whether the scale developed in our methodology measures the herding bias adequately. This check will be done with the help of two Exploratory Factor Analyses (EFA) on both the sustainable framed and traditional framed scales. The results of the two EFA's will be compared to choose the most adequate scale structure as well as the best way to form a composite herding variable. Last, we will move to the test of our different hypotheses through appropriate statistical tests: independent t-test for between comparisons, pairwise t-test for within comparisons and Mixed-Model ANOVA's in the case of within-between analyses.

Finally, the third chapter will discuss all key findings and results of our empirical study.

CHAPTER 1: METHODOLOGY

I. Research Typology

Our study aims at understanding whether an investor can be more subject to herding depending on the type of investment (sustainable or financial) decision he has to make. In order to answer this question, we will adopt a deductive approach, developing hypotheses and testing them. We will measure how herding is impacted by the type of investment (state) for a same investor and whether socio-demographic and investment habits (traits) influence that relationship. Furthermore, we will explore whether the two herding measures for mixed investors compare to those of pure sustainable and pure financial investors.

1. Target population

Our target population consists of all investors taking investment decisions themselves. We exclude people who do not invest their money but also people who let someone else (e.g. advisor) manage their investment pool. As these people do not take investment decisions themselves, their own herding tendency does not influence on their actual investment choices and hence behavior.

Inside this population of investors, we are targeting three sub-groups: “pure” investors who only invest for financial reasons, “pure” investors who only invest for sustainable reasons and “mixed” investors who invest both for financial and sustainable reasons with varying degrees. The latter group is the focal point of our analysis.

2. Data collection method

There are two main ways of working in the literature on testing the presence of herding among a population of investors. One is to measure the bias through the analysis of macro data on financial market (see Lakonishok et al., 1992; Christie & Huang, 1995). The issue with this approach is that it gives little information on the intention of investors and hence the distinction between spurious and intentional herding is harder to make. The other approach is through a survey (Dewan & Dharni, 2019).

The survey combines numerous benefits, which explains its popularity. First, it gives information on intent and cognitive behavior, measuring the psychology of investors more adequately and increasing the internal validity of the measure. Second, it can be shared easily to a large sample, reaching a bigger proportion of the population and hence increases the external validity of the conclusions. Furthermore, the anonymization of data encourages truthful responses, which is key in our case.

Nonetheless the use of an online survey suffers some limitations as its understanding depends on the interpretation of subjects: they might be tempted to prefer socially desirable answers or interpret the questions and rating scale presented in various ways. Furthermore, it limits the population sample to the online channels used to circulate the survey. Finally, in the specific case of herding, the survey allows to identify intentional herding, but it does not assess whether the herding behavior is rational or not.

Taking all of this in consideration, the choice of a closed-ended question online survey (using Qualtrics) relying on self-reported data seemed the most adequate in our case. We will use this primary data collected for a quantitative study to answer our research question.

II. Hypothesis building

The different hypotheses we will test in our thesis fall under three main axes: the effect of investment type on the herding bias of mixed investors, the influence of socio-demographic factors and investment habits on that relationship and the difference in herding between mixed and pure investors.

With the help of behavioral finance literature findings, we will look at *how* these investors implement their investment decisions. The implementation of such an investment decision can be done with the help of mental shortcuts (biases and heuristics) and especially the herding bias (hereafter referred to as "herding"). As mixed investors face two types of investment decisions: traditional and sustainable investments, we will look at herding differences between the two types of investment for a same individual. This contributes to the strand in the literature looking at the impact of state variations (context and portrayal of information) on the biases of an investor. As socio-demographic and investor traits have previously found to significantly impact biases in investment decision making, their effect will also be analyzed depending on the type of investment. This study will be performed with the help of a survey.

1. Effect of investment type

There are two important decision moments in investment decision making: the initial decision (investing or not and what type) and the implementation decision (how to allocate the capital). Once the initial decision of the type of investment is taken, the question is then how people implement that decision, how they choose between different financial products. We have seen that at this stage of the decision process, people follow cognitive shortcuts to make their decision. One of these cognitive shortcuts is the herding bias (i.e. following its peers). Our **H1** aims at testing whether the decision process is different for sustainable and financial (hereafter referred to as "traditional") investments at the allocation phase.

H1: There is a difference in the herding bias of a same investor depending on the type of investment (traditional or sustainable)

If we find a significant difference between both (accept **H1**) then there are two ways in which the herding bias can vary for a same individual between his traditional and sustainable investments. As this hypothesis has, to our knowledge, never been tested in previous studies, we are unsure into which direction the difference could be.

In the literature we have found that investors aim at satisfying different needs with their investments: expressive, emotional and utilitarian among other things (Statman, 2017). Expressive and emotional needs can be fulfilled by opting for socially responsible investments in the initial investment decision (Statman, 2017). In that case, their need is strongly influenced by their peer group (Beal et al., 2005), it becomes socially desirable to invest sustainably. The initial decision of opting for a sustainable investment is hence influenced by peers.

The first possibility is that peer influence exercised in the initial decision of investment reinforces the peer influence we can find in the subsequent allocation decision. To put it in other words, as investors already rely on peer influence for the initial investment decision in sustainable investment, we also expect them to rely on peer influence for the allocation between different products. In the case of traditional investment that satisfy the utilitarian need (Statman, 2017), we expect the effect of peer influence on their allocation decision to be of smaller importance as peers do not impact the initial decision.

H1a: Mixed investors are more subject to a herding bias for their sustainable investments than for their traditional investments

The second possibility is that the peer influence exercised in the initial investment decision diminishes the peer influence one could feel and follow in the allocation decision. We know that investing sustainably, apart from being influenced by peers, also generates a psychic return (a positive feeling) for investors (Beal et al., 2005). We also know that this positive feeling does not depend on the size of the investment (Dorfleitner & Nguyen, 2016; Hafenstein & Bassen,

2016) nor on the actual outcome (Pasewark & Riley, 2010). Furthermore, investors are less concerned about generating returns for their sustainable investments (Hafenstein & Bassen, 2016). These are all arguments that support the idea that the initial investment decision is the most important for sustainable investment. Hence their subsequent allocation decision is less impacted by their peers.

H1b: Mixed investors are more subject to a herding bias for their traditional investments than for their sustainable investments

2. Influence of personal characteristics

Socio-demographic traits and investor profile differences have an effect on the tendency to be subject to a bias (cf. supra). For all the following set of hypotheses, we will test out two different relationships represented by the generic forms **HX** as well as **HXa** and **HXb**(X being the number of the hypothesis).

In the literature we have mainly found conclusions on a more general tendency to be subject to biases. We will test whether the most established and researched relationships between socio-demographic and investor traits and biases hold in the case of the herding bias (**HX**).

No past study has made the distinction between herding in sustainable investments and herding in traditional investments. Nonetheless, we know that the same socio-demographic traits influencing biases also influence the propensity to opt for sustainable or traditional investments. There is hence a possibility that these two effects interact with each other, and that the relationships between socio-demographic traits and (herding) bias are affected by the investment type. With the help of information found in the literature we will hypothesize on the way these two effects can interact with each other (**HXa**). When the conclusions in the literature are unclear, different interactions are tested (**HXa** and **HXb**).

However, no relationship has been found between investor traits and the propensity to opt for a certain type of investment. Which is why for investor profile characteristics we will only test out the existence of an unexpected interaction effect (**HXa**).

2.1. Influence of socio-demographic factors

The most common socio-demographic factors found to have an impact on biases are gender, age, education and income.

In the case of gender, most scholars agree that women are less subject to biases than men (V2; Kumar & Goyal, 2015; Barber and Odean, 2001;Da Costa et al., 2008). However, in the case of herding specifically, Lin (2012) finds that women are more subject to the bias than men.

H2: Women are more subject to herding than men

However, we also know that gender not only impacts the herding bias but also the type of investment chosen, women for instance are more prone to invest sustainably (Beal et al., 2005; Dorfleitner & Nguyen, 2016; Williams, 2007). It is possible to consider that these two effects interact with each other and mutually reinforce one another, and hence:

H2a: Being a woman increases herding in the case of sustainable investments

There is no unified definition of how age should be categorized. We have divided age into 4 categories reflecting professional life evolution. In the majority of studies, young people are found to be more subject to biases (Kumar & Goyal, 2016; Lin, 2012). In our case, young people are the under 26 age category.

H3: Young people are more subject to herding

Similarly to gender, age has an impact on the tendency to invest sustainably. Younger investors also tend to go more often for sustainable investments (Beal et al., 2005; Dorfleitner & Nguyen, 2016; Dumas & Louche, 2016; Rosen et al., 1991; Williams, 2007). The interaction between the two effects can be expected to be reinforcing.

H3a: Being young increases herding in the case of sustainable investments

There is no consensus in the literature on the impact of education on the presence of biases. However, the majority of authors agree that higher levels of education reduce the presence of biases for investors (Calvet et al., 2009; Jaiyeoba et al., 2019). A high level of education is usually understood as a university degree.

H4: Higher educated investors are less subject to herding

We also know that the level of education has an influence on the investment choice. The higher educated investing more sustainably (Beal et al., 2005; Dorfleitner & Nguyen, 2016; Rosen et al., 1991; Williams, 2007). It is unclear however how these effects will interact with each other.

H4a: Being highly educated increases herding in the case of sustainable investments

H4b: Being highly educated decreases herding in the case of sustainable investments

The effect of income level on biases is attested by numerous authors, who all agree that lower income investors are more subject to biases (Agnew, 2006; Calvet et al., 2009; Dhar & Zhu, 2006; Kumar & Goyal, 2015). Yet again there is no unified definition of what can be considered a low income, probably due to the various geographical locations where studies are conducted and their corresponding differences in purchasing power. In our case, under 10.000€ net is considered low income.

H5: Investors with a lower income are more subject to herding

Wealth also seems to impact the investment choice of investors, although no consensus has been found in the literature. Paetzold and Busch (2014) and Williams (2007) believe that wealthier investors opt more for SRI due to their longer-term perspective though Beal et al. (2005) and Dorfleitner and Nguyen (2016) support that lower salaried opt for sustainability in investments. Either way we believe an interaction effect may exist between income and type of investment on herding.

H5a: Having a low income increases herding in the case of sustainable investments

H5b: Having a low income increases herding in the case of financial investments

2.2. Influence of investor profile

The investor profile factors found to have an impact on biases are strategy, experience, size and investment horizon.

Regarding the strategy, Ullah et al. (2020) finds that active investors are more subject to biases

H6: Active investors are more subject to herding

H6a: The effect of investment strategy on herding depends on the type of investment

It is shared by most authors that the higher the level of investment experience, the less the investor will fall for behavioral biases (Jaiyeoba et al.; Kumar & Goyal, 2016; Ullah et al., 2020;).

H7: More experienced investors are less subject to herding

H7a: The effect of experience on herding depends on the type of investment

Kumar & Goyal (2015) and Ullah et al. (2020) find that the investor's size impacts the tendency to be subject to a bias as smaller investors rely more on biases and heuristics. We represent size as a relative measure of wealth, the smallest proportion being under 25% of wealth.

H8: People investing a small proportion of their wealth are more subject to herding

H8a: The effect of size on herding depends on the type of investment

Finally, Ullah et al. (2020) find that the shorter the investment horizon, the more the investor will be subject to biases. An often-used metric for measuring investment horizon is the amount of years before which the investor expects to need to retrieve a significant portion of his capital. We consider a short investment horizon as under 5 years.

H9: Investors who plan on retrieving a significant proportion of their capital from the markets in a near future are more subject to herding

H9a: The effect of horizon on herding depends on the type of investment

3. Difference in herding between pure and mixed investors

The focus of our study is primarily on investors investing in both sustainable and traditional investments as this is considered to be the most common case of investors (Statman, 2000; Pasewark & Riley, 2010; Diouf et al., 2016). For those investors we have looked at whether the context of the investment decision (type of investment) could explain differences in herding for the same investor. We have hence implicitly assumed all along that it was more the type of investment rather than the type of investor that impacted the variables and information taken into consideration in a decision.

In the past however it was much more common to oppose two distinct groups of investors: socially responsible investors and conventional investors (Widyawati, 2020) (what we have referred to as "pure" investors) and analyze how they used different variables (and biases) in their investment decision making (Diouf et al., 2016).

The question is now whether the type of investment is the main explanatory variable for differences in herding or if the type of investor also explains herding differences. If mixed investors are more subject to herding for their sustainable investments, is their level of herding comparable to that of investors investing purely sustainably? And similarly, are their level of herding in traditional investments similar to that of pure financial investors?

To our knowledge there is no study investigating the difference in investment decision making and biases between mixed and pure investors, so we test the following set of hypotheses.

H10a: There is no difference between the herding level of pure financial investors and mixed investors investing financially

H10b: The herding level of pure financial investors is higher than the herding level of mixed investors investing financially

H10c: The herding level of pure financial investors is lower than the herding level of mixed investors investing financially

H11a: There is no difference between the herding level of pure sustainable investors and mixed investors investing sustainably
H11b: The herding level of pure sustainable investors is higher than the herding level of mixed investors investing sustainably
H11c: The herding level of pure sustainable investors is lower than the herding level of mixed investors investing sustainably

III. Survey

The survey we circulated (see Appendix 1) is divided in three parts. The first part aims at understanding the profile of an investor and identify factors that can influence his/her tendency to be subject to a bias, more specifically herding bias. In this part we also filter out participants that do not correspond to our sample target. The second part aims at classifying the investor as mixed or pure depending on his investment habits. Finally, the last part measures the herding bias level for each investor. Each participant was forced to answer all questions presented to him/her in order to produce complete answers.

Part 1: Socio-demographic profile and investment habits

We first draft the socio-demographic profile of the respondent through a series of questions. In order to make the survey as user-friendly as possible we have decided to limit the number of socio-demographic questions. The criteria used to select which socio-demographic factors would be analyzed were the popularity and/or the consistency in results found in the literature (cf. literature review). We were left with four demographic traits to measure: gender, age, education and income.

All traits were measured with ordinal or nominal variables, separating the respondents in categories (max. 5) rather than measuring answers on a continuous scale. This was chosen to facilitate the ease of answer for the respondent as well as to make comparisons between groups easier, considering the expected small size of our sample.

For gender, apart from the obvious “male” and “female” options, we added the option “prefer not to say”. Age was measured in four categories corresponding approximately to a studying phase (<26), an early career phase (26-45), an end of career phase (46-65) and a retirement phase (66+). Education was divided into five categories: “High School”, “Higher education with no degree” and three higher education categories: “Bachelor”, “Masters” and “PhD”. As we expect our sample to be predominantly composed of investors with a higher education, we wanted to have a more precise separation for that category. Finally, income was split up in four income ranges measured in net annual income: “<10.000”, “10.000-30.000”,”30.000-50.000” and “>50.000”. Income questions can sometimes be considered sensitive, as confirmed in our pilot study findings (cf. infra), which is why we added a “Prefer not to say” option. The primary goal of our study is to collect data on herding; hence we did not want a socio-demographic question to discourage people from answering further.

As our population of interest only includes people that already invest their own money, we added a filtering question at the end of this part. The definition of investment was left rather broad as we are not interested in a specific type of asset class.

After our pilot phase (cf.infra) we added a second filtering question to exclude investors who do not take investment decisions themselves. Indeed, as they do not take decisions themselves, their own herding tendency does not impact their investment choice and allocation. It is rather the herding tendency of their advisor that can impact their investment decision. We left the possibility of giving multiple answers to that question as it is possible that some investors make decisions for a part of their capital and let someone else manage another part for example.

For our investment habits questions, and for the same reasons as for our socio-demographic traits questions, we exclusively used ordinal and nominal questions, separating the respondents in categories. The variables measured were: strategy, experience, size and horizon. The strategy of investors, defined as “active” or “passive”, was assessed with the help of two small statements: one corresponding to an active strategy and one to a passive strategy. Following our pilot study, we added the option “Other”, offering the possibility to investors finding the statements too limiting to develop their own understanding of their strategies. Experience was measured in the number of years an investor has been investing his money: “Up to 1 year”, “1-3 years”, “3-5 years”, “5-10 years” and “more than 10 years”. The investor size was measured in relative rather than in absolute terms, as a proportion of total wealth: “<25%”, “25-50%”, “50-75%” and “>75%”. Finally, the horizon of investment was estimated with the number of years before which an investor expected to withdraw a significant portion of his capital “0-5 years”, “5-10 years”, “10-30 years” and “More than 30 years”.

Part 2: Mixed or Pure

In order to test our hypotheses, we would like to split investors in three categories: pure financial investors, investors investing in both sustainable and traditional investments and investors who only invest sustainably. These categories were created based on the answers given to two questions measuring the frequency at which an investor used financial/sustainable considerations for their investment. The classification of investors in three categories based on these answers can be found in the following table. Respondents answering "Never" and "Never" to both questions would be ejected from the survey as they would not fall under our understanding of an investor.

Table 1:Investor classification criteria

		How often do you take financial data into consideration before going for an investment?			
		Always	Often	Sometimes	Never
How often do you consider sustainability aspects before going for an investment?	Always	**Mixed investor**			**Pure sustainable investor**
	Often				
	Sometimes				
	Never	**Pure financial investor**			**N/A**

Our aim was to identify an often-overlooked category of investors (Widyawati, 2020): mixed investors but not to quantify the share of financial and sustainable in their mix. As suggested by Pasewark and Riley (2010), the SRI investment level should be measured on a continuous level. This is why each respondent is able to choose among multiple combinations of sustainable and financial investments. We voluntarily left the interpretation of the two questions open to the respondents as it was the most intuitive. This leads to some potential drawbacks. First, we are not able to determine if one investor answering Always-Always for example understands it the same way than another investor with exactly the same answer. Furthermore, it does not give us a quantitative and precise information on the actual investment allocation, obliging us to categorize any investor interested in both considerations (irrespective of the combination) as a mixed investor. We acknowledge that this puts investor within the same "mixed" category although their decision process is probably very different (Always-Sometimes vs. Sometimes-Always for instance). Finally, it severely limits the possibility of having "pure" investors. We only categorize investors as such if they never consider one type of data, which is a very restrictive assumption.

The rather broad understanding of "sustainable considerations" is also intentional. First, it is suggested in the literature that the classification of an investment as sustainable should be left to the interpretation of the investor. Which is why we include a broad definition of sustainable investment. Second it is in line with the approach followed by Williams (2007) and Yakuban et al. (2015) who qualify an investment as sustainable when sustainability criteria were considered before deciding for it.

Part 3: Test for herding bias

The final part of the survey was aimed at measuring the herding bias of investors. The herding bias, as any psychological construct, is by essence unobservable directly and hard to measure. To remedy this, we used a multi-item scale in the form of a questionnaire, as this is the most commonly used method in the literature on behavioral bias surveys. We did not find a universally accepted scale for herding bias in the literature, so we constructed our own.

Participants in our study are asked to rate their level of agreement to 10 different items on a Likert Scale with metric indications from 1 to 5 (1= Strongly Disagree, 2= Disagree, 3=Neither agree nor disagree, 4= Agree, 5= Strongly Agree). The combination of these ten items is believed to reveal the underlying and non-measurable herding bias. The 10 items of our scale are originating from previous herding bias studies (see Jain et al., 2019; Jaiyeoba et al., 2019; Kudryavtsev et al., 2013; Ngoc, 2013; Prosad et al., 2015; Shantha, 2019; Shusha & Touny, 2016; Ullah et al., 2020).

Through the literature, we selected a list of 40 items that were used in identifying herd behavior through surveying of an investor population. We eliminated repetitive statements, statements limited to a certain category of investment (e.g. only the stock market) and non-neutral statements, framing the expected answer in a positive or negative way (e.g. "*I blindly follow others in stock selection as I don't have much idea of share investment*"). We then proceeded to reduce further the list of items in order to maximize survey completion by each participant. We subdivided the remaining items in 5 hypothetical sub-categories, all of whom we believe are components of herd behavior: importance of peers, use of information, reaction to a loss, following of general trends and answering to arguments of authority. For each sub-category we chose 2 statements. This left us, out of our original pool of 40 items with a reduced set of 10. Each statement was then reworded in order to appear consistent compared to the 9 others and unidentifiable from its original source.

The list of items was duplicated in two sets (20 questions in total): one set framed the investment decision as sustainable, the second set framed the investment decision as purely financial (Table 2). Mixed investors were being presented with the two sets of questions and pure investors with the set corresponding to their investment philosophy: the sustainable framed statements for pure sustainable investors and the financially framed statements for pure financial investors.

As our study relies on the difference in response observed between both sets of items for mixed investors, it was key to ensure that each set of statements was responded to accurately and without potential learning and transfer effects between the two treatments. This is of uttermost importance to reduce the possibility of biased results.

As our two sets of statements are fairly similar (apart from the financial and sustainable wording) we proceeded to a double randomization process.

First, in the case of mixed investors, who were presented with both sets, the order in which the sets were presented to participants was completely randomized.

Second, within each set, the order of individual statements was also randomized to limit as much as possible a feeling of similarity between both sets. This was also done for pure investors, presented with only one set, in order to keep the measurement as homogeneous as possible and ensure comparability of results between mixed and pure investors.

The process of reducing the number of items, combining statements from different sources and rewording the items twice (once to give consistence and once to frame them in a sustainable or financial way) makes our scale unique and will require it to be tested (cf. infra).

Table 2:List of items in herding measurement scale

Item #	**Framing**	**Question**	**Sub-category of herding**
1	Financial	I follow my peers recommendation when choosing a financial product for its financial performance	Importance of peers
	Sustainable	I follow my peers recommendation when choosing a financial product for its sustainability contribution	
2	Financial	I invest in the same return-oriented financial products as my friends and relatives	Importance of peers
	Sustainable	I invest in the same ethical/sustainable financial products as my friends and relatives	
3	Financial	My decision to invest relies on my personal impression of the expected performance and fundamental analysis of a company when choosing for a financial product	Use of information
	Sustainable	My decision to invest relies on my personal impression of the sustainability performance and values of a company when choosing for a financial product	
4	Financial	I consider information given by the media (news) on the financial fundamentals of a company before an investment decision	Use of information
	Sustainable	I consider information published by the media (news) on the sustainability dimensions of a company before an investment decision	

5	Financial	Situation: *I have decided to take a position opposite to the general trend because I believe in the future financial performance of a company. My friends follow the general trend.* If I lose while my friends make profits, I feel disappointed.	Reaction to a loss
	Sustainable	Situation: *I have decided to take a position opposite to the general trend because I believe in the values and sustainability aspects of a company. My friends follow the general trend.* If I lose while my friends make profits, I feel disappointed.	
6	Financial	My disappointment after losing money on an investment aimed at the best return diminishes if others have also experienced the same loss	Reaction to a loss
	Sustainable	My disappointment after losing money on a sustainable investment diminishes if others have also experienced the same loss.	
7	Financial	When I aim for the best risk/return, I follow what I see other investors are doing (e.g. buying or selling, choice of volume) on the financial markets	Following of a general trend
	Sustainable	When I aim for the most ethical or sustainable company, I follow what I see other investors are doing (e.g. buying or selling, choice of volume) on the financial markets	
8	Financial	I would buy (sell) financial securities whose price have risen (declined) for a period	Following of a general trend
	Sustainable	I would buy (sell) sustainable securities whose price have risen (declined) for a period	
9	Financial	I usually follow the advice given by my broker regarding financial investment opportunities	Argument of authority
	Sustainable	I usually follow the advice given by my broker regarding sustainable investment opportunities	
10	Financial	I make investment decisions based on comments given by financial experts	Argument of authority
	Sustainable	I make investment decisions based on comments given by sustainability experts	

IV. Target population and sampling technique

Our target population is broad as it covers all people investing money themselves. Due to limited resources and time constraints, we are unable to cover this entire population with probability sampling. The sampling technique chosen was a mix of convenience and snowball sampling methods. The main channel used was the professional social media platform LinkedIn.

