RADBOUD UNIVERSITY
Nijmegen School of Management
Master's thesis

The Effects of Emotion Evocation by Sustainability Imagery on Investor Decision-Making

Thesis by: KOEN VAN BOXEL (S4743334)
Supervised by: DR. SVEN NOLTE, ASSISTANT PROFESSOR OF FINANCIAL ECONOMICS

The presented paper employs a between-subjects experimental method (with some within-subject elements) to investigate the role of imagery in investment decision-making processes. Participants were put in a simplified investment environment and enrolled in different imagery treatments groups, as to make distinction between positive and negative imagery. In addition, distinction was made in intensity of the imagery, and whether imagery reflects nature, and thereby sustainability or not. Using cross-sectional analyses with OLS regression estimations, it can be shown that both positive imagery and negative imagery can respectively increase and decrease investment percentages substantially. These effects are found most consistently for medium-intensity imagery and can be amplified by presenting nature, sustainability-related imagery. This increases already higher investments for positive, and decreases already lower investments for negative imagery. The results provide applications, as by legislating imagery to be presented in company documents as a way of 'rewarding' or 'punishing' certain company behaviours, monetary incentives may be offered through non-monetary means. Negative imagery may be most suitable for policy use, as it is found not to be as dependent on affectional attitude compared to positive imagery, and may influence investment behaviour of persons that have a higher willingness to invest more severely.

27th of July, 2020
Nijmegen, the Netherlands

Table of Contents

1. Introduction

In 2009, the *Family Smoking Prevention and Tobacco Control Act* was passed in the United States' legislation. This act stated that cigarette packaging had to contain stronger warnings by including graphic pictures with the negative health consequences of smoking, in an attempt to decrease smoking rates. Kees, Burton, and Andrews (2010) elaborate on these effects, showing that highly graphic pictures evoke fear, which mediates a decrease in intent to purchase cigarettes, and causes a significant increase in intentions to quit smoking. Monarrez-Espino, Liu, Greiner, Bremberg, and Galanti (2014) provide a meta-analysis and show that the effect is substantial and persistent in health and psychology literature. It is the result of an upstream intervention that bridges the so-called intention-behaviour gap (Papies, 2017). In other words, when using imagery as such, one can align people's habits with a certain guide behaviour (less smoking). Of course, imagery on cigarette packages is merely a well-known example, but it creates a rough idea of how imagery may be used as a cognitive tool. As Carruthers (2014) mentions, using visual imagery may activate additional stored information or relevant goals that influence decisions indirectly.

This can be expanded to fields such as economics and finance. A case in point would be Key Investor Information Documents (KIIDs). Walther (2015) explains that KIIDs were made mandatory by European Union regulation halfway 2012, and can be described as "a standardized fact sheet with a length of two pages including comparable information about a specific financial product" (p. 130). Despite empirical evidence that KIIDs offer a first step in informing investors (Oehler, Hofer, & Wendt, 2014), there is behavioural evidence against investors fully understanding them and basing decisions solely on the financial information provided by them (Walther, 2015). In the paper by Walther (2015), 50% of the subjects are not able to understand the information (p.136) and "participants still do not feel able to appraise the fund they are offered very well" (p.136). Visual imagery is shown to be very closely linked to brain mechanisms involved in perception (Rademaker & Pearson, 2012), and perception again has become a very relevant topic in explaining investor attitudes (Veld & Veld-Merkoulva, 2008). Moreover, Huber, Palan, and Zeisberger (2017) review a multitude of risk measures and see if they corroborate with risk perception. They find that loss probability explains risk perception very well, contrary to the standardly used variance found also in KIIDs (Huber et al, 2017). Hence, imagery could play an important role as an explanatory factor with regard to perception, and thereby actual investment decision-making.

One may then wonder what imagery is relevant to be shown for investment decision-making? The study by Huber et al. (2017) is descriptive, as it makes clear that loss probability is a better fit for capturing risk behaviour. However, imagery is also commonly used normatively to promote desired behaviour, as demonstrated with the smoking example above. Mykolas, Rasa, and Arvydas (2019) elaborate on the effect of using visuals for public service announcements, which they state to be "universally effective regardless of their presentation" (p.12). Moreover, Mykolas et al. (2019) mention that "the affective component of a pro-environmental public service announcement is an important, yet untapped factor of its effectiveness" (p.12). Note here that there is already being spoken of pro-environmental affect, which is the following lead.