The use of LinkedIn, a professional social platform, was particularly indicated in this case as investment behavior and habits is a topic frequently mentioned on the platform. We would hence expect to reach out to investors more effectively through LinkedIn than other available media. The participation of the survey is purely on a voluntary basis and it was circulated predominantly in my personal network. The drawback is that this can create a biased sample. Indeed, we would expect respondents to be predominantly young and highly educated. However, it was asked to all successful participants (investors) to circulate the survey among their networks as well (targeting more investors), this belongs to the snowball sampling method. The use of the professional social media LinkedIn enhances the snowball method as its algorithm amplifies a post shared many times even to people outside of my original network, hence reaching a broader set of the population.

In order to not limit our population to investors active on LinkedIn and to reach a broader set of the population, members of my network active in the finance world and part of Belgian business clubs were asked to share it with their contacts and respective mailing lists. However, this also had the potential of creating a biased sample of highly educated, high income and older investors.

The survey was open from November 25^{th}, 2021 to December 12^{th}, 2021 where it reached 2.725 people and was shared 8 times on LinkedIn. We collected 175 answers over the course of these two weeks. 39 answers did not belong to the sample frame as they did not invest their money, 30 answers did not make investment decision themselves, 5 respondents quit the survey early leading to incomplete answers and none answered that they never considered financial nor sustainable data in their investments. This left us with a usable sample of 101 responses. The demographics of respondents not investing their money and not making investment decisions themselves can be found in Appendix 2 for curiosity of interest.

V. Pilot: pre-test phase of the survey

Before sharing the survey widely and starting to collect data it was reviewed by a psychometric professor and a survey professional as well as tested on a small sample of 6 people, all corresponding to the target group of investors. As our study aims at understanding the psychology of investors it was key to ensure that all questions were comprehensible and triggering a clear answer, limiting any bias. Furthermore, we wanted to test how respondents felt answering more personal questions, we did not want this to be an obstacle to the completion of the questionnaire. Finally, although our survey was kept as short as possible to keep respondents motivated, it was important to test out the motivation to answer as well as the average answer time.

Out of this pilot phase we found that the survey took between 5 and 8 minutes to be answered, which corresponded to what was predicted by the Qualtrics software (7.7 minutes). The respondents all agreed that the questionnaire had a good face validity (i.e. their subjective assessment that it measured what it is supposed to measure). Regarding the content of the survey, several questions were adapted based on their feedback namely: the statements in the third section were reformulated when understood differently by different participants, a “prefer not to say” option was added to the income question as participants felt it was too intrusive, the statements of the investment strategy question were shortened to facilitate reading and a third option “Other” was added as they were believed to be too limiting.

Regarding the structure of the survey, the following changes were made: the definition of investment was modified to limit some investor categories (e.g. real estate), the definition of sustainable investment was adapted to insist on the fact that it was up to participants interpretation, we added a question to filter out investors that did not make investment decisions themselves, the introduction and the message of thanks at the end were fleshed out to motivate respondents and encourage completion/subsequent sharing.

CHAPTER 2 : RESULTS

I. Sample description

After narrowing down our data to a sample of 101 responses, we had to split the different investors into categories (Table 3). 14 of them were classified as pure financial investors (never considering sustainable data) and none as pure sustainable investors. The apparent low level of “pure” answers could be explained by our categorization criteria (cf. supra) as we only categorize investors as such if they never consider one type of data, which is a very restrictive assumption. All in all, this gave us a large share of mixed investors (n=87) which was our goal. This is in line with the finding that the popularity of sustainable investment is rising and that very few investors invest their entire portfolio in one category or the other. The downside was that we got a small sample of pure financial investors and simply no pure sustainable investor. Unfortunately, this makes the test of **H11a, H11b** and **H11c** impossible.

Table 3:Investor classification

n=101
Frequency

		Financial considerations				
		Always	Often	Sometimes	Never	Total
Sustainable considerations	Always	19	12	2	0	33
	Often	12	16	9	0	37
	Sometimes	11	6	0	0	17
	Never	7	4	3	0	14
	Total	49	38	14	0	101

1. Pure investors

It is interesting to note that our sample of 14 pure financial investors (Table 4) is composed primarily of highly educated (all have a Master's degree), high income (71% earn over 50.000€ net per year), older (more than half of them are over 46 years old) male (86%) investors. Almost 60% of them have more than 10 years of investing experience, and they strongly prefer an active strategy (86%) combined with a lower expected investment horizon (more than 90% will withdraw it within 10 years). It appears that the consideration of only financial criteria for investment choices is predominant in a certain group of investors. Our sample size (n=14) is too small to infer general conclusions for the population, but larger scale studies could confirm this finding in the future. This would corroborate our finding that mixed investors are becoming the norm and that "pure" investors are becoming a minority, probably limited to specific category of the population.

2. Mixed investors

Our mixed investors sample (Table 4) is more diverse than our pure financial sample. Socio-demographic traits appear to be clustered in some categories: 75% of male respondents and 76% of master's graduates. The age distribution is similar to that of pure investors: 16% under 26 years old, 30% between 26 and 45 and almost 50% between 46-65. The income categories however are better spread out: 54% of high income (more than 50.000€ net a year) individuals, 17% of medium income (between 30 and 50.000€) as well as 18% of low income (between 10 and 30.000€) and 10% of very low income (less than 10.000€), categories that were not represented at all for pure financial investors.

Investment habits traits however are more evenly distributed: a fair share of both active and passive investors and an almost equal distribution in terms of investment size. Though roughly half of investors have more than 10 years of experience and plan on withdrawing their investment in 5 to 10 years (53% and 47% respectively).

Table 4:Socio-demographic and investment habits distribution of mixed and pure investors

	Mixed investors n=87		Pure financial investors n=14	
Socio-demographic				
Gender	Frequency	Percentage	Frequency	Percentage
Male	65	75%	12	86%
Female	21	24%	2	14%
Prefer not to say	1	1%	0	0%
Total	87	100%	14	100%
Age	Frequency	Percentage	Frequency	Percentage
<26	14	16%	2	14%

26-45	26	30%	4	29%
46-65	41	47%	7	50%
66+	6	7%	1	7%
Total	87	100%	14	100%

Education	Frequency	Percentage	Frequency	Percentage
High School	0	0%	0	0%
Higher education with no degree	1	1%	0	0%
Bachelor	10	11%	0	0%
Masters	66	76%	14	100%
PhD	10	11%	0	0%
Total	87	100%	14	100%

Income	Frequency	Percentage	Frequency	Percentage
<10.000	9	10%	0	0%
10.000 - 30.000	16	18%	0	0%
30.000 - 50.000	15	17%	4	29%
>50.000	47	54%	10	71%
Prefer not to say	0	0%	0	0%
Total	87	100%	14	100%

Investment habits

Way	Frequency	Percentage	Frequency	Percentage
SELF	50	57%	9	64%
OTHER,SELF	17	20%	0	0%
GUIDELINE,SELF	18	21%	5	36%
OTHER,GUIDELINE,SELF	2	2%	0	0%
Total	87	100%	14	100%

Strategy	Frequency	Percentage	Frequency	Percentage
ACTIVE	48	55%	12	86%
PASSIVE	39	45%	2	14%
Total	87	100%	14	100%

Experience	Frequency	Percentage	Frequency	Percentage
up to 1 year	1	1%	0	0%
1-3 years	21	24%	2	14%
3-5 years	7	8%	4	29%
5-10 years	12	14%	0	0%
more than 10 years	46	53%	8	57%
Total	87	100%	14	100%

Size	Frequency	Percentage	Frequency	Percentage
<25%	24	28%	5	36%
25-50%	16	18%	0	0%
50-75%	22	25%	1	7%
>75%	25	29%	8	57%
Total	87	100%	14	100%

Horizon	Frequency	Percentage	Frequency	Percentage
0-5 years	4	5%	5	36%
5-10 years	41	47%	8	57%
10-30 years	24	28%	1	7%
More than 30 years	18	21%	0	0%
Total	87	100%	14	100%

3. Sample biasedness

This apparent biasedness of sample can be explained by our choice of sampling method: a mix of convenience and snowball sampling methods. A potential issue we identified in our methodology part.

However, these findings are not true if we look at our non-used data (Appendix 2) on non-investors (n=39) and investor with discretionary managed portfolios (n=30). The share of women is higher in both categories (36% for non-investors and up to 43% of the respondents with discretionary managed portfolios). The age categories of under 26 and between 26 and 45 are predominant among non-investors (33% and 44% respectively). Similarly, regarding income, 21% of non-investors earn below 10.000€ net a year and 46% between 10.000€ and 30.000€. For investors with discretionary managed portfolios however these two variables appear to be similar to the levels found in our investor population (84% of our respondents above 46 years old and 70% earning over 50.000€ net a year). The only category in which we find a clear bias over our entire sample population is the education level with a strong majority of master's graduates.

It is hence legitimate to wonder if our seemingly biased sample only stems from our sampling technique or if, more simply, the share of people investing their money and deciding on it is unevenly distributed among the entire population.

II. Data preparation

Before moving on to testing our hypothesis, we had to make sure that the data available was in the format required and that the different variables we wanted to measure where constructed properly. Most of the variable defining and coding was done directly through Qualtrics. However, some treatments had to be performed after the data collection and import. For an overview of all the different variables used in our analysis see Appendix 3.

The first step was to filter out non-investors and investors with discretionary managed portfolios and classify the rest of investors between "pure" and "mixed" categories. This step was done according to the criteria developed in the sample description section and through the creation of a new variable "Type" with two possible values: "pure" and "mixed".

Then, we reclassified the "other" answers of the investment strategy question as Active or Passive based on the information given by the respondent (Appendix 4).

Furthermore, the data collected for pure financial investors was downloaded as separate variables (PTRAD_1, PTRAD_2 etc.). We grouped them with the corresponding data of mixed

investors for the ease of future comparisons. Their observations were now recorded as (TRAD_1, TRAD_2 etc.)
Finally, we had to transform the data obtained for the third statement in our scale (TRAD_3 and SUST_3) as it goes in an opposite direction to that of the 9 other statements. A high score on TRAD_3 or SUST_3 indicates a lower level of herding. Each value was hence transformed to 6-TRAD_3 and 6-SUST_3 to reflect this opposite relationship.

III. Measurement of herding

In our survey the herding variable was measured with the use of a 5-point Likert Scale. This method was chosen as it was the most frequently used in previous studies on cognitive biases and in psychometrics studies in general (Hillenbrand et al., 2020; Kumar & Goyal, 2015; Kumar & Goyal, 20116; Lathif & Aktharsha, 2016; Ullah et al., 2020; Yakuban et al., 2015; Zahera & Bansal, 2018). In order to now use these measures as a reliable herding variable and perform the subsequent hypothesis testing, some points had to be taken into consideration: how to deal with our Likert items, finding the best factor structure to represent the herding bias, assess the comparability of both scales used in our survey and the creation of a composite herding variable.

1. The use of Likert items

The first step was to decide whether we could use our survey scale with parametrical statistical tests. There is an unresolved ongoing debate in the literature as whether Likert scales should be considered an interval or ordinal level of measurement (Joshi et al., 2015). A great number of scholars argue that it is tedious to quantify attitude and feelings, the interpretation of a quantifiable scale in such contexts is heavily up to interpretation (Yusoff & Mohd Janor, 2014). In that case it is impossible to assume equidistance between the different measurement points in a Likert scale and we should perform adequate non-parametric statistical methods (Harwell & Gatti, 2001 ;Knapp, 1990; Jamieson, 2004, Kuzon et al., 1996). However, another group of scholars notes that in the case of social science research it is of common practice to use Likert scale data as intervals (Yusoff & Mohd Janor, 2014; Joshi et al., 2015) and doing so does not provoke significant statistical problems (Dolnicar & Grun, 2007; Kemp & Grace, 2010; Norman, 2010).

In our case we have decided to use our Likert scale data as intervals, allowing us to perform more powerful parametrical tests. There are three reasons that pushed us to make that choice.

First, our sample size is large enough (n>30 or n>10 for each group) (Norman, 2010; Kuzon et al., 1996). Second, our Likert scale is composed of the minimum required of 5 measurement points. The largest the number of measuring points, the more it can be assumed that the data points are continuous (Wu & Leung, 2017). Third, and most importantly, we use our Likert scale measurements as a composite score and not as individual items. A summated scale (composite score) of Likert type data can be considered as an interval level of measurement and can hence be analyzed with parametric methods (Boone & Boone, 2012 ;Carifio & Perla, 2008 ;Norman, 2010 ; Russel 2010).

2. Measuring the herding variable

Our study aims at measuring the herding bias of investors in their traditional and sustainable investments. As is the case with most psychometric studies, cognitive biases (and hence the herding bias) are by essence hard to observe (Figureau et al., 2020). The most frequent methodology in psychometrics to palliate this problem is to measure an unobservable construct by combining observable items into a scale. In our case the unobservable construct is herding, and the observable items are the 10 statements we evaluated in our survey.

When developing such a psychometric scale it is important to assess its validity and reliability. A step unfortunately often overlooked by most cognitive bias researchers (Parsons et al., 2019). We want to know whether our scale measures what it is supposed to measure, its validity and whether the measure is consistent and replicable, its reliability.

3. Validity

We first need to find out what is the best way to represent the herding construct. In past studies a list of statements linked to herding tended to be combined to form one single composite variable: herding. However, we have hypothesized that herding could be represented by a set of related components (factors) rather than a single unified entity.

We then need to assess whether we can compare the results between the first and second set (sustainable and financial) of statements presented to the mixed investors. As we change the wording of the statements between the two sets of questions, they can be considered to be two different scales. Are the two scales measuring the same construct, can we compare the answers of the investors on the first set of questions to the second set of questions?

To tackle these two issues of internal validity we opted for a factor analysis. We chose a factor analysis over a principal component analysis as we were most interested in identifying an underlying factor structure and evaluate our survey construction rather than reduce the number of variables into a smaller set of components (Kieffer (1999) as cited in Henson & Roberts, 2006; Taherdoost et al., 2020; Williams et al., 2010). It is also considered the best method to interpret self-reported survey data (Williams et al., 2010).

Among possible factor analytic techniques, we have privileged the Exploratory Factor Analysis (EFA). This for three reasons: First, the items of our scale are based on items found in the literature for the herding bias, but the final combined list of items is specific to our study. Second, the items have been reworded to give a sustainable investment or traditional investment feel. This qualifies our scale as a "new scale" and it should hence be tested with the help of an EFA and tested in further studies with a CFA (Henson & Roberts, 2006). Third, although theory expects one factor to be sufficient to describe our data, we expect a higher number of underlying factors to exist (Henson & Roberts, 2006).

An EFA is used in order to identify the latent constructs (factors) that best represent the observed items (variables) of the scale (Henson & Roberts, 2006; Watkins, 2018). The latent construct herding is believed to cause the answers to the items asked on the questionnaire. i.e. it is because an investor suffers from a herding bias that he will agree or not to a statement, not the other way around.

We performed two Exploratory Factor Analysis (EFA): one on the sustainable herding scale and one on the traditional herding scale given to mixed investors. The results of both EFA were used to choose the number of factors needed to represent herding and the individual loading of the factors were then compared to assess whether both scales can be compared.

Before the extraction of factors and moving on with our EFA's we had to check whether our sample size (n=87) is adequate. There is no consensus in the literature on the required sample size for an EFA (Henson & Roberts, 2006; Watkins, 2018). Some authors recommend a sample size in absolute numbers, our sample size can be considered "poor" with regards to this criterion as it falls below the n=200 threshold (Comrey and Lee, 1992 as cited in Henson & Roberts , 2006). Others mention that the sample size is based on the number of scale items, where our sample satisfies the condition of a minimum of 5 observations per item (Stevens, 1996 as cited in Henson & Roberts, 2006; Watkins, 2018). These rules of thumb are however criticized as the most important criteria are the communalities observed within items (MacCallum et al., 1999 as cited in Henson & Roberts, 2006; Watkins, 2018). We carry on with our factor analysis, noting its apparent small sample size.

In the subsequent section we will develop the methodology followed for our two EFA's: preliminary checks, choice of number of factors, extraction and rotation method and model evaluation. Afterwards we will move on to their individual results and comparison.

IV. EFA methodology

1. Preliminary checks

Considering the fact that we were trying to identify an underlying construct measured through a set of items in a social science scale, it seemed obvious that a factor analysis was the right way to go. In order to formerly confirm our intuition, we performed three preliminary checks: the analysis of the correlation matrix, the Bartlett's test of sphericity and the analysis of KMO values.

We first checked for the correlation matrix of the items in our sample, as a factor analysis is indicated only if the measured variables are intercorrelated (Watkins, 2018). A commonly used criteria is a high number of correlations of >0.3 (Hair et al., 2010 as cited in Watkins, 2018; Williams et al., 2010). We computed two correlation matrices based on both Polychoric and Pearson correlations. As our variables are measured through the help of a Likert scale, their distribution is unlikely symmetrical and hence Polychoric correlations are more indicated (Baglin, 2014). However, our variables are measured by 5 or more categories which makes a Pearson correlation usable as well (Watkins, 2018). The criteria of number of correlations higher than 0.3 was assessed for both matrices.

The second check was the Bartlett's test of sphericity. A p-value below 0.05 would indicate that our data was suitable for factor analysis.

Our third criterion was to check whether the criteria for the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy were verified. Traditionally, KMO values above 0.7 are used as a threshold (Hoelzle & Meyer, 2013; Loret et al., 2017 as cited in Watkins, 2018). Some authors, such as Hair et al. (2006) consider that values above 0.5 can still be used for factor analysis.

2. Number of factors

As recommended by Thompson and Daniel (1996, as cited in Henson & Roberts, 2006) and Williams et al. (2010) we used multiple decision rules rather than a single criterion to determine the number of factors to retain. We used three different methods: Kaiser criteria (eigenvalues >1), Scree plot and Parallel Analysis.

The most frequently used method to determine the number of factors to retain is the Kaiser criteria (eigenvalue > 1) rule (Henson & Roberts, 2006) and is the norm in the literature (Costello & Osborne, 2005). However, the Kaiser criteria and Scree plot are often believed to overestimate the number of factors (Balgin, 2014). Parallel analysis has been found to correctly identify the number of dimensions and is considered to be the best method to choose the number of factors to retain (Balgin, 2014; Taherdoost et al., 2020).

Depending on the results obtained for the different methods we created different models with varying number of factors. The multiple models created will then be compared in the following phases.

3. Extraction and rotation method

For each model we had to decide on the factor extraction method as well as the subsequent rotation method.

Among the extraction methods available for a true factor analysis, we opted for Principle Axis Factoring (PAF) as it requires no assumption on the distribution of our data (Costello & Osborne, 2005). Moreover, it is the most adequate when the objective of the study is to identify the underlying factor structure (Taherdoost et al., 2020), which is our case.

Regarding the rotation method we opted for the “oblimin” oblique rotation. An oblique rotation has the advantage of allowing a correlation between factors. This is of particular interest in social sciences studies as behavioral factors are seldom completely independent of each other (Costello & Osborne, 2005; Balgin, 2014; Taherdoost et al., 2020).

4. Goodness of fit and model evaluation

According to Preacher et al. (2013) there are two distinct goals to keep in mind when assessing the fit of a model: identifying the number of factors corresponding to the truth (verisimilitude) and producing a model that can be used in multiple settings (generalization). Both goals were important in our case.

Regarding the first objective, goodness of fit measures is the main preoccupation of the researcher (Preacher et al., 2013). A myriad of goodness-of-fit measures have been developed to assess the usefulness of a model. We have reported some of the most commonly used measures in the literature offered in the psych package in R. These measures are the Tucker Lewis Index of factoring reliability with a cutoff value of 0.95 (Shi et al., 2019) , the Root Mean

Square of Error Approximation (RMSEA) with a threshold of under 0.1 considered as mediocre and under 0.06 as acceptable (Shi et al., 2019) and the Bayesian Information Criteria (BIC) with the lower the value the better (Preacher et al., 2013). We also referenced the value of the "Fit based upon off diagonal values" given in the output although we did not find documentation on the measure. Finally, as we used the principle axis factoring method for our factor extraction, we were not able to use the explained variability of a model as a reliable goodness of fit measure (Balgin, 2014).

However, for the second objective of generalization, which would allow us a higher scale comparability within our sample, goodness of fit is not adequate as a model retention criterion (Preacher et al. 2013).

Ultimately the choice between the different possible models was made based on this tradeoff between generalizability and verisimilitude (Preacher et al., 2013).

V. EFA on traditional investment scale

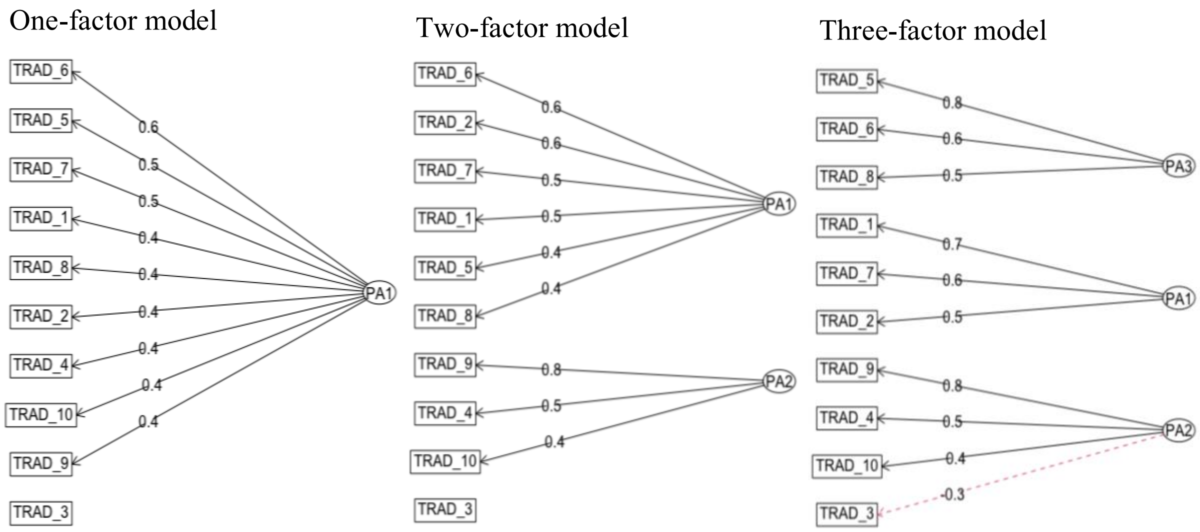
The preliminary checks performed for our traditional investment data indicated overall that a factor analysis was useful in our study. The two correlation matrices based on Polychoric correlations (Table 5) and Pearson correlations (Appendix 5) yielded similar results and both have values above 0.3. The Bartlett's test of sphericity (Appendix 6) gave a p-value of 4.8e-09, well below the threshold of 0.05. The KMO values obtained for our sample (Appendix 7) however were considered miserable to mediocre according to the criteria set by Kaiser himself (Kaiser & Rice, 1974). The overall value was of 0.62 and the individual variables values were between 0.51 (TRAD_3) and 0.69 (TRAD_1). Nonetheless, they are above the 0.5 threshold set by Hair et al.(2006) for a factor analysis.

Table 5:Polychoric correlation matrix traditional investment

	TRAD_1	TRAD_2	TRAD_3	TRAD_4	TRAD_5	TRAD_6	TRAD_7	TRAD_8	TRAD_9	TRAD_10
TRAD_1	1	**0.38**	-0.12	0.15	0.06	0.24	**0.33**	0.09	0.05	0.11
TRAD_2	0.38	1	0.08	0.05	0.15	0.17	**0.32**	0.14	-0.04	0.24
TRAD_3	-0.12	0.08	1	-0.23	-0.004	-0.03	-0.24	-0.07	-0.20	-0.03
TRAD_4	0.15	0.05	-0.23	1	0.17	0.22	0.10	0.08	**0.27**	0.23
TRAD_5	0.06	0.15	-0.004	0.17	1	**0.35**	0.09	**0.32**	0.21	0.16
TRAD_6	0.24	0.17	-0.03	0.22	0.35	1	**0.29**	**0.31**	0.07	0.08
TRAD_7	0.33	0.32	-0.24	0.10	0.09	0.29	1	0.05	0.09	0.07
TRAD_8	0.09	0.14	-0.07	0.08	0.32	0.31	0.05	1	0.16	0.17
TRAD_9	0.05	-0.04	-0.20	0.27	0.21	0.07	0.09	0.16	1	**0.33**
TRAD_10	0.11	0.24	-0.03	0.23	0.16	0.08	0.07	0.17	0.33	1

The different factor retention methods we used suggested models with two to four factors. The Kaiser criteria suggested that four factors should be retained. The inspection of the Scree plot (Appendix 8) showed us a break point in the data situated at 3 factors, indicating that we should retain 2 factors for our model (Costello & Osborne, 2005).Finally, the interpretation of the parallel analysis output (Appendix 9) suggested 4 factors. Ultimately, for future comparability with the EFA on the sustainable investment dataset (cf. infra), we have created three different models: one-factor, two-factor and three-factor (Figure 1). The complete output as well as the factor loadings for the three different models can be found in (Appendix 10, 11 and 12).

Figure 1:Factor structure comparison of the three traditional investment models



9 out of the 10 variables load significantly for each model (loading factor >0.4). The variable TRAD_3 does not seem to fit in any model. The three-factor model seems to be the most adequate for the verisimilitude of our scale as it has the cleanest factor structure (highest loading of the factors) (Costello & Osborne, 2005) as well as overall better scores for the goodness of fit measures. We have reported in Table 6 some of the most commonly used measures of goodness of fit. If we look at the Tucker Lewis Index, none of the models reach the common cutoff value of 0.95 (Shi et al., 2019). Although the three-factor model is the closest to reaching this value. Similarly, with an RMSEA of above 0.06, none of the proposed models are considered to be acceptable (Shi et al., 2019). But the three-factor model falls at least under the 0.1 threshold. Finally, with a BIC of -51.62 the three-factor model is the best.

Table 6:Goodness of fit measures traditional investment

	One factor	Two-factor	Three-factor
Tucker Lewis Index of factoring reliability	0.441	0.552	0.761

RMSEA index	0.128	0.114	0.082
BIC	-71.17	-60.61	-51.62
Fit based upon off diagonal values	0.7	0.84	0.93

VI. EFA on sustainable investment scale

Similarly to what we discovered in our EFA on the traditional investment items, the preliminary checks performed for our sustainable investment data suggested that a factor analysis was adequate. The two correlation matrices based on Polychoric correlations (Table 7) and Pearson correlations (Appendix 13) have values above 0.3. The correlation coefficients between both matrices are similar, although slightly higher for the Polychoric correlation. Moreover, the Bartlett's test of sphericity (Appendix 14) gave a p-value of 3.54e-08, again below the threshold of 0.05. Three out of the 10 individual item KMO values (Appendix 15) were considered middling (ranging from 0.7 for SUST_6 to 0.77 for SUST_10). The rest of the KMO values were similar to the ones obtained for our traditional investment sample. The overall value was of 0.65 and the lowest individual variables value was of 0.57 (SUST_7).

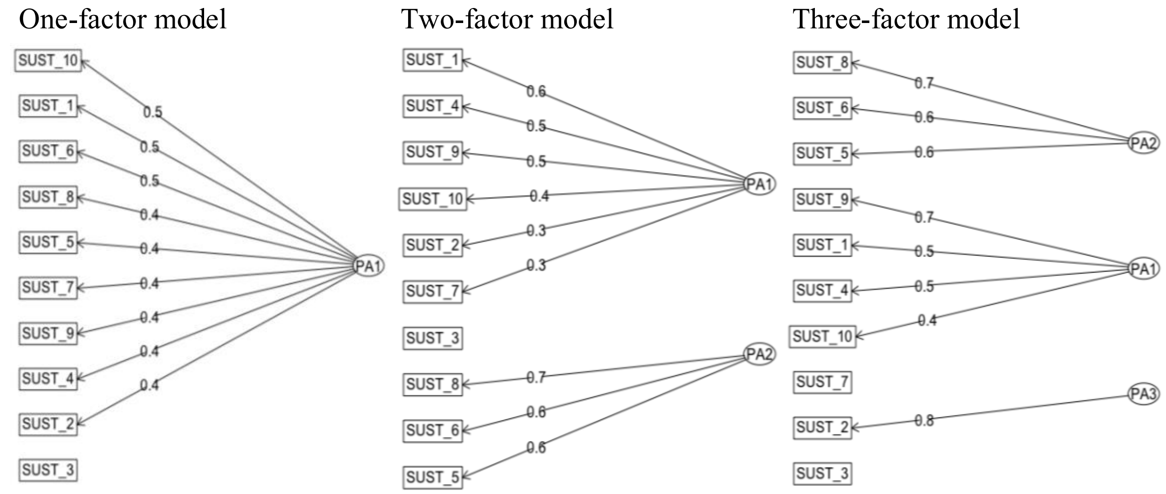
Table 7:Polychoric correlation matrix sustainable investment

	SUST_1	SUST_2	SUST_3	SUST_4	SUST_5	SUST_6	SUST_7	SUST_8	SUST_9	SUST_10
SUST_1	1	**0.32**	-0.07	**0.28**	0.10	0.11	0.24	0.03	**0.29**	**0.35**
SUST_2	0.32	1	-0.21	0.19	0.01	0.22	0.24	0.14	0.01	0.17
SUST_3	-0.07	-0.21	1	-0.17	0.02	-0.07	-0.03	-0.12	0.03	-0.04
SUST_4	0.28	0.19	-0.17	1	0.11	0.02	0.07	0.13	**0.42**	**0.29**
SUST_5	0.10	0.01	0.02	0.11	1	**0.38**	**0.27**	**0.47**	0.10	0.15
SUST_6	0.11	0.22	-0.07	0.02	0.38	1	0.20	**0.52**	0.07	**0.26**
SUST_7	0.24	0.24	-0.03	0.07	0.27	0.20	1	0.02	**0.33**	0.14
SUST_8	0.03	0.14	-0.12	0.13	0.47	0.52	0.02	1	0.08	0.18
SUST_9	0.29	0.01	0.03	0.42	0.10	0.07	0.33	0.08	1	**0.29**
SUST_10	0.35	0.17	-0.04	0.29	0.15	0.26	0.14	0.18	0.29	1

The different factor retention methods we used suggested models with two to four factors. The Kaiser criteria suggested that four factors should be retained. The inspection of the Scree plot (Appendix 16) showed us a break point in the data situated at 3 factors, indicating that we should retain 2 factors for our model (Costello & Osborne, 2005).Finally, the interpretation of the parallel analysis output (Appendix 17) suggested 2 factors. Ultimately, for future comparability we have created three different models: one factor, two-factor and three-factor (Figure 2).

The complete output as well as the factor loadings for the three different models can be found in (Appendix 18, 19 and 20).

Figure 2:Factor structure comparison of the three sustainable investment models



Yet again, the variable SUST_3 does not load on any factor in any model. For the three-factor model the variable SUST_7 does not load either. The rest of the 10 variables load significantly for each model (loading factor >0.4). The three-factor model also seems to be the most adequate for the verisimilitude of our scale as it has the cleanest factor structure (highest loading of the factors) (Costello & Osborne, 2005) as well as overall better scores for the goodness of fit measures.

We have reported in Table 8 some of the most commonly used measures of goodness of fit. It is interesting to note that overall, the goodness of fit measures are better for the models on the sustainable investment data than for the traditional investments. If we look at the Tucker Lewis Index, the two-factor and three-factor model are above the cutoff value of 0.95 (Shi et al., 2019) (1.01 and 1.114 respectively). These two models also have an RMSEA of under 0.6. This is not the case for the one factor model, who has a value of 0.078, under the 0.1 threshold (Shi et al., 2019). The analysis of the BIC reaches the same conclusion with the lowest BIC value (-65.49) in the case of the three-factor model.

Table 8:Goodness of fit measures sustainable investment

	One factor	Two factor	Three factor
Tucker Lewis Index of factoring reliability	0.652	1.01	1.114
RMSEA index	0.078	0	0
BIC	-102.35	-90.51	-65.49
Fit based upon off diagonal values	0.73	0.9	0.95

VII. Comparison EFA results between both scales

The purpose of conducting an EFA on both the sustainable and traditional scale was to assess whether they had a similar factor structure and could hence be used for valid group comparisons. Indeed, if the construct is understood significantly differently in two different measuring points (in the sustainable context and in the traditional context), mean difference comparisons between both groups may lead to inaccurate results (Putnick & Bornstein, 2016).

The most accurate way to check whether two scales are comparable is by measuring their measurement invariance (MI) with the help of a multi-group confirmatory analysis (MCFA). However, most researchers in psychometrics neglect MI issues (Schoot et al., 2015). As we have already performed an EFA on our data (cf. supra) it is advised against performing a CFA on the same sample (Henson & Roberts, 2006). We follow the alternative approach suggested by Finch and French (2008) which consists in comparing the loading estimates between two EFA models and assess which appear to be invariant without a formal statistical test.

We have seen that for both datasets a three-factor model seems to be the most appropriate if our aim was to increase the verisimilitude of our construct. This confirms our original intuition that the herding bias was better measured through a subset of categories rather than through an overall composite variable. Nonetheless the categories identified through our factor analysis differ significantly from the ones we hypothesized on in our methodology. A new version of these sub-categories based on our EFA findings can be found in Table 9. These vary depending on the type of investment.

Table 9:New sub-categories of herding

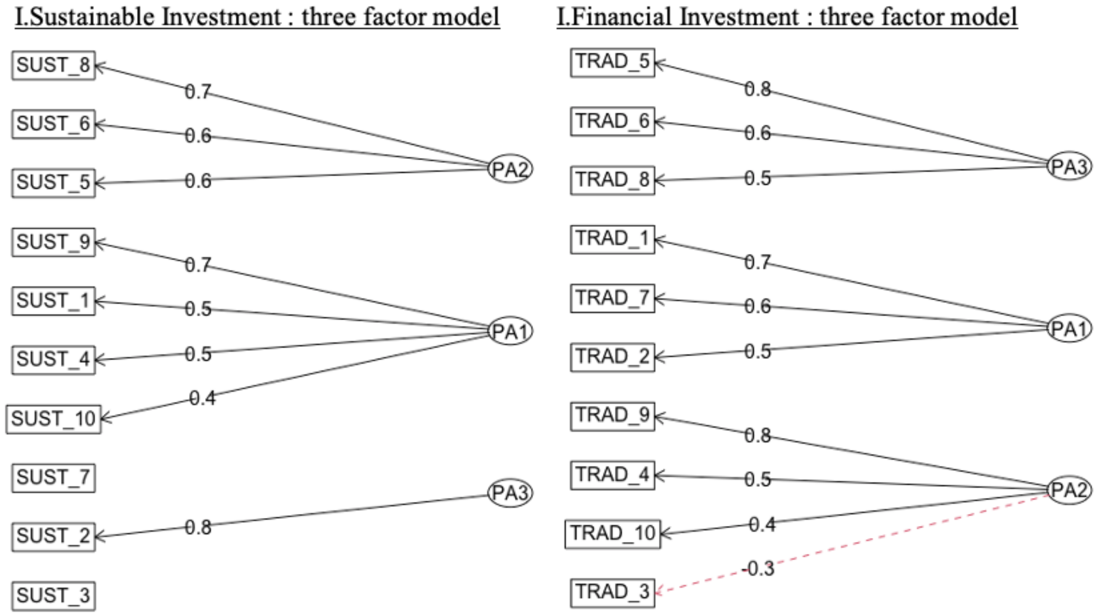
Traditional investment scale		Sustainable investment scale	
Item code	hypothesized sub-categories	Item code	hypothesized sub-categories
TRAD_1	I. Following of peers (including friends, relatives and others)	SUST_1	II. Advice by media, experts and peers
TRAD_2	I. Following of peers (including friends, relatives and others)	SUST_2	I. Following friends and relatives
TRAD_3	N/A	SUST_3	N/A
TRAD_4	II. Advice by media and experts	SUST_4	II. Advice by media, experts and peers
TRAD_5	III. Reaction to a loss	SUST_5	III. Reaction to a loss
TRAD_6	III. Reaction to a loss	SUST_6	III. Reaction to a loss
TRAD_7	I. Following of peers (including friends, relatives and others)	SUST_7	N/A
TRAD_8	III. Reaction to a loss	SUST_8	III. Reaction to a loss
TRAD_9	II. Advice by media and experts	SUST_9	II. Advice by media, experts and peers
TRAD_10	II. Advice by media and experts	SUST_10	II. Advice by media, experts and

For the traditional investment scale, we have renamed the categories as follows: following of peers (friends, relatives and others), reaction to a loss and advice given by media and experts. Regarding the following of peers factor we find that there is no difference if one has a personal relationship to the peer (relatives and friends) or if it is an unknown investor. The reaction to a loss factor also appears to be determinant but it also includes the item TRAD_8, which we had thought would belong to the following of peers factor. A possible explanation is that this item highlights the terms “buying”, “selling” and “price rise” and “decline”. This terminology could trigger a reaction to a loss in the investor behavior and hence answer. Furthermore, the advice given by experts (broker and general experts) is completed by the importance of media. This indicates that the information published by the media appears to an investor similar to that of an expert. Finally, the item TRAD_3, although recoded, had an opposite relationship to the media and expert advice. This leads us to think that this item was not always well understood or interpreted by investors, potentially due to the opposite wording it had compared to other items. This confirms our decision to drop it out of the scale.

For the sustainable investment scale, the reaction to a loss sub-category is understood in the same way as for the traditional investment scale (with the inclusion of SUST_8). Regarding the advice given by media and experts, the item representing peers is included in the sub-category. We wonder if that may be explained by the fact that peers appear to have more of an authority knowledge regarding sustainable investments than traditional investments. This could be due to the impression that less technical knowledge is required to assess sustainability performance. Finally, friends and relatives are a sub-category of their own. In the case of sustainable investments, investors seem to pay less attention to the behavior of unknown investors (SUST_7). This is easily understandable if we believe investors act more on their own opinion for sustainable investments. Yet again the SUST_3 item was not represented in a factor, indicating that it was incorrectly understood or too different for investors.

However, if we compare the factor loadings between the two scales, we see that the two different three-factor models have a different factor structure (Figure 3) and different factor loadings (Table 10.III). According to these findings, subjects understood the two scales relatively differently and hence they cannot be compared.

Figure 3:Comparison of the sustainable and financial investment three-factor model structure



We have also seen that the verisimilitude of a construct was not always the only objective to pursue. In our case the generalization of the scale and the subsequent within comparison possibilities were of uttermost importance for our study. With this in mind, we moved away from our objective to measure the most accurately possible the herding construct and we consider the other factor models generated and see which are the most comparable (Table 10). Both the two factor and three factor models have different structures between the sustainable and traditional investment scales. As their factor loadings and factor structure differ significantly, comparing both samples with a scale based on their structure would lead to erroneous results. The sub-categories within herding are not the same depending on the context and hence it is not possible to compare them.

Table 10:Comparison of factor loadings between sustainable investment and traditional investment models

I. Factor loadings for one factor model

Traditional investment		Sustainable investment	
	PA1		PA1
TRAD_1	0.45	SUST_1	0.49
TRAD_2	0.44	SUST_2	0.36
TRAD_3	-0.16	SUST_3	-0.21
TRAD_4	0.42	SUST_4	0.38
TRAD_5	0.53	SUST_5	0.41
TRAD_6	0.59	SUST_6	0.48
TRAD_7	0.47	SUST_7	0.39
TRAD_8	0.44	SUST_8	0.44
TRAD_9	0.37	SUST_9	0.39

TRAD_10	0.37	SUST_10	0.50

II. Factor loadings for two factor model

Traditional investment			Sustainable investment		
	PA1	PA2		PA1	PA2
TRAD_1	0.53	-0.03	SUST_1	0.63	-0.03
TRAD_2	0.60	-0.13	SUST_2	0.34	0.09
TRAD_3	-0.01	-0.25	SUST_3	-0.18	-0.06
TRAD_4	0.16	0.47	SUST_4	0.50	-0.04
TRAD_5	0.41	0.23	SUST_5	0.02	0.55
TRAD_6	0.60	0.06	SUST_6	0.04	0.64
TRAD_7	0.55	-0.01	SUST_7	0.33	0.13
TRAD_8	0.35	0.17	SUST_8	-0.04	0.70
TRAD_9	-0.04	0.84	SUST_9	0.49	-0.03
TRAD_10	0.15	0.40	SUST_10	0.43	0.16

III. Factor loadings for three factor model

Traditional investment				Sustainable investment			
	PA3	PA1	PA2		PA2	PA1	PA3
TRAD_1	-0.08	0.74	0.05	SUST_1	-0.01	0.45	0.29
TRAD_2	0.19	0.51	-0.11	SUST_2	0.01	-0.01	0.83
TRAD_3	0.12	-0.11	-0.30	SUST_3	-0.05	-0.05	-0.24
TRAD_4	0.02	0.17	0.50	SUST_4	-0.02	0.45	0.13
TRAD_5	0.81	-0.08	0.05	SUST_5	0.60	0.08	-0.12
TRAD_6	0.57	0.25	-0.06	SUST_6	0.63	-0.02	0.10
TRAD_7	0.06	0.59	0.03	SUST_7	0.13	0.28	0.14
TRAD_8	0.50	0.03	0.05	SUST_8	0.69	-0.04	0.00
TRAD_9	0.02	-0.04	0.82	SUST_9	-0.01	0.70	-0.11
TRAD_10	0.06	0.13	0.41	SUST_10	0.18	0.38	0.10

When we look at the factor loadings for the one factor model, we see that they are approximately similar and that the same items (all except the third statement) load on the factor. A comparison between two samples based on this scale does not suffer measurement variance (Finch and French, 2008) and is then possible. However, as the third item was not correlated with any other item and did not load on any of the factors, we dropped that item of our scale and kept the 9 others.

It is rather unfortunate that the discrepancies between the factor loadings of the two scales prevent us from using the insights gained through our EFA's about the possible herding sub-categories that clearly seem to exist. We would however like to add that although the results of both EFA's seem to support the case of herding sub-categories, more robust analysis should be conducted on the topic before using these sub-categories as components of a new three factor scale for herding. Indeed, we performed an EFA analysis despite a relatively small sample size (n=87), low KMO values (mainly below 0.7) and most of our models had low goodness of fit measures.

All in all, this leads us to conclude that our EFA findings are interesting as part of an exploration analysis and are worth investigating further but using them to construct a new herding scale and compare our sample could lead to biased results. In this case we decide to favor the comparability and generalizability of our scale to its apparently verisimilitude. We hence use the scale based on the one factor model.

VIII. Reliability

In order to create a composite score sufficiently representative of the latent variable herding we would like to measure we had to assess the reliability of our multiple Likert items scale.
We checked the internal consistency of our multi item scale: whether the items chosen in our questionnaire are sufficiently intercorrelated (Joshi et al. 2015).

We verified if a strong coefficient of reliability could be found for the overall herding variable (measured by 9 individual Likert items) with the help of the Cronbach Alpha test. By concern for academic accuracy, the Cronbach Alpha was performed on both the herding component in traditional investments as well as the herding component in sustainable investments, expecting to not find significant differences in results between both.

The Cronbach alpha for the traditional investment scale was of 0.698 and that of the sustainable investment scale 0.664. With both values very close to the 0.7 "acceptable" threshold, we can conclude that our scales are reliable.

IX. The composite variable herding

The next step was to decide how to represent the herding variable. The options we had were between a sum or an arithmetic mean (equivalent statistically) assuming that every item was equally important to describe herding. Or we could assign specific weights on the items based on the factor loadings results obtained in our factor analysis. The latter possibility was not adapted in our case as the factor loadings differ between the two scales (cf. supra) and our relatively low sample size (n=87) makes the results of our factor analysis sample dependent on its context.

We hence decided to sum up all the relevant items (9 out of the 10 original items, excluding SUST_3 and TRAD_3) for each respondent in order to create two new variables: SUST (the sum of all 9 sustainable investment items) and TRAD (the sum of all 9 traditional investment items).

Due to a very small sample size (n=14) for pure investors, we were not able to perform a factor analysis, nor an assessment of the reliability and validity of the scale used. We assumed that their variable structure was similar to that of mixed investors and also created a new variable for them: PTRAD (sum of the 9 items). This variable was then recoded as TRAD (with the addition of the variable TYPE to specify if the investor was mixed or pure) for the testing of our hypotheses **H10a, H10b** and **H10c**.

Now that we have constructed a valid measure of herding, we can move on to the testing of our hypotheses.

X. Hypotheses testing

1. Effect of investment type

H1: There is a difference in the herding bias of a same investor depending on the type of investment (financial or sustainable)

We use a paired t-test to test this hypothesis as we want to make a within group comparison for the herding variable. If we can reject *H0*, there is a significant difference in herding between sustainable and financial investments

H0:No difference in herding between sustainable and financial investments for mixed investors.

H1: There is a difference between the mean of the herding bias for sustainable investments and financial investments for mixed investors

Before moving on with the t-test we had to check whether some conditions were met. We computed the difference "d" found between the two variables TRAD and SUST (measuring the herding bias for a same investor in traditional or sustainable investments respectively). We found no outliers in all values of "d" and an analysis of the QQplot (preferred to the Shapiro test due to our sample size) indicated that the differences "d" follow roughly a normal distribution (Appendix 21) .

The test revealed that there is a significant difference ($p<0.05$) between the herding bias of mixed investors for their sustainable and financial investments (Table 11). We reject *H0* and this validates our first hypothesis **H1**.

We are now interested in the direction of this difference.

H1a: Mixed investors are more subject to a herding bias for their sustainable investments than for their traditional investments

H1b: Mixed investors are more subject to a herding bias for their traditional investments than for their sustainable investments

We see that the t-statistic between both groups is of -5.42 points. This means that mixed investors are more subject to herding for their traditional investments than for their sustainable investments. Furthermore, the computation of Cohen's d indicates that this is a medium effect size. We validate **H1b.**

Table 11:Results H1,H1a and H1b

Paired t-test within mixed investors group

.y.	group1	group2	n1	n2	statistic	df	p
herding	SUST	TRAD	87	87	-5.42	86	0.000000531

Computation of Cohen's d

.y.	group1	group2	n1	n2	effsize	magnitude
herding	SUST	TRAD	87	87	-0.581	moderate

2. Influence of personal characteristics

Now that we have established that there exists a difference in herding bias for a same investor depending on the type of investment he decides for, we can test out the second part of our hypotheses. We will see how socio-demographic and investor profile factors impact the herding bias in general (main effect of each factor) as well as whether there is an interaction between the personal characteristic factor and the investment type (i.e. whether the effect of personal characteristics depends on investment type). Both these tests will be computed for all personal characteristics factors (4 socio-demographic and 4 investment behavior) with the help of Mixed

Model ANOVA's (a combination of a between unit ANOVA based on personal characteristics and of a within unit ANOVA based on investment type).

For every Mixed Model ANOVA we will perform the same preliminary checks on the data: identification of outliers in each cell of the design using the Inter-Quantile Range (or IQR) outliers identifying method using boxplots (Bakker & Wicherts, 2014), assumption of a normal distribution of herding in each cell of the design through the visual analysis of QQ plots as our sample size is bigger than n=50, the Levene test of variance homogeneity of herding between groups and the Box's M-test for homogeneity of covariances of the between-subject factor . The Mauchly test of sphericity was not needed as our within analysis is performed on only two dimensions.

For the sake of this study we have decided to only exclude outliers considered extreme (outside the range of Q1-3*IQR and Q3+3*IQR) as opposed to mild outliers. This choice was made for various reasons. First, we believe we are in the presence of interesting outliers (as opposed to error outliers), data points that contain valuable information (Aguinis et al., 2013) and who are actual values of the investigated population (Bakker & Wicherts, 2014). Their removal would hence lead to biased results. Second, the grouping of our data according to personal characteristics for a within-between analysis reduces the compared sample sizes (e.g. n=87 to be distributed over 5 education categories). Smaller sample sizes may produce an unrepresentative small IQR and identify more outliers than necessary. Furthermore, when the sample size is already reduced, dropping outliers would result in the loss of valuable information. Nonetheless, as even mild outliers can affect conclusions, we include all outliers identified in Appendix.

2.1. Gender

We want to test two hypotheses for the effect of gender:

H2: Women are more subject to herding than men

This is done with the help of the following test

H0: No difference in herding depending on the gender

H1: Difference in herding depending on the gender

And **H2a: Being a woman increases herding in the case of sustainable investments** which we test with

H0: The effect of gender on herding does not depend on the type of investment

H1: The effect of gender on herding depends on the type of investment

Our preliminary checks reported no outliers and the visual analysis of the QQ plots (Appendix 22) indicated that the data was approximately normally distributed for both male and female in both investment types as the datapoints fall approximately close to the reference line. The Levene test of variance homogeneity (Appendix 23) indicated that there was homogeneity of variances between groups for each investment type (both p-values>0.05). Finally, the Box's M-test (Appendix 23) assessed that the covariances are equal (p>0.001).

The output of our ANOVA (Table 12) indicates that only the main effect of investment_type (p-value=0.007) is significant on the herding bias, in line with what we found in our first hypothesis. Gender has no main effect on the herding bias nor does the interaction between gender and investment type significantly impact the herding bias. This means we cannot reject the *H0* of both tests and we do not validate **H2** nor **H2a**. This is quite surprising as gender has found to be of significant influence on biases (Kumar & Goyal, 2015; Barber and Odean, 2001;Da Costa et al., 2008;Lin, 2012) even if the direction of the influence is debated.

Table 12: ANOVA Table (type III tests) : Gender and investment_type

	Effect	DFn	DFd	F	p	p<.05	ges
1	Gender	2	84	0.231	0.794		0.004
2	investment_type	1	84	7.640	0.007	*	0.023
3	Gender:investment_type	2	84	0.808	0.449		0.005

2.2.Age

We want to test two hypotheses for the effect of age:

H3: Young people are more subject to herding

This is done with the help of the following test

H0: No difference in herding depending on age

H1: Difference in herding depending on age

And **H3a: Being young increases herding in the case of sustainable investments** which we test with

H0: The effect of age on herding does not depend on the type of investment

H1: The effect of age on herding depends on the type of investment

We identified four outliers (Appendix 24) through our preliminary checks, however none were considered extreme and hence all were kept for our analysis. The visual analysis of the QQ plots (Appendix 25) confirmed the presence of four outliers for the 26-45 age category (3 above the expected distribution and one below). The rest of the data was roughly normally distributed (datapoints close to reference line). The Levene test and Box's M-test (Appendix 26) indicated that there was homogeneity of variance (p>0.05) and homogeneity of covariance (p>0.001) between age category groups.

If we take a look at the results of our Mixed Model ANOVA (Table 13) within investment type and between age categories, we find that the main effect of investment type (p-value= 1.31e-05), the main effect of age (p-value=1.70e-02) and the interaction effect between age and investment type (p-value=4.00e-03) are all statistically significant.

Table 13: ANOVA Table (type III tests) : Age and investment_type

	Effect	DFn	DFd	F	p	p<.05	ges
1	Age	3	83	3.583	1.70e-02	*	0.088
2	investment_type	1	83	21.479	1.31e-05	*	0.063
3	Age:investment_type	3	83	4.739	4.00e-03	*	0.042

As the main effect of age is significant, we can validate **H3**. However due to the presence of a significant two-way interaction, we cannot interpret the main effect individually and **H3** will have to be nuanced, which is where the test of **H3a** intervenes. We first looked at the effect of age for each investment type with the help of a one-way ANOVA (Table 14). We found that age only had a significant impact on the herding bias for traditional investments. This rejects the *H0* of our second test, the effect of age on herding depends on the type of investment.

Table 14:One-way ANOVA: effect of age for each investment type

	investment_type	Effect	DFn	DFd	F	p	\`p<.05\`	ges	p.adj
1	SUST	Age	3	83	0.556	0.646		0.02	1
2	TRAD	Age	3	83	7.26	0.000221	*	0.208	0.000442

The next step was then to find out how this significant impact of age on the herding bias for traditional investments translated among the different age categories. This was done through a pairwise t-test comparison of the herding bias between different age categories depending on the investment type (Table 15).

Table 15:Pairwise t-test age categories

	investment_type	.y.	group1	group2	n1	n2	p	p.signif	p.adj	p.adj.signif
1	SUST	herding	<26	26-45	14	26	0.3	ns	1	ns
2	SUST	herding	<26	46-65	14	41	0.325	ns	1	ns
3	SUST	herding	26-45	46-65	26	41	0.877	ns	1	ns
4	SUST	herding	<26	66+	14	6	0.975	ns	1	ns
5	SUST	herding	26-45	66+	26	6	0.427	ns	1	ns
6	SUST	herding	46-65	66+	41	6	0.463	ns	1	ns
7	TRAD	herding	<26	26-45	14	26	0.000368	***	0.00221	**

8	TRAD	herding	<26	46-65	14	41	0.0000201	****	0.000121	***
9	TRAD	herding	26-45	46-65	26	41	0.503	ns	1	ns
10	TRAD	herding	<26	66+	14	6	0.00371	**	0.0223	*
11	TRAD	herding	26-45	66+	26	6	0.619	ns	1	ns
12	TRAD	herding	46-65	66+	41	6	0.896	ns	1	ns

The results of the t-test indicate that the differences of herding between age categories are only significant in the comparison of the youngest category of investors to the older categories. A subsequent one-tailed pairwise t-test (Appendix 27) indicates that older investors are less subject to herding than younger investors. We can conclude that the differences between age categories are only significant when comparing the youngest group of investors to their older counterparts. However, the differences between older age categories are not significant (e.g. between the 26-45 and 46-65 age categories). Investors under 26 years old are significantly more subject to herding than older investors for their traditional investments.

Looking at what we hypothesize previously, the results only partially verify our **H3**. In line with what was found in the literature (Kumar & Goyal, 2016; Lin, 2011), age has an impact on herding. However, this effect depends on the type of investment. We find another interaction than the one we hypothesized in **H3a**. Indeed, the impact of age on herding depends on the type of investment but this relationship holds true for traditional investments (as opposed to sustainable investments). We had expected both effects to reinforce each other but it does not seem to be the case. The literature on the effect of age on investment decision making was only conducted in financial investment decisions which might explain why the relationship only holds in traditional investment context. Ultimately, we conclude that **being young increases the herding bias of a mixed investor in the case of a traditional investment.** As there was no consensus in the literature on what was considered a "young" investor we specify that young investors are investors under the age of 26.

2.3.Education

We want to test the following hypotheses for the effect of education:

H4: Higher educated investors are less subject to herding

This is done with the help of the following test

H0: No difference in herding depending on education

H1: Difference in herding depending on education

And **H4a: Being highly educated increases herding in the case of sustainable investments** as well as **H4b: Being highly educated decreases herding in the case of sustainable investments** which we test with

H0: The effect of education on herding does not depend on the type of investment

H1: The effect of education on herding depends on the type of investment

Our preliminary checks reported no outliers and the visual analysis of the QQ plots (Appendix 28) indicated that the data roughly followed a normal distribution for the different education levels. The Levene test and the Box's M-test (Appendix 29) indicated that the variance (both p-values>0.05) and covariance (p-value=0.493>0.001) were homogeneous between education level groups for each investment type.

The output of our ANOVA (Table 16) indicates that only the main effect of investment_type (p-value=0.016) is significant on the herding bias. Education level has no main effect on the herding bias. We hence cannot reject the *H0* of our first test. Nor reject the *H0* of our second test, as the interaction is not significant. We do not validate any of the **H4, H4a** and **H4b** hypothesis.

There can be two explanations to this lack of hypotheses validation. The first is based on literature findings. Zaidi and Tauni (2012), as opposed to the majority of authors, found that education level has no impact on the tendency to be subject to a bias. The second explanation can be the education level repartition in our sample, as master's graduates are overly represented.

Table 16:ANOVA Table (type III tests) : Education and investment_type

	Effect	DFn	DFd	F	p	p<.05	ges
1	Education	3	83	1.334	0.269		0.034
2	investment_type	1	83	5.992	0.016	*	0.019
3	Education :investment_type	3	83	1.327	0.271		0.013

2.4.Income

We want to test the following hypotheses for the effect of income:

H5: Investors with a lower income are more subject to herding

This is done with the help of the following test

H0: No difference in herding depending on income

H1: Difference in herding depending on income

And **H5a: Having a low income increases herding in the case of sustainable investments** as well as **H5b: Having a low income increases herding in the case of financial investments** which we test with

H0: The effect of income on herding does not depend on the type of investment

H1: The effect of income on herding depends on the type of investment

No outliers were found for the herding values of investors across different income levels. The QQ plots (Appendix 30) indicate a roughly normal distribution of the data. However, in this case both the Levene test and the Box's M-test (Appendix 31) indicated that the variance (p-value for the sustainable investment type = 0.0272<0.05) and covariance (p-value= 0.000580<0.001) are not homogeneous between the different income levels. This makes the interpretation of a mixed model ANOVA subject to biasedness. We resolve the violation of the homogeneity of variance by carrying two one-way Welch ANOVA's between the different income groups. The use of two one-way ANOVA instead of a mixed model ANOVA has as downside that it does not compute an interaction effect between income and investment type. Furthermore, we will only get results on group differences per investment type rather than over the entire population.

The results of the two one-way Welch ANOVA (Table 17) indicate that for neither of the investment types the mean difference between income groups is statistically significant (p-value of 0.165 in the case of traditional investments and p-value of 0.395 for sustainable investment). As the main effect of income is insignificant in both cases, we cannot reject the *H0* of our tests and we do not validate any of **H5**, **H5a** or **H5b**. As was already the case for gender and education, our findings differ with what was found in the literature, in our case income has no effect on herding.

Table 17:One-way Welch ANOVA income groups

Welch ANOVA herding traditional investment: between income groups

.y.	n	statistic	DFn	DFd	p	method
TRAD	87	1.84	3	25.6	0.165	Welch ANOVA

Welch ANOVA herding sustainable investment: between income groups

.y.	n	statistic	DFn	DFd	p	method
SUST	87	1.03	3	26.7	0.395	Welch ANOVA

2.5.Strategy

We want to test the following hypotheses for the effect of strategy:

H6: Active investors are more subject to herding

This is done with the help of the following test

H0: No difference in herding depending on strategy

H1: Difference in herding depending on strategy

And **H6a: The effect of investment strategy on herding depends on the type of investment** which we test with

H0: The effect of strategy on herding does not depend on the type of investment

H1: The effect of strategy on herding depends on the type of investment

We identified two outliers (Appendix 32) through our preliminary checks, though not considered extreme, and were hence kept for our analysis. The visual analysis of the QQ plots (Appendix 33) confirmed the presence of two outliers for passive investors investing financially. The rest of the data was roughly normally distributed (datapoints close to reference line). The Levene test (Appendix 34) indicated that the assumption of homogeneity of variance was violated for sustainable investments (p-value of 0.0194<0.05). The Box's M-test (Appendix 34) was not significant (p value of 0.00877>0.001) and the homogeneity of covariance was not violated. As we did with H5 (on income) we resolve the violation of the homogeneity of variance by carrying two one-way Welch ANOVA's between the different strategy groups. No interaction effect will be computed.

The results of the one-way Welch ANOVA's (Table 18) tell us that there is a significant difference (p-value=0.007) between the herding bias of active and passive investors in the case of sustainable investments. This relationship does not hold for traditional investments (p-value=0.344). We validate **H6a** according to which the effect of investment strategy on herding depends on the type of investment. We are now interested in knowing in which direction this difference is found for sustainable investments.

Table 18:Results one-way Welch ANOVA strategies

Welch ANOVA herding traditional investment: between strategies

.y.	n	statistic	DFn	DFd	p	method
TRAD	87	0.91	1	85.0	0.344	Welch ANOVA

Welch ANOVA herding sustainable investment: between strategies

.y.	n	statistic	DFn	DFd	p	method
SUST	87	7.68	1	82.9	0.007	Welch ANOVA

Through two one-tailed t-tests (Table 19) we find that the herding bias of passive mixed investors is greater than the herding bias of active mixed investors in the case of sustainable investments. We completely reject **H6** according to which active investors were more subject to herding. Although our conclusion only applies to sustainable investments, the fact that we find that passive investors are more subject to herding can be counterintuitive with regards to what was found in the literature previously.

Table 19:One-tailed t-tests strategy

One-tailed t-test, alternative=less

.y.	group1	group2	n1	n2	p	p.signif	p.adj	p.adj.signif
SUST	ACTIVE	PASSIVE	48	39	0.995	ns	0.995	ns

One-tailed t-test, alternative=greater

.y.	group1	group2	n1	n2	p	p.signif	p.adj	p.adj.signif
SUST	ACTIVE	PASSIVE	48	39	0.00455	**	0.00455	**

2.6.Experience

We want to test the following hypotheses for the effect of experience:

H7: More experienced investors are less subject to herding

This is done with the help of the following test

H0: No difference in herding depending on experience

H1: Difference in herding depending on experience

And **H7a: The effect of experience on herding depends on the type of investment**

which we test with

H0: The effect of experience on herding does not depend on the type of investment

H1: The effect of experience on herding depends on the type of investment

We identified four outliers (Appendix 35) through our preliminary checks. As none of them were considered extreme, we kept them in our analysis. The visual analysis of the QQ plots (Appendix 36) confirmed the presence of these outliers, but the rest of the data was roughly normally distributed (datapoints close to reference line). The Levene test and Box's M-test (Appendix 37) indicated that the assumptions of homogeneity of variance and covariance were satisfied. The p-values of the Levene test for both investment types were of 0.317 and 0.710 (greater than 0.05) and the p-value of the Box's M-test was of 0.643 (greater than 0.001).

Looking at the results of our Mixed Model ANOVA (Table 20) within investment type and between experience, we find that the main effect of investment type (p-value= 7.73e-06), the main effect of experience (p-value=6.23e-04) and the interaction effect between experience and investment type (p-value=1.30e-02) are all statistically significant.

Table 20:ANOVA Table (type III tests) : Experience and investment_type

Effect	DFn	DFd	F	p	p<.05	ges

1	Experience	4	82	5.435	6.23e-04	*	0.160
2	investment_type	1	82	22.808	7.73e-06	*	0.073
3	Experience:investment_type	4	82	3.362	1.30e-02	*	0.044

The main effect of experience is significant which means we can already reject the *H0* of our first test and validate **H7.** As the two-way interaction is significant, we have to perform post-hoc tests to see how the effects interact with each other. We first looked at the effect of experience for each investment type with the help of a one-way ANOVA (Table 21). We found that experience had a significant impact on the herding bias for both traditional and sustainable investments.

Table 21:One-way ANOVA: effect of experience for each investment type

	investment_type	Effect	DFn	DFd	F	p	`p<.05`	ges	p.adj
1	SUST	Experience	4	82	2.84	0.029	*	0.122	0.058
2	TRAD	Experience	4	82	6.78	0. 0000911	*	0.249	0.000182

We then proceeded through a pairwise t-test between different experience levels depending on the investment type (Table 22). In order to make the test work, we had to exclude the only respondent with an experience of up to 1 year in our sample.

Table 22:Pairwise t-test experience levels

	investment_type	.y.	group1	group2	n1	n2	p	p.signif	p.adj	p.adj.signif
1	SUST	herding	1-3 years	3-5 years	21	7	0.00631	**	0.0379	*
2	SUST	herding	1-3 years	5-10 years	21	12	0.178	ns	1	ns
3	SUST	herding	3-5 years	5-10 years	7	12	0.128	ns	0.766	ns
4	SUST	herding	1-3 years	more than 10 years	21	46	0.0283	*	0.17	ns
5	SUST	herding	3-5 years	more than 10 years	7	46	0.121	ns	0.727	ns
6	SUST	herding	5-10 years	more than 10 years	12	46	0.767	ns	1	ns
7	TRAD	herding	1-3 years	3-5 years	21	7	0.00742	**	0.0445	*
8	TRAD	herding	1-3 years	5-10 years	21	12	0.00123	**	0.00738	**
9	TRAD	herding	3-5 years	5-10 years	7	12	0.978	ns	1	ns
10	TRAD	herding	1-3 years	more than 10 years	21	46	0.0000027	****	0.0000162	****
11	TRAD	herding	3-5 years	more than 10 years	7	46	0.75	ns	1	ns
12	TRAD	herding	5-10 years	more than 10 years	12	46	0.72	ns	1	ns

The results of the t-test indicate that the differences of herding between experience levels are only significant in the comparison of the least experienced category of investors to the older categories. A subsequent one-tailed pairwise t-test (Appendix 38) indicates that less experienced investors are more subject to herding than more experienced investors. This effect is only valid when comparing the group of investors with 1-3 years of experience compared to the more experienced groups. Among more experienced groups (e.g. between 3-5 years and more than 10 years) this difference does not hold. Furthermore, the difference between less and more experienced investors holds for all categories only in the case of traditional investments.

For sustainable investments, the difference is only significant when comparing 1-3 years of experience and 3-5 years. We reject *H0* of our second test as well and validate **H7a**. We can conclude that there seems to be a learning effect of herding implied by the level of experience of an investor. This learning effect is striking for traditional investments, where reaching 3 years of investment experience seems to significantly decrease the herding of an investors. Whereas for sustainable investments this effect is less clear.

2.7.Size

We want to test the following hypotheses for the effect of size:

H8: People investing a small proportion of their wealth are more subject to herding

This is done with the help of the following test

H0: No difference in herding depending on size

H1: Difference in herding depending on size

And **H8a: The effect of size on herding depends on the type of investment**

which we test with

H0: The effect of size on herding does not depend on the type of investment

H1: The effect of size on herding depends on the type of investment

We identified two outliers (Appendix 39) through our preliminary checks, though not considered extreme, and were hence kept for our analysis. The visual analysis of the QQ plots (Appendix 40) showed that the data was roughly normally distributed (datapoints close to reference line). Finally, with p-values of 0.764 (SUST) and 0.104 (TRAD) for the Levene test and of 0.575 for the Box's M-test (Appendix 41) the assumptions of homogeneity of variance and covariance were verified.

Looking at the results of our Mixed Model ANOVA (Table 23) within investment type and between investment sizes, we find that only the main effects of investment type (p-value=1.64e-06) and of size (p-value=2.80e-02) are statistically significant. As there is no interaction effect between size and investment type but a main effect of size, we reject *H0* of our first test, but we cannot reject *H0* of our second test and we do not validate **H8a**.

Table 23:ANOVA Table (type III tests) : Size and investment_type

	Effect	DFn	DFd	F	p	p<.05	ges
1	Size	3	83	3.181	2.80e-02	*	0.076
2	investment_type	1	83	26.646	1.64e-06	*	0.084
3	Size:investment_type	3	83	0.268	8.48e-01		0.003

Now that we know that size has a significant effect on herding irrespective of the investment type, we would like to know in which direction this effect goes. In order to test out **H8** we conduct two one-tailed pairwise t-tests to find out the direction of the impact of size. In table 24 we see that the difference between investment sizes of more than 75% and smaller investment sizes are all statistically significant. The herding level of large investors (>75%) is smaller than that of smaller investors. Among smaller investors, the differences are not statistically significant. **H8** is hence partially verified but it is more accurate to rephrase it as: **Mixed investors investing a large proportion of their wealth are less subject to herding**

Table 24:One-tailed t-tests effect of size

One-tailed pairwise t-test (alternative=less): size

	.y.	group1	group2	n1	n2	p	p.signif	p.adj	p.adj.signif
1	herding	<25%	>75%	48	50	0.00197	**	0.0118	*
2	herding	<25%	25-50%	48	32	0.657	ns	1	ns
3	herding	>75%	25-50%	50	32	0.999	ns	1	ns
4	herding	<25%	50-75%	48	44	0.33	ns	1	ns
5	herding	>75%	50-75%	50	44	0.992	ns	1	ns
6	herding	25-50%	50-75%	32	44	0.214	ns	1	ns

One-tailed pairwise t-test (alternative=greater): size

	.y.	group1	group2	n1	n2	p	p.signif	p.adj	p.adj.signif
1	herding	<25%	>75%	48	50	0.998	ns	1	ns
2	herding	<25%	25-50%	48	32	0.343	ns	1	ns
3	herding	>75%	25-50%	50	32	0.00147	**	0.00882	**
4	herding	<25%	50-75%	48	44	0.67	ns	1	ns
5	herding	>75%	50-75%	50	44	0.00847	**	0.0423	*
6	herding	25-50%	50-75%	32	44	0.786	ns	1	ns

2.8.Horizon

We want to test the following hypotheses for the effect of horizon:

H9: Investors who plan on retrieving a significant proportion of their capital from the markets in a near future are more subject to herding

This is done with the help of the following test

H0: No difference in herding depending on investment horizon

H1: Difference in herding depending on investment horizon

And **H9a: The effect of horizon on herding depends on the type of investment**

which we test with

H0: The effect of investment horizon on herding does not depend on the type of investment

H1: The effect of investment horizon on herding depends on the type of investment

Our preliminary checks reported four outliers (Appendix 42) that were kept in the analysis. Apart from the outliers, the visual analysis of the QQ plots (Appendix 43) indicated that the rest of the data was approximately normally distributed for all investment horizons in both investment types as the datapoints fall approximately close to the reference line. The Levene test of variance homogeneity (Appendix 44) indicated that there was homogeneity of variances between groups for each investment type (both p-values>0.05). Finally, the Box's M-test (Appendix 44) assessed that the covariances are equal (p>0.001).

The output of our ANOVA table (Table 25) indicates that only the main effect of investment_type (p-value<0.05) is significant on the herding bias. This holds among all horizon groups. Horizon has no main effect on the herding bias nor does the interaction between horizon and investment type significantly impact the herding bias. This means we do not reject *H0* of either tests and we do not validate **H9** or **H9a**. This finding does not correspond to what we expected from the literature.

Table 25: ANOVA Table (type III tests) : Horizon and investment_type

	Effect	DFn	DFd	F	p	p<.05	ges
1	Horizon	3	83	2.302	8.30e-02		0.057
2	investment_type	1	83	18.931	3.83e-05	*	0.060
3	Horizon:investment_type	3	83	0.433	7.30e-01		0.004

3. Investment and investor type

Finally, we want to know whether the herding bias is impacted by the type of investor (pure or mixed) or only by the type of investment. If it is impacted only by the type of investment, then there should not be any difference in herding between pure investors investing financially and mixed investors investing financially. This part tests out **H10a**, **H10b** and **H10c**. As we did not gather data on pure sustainable investors, we are unable to test **H11a**, **H11b** and **H11c**.

In order to test our set of hypotheses we performed a t-test for independent samples between the pure (n=14) and mixed (n=87) investors. Prior to the t-test we checked for the presence of outliers (none identified) as well as for a normal distribution of the TRAD variable among investor categories. The analysis of the QQplot (Appendix 45) indicated that the data was roughly normally distributed. Finally, the Levene test of variance (Appendix 46) homogeneity failed to reject the H0 hypothesis, with a p-value of 0.718 (<0.05).

The result of the t-test between Mixed and Pure investors indicate that there is a statistically significant (p-value<0.05) difference in herding bias between both samples (Table 26). The statistic of 5.86 tells us that this difference is positive between mixed and pure investors (i.e.

mixed investors are more subject to herding) and the computation of Cohen's d (d=1.69) indicates that this effect is large.

Table 26: Results H10a, H10b and H10c

T-test for independent samples

.y.	group1	group2	n1	n2	statistic	df	p
TRAD	Mixed	Pure	87	14	5.86	99	0.0000000597

Computation of Cohen's d

.y.	group1	group2	n1	n2	effsize	magnitude
TRAD	Mixed	Pure	87	14	1.69	large

This allows us to validate **H10c** according to which the herding level of pure financial investors is lower than the herding level of mixed investors investing financially.

CHAPTER 3: Discussion

There are some key takeaways from the results of our study. First, we find that the herding bias of **mixed investors** indeed depends on the type of investment. Mixed investors are more subject to herding for traditional investments than for sustainable investments. Second, **pure financial investors** are less subject to herding than mixed investors. Third, most socio-demographic characteristics (except from age) do not impact the herding behavior. Investment habit characteristics however (except from investment horizon) do impact herding tendency. The impact of some of these individual characteristics however depends on the type of investment. Finally, herding appears to be better represented by a series of sub-factors rather than just one composite variable.

The most important finding is that the herding bias of mixed investors depends on the type of investment. We hence contribute to the emerging literature on the fact that behavioral biases not only depend on trait characteristics of individuals but also on the context in which they take a decision. This difference is significant even for decisions who appear to be taken in a similar context such as investment decisions. Investors who have both financial and sustainable investments in their portfolios are more subject to herding for their financial investments than for their sustainable investments. We believe this is likely due to the motivation behind sustainable investments. As they are predominantly made in response to social pressure or to procure a sense of "doing good", their performance matters less. As their performance does not matter as much, investors do not feel the need to take an optimal allocation decision and hence do not use the heuristics (such as the herding bias) they use for their traditional investment decisions. Another possibility is that sustainable investments are made predominantly in accordance with one's values. In that case the alignment to the values matters more than the performance and hence investors do not tend to herd. Finally, the last explanation could be that sustainable investments matter more to individuals than financial investments. As they matter more, investors are less inclined to use shortcuts in their decisions and relying on their intuitive system (System 1). Due to the importance of the decision taken they are able to use their reasoning system (System 2) and hence do not rely on biases.

Moreover, the high herding levels for mixed investors in financial investments are not found for pure investors who invest only in financial investments. We believe this is due to the decreasing number of investors interested only in financial profit. The vast majority of retail investors are now turning more and more to sustainable investments which leaves a smaller sample of investors in the purely financial category. These investors tend to be more experienced, wealthier, older and trade more actively. This finer segmentation of pure investors might explain the difference found in herding. The profile of such investors are people who typically spend a lot of time investing and who decide to use a significant proportion of time and energy in it. They are hence less subject to heuristics when making an investment decision, which is why we found that they are less subject to herding. It is also interesting to note that we have not found the existence of pure sustainable investors. However, as developed previously, we believe that that is due to our strict definition of pure investors.

Regarding the trait differences we expected to find in determining herding it is interesting to note that all but one of the socio-demographic traits are non-significant in explaining differences in herding. This is rather surprising considering the abundant literature on the topic. We believe this lack of socio-demographic significance can be explained by the apparent demographic clustering of our sample (cf. supra) and the relatively small sizes of the different categories for each socio-demographic trait. Future studies with larger samples could help determine if socio-demographic differences are indeed not significant in the case of herding or if our findings are biased by our sample. Investment habits traits however are found to be more relevant in explaining herding differences.

The individual traits that are not significant in explaining herding differences are gender, income, education and investment horizon. The individual traits that are found to be significant tend to depend on the investment type. The only determining traits for explaining herding differences in sustainable investments are investment strategy and size as well as investor experience (although weakly). For herding differences in financial investments, age is also found to be significant and the impact of experience is bigger. Investors investing a significant portion of their wealth (more than 75%) are less subject to herding irrespective of the type of investment. We can hypothesize that, as the investment decision concerns a large part of their capital, investors are more careful in their decision process and try to be more rational. A mistake in judgement would cost them a significant portion of their wealth. Investors investing passively are found to be more subject to herding in sustainable investments. A possible explanation to this finding may be that investors who invest more passively are also less experienced or less knowledgeable on financial markets. These latter two characteristics are found to be linked to herding. Young investors (under 26) are also more subject to herding than their older counterparts but only for financial investments. It is reasonable to assume that younger investors are also less experienced on financial markets, which makes them more sensitive to biases and heuristics in their decisions. If they aim for financial profit through their investment, they try to adopt the best strategy to generate returns, as they are novices, they tend to follow what others do. Regarding sustainable investments however they tend to focus less on generating returns and hence they do not aim for the best strategy, which makes the use of a herding heuristic unnecessary. Finally, there seems to be a learning effect of investors over the years. After an initial learning period of up to 3 years, investors are less subject to herding. This learning effect is particularly salient for traditional investments but less for sustainable investments.

Nonetheless we believe that some of these variables are fairly correlated (e.g. age and experience) which makes the identification of a single effect difficult.

Ultimately the decision process of an investor for both types of investment clearly appears to be different, as attested by the observed differences in herding as well as the mitigating effect of personal characteristics on herding that depend also on the type of investment.

Finally, our study hypothesized that herding was better represented through sub-factors rather than one composite variable. This was confirmed by our EFA's. However, the number and grouping of these factors is different than what we had originally thought. First of all, our EFA's concluded that 3 sub-categories (factors) would reflect herding the best (rather than 5). Second, we found that the factors representing herding depended on the type of investment. For traditional investment, whether the relationship to the other was personal (relatives, friends or peers) or not had no impact on the factor of herding whereas it mattered for sustainable investments. In sustainable investments, peers were more associated with the authority of experts and media whereas for traditional investments peers were more associated with friends and relatives' impact. The behavior of other unknown investors was associated with herding behavior for traditional investments and not for sustainable investments. The herding factor driven by the reaction to a loss however appeared to be similar between both types of investments.

PART III: Final conclusions

I. Limitations and future research

The limited scope and resources available for our study resulted in some limitations that are important to note.

Regarding **the scope of the study.**

Our original aim was to research the effect of the context on one's investment decision process. We were interested in scrutinizing whether the type of investment (sustainable or financial) influenced an individual's decision process. We limited ourselves to the analysis of the herding behavior. We hence cannot infer (yet) a general effect of investment type on an overall decision process. Future research incorporating the analysis of a higher number of biases with a similar methodology would allow to conclude for an overall effect of investment type.

Moreover, we focused ourselves on intentional herding, measuring the latter construct through a multi-item scale. This allowed us to conclude for the presence of herding behavior or not, but it does not give us information on the reasons behind herding, whether the herding bias observed is rational or non-rational. Even though herding is typically considered non-rational, there are some situations in which it can be considered rational. Future research with a more qualitative approach, questioning more the intention and reasoning of investors would allow to find a conclusion on that question.

Furthermore, we have deliberately focused on the investment allocation decision (the "how") and not the choice of investment decision (the "why"). We have hence neglected the part on why people invest sustainably/financially and in which proportions. We believe that the literature on the question is profuse. Nonetheless we consider the possibility that the two decisions interact more with each other. The factors that encourage investors to opt for SRI such as personal ethics or investment philosophy influences on herding intensity later on. Future research linking more both decisions would be of interest.

Finally, we have followed the suggestion in the literature (Diouf et al., 2016; Dumas & Louche, 2016; Pasewark & Riley, 2010) to address the category of mixed investors (i.e. investors invested in both financial and sustainable investments). The segmentation criteria adopted in our study led to a highly represented “mixed” investors category and little representation of “pure” investors. The “mixed” category also encompassed a large spectrum of possibilities that were considered equally “mixed” in our study. Future research allowing for a more granular segmentation of investors would allow for more nuanced conclusions and reflect the reality of investor diversity much better.

Considering the **methodology used in our study**.

First, we used a within-subject design to assess herding differences within a population. This had the advantage of requiring a much smaller sample of answers. However, within-subject designs face the problem that asking the same questions to a same respondent twice (although framed differently and completely randomized) require a strong assumption of the capacity of the respondent to differentiate correctly between both questions sets (i.e. coherence rationality). (Aczel et al., 2015)

Second, the use of a survey to collect primary data can result in a social desirability bias of the respondent (Figureau et al., 2020). This bias was mitigated by the use of an anonymous online survey, but it does not guarantee its absence.

Finally, our sampling method resulted in an apparent clustering of our sample population. Future research with more resources to collect data might be able to palliate this problem and improve the generalizability of our findings.

II. Literature contribution and societal implications

Our study contributes to the literature by improving the understanding of the investment decision process experienced by individuals with portfolios composed of both sustainable and traditional investments. We find evidence that this investment decision process (at least the use of a herding bias) can vary for a same individual depending on the type of investment he is looking at. Furthermore, we build on the literature looking at the influence of personal characteristics on the herding behavior. We contribute by finding that investment habits more than socio-demographic traits influence the propensity to be subject to the herding bias. Moreover, the effect of these individual characteristics seem to depend on the type of investment, they are more present for traditional investments.

We see three potential societal implications to the results of our study. First of all, for financial advisors dealing with mixed investors. Knowing that their clients have a different decision making process depending on the type of investment, means they should adapt the information that they give to investors. Secondly, herding behavior is believed to cause bubbles and crashes on financial markets. The share of sustainable investments is increasing on these markets. As herding is less present for sustainable investments, will that result in less bubbles and crashes on financial markets in the future? Finally, framing something as sustainable or not (which we have applied to investments) results in herding behavior differences for a same individual. Could this finding be applied to other decisions in society as well? For instance, we can imagine that the herding behavior observed in the purchase of a traditional or sustainable consumer good could be different as well.

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Appendix

Appendix 1: Qualtrics survey

Welcome

Hello and welcome to this survey!

My name is Roxane and I am conducting my master's thesis on investment decision making.

Before you get started I wanted to thank you in advance for the time spent answering this survey.
Your participation will tremendously help my research.

The survey consists of only three parts and should last in total between **5 and 8 minutes**. Please answer as accurately and honestly as possible, all answers are anonymous.

Let's get started!

Background Information

Background Information

What is your gender?

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

In which age category are you situated?

- ◯ <26
- ◯ 26-45
- ◯ 46-65
- ◯ 66+

What is the highest education level you have attained?

- ◯ High School
- ◯ Higher education with no degree
- ◯ Bachelor
- ◯ Masters

- 3-5 years
- 5-10 years
- more than 10 years

What % of your total wealth is invested (in securities: stocks, bonds, ETF, funds)?

- <25%
- 25-50%
- 50-75%
- >75%

What is the time horizon in which you expect to need to withdraw a significant portion (more than 30%) of the money in your investment portfolio?

- 0-5 years
- 5-10 years
- 10-30 years
- More than 30 years

Sustainable Investments

Investment Decisions

Sustainable investment refers to creating long-term social, environmental and economic value (sustainable) with your investment by taking other criteria than purely financial into account. The topics covered can include climate change, animal welfare, country or company corruption, working conditions etc. Sustainable investment can take various forms such as impact investing, ethical investing, green investing, ESG investing etc. The way you decide to invest sustainably is open to your own interpretation.

If you think about your investment decisions

	Always	Often	Sometimes	Never
How often do you take financial data into consideration before going for an investment?	○	○	○	○
How often do you consider sustainability aspects before going for an investment?	○	○	○	○

Investment Decision

Investment Habits

Financial Investment

When you evaluate your investment habits, how would you best describe your attitude? (1=Strongly disagree to 5=Strongly agree)

	1 Strongly disagree	**2** Somewhat disagree	**3** Neither agree nor disagree	**4** Somewhat agree	**5** Strong agree
I follow my peers recommendation when choosing a financial product for its financial performance	○	○	○	○	○
I invest in the same return-oriented financial products as my friends and relatives	○	○	○	○	○
My decision to invest relies on my personal impression of the expected performance and fundamental analysis of a company when choosing for a financial product	○	○	○	○	○
I consider information given by the media (news) on the financial fundamentals of a company before an investment decision	○	○	○	○	○
Situation: *I have decided to take a position opposite to the general trend because I believe in the future financial performance of a company. My friends follow the general trend.* If I lose while my friends make profits, I feel disappointed.	○	○	○	○	○
My disappointment after losing money on an investment aimed at the best return diminishes if others have also experienced the same loss	○	○	○	○	○
When I aim for the best risk/return, I follow what I see other investors are doing (e.g. buying or selling, choice of volume) on the financial markets	○	○	○	○	○
I would buy (sell) financial securities whose price have risen (declined) for a period	○	○	○	○	○
I usually follow the advice given by my broker regarding financial investment opportunities	○	○	○	○	○
I make investment decisions based on comments given by financial experts	○	○	○	○	○

Sustainable Investment

When you evaluate your investment habits, how would you best describe your attitude? (1=Strongly disagree to 5=Strongly agree)

	1 Strongly disagree	**2** Somewhat disagree	**3** Neither agree nor disagree	**4** Somewhat agree	**5** Strong agree
I follow my peers recommendation when choosing a financial product for its sustainability contribution	○	○	○	○	○

	1 Strongly disagree	2 Somewhat disagree	3 Neither agree nor disagree	4 Somewhat agree	5 Strong agree
I invest in the same ethical/sustainable financial products as my friends and relatives	○	○	○	○	○
My decision to invest relies on my personal impression of the sustainability performance and values of a company when choosing for a financial product	○	○	○	○	○
I consider information published by the media (news) on the sustainability dimensions of a company before an investment decision	○	○	○	○	○
Situation: *I have decided to take a position opposite to the general trend because I believe in the values and sustainability aspects of a company. My friends follow the general trend.* If I lose while my friends make profits, I feel disappointed.	○	○	○	○	○
My disappointment after losing money on a sustainable investment diminishes if others have also experienced the same loss.	○	○	○	○	○
When I aim for the most ethical or sustainable company, I follow what I see other investors are doing (e.g. buying or selling, choice of volume) on the financial markets	○	○	○	○	○
I would buy (sell) sustainable securities whose price have risen (declined) for a period	○	○	○	○	○
I usually follow the advice given by my broker regarding sustainable investment opportunities	○	○	○	○	○
I make investment decisions based on comments given by sustainability experts	○	○	○	○	○

Powered by Qualtrics

Appendix 2: Demographics of non-used answers

	Non-investors n=39		**Investors with discretionary managed portfolios** n=30	
Gender	Frequency	Percentage	Frequency	Percentage
Male	25	64%	16	53%
Female	14	36%	13	43%
Prefer not to say	0	0%	1	3%
Total	39	100%	30	100%
Age	Frequency	Percentage	Frequency	Percentage
<26	13	33%	2	7%
26-45	17	44%	3	10%
46-65	5	13%	20	67%
66+	4	10%	5	17%
Total	39	100%	30	100%
Education	Frequency	Percentage	Frequency	Percentage
High School	1	3%	2	7%
Higher education with no degree	2	5%	1	3%
Bachelor	5	13%	4	13%
Masters	29	74%	20	67%
PhD	2	5%	3	10%

Total	39	100%	30	100%
Income	**Frequency**	**Percentage**	**Frequency**	**Percentage**
<10.000	8	21%	1	3%
10.000 - 30.000	18	46%	2	7%
30.000 - 50.000	3	8%	4	13%
>50.000	9	23%	21	70%
Prefer not to say	1	3%	2	7%
Total	39	100%	30	100%
Way			**Frequency**	**Percentage**
Guidelines			16	53%
Advisor			13	43%
Both			1	3%
Total			30	100%

Appendix 3: Reclassification of responses "Other" to strategy question

Survey Input	Type of strategy
Follow Daddy Elon's tweets	ACTIVE
a mix of both. some mutual funds for the longer term, complemented by some single stocks	ACTIVE
Both strategies	ACTIVE

Appendix 4: Variables

Q #	Question in survey	Variable name	Answer options	Variable values	Measuring scale	Note
1	What is your gender?	Gender	Male Female Prefer not to say	Idem	Nominal	
2	In which age category are you situated?	Age	<26 26-45 46-65 66+	Idem	Interval	
3	What is the highest education level you have attained?	Education	High School Higher education with no degree Bachelor Masters PhD	Idem	Ordinal	
4	What is your net average annual income (in €)?	Income	<10.000 10.000-30.000 30.000-50.000 >50.000 Prefer not to say	Idem	Interval	
5	Do you invest your own money?	Invest	Yes No	Idem	Nominal	Filtering question #1
6	How do you make investment decisions in securities (stocks and shares, bonds, funds ETFs)?	Way	I let someone make investment decisions for me (e.g. advisor) , I let someone make investment decisions (e.g. advisor) for me based on the guidelines and preferences I give them, I make investment decisions myself	Guidelines, Advisor, Self	Nominal	Filtering question #2, Multiple answers possible

7	How would you best describe your investment strategy?	Strategy	I want to manage my own investment portfolio, picking individual stocks. I spend time checking and rebalancing my portfolio, I tend to track an index or invest in a mutual fund. I rarely check my portfolio and adopt a buy and hold strategy. Other	Active, Passive	Nominal	Answer "other" recoded as Active or Passive
8	For how long have you been investing your money?	Experience	up to 1 year 1-3 years 3-5 years 5-10 years more than 10 years	Idem	Interval	
9	What % of your total wealth is invested (in securities: stocks, bonds, ETF, funds)?	Size	<25% 25-50% 50-75% >75%	Idem	Interval	
10	What is the time horizon in which you expect to need to withdraw a significant portion (more than 30%) of the money in your investment portfolio?	Horizon	0-5 years 5-10 years 10-30 years More than 30 years	Idem	Interval	
11	How often do you take financial data into consideration before going for an investment?	FINANCIAL	Always Often Sometimes Never	Idem	Ordinal	
12	How often do you consider sustainability aspects before going for an investment?	SUSTAINABLE	Always Often Sometimes Never	Idem	Ordinal	
	N/A	Type	N/A	Mixed, Pure	Nominal	Based on answers given in Q11 and Q12
13	When you evaluate your investment habits, how would you best describe your attitude?	N/A	N/A	N/A		
13	I follow my peers recommendation when choosing a financial product for its financial performance	TRAD_1	Strongly disagree Somewhat disagree Neither agree not disagree Somewhat agree Strongly agree	1 2 3 4 5	5-point Likert scale (ordinal/interval)	
13		TRAD_2	Idem	Idem	Idem	
13		TRAD_3	Idem	Idem	Idem	Recoded as 6-TRAD_3
13		TRAD_4	Idem	Idem	Idem	
13		TRAD_5	Idem	Idem	Idem	
13		TRAD_6	Idem	Idem	Idem	
13		TRAD_7	Idem	Idem	Idem	
13		TRAD_8	Idem	Idem	Idem	
13		TRAD_9	Idem	Idem	Idem	
13		TRAD_10	Idem	Idem	Idem	
13		TRAD	N/A	Score between 9 and 45	Interval	Sum of all TRAD items excluding TRAD_3
14	When you evaluate your investment habits, how would you best describe your attitude?	N/A	N/A	N/A		
14		SUST_1	Strongly disagree Somewhat disagree Neither agree not disagree Somewhat agree	1 2 3 4	5-point Likert scale	

		Strongly agree	5	(ordinal/interval)	
14	SUST_2	Idem	Idem	Idem	
14	SUST_3	Idem	Idem	Idem	Recoded as 6-SUST_3
14	SUST_4	Idem	Idem	Idem	
14	SUST_5	Idem	Idem	Idem	
14	SUST_6	Idem	Idem	Idem	
14	SUST_7	Idem	Idem	Idem	
14	SUST_8	Idem	Idem	Idem	
14	SUST_9	Idem	Idem	Idem	
14	SUST_10	Idem	Idem	Idem	
14	SUST	N/A	Score between 9 and 45	Interval	Sum of all SUST items excluding SUST_3

Appendix 5: Pearson correlation matrix traditional investment items

Correlation traditional investment items

	TRAD_1	TRAD_2	TRAD_3	TRAD_4	TRAD_5	TRAD_6	TRAD_7	TRAD_8	TRAD_9	TRAD_10
TRAD_1	1	**0.41**	-0.11	0.18	0.05	0.24	**0.41**	0.11	0.07	0.12
TRAD_2	0.41	1	0.10	0.05	0.22	0.20	**0.34**	0.19	-0.05	0.27
TRAD_3	-0.11	0.10	1	-0.24	0.02	-0.02	-0.16	-0.08	-0.22	0.01
TRAD_4	0.18	0.05	-0.24	1	0.19	0.23	0.13	0.07	**0.38**	**0.30**
TRAD_5	0.05	0.22	0.02	0.19	1	**0.47**	0.13	**0.40**	**0.25**	0.16
TRAD_6	0.24	0.20	-0.02	0.23	0.47	1	**0.37**	**0.36**	0.07	0.05
TRAD_7	0.41	0.34	-0.16	0.13	0.13	0.37	1	0.07	0.11	0.06
TRAD_8	0.11	0.19	-0.08	0.07	0.40	0.36	0.07	1	0.17	0.16
TRAD_9	0.07	-0.05	-0.22	0.38	0.25	0.07	0.11	0.17	1	**0.40**
TRAD_10	0.12	0.27	0.01	0.30	0.16	0.05	0.06	0.16	0.40	1

Appendix 6 : Bartlett's test of sphericity traditional investment

Bartlett's test of sphericity	
$chisq	161.547
$p.value	4,80E-09
$df	45

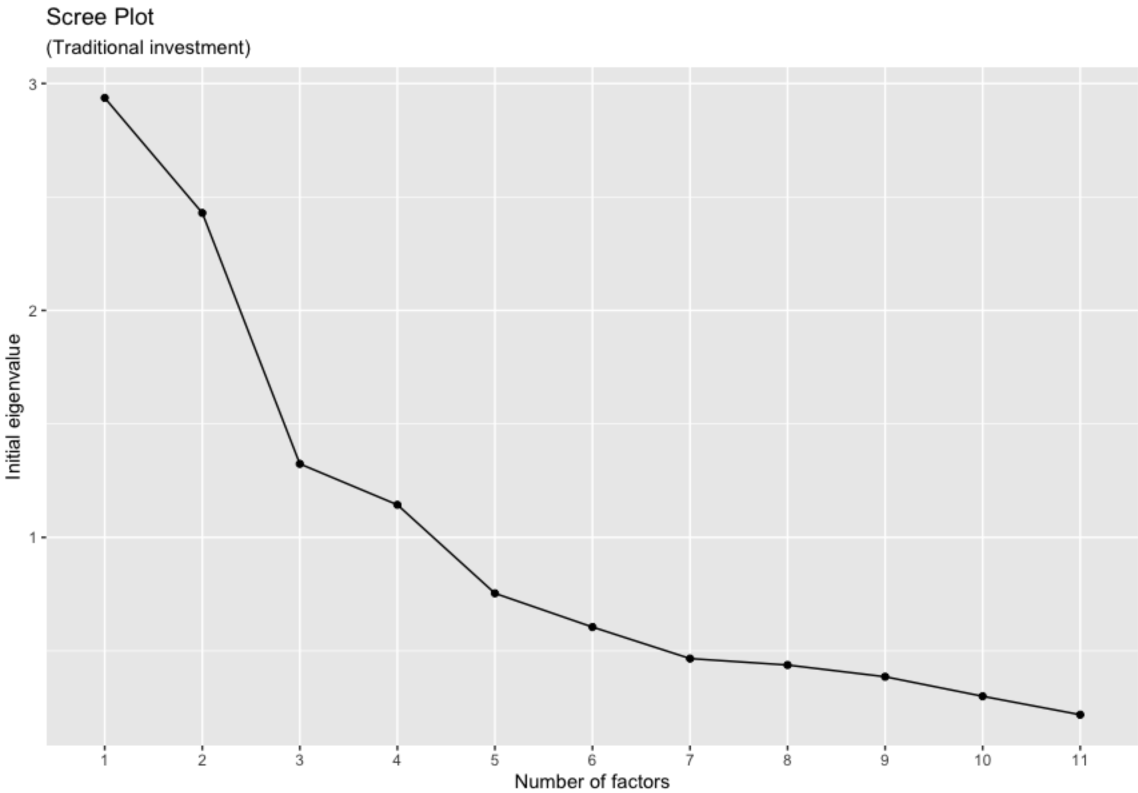
Appendix 7: KMO values traditional investment

Kaiser-Meyer-Olkin factor adequacy
Call:KMO(r=cor(X))
Overall MSA = 0.62

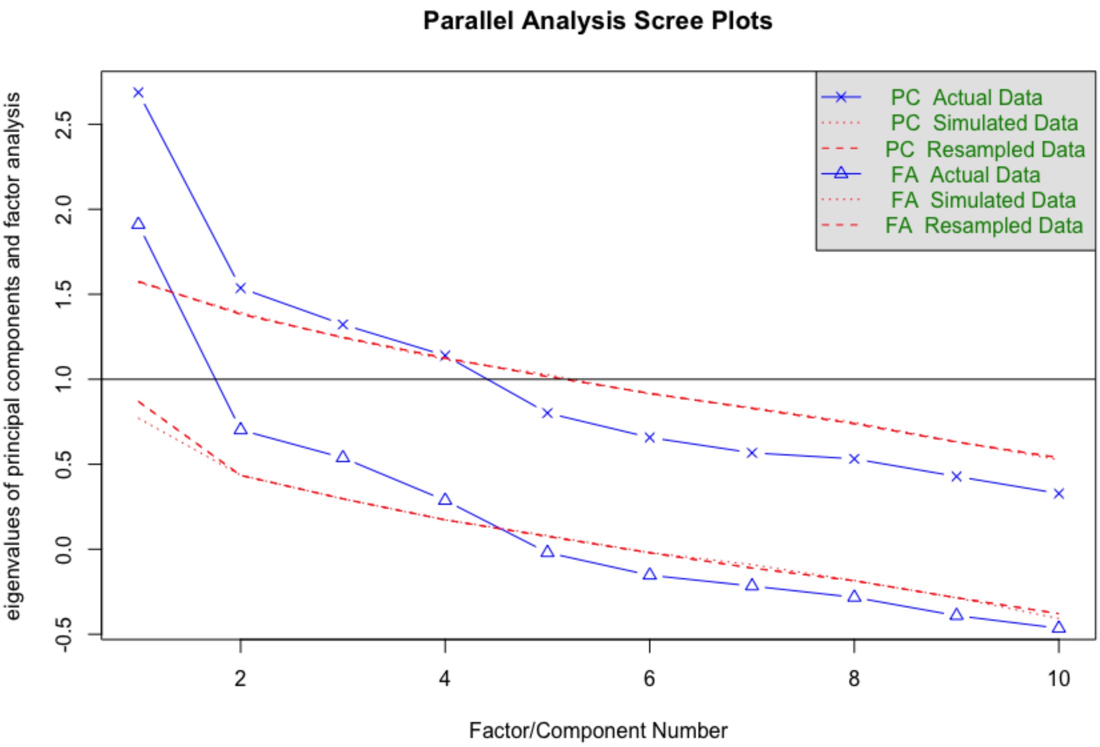
MSA for each item=

TRAD_1	TRAD_2	TRAD_3	TRAD_4	TRAD_5	TRAD_6	TRAD_7	TRAD_8	TRAD_9	TRAD_10
0.69	0.57	0.51	0.68	0.65	0.62	0.63	0.68	0.57	0.59

Appendix 8 : Scree Plot traditional investment



Appendix 9 :Parallel Analysis traditional investment



Appendix 10: R output one-factor model traditional investment

Factor Analysis using method = pa
Call: fa(r=X,nfactors=1,rotate=oblimin,fm=pa)
Standardized loadings (pattern matrix) based upon correlation matrix

	PA1	h2	u2	com
TRAD_1	0.45	0.198	0.80	1
TRAD_2	0.44	0.190	0.81	1
TRAD_3	-0.16	0.025	0.97	1
TRAD_4	0.42	0.172	0.83	1
TRAD_5	0.53	0.282	0.72	1
TRAD_6	0.59	0.350	0.65	1
TRAD_7	0.47	0.223	0.78	1
TRAD_8	0.44	0.195	0.81	1
TRAD_9	0.37	0.137	0.86	1
TRAD_10	0.37	0.137	0.86	1

	PA1
SS loadings	1.91
Proportion Var	0.19

Mean item complexity = 1
Test of the hypothesis that 1 factor is sufficient.

The degrees of freedom for the null model are 45 and the objective function was 1.97 with ChiSquare of 161.55
The degrees of freedom for the model are 35 and the objective function was 1.05

The root mean square of the residuals (RMSR) is 0.12
The df corrected root mean square of the residuals is 0.14

The harmonic number of observations is 87 with the empirical chisquare 120.39 with prob <2.7e-11
The total number of observations was 87 with Likelihood ChiSquare=85.14 withprob < 4.6e-06

Tucker Lewis Index of factoring reliability=0.441
RMSEA index = 0.128 and the 90% confidence intervals are 0.094 0.164
BIC=-71.17
Fit based upon off diagonal values = 0.7
Measures of factor score adequacy

	PA1
Correlation of (regression) scores with factors	0.84
Multiple Rsquare of scores with factors	0.71
Minimum correlation of possible factor scores	0.43

Appendix 11: R output two-factor model traditional investment

Factor Analysis using method = pa
Call: fa(r=X,nfactors=2,rotate=oblimin,fm=pa)
Standardized loadings (pattern matrix) based upon correlation matrix

	PA1	PA2	h2	u2	com
TRAD_1	0.53	-0.03	0.274	0.73	1.0
TRAD_2	0.60	-0.13	0.345	0.66	1.1
TRAD_3	-0.01	-0.25	0.064	0.94	1.0
TRAD_4	0.16	0.47	0.279	0.72	1.2
TRAD_5	0.41	0.23	0.257	0.74	1.6
TRAD_6	0.60	0.06	0.378	0.62	1.0
TRAD_7	0.55	-0.01	0.298	0.70	1.0
TRAD_8	0.35	0.17	0.178	0.82	1.4
TRAD_9	-0.04	0.84	0.697	0.30	1.0
TRAD_10	0.15	0.40	0.211	0.79	1.3

	PA1	PA2
SS loadings	1.68	1.30
Proportion Var	0.17	0.13
Cumulative Var	0.17	0.30
Proportion Explained	0.56	0.44
Cumulative Proportion	0.56	1.00

With factor correlations of

	PA1	PA2
PA1	1.0	0.2
PA2	0.2	1.0

Mean item complexity = 1.2
Test of the hypothesis that 2 factors are sufficient.

The degrees of freedom for the null model are 45 and the objective function was 1.97 with ChiSquare of 161.55
The degrees of freedom for the model are 26 and the objective function was 0.69

The root mean square of the residuals (RMSR) is 0.09
The df corrected root mean square of the residuals is 0.12

The harmonic number of observations is 87 with the empirical chisquare 64.94 with prob <3.5e-05
The total number of observations was 87 with Likelihood ChiSquare=55.5 withprob < 0.00065

Tucker Lewis Index of factoring reliability=0.552
RMSEA index = 0.114 and the 90% confidence intervals are 0.073 0.157
BIC=-60.61
Fit based upon off diagonal values = 0.84
Measures of factor score adequacy

	PA1	PA2
Correlation of (regression) scores with factors	0.84	0.87
Multiple Rsquare of scores with factors	0.71	0.76
Minimum correlation of possible factor scores	0.42	0.52

Appendix 12: R output three factor model traditional investment

Factor Analysis using method = pa
Call: fa(r=X,nfactors=3,rotate=oblimin,fm=pa)
Standardized loadings (pattern matrix) based upon correlation matrix

	PA3	PA1	PA2	h2	u2	com
TRAD_1	-0.08	0.74	0.05	0.531	0.47	1.0
TRAD_2	0.19	0.51	-0.11	0.330	0.67	1.4
TRAD_3	0.12	-0.11	-0.30	0.099	0.90	1.6
TRAD_4	0.02	0.17	0.50	0.305	0.69	1.2
TRAD_5	0.81	-0.08	0.05	0.646	0.35	1.0
TRAD_6	0.57	0.25	-0.06	0.446	0.55	1.4
TRAD_7	0.06	0.59	0.03	0.375	0.62	1.0
TRAD_8	0.50	0.03	0.05	0.273	0.73	1.0
TRAD_9	0.02	-0.04	0.82	0.678	0.32	1.0
TRAD_10	0.06	0.13	0.41	0.216	0.78	1.2

	PA3	PA1	PA2
SS loadings	1.33	1.34	1.23
Proportion Var	0.13	0.13	0.12
Cumulative Var	0.13	0.27	0.39
Proportion Explained	0.34	0.34	0.31
Cumulative Proportion	0.34	0.69	1.00

	With factor correlations of		
	PA3	PA1	PA2
PA3	1.00	0.27	0.28
PA1	0.27	1.00	0.11
PA2	0.28	0.11	1.00

Mean item complexity = 1.2
Test of the hypothesis that 3 factors are sufficient.

The degrees of freedom for the null model are 45 and the objective function was 1.97 with ChiSquare of 161.55
The degrees of freedom for the model are 18 and the objective function was 0.36

The root mean square of the residuals (RMSR) is 0.06
The df corrected root mean square of the residuals is 0.09

The harmonic number of observations is 87 with the empirical chisquare 27.68 with prob <0.067
The total number of observations was 87 with Likelihood ChiSquare=28.76 withprob < 0.051

Tucker Lewis Index of factoring reliability=0.761
RMSEA index = 0.082 and the 90% confidence intervals are 0 0.138
BIC=-51.62
Fit based upon off diagonal values = 0.93
Measures of factor score adequacy

	PA3	PA1	PA2
Correlation of (regression) scores with factors	0.87	0.84	0.86
Multiple Rsquare of scores with factors	0.75	0.71	0.74
Minimum correlation of possible factor scores	0.50	0.41	0.49

Appendix 13: Pearson correlation matrix sustainable investment

Correlation sustainable investment items

	SUST_1	SUST_2	SUST_3	SUST_4	SUST_5	SUST_6	SUST_7	SUST_8	SUST_9	SUST_10
SUST_1	1	**0.30**	-0.09	**0.27**	0.08	0.13	0.20	0.06	**0.27**	**0.36**
SUST_2	0.30	1	-0.21	0.18	0.003	0.20	0.23	0.12	0.01	0.14
SUST_3	-0.09	-0.21	1	-0.17	-0.01	-0.06	-0.07	-0.13	-0.01	-0.08
SUST_4	0.27	0.18	-0.17	1	0.11	0.01	0.09	0.10	**0.34**	0.21
SUST_5	0.08	0.003	-0.01	0.11	1	**0.34**	0.23	**0.41**	0.08	0.15
SUST_6	0.13	0.20	-0.06	0.01	0.34	1	0.20	**0.45**	0.06	0.22
SUST_7	0.20	0.23	-0.07	0.09	0.23	0.20	1	0.03	**0.28**	0.13
SUST_8	0.06	0.12	-0.13	0.10	0.41	0.45	0.03	1	0.08	0.19
SUST_9	0.27	0.01	-0.01	0.34	0.08	0.06	0.28	0.08	1	**0.25**
SUST_10	0.36	0.14	-0.08	0.21	0.15	0.22	0.13	0.19	0.25	1

Appendix 14 : Bartlett’s test of sphericity sustainable investment

Bartlett's test of sphericity

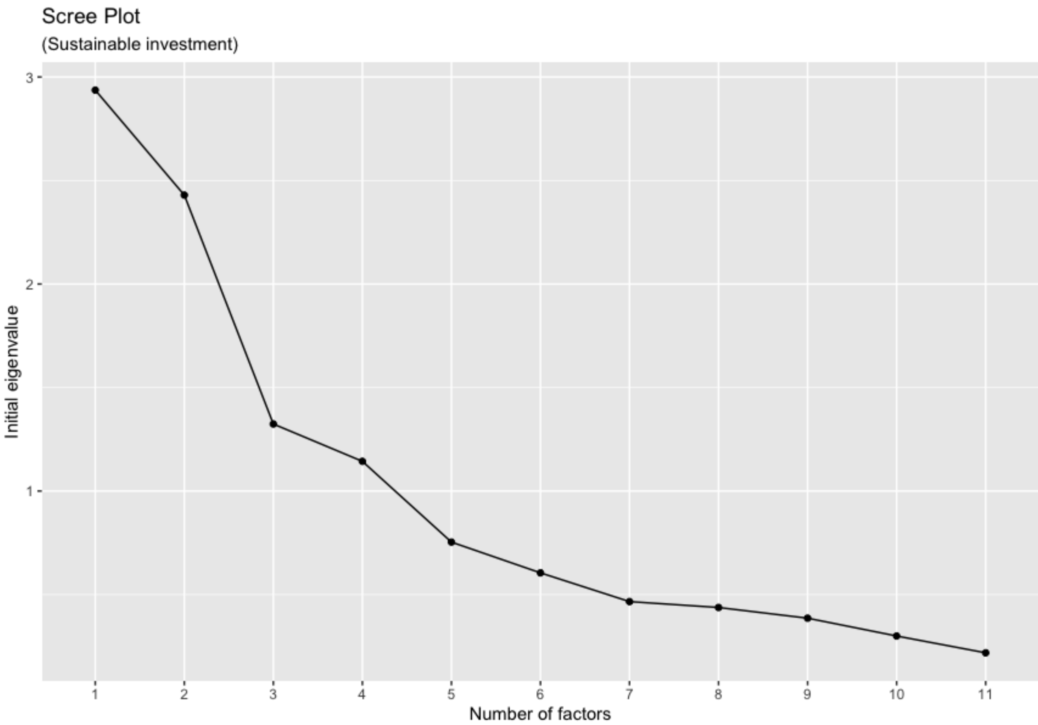
$chisq	115.9512
$p.value	3.540011e-08
$df	45

Appendix 15 : KMO values sustainable investment

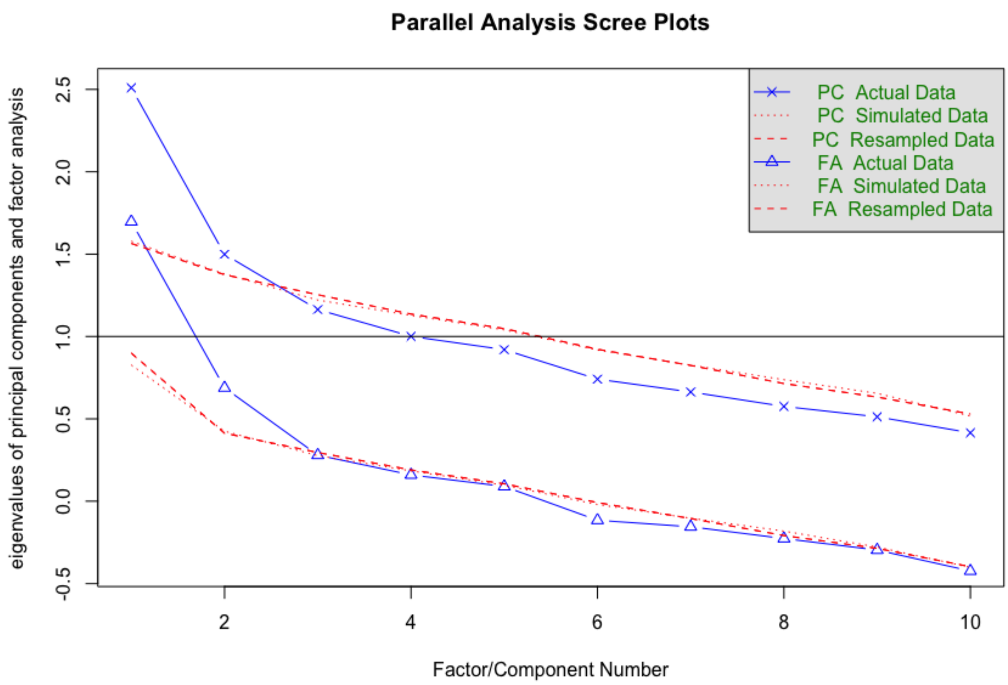
Kaiser-Meyer-Olkin factor adequacy
Call:KMO(r=cor(Y))
Overall MSA = 0.65
MSA for each item=

SUST_1	SUST_2	SUST_3	SUST_4	SUST_5	SUST_6	SUST _7	SUST _8	SUST_ 9	SUST _10
0.72	0.58	0.64	0.65	0.63	0.70	0.57	0.62	0.59	0.77

Appendix 16 : Scree Plot sustainable investment



Appendix 17 : Parallel Analysis sustainable investment



Appendix 18: R output one-factor model sustainable investment

Factor Analysis using method = pa
Call: fa(r=Y,nfactors=1,rotate=oblimin,fm=pa)
Standardized loadings (pattern matrix) based upon correlation matrix

	PA1	h2	u2	com
SUST_1	0.49	0.235	0.76	1
SUST_2	0.36	0.130	0.87	1
SUST_3	-0.21	0.043	0.96	1
SUST_4	0.38	0.148	0.85	1
SUST_5	0.41	0.171	0.83	1
SUST_6	0.48	0.228	0.77	1
SUST_7	0.39	0.154	0.85	1
SUST_8	0.44	0.193	0.81	1
SUST_9	0.39	0.150	0.85	1
SUST_10	0.50	0.245	0.75	1

	PA1
SS loadings	1.70
Proportion Var	0.17

Mean item complexity = 1
Test of the hypothesis that 1 factor is sufficient.

The degrees of freedom for the null model are 45 and the objective function was 1.42 with ChiSquare of 115.95
The degrees of freedom for the model are 35 and the objective function was 0.66

The root mean square of the residuals (RMSR) is 0.1
The df corrected root mean square of the residuals is 0.12

The harmonic number of observations is 87 with the empirical chisquare 81.92 with prob <1.2e-05
The total number of observations was 87 with Likelihood ChiSquare=53.96 withprob < 0.021

Tucker Lewis Index of factoring reliability=0.652
RMSEA index = 0.078 and the 90% confidence intervals are 0.031 0.119
BIC=-102.35
Fit based upon off diagonal values = 0.73
Measures of factor score adequacy

	PA1
Correlation of (regression) scores with factors	0.82
Multiple Rsquare of scores with factors	0.68
Minimum correlation of possible factor scores	0.35

Appendix 19: R output two-factor model sustainable investment

Factor Analysis using method = pa
Call: fa(r=Y,nfactors=2,rotate=oblimin,fm=pa)
Standardized loadings (pattern matrix) based upon correlation matrix

	PA1	PA2	h2	u2	com
SUST_1	0.63	-0.03	0.391	0.61	1.0
SUST_2	0.34	0.09	0.138	0.86	1.1
SUST_3	-0.18	-0.06	0.043	0.96	1.2
SUST_4	0.50	-0.04	0.243	0.76	1.0
SUST_5	0.02	0.55	0.313	0.69	1.0
SUST_6	0.04	0.64	0.429	0.57	1.0
SUST_7	0.33	0.13	0.151	0.85	1.3
SUST_8	-0.04	0.70	0.482	0.52	1.0
SUST_9	0.49	-0.03	0.235	0.77	1.0
SUST_10	0.43	0.16	0.251	0.75	1.3

	PA1	PA2
SS loadings	1.38	1.30
Proportion Var	0.14	0.13
Cumulative Var	0.14	0.27
Proportion Explained	0.51	0.49
Cumulative Proportion	0.51	1.00

With factor correlations of

	PA1	PA2
PA1	1.0	0.29
PA2	0.29	1.0

Mean item complexity = 1.1
Test of the hypothesis that 2 factors are sufficient.

The degrees of freedom for the null model are 45 and the objective function was 1.42 with ChiSquare of 115.95
The degrees of freedom for the model are 26 and the objective function was 0.32

The root mean square of the residuals (RMSR) is 0.06
The df corrected root mean square of the residuals is 0.08

The harmonic number of observations is 87 with the empirical chisquare 30.46 with prob <0.25
The total number of observations was 87 with Likelihood ChiSquare=25.6 withprob < 0.49

Tucker Lewis Index of factoring reliability=1.01
RMSEA index = 0 and the 90% confidence intervals are 0 0.084
BIC=-90.51
Fit based upon off diagonal values = 0.9
Measures of factor score adequacy

	PA1	PA2
Correlation of (regression) scores with factors	0.81	0.83
Multiple Rsquare of scores with factors	0.66	0.69
Minimum correlation of possible factor scores	0.32	0.39

Appendix 20: R output three-factor model sustainable investment

Factor Analysis using method = pa
Call: fa(r=Y,nfactors=3,rotate=oblimin,fm=pa)
Standardized loadings (pattern matrix) based upon correlation matrix

	PA2	PA1	PA3	h2	u2	com
SUST_1	-0.01	0.45	0.29	0.337	0.66	1.7
SUST_2	0.01	-0.01	0.83	0.687	0.31	1.0
SUST_3	-0.05	-0.05	-0.24	0.072	0.93	1.2
SUST_4	-0.02	0.45	0.13	0.239	0.76	1.2
SUST_5	0.60	0.08	-0.12	0.365	0.63	1.1
SUST_6	0.63	-0.02	0.10	0.426	0.57	1.1
SUST_7	0.13	0.28	0.14	0.152	0.85	2.0
SUST_8	0.69	-0.04	0.00	0.470	0.53	1.0
SUST_9	-0.01	0.70	-0.11	0.472	0.53	1.1
SUST_10	0.18	0.38	0.10	0.240	0.76	1.6

	PA3	PA1	PA2
SS loadings	1.31	1.19	0.96
Proportion Var	0.13	0.12	0.10
Cumulative Var	0.13	0.25	0.35
Proportion Explained	0.38	0.34	0.28
Cumulative Proportion	0.38	0.72	1.00

	With factor correlations of		
	PA3	PA1	PA2
PA3	1.00	0.21	0.20
PA1	0.21	1.00	0.18
PA2	0.20	0.18	1.00

Mean item complexity = 1.3
Test of the hypothesis that 3 factors are sufficient.

The degrees of freedom for the null model are 45 and the objective function was 1.42 with ChiSquare of 115.95
The degrees of freedom for the model are 18 and the objective function was 0.19

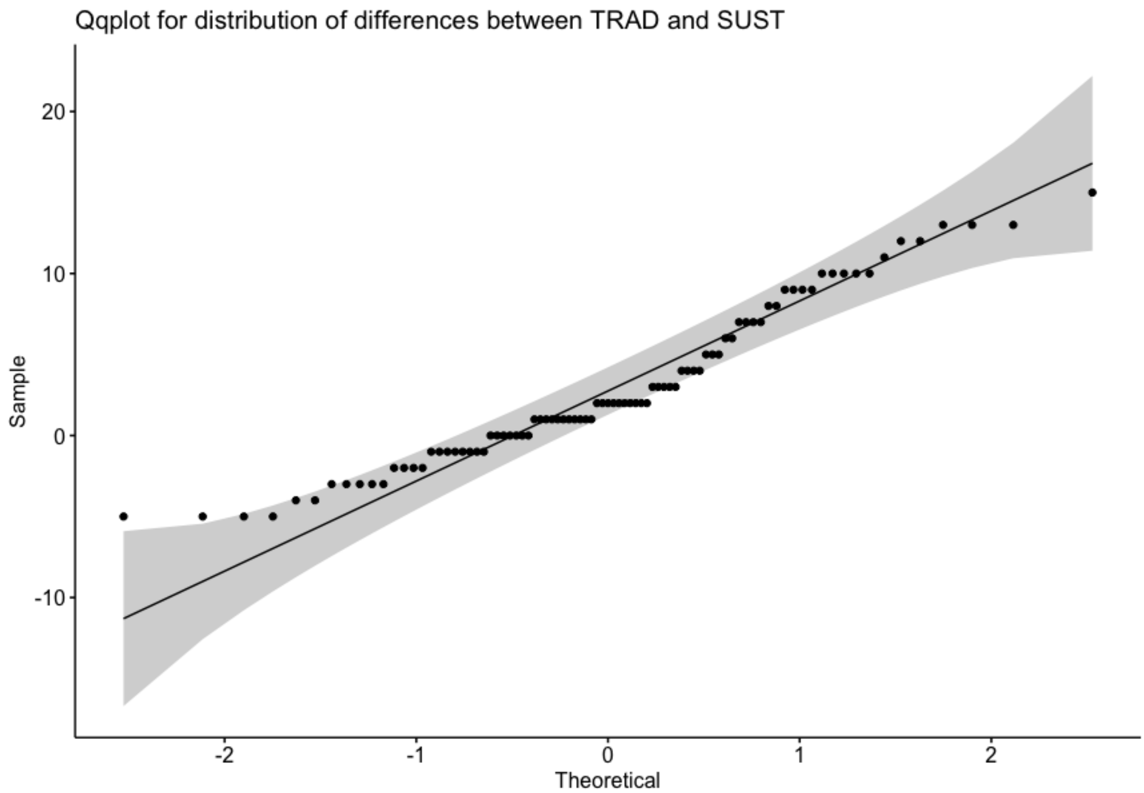
The root mean square of the residuals (RMSR) is 0.04
The df corrected root mean square of the residuals is 0.07

The harmonic number of observations is 87 with the empirical chisquare 15 with prob <0.66
The total number of observations was 87 with Likelihood ChiSquare=14.89 withprob < 0.67

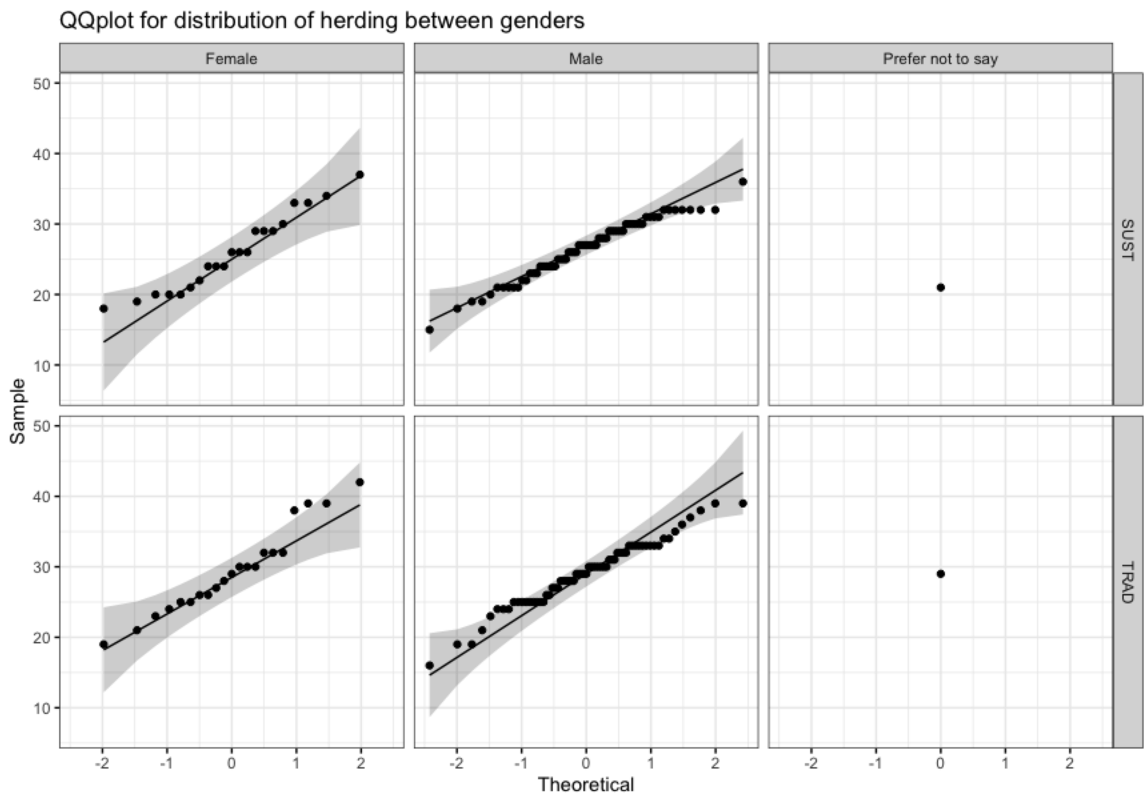
Tucker Lewis Index of factoring reliability=1.114
RMSEA index = 0 and the 90% confidence intervals are 0 0.078
BIC=-65.49
Fit based upon off diagonal values = 0.95
Measures of factor score adequacy

	PA3	PA1	PA2
Correlation of (regression) scores with factors	0.83	0.81	0.85
Multiple Rsquare of scores with factors	0.70	0.65	0.72
Minimum correlation of possible factor scores	0.39	0.31	0.44

Appendix 21: QQPlot distribution of differences between TRAD and SUST



Appendix 22: QQplot gender and type of investment distribution



Appendix 23: Preliminary checks: gender

Levene test for variance homogeneity: gender

	investment_type	df1	df2	statistic	p
1	SUST	2	84	2.28	0.108
2	TRAD	2	84	1.77	0.176

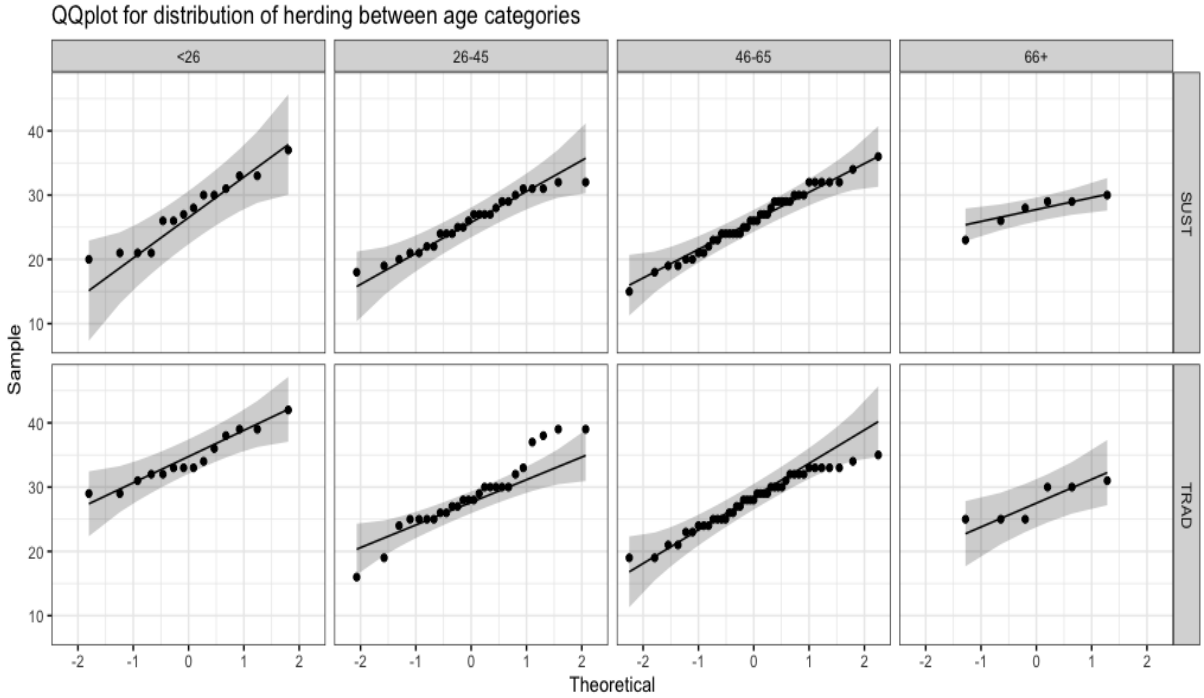
Box's M-test for Homogeneity of Covariance Matrices: gender

statistic	p.value	parameter
3.89	0.143	2

Appendix 24: Outliers age

Age	investment_type	ID	Gender	Education	Income	Strategy	Experience	Size	Horizon	herding	is.outlier	is.extreme
26-45	TRAD	4	Male	Masters	>50.000	ACTIVE	more than 10 years	>75%	More than 10 years	16	TRUE	FALSE
26-45	TRAD	44	Male	Masters	>50.000	ACTIVE	1-3 years	25-5…	5-10 years	38	TRUE	FALSE
26-45	TRAD	51	Male	Masters	>50.000	PASSIVE	1-3 years	>75%	5-10 years	39	TRUE	FALSE
26-45	TRAD	52	Male	Masters	>50.000	ACTIVE	5-10 years	<25%	0-5 years	39	TRUE	FALSE

Appendix 25: QQ plot distribution age



Appendix 26: Preliminary checks age

Levene test for variance homogeneity: age

	investment_type	df1	df2	statistic	p
1	SUST	3	83	1.43	0.240
2	TRAD	3	83	0.582	0.628

Box's M-test for Homogeneity of Covariance Matrices: age

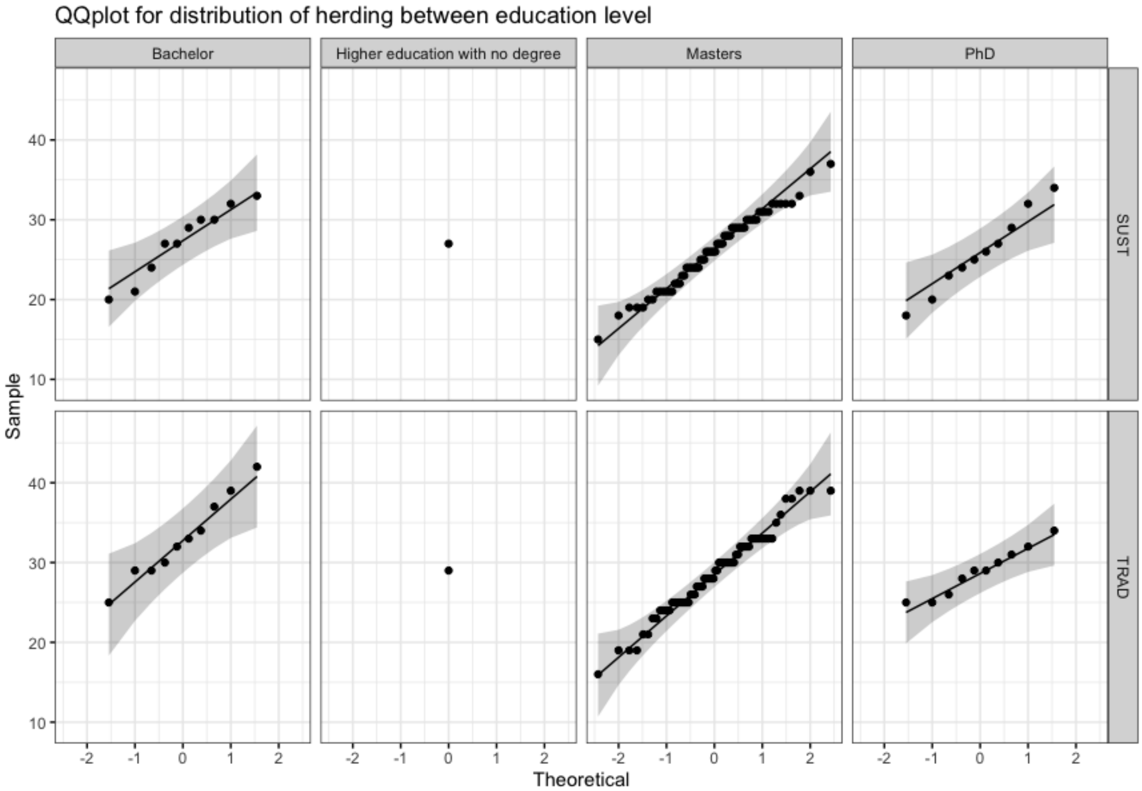
statistic	p.value	parameter
7.98	0.0464	3

Appendix 27: One-tailed pairwise t-test for age

One-tailed pairwise t-test (alternative=less): age categories

	investment_type	.y.	group1	group2	n1	n2	p	p.signif	p.adj	p.adj.signif
1	SUST	herding	<26	26-45	14	26	0.15	ns	0.9	ns
2	SUST	herding	<26	46-65	14	41	0.162	ns	0.974	ns
3	SUST	herding	26-45	46-65	26	41	0.562	ns	1	ns
4	SUST	herding	<26	66+	14	6	0.513	ns	1	ns
5	SUST	herding	26-45	66+	26	6	0.786	ns	1	ns
6	SUST	herding	46-65	66+	41	6	0.769	ns	1	ns
7	TRAD	herding	<26	26-45	14	26	0.000184	***	0.0011	**
8	TRAD	herding	<26	46-65	14	41	0.0000101	****	0.0000604	****
9	TRAD	herding	26-45	46-65	26	41	0.252	ns	1	ns
10	TRAD	herding	<26	66+	14	6	0.00186	**	0.0111	*
11	TRAD	herding	26-45	66+	26	6	0.31	ns	1	ns
12	TRAD	herding	46-65	66+	41	6	0.448	ns	1	ns

Appendix 28: QQplot education and type of investment distribution



Appendix 29: Preliminary checks education

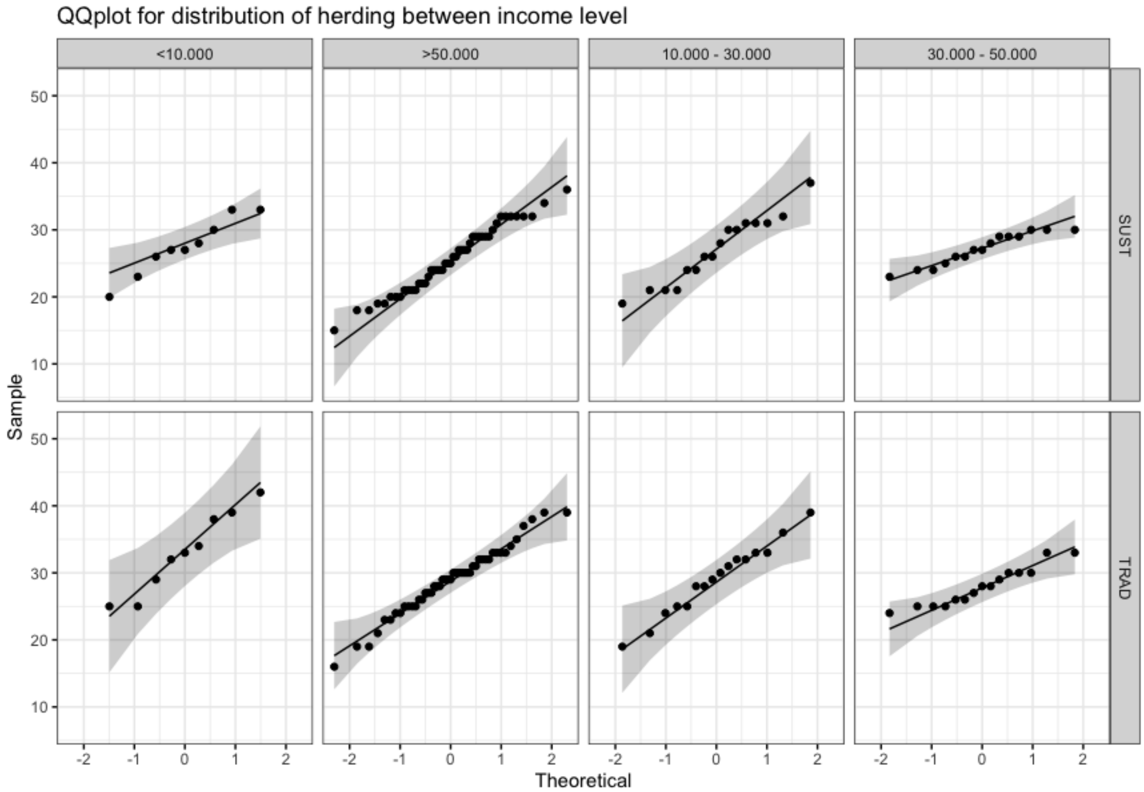
Levene test for variance homogeneity: education

	investment_type	df1	df2	statistic	p
1	SUST	3	83	0.698	0.556
2	TRAD	3	83	1.62	0.191

Box's M-test for Homogeneity of Covariance Matrices: education

statistic	p.value	parameter
2.41	0.493	3

Appendix 30: QQplot income and type of investment distribution



Appendix 31: Preliminary checks income

Levene test for variance homogeneity: income

	investment_type	df1	df2	statistic	p
1	SUST	3	83	3.21	0.0272
2	TRAD	3	83	1.52	0.216

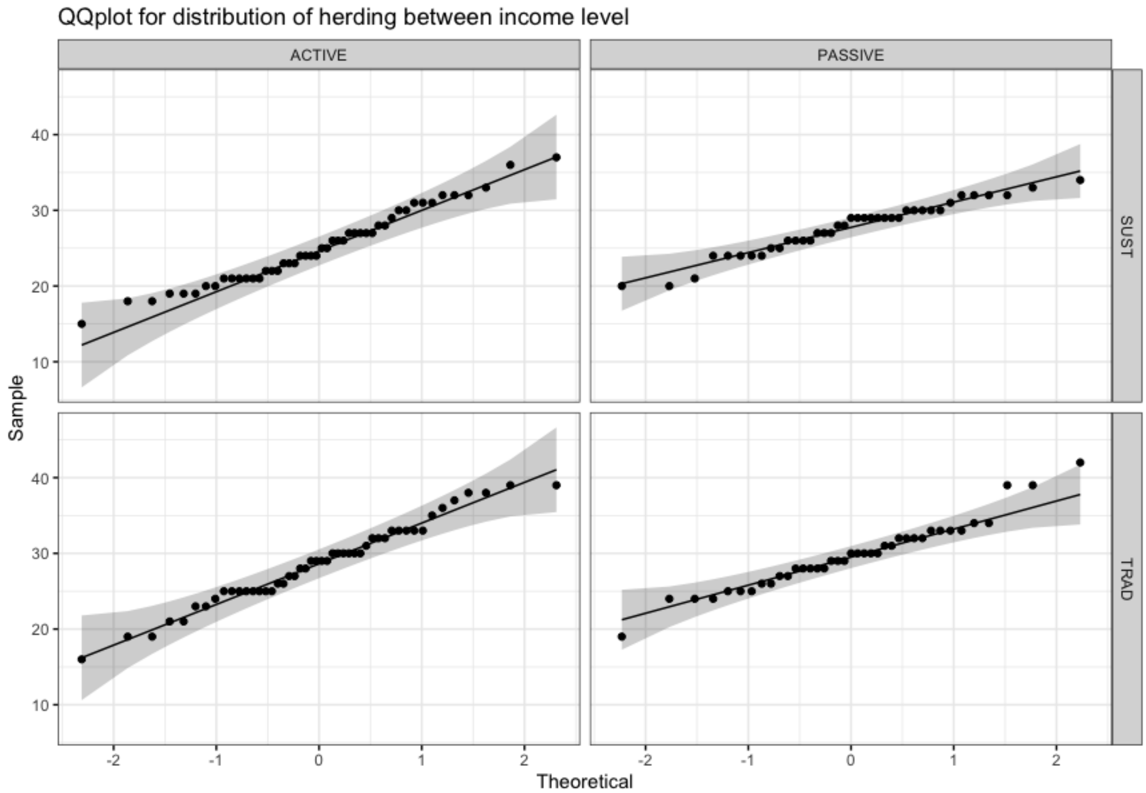
Box's M-test for Homogeneity of Covariance Matrices: income

statistic	p.value	parameter
17.4	0.000580	3

Appendix 32: Outliers strategy

Strategy	investment_type	ID	Gender	Age	Education	Income	Experience	Size	Horizon	herding	is.outlier	is.extreme
PASSIVE	TRAD	18	Female	46-65	Masters	10.000	more than 10 years	25-5…	10-30 years	19	TRUE	FALSE
PASSIVE	TRAD	54	Female	<26	Bachelor	<10.000	1-3 years	<25%	5-10 years	42	TRUE	FALSE

Appendix 33: QQplot strategy and type of investment distribution



Appendix 34: Preliminary checks strategy

Levene test for variance homogeneity: strategy

	investment_type	df1	df2	statistic	p
1	SUST	1	85	5.68	0.0194
2	TRAD	1	85	1.93	0.168

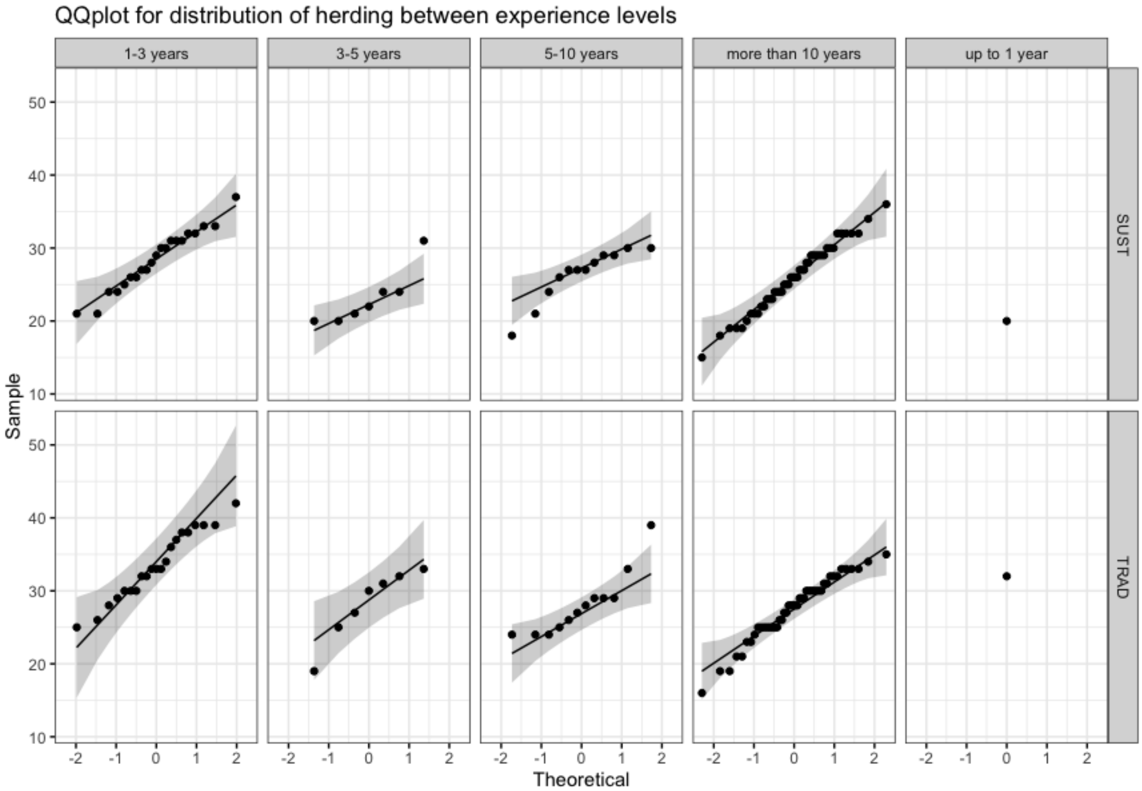
Box's M-test for Homogeneity of Covariance Matrices: strategy

statistic	p.value	parameter
6.87	0.00877	1

Appendix 35: Outliers experience

Experience	investment_type	ID	Gender	Age	Education	Income	Strategy	Size	Horizon	herding	is.outlier	is.extreme
3-5 years	SUST	7	Male	26-45	Masters	>50.0…	ACTIVE	<25%	5-10 years	31	TRUE	FALSE
5-10 years	SUST	47	Male	26-45	PhD	>50.0…	ACTIVE	50-75%	10-30 years	18	TRUE	FALSE
5-10 years	TRAD	52	Male	26-45	Masters	>50.0…	ACTIVE	<25%	0-5 years	39	TRUE	FALSE
more than 10 years	TRAD	4	Male	26-45	Masters	>50.0…	ACTIVE	>75%	More than 30 years	16	TRUE	FALSE

Appendix 36: QQplot distribution between experience levels



Appendix 37: Preliminary checks experience

Levene test for variance homogeneity: experience

	investment_type	df1	df2	statistic	p
1	SUST	4	82	1.20	0.317
2	TRAD	4	82	0.536	0.710

Box's M-test for Homogeneity of Covariance Matrices: experience

statistic	p.value	parameter
2.51	0.643	4

Appendix 38: One-tailed t-test between experience levels

One-tailed pairwise t-test (alternative=less): experience levels

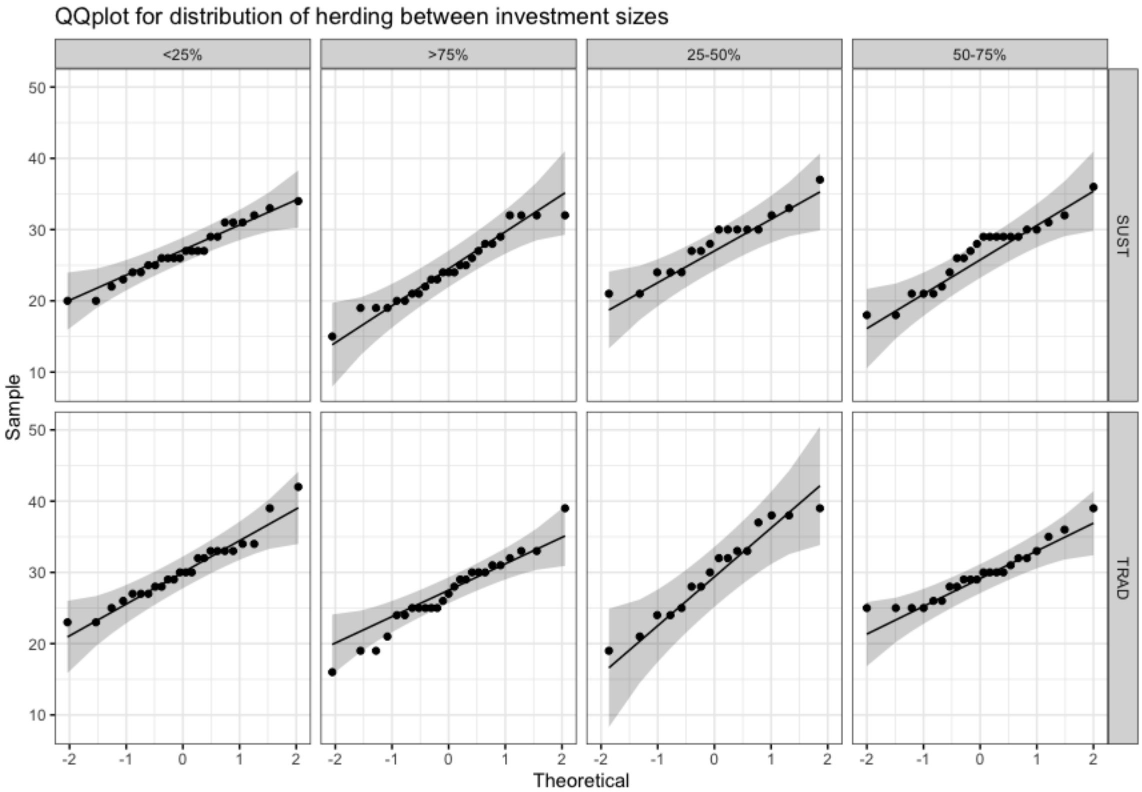
	investment_type	.y.	group1	group2	n1	n2	p	p.signif	p.adj	p.adj.signif
1	SUST	herding	1-3 years	3-5 years	21	7	0.00316	**	0.0189	*
2	SUST	herding	1-3 years	5-10 years	21	12	0.089	ns	0.534	ns
3	SUST	herding	3-5 years	5-10 years	7	12	0.936	ns	1	ns
4	SUST	herding	1-3 years	more than 10 years	21	46	0.0142	*	0.0849	ns
5	SUST	herding	3-5 years	more than 10 years	7	46	0.939	ns	1	ns
6	SUST	herding	5-10 years	more than 10 years	12	46	0.383	ns	1	ns
7	TRAD	herding	1-3 years	3-5 years	21	7	0.00371	**	0.0223	*
8	TRAD	herding	1-3 years	5-10 years	21	12	0.000615	***	0.00369	**
9	TRAD	herding	3-5 years	5-10 years	7	12	0.489	ns	1	ns
10	TRAD	herding	1-3 years	more than 10 years	21	46	0.00000135	****	0.0000081	****

11	TRAD	herding	3-5 years	more than 10 years	7	46	0.375	ns	1	ns
12	TRAD	herding	5-10 years	more than 10 years	12	46	0.36	ns	1	ns

Appendix 39: Outliers size

	Size	investment_type	ID	Gender	Age	Education	Income	Strategy	Experience	Horizon	herding	is.outlier	is.extreme
1	>75%	TRAD	4	Male	26-45	Masters	>50.000	ACTIVE	more than 10 years	More than 30 years	16	TRUE	FALSE
2	>75%	TRAD	51	Male	26-45	Masters	>50.000	PASSIVE	1-3 years	5-10 years	39	TRUE	FALSE

Appendix 40: QQplot distribution between sizes



Appendix 41: Preliminary checks size

Levene test for variance homogeneity: size

	investment_type	df1	df2	statistic	p
1	SUST	3	83	0.385	0.764
2	TRAD	3	83	2.12	0.104

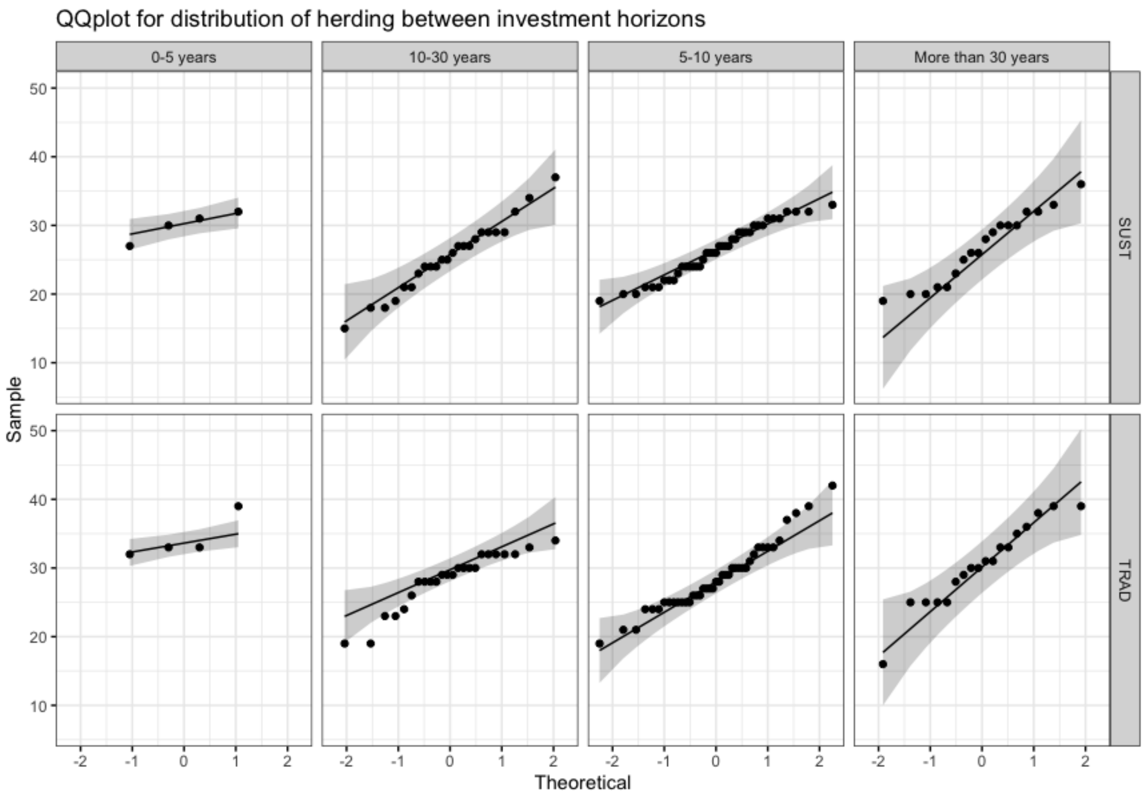
Box’s M-test for Homogeneity of Covariance Matrices: experience

statistic	p.value	parameter
1.99	0.575	3

Appendix 42: Outliers investment horizon

	Horizon	investment_type	ID	Gender	Age	Education	Income	Strategy	Experience	Size	herding	is.outlier	is.extreme
1	0-5 years	TRAD	52	Male	26-45	Masters	>50.000	ACTIVE	5-10 years	<25%	39	TRUE	FALSE
2	10-30 years	TRAD	18	Female	46-65	Masters	10.000-30.000	PASSIVE	more than 10 years	25-5…	19	TRUE	FALSE
3	10-30 years	TRAD	19	Male	46-65	Masters	>50.000	ACTIVE	more than 10 years	>75%	19	TRUE	FALSE
4	5-10 years	TRAD	54	Female	<26	Bachelor	<10.000	PASSIVE	1-3 years	<25%	42	TRUE	FALSE

Appendix 43: QQplot distribution between investment horizons



Appendix 44: Preliminary checks investment horizon

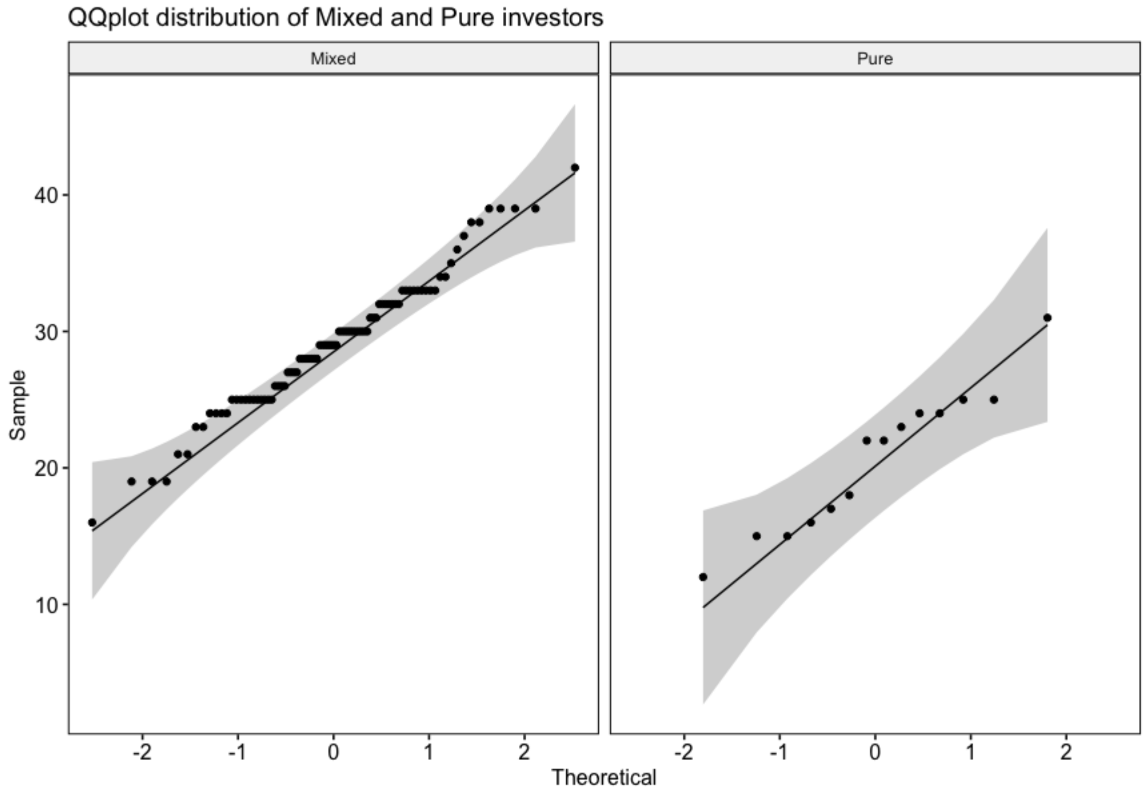
Levene test for variance homogeneity: horizon

	investment_type	df1	df2	statistic	p
1	SUST	3	83	2.03	0.117
2	TRAD	3	83	1.34	0.268

Box’s M-test for Homogeneity of Covariance Matrices: horizon

statistic	p.value	parameter
4.45	0.217	3

Appendix 45: QQplot distribution between pure and mixed investors



Appendix 46: Levene test pure and mixed investors

Levene test for variance homogeneity pure and mixed investors

df1	df2	statistic	p
1	99	0.131	0.718

Abstract : This master thesis aims to measure the herding behavior differences between sustainable investments and traditional investments for mixed investors. Mixed investors are individuals whose portfolio is composed of both investments aimed at financial returns and at sustainability contributions. As the community of mixed investors has been steadily increasing over time, it is therefore key to understand their decision process better.

After a literature review on both sustainable investing and behavioral finance (with a focus on investment decision making) we tested different hypotheses for variations in herding behavior. The main hypothesis was the relationship between investment type and herding behavior. We also looked at the relationship between socio-demographic factors and investment habit characteristics on herding behavior as well as the interaction effect these two relationships could have. The different hypotheses were tested with the help of a quantitative study on data collected through an online survey circulated between November and December 2021. The sample obtained was of 175 respondents, of which 101 were usable responses and among these 87 qualified as mixed investors.

We found that the herding behavior of mixed investors depends on the type of investment. Mixed investors seem to be more subject to herding for their traditional investments than for their sustainable investments. Socio-demographic traits such as income, education and gender appeared to not have an influence on herding behavior. Younger investors (under 26) tend to be more subject to herding than older investors but only in the case of traditional investments. Investment habit traits such investment size impact the herding behavior irrespective of the type of investment. Investors investing a significant portion of their wealth (>75%) were less subject to herding. Passive investor seem to be more subject to herding than active investors in the case of sustainable investments. There seems to be a learning effect, as after three years of investment experience, investors become less subject to herding. This effect is found for both sustainable and traditional investments but is stronger for the latter category.
Finally, our findings in Exploratory Factor Analyses suggest that the herding bias is better represented by sub-factors rather than one composite variable. We also found that pure traditional investors are less subject to herding than mixed investors.

Finally, we propose paths for future research on the analysis of the investment decision making process of mixed investors.

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