Namely, there has been a drastic increase in awareness during the last decades on climate change and its consequences (Iturriza, Labaka, Ormazabal, & Borger, 2020). It has had a significant effect on consumption (Ibrahim & Al-Ajlouni, 2018), and investment decisions (Williams et al., 2010). Moreover, empirical research such as by Liesen (2015) has shown investment strategies where long positions in companies that do report emissions, and short positions in those that do not can yield significant positive abnormal returns. Environment and sustainability therefore have a role in modern finance, but imagery on it may have an even greater role. Not only is it an "untapped factor" (Mykolas et al., 2019, p.12); sustainability and environmental roles are often measured by disclosure of emissions (Nelson, 2018) or cost benefits analyses using monetary terms (Williams et al, 2010). Though these methods have given valuable practical insights, one should note that transferring into monetary terms may cause them to "do more harm than good, and it is critical that their biases be given due to consideration when results are interpreted" (Schulze, 1994, p. 199). Thus, imagery may give interesting findings that are based more related to the affect-side, which can have both descriptive and normative implications for investment decision-making. The question can be asked: *what is the effect of emotion evocation by sustainability imagery on investor decision-making?*

To answer this question, this paper will firstly elaborate on relevant literature with regard to asset valuation, emotion in economics, and a link to sustainability. Secondly, the way to test the research question will be given by stating hypotheses, and explaining the experimental method and design that were used. Thirdly, statistical analyses on the experimental data will follow in the results section. This will be followed by a robustness and discussion section that cover generalizability and limitations of the analyses. Finally, a conclusion will be given with policy implications.

2. Literature Review

2.1. Theories on investor decision-making

Neoclassical finance has dominated the financial discipline for decades since the late 1950s, with its decision makers that maximize their expected utility and have rational expectations (De Bondt, Muradoglu, Shefrin, Staikouras, 2008). These actors come together in "beautiful markets" (De Bondt et al., 2008, p.8) where asset pricing is based on mean-variance models, such as the Capital Asset Pricing Model (Sharpe, 1964; Treynor, 1962) that captures all compensable risk perfectly in its excess market return (ß), allowing investors to hold an optimum portfolio only containing idiosyncratic risk (De Bondt et al, 2008). This view has been contrasted heavily by behavioural finance, which has come to set itself within the economic discipline the last few decades (De Bondt et al, 2008; Barberis & Thaler, 2003).

In the words of Slovic, (1972): "a full understanding of human limitations will ultimately benefit the decision-maker more than will naive faith in the infallibility of his intellect" (p.780). This is exactly what behavioural finance does. Kapor (2014) states behavioural finance to be "a combination between financial economics and cognitive psychology" (p.74) that investigates the psychological and sociological issues that have an impact on decision-making processes. Shefrin (2001) elaborates on how it does so. Namely, the three concepts that are returning in traditional finance literature being rational behaviour, the Capital Asset Pricing Model (Treynor, 1962; Sharpe, 1964), and efficient markets, have psychological forces that interfere with them preventing them to reach these optimal values (Shefrin, 2001). Behavioural finance investigates these limitations by considering biases that prevent us from acting rationally (Shefrin, 2001), which inevitably cause limits to arbitrage (De Bondt, 2008). That is, assets are not always priced at their fundamentally right value ('The price is right') due to noise, which can be seen as traders that "trade on a spurious signal that they (incorrectly) believe to be informative" (Banerjee & Green, 2015, p. 399). Given that the market contains a lot of this noise (Mendel & Shleifer, 2012), it may thus be very interesting to study it to gain descriptive insights; this is the premise of behavioural finance.

2.2. Emotion and imagery in economics

How does one then relate emotion to this noise in financial markets? Firstly, it should be noted that there has been a lot of discussion around the concept and definition of an 'emotion' and it differs across various disciplines (Dixon, 2012). In economics, the concept of an 'emotion' has been unpopular, and was rather referred to or replaced by an 'interest' or 'expectation' in orthodox economics (Pixley, 2002). According to Pixley (2002), "Post-Keynesians are among the few economists who readily acknowledge emotions in economic life" (p.83). However, they still see emotions rather as biases, that show irrationality

(Pixley, 2002). Loewenstein (2000) argued that it is not just this focus on irrationality, but also the type of emotions that are the research focus. Economists had been mostly interested in expected emotions, such as regret and disappointment, whereas psychologists were looking at immediate emotions, at the time of a decision (Loewenstein, 2000). This paper will not furtherly discuss the definition of emotions, as this forms a discussion on its own, especially given its different definitions between disciplines (Loewenstein, 2000, p.481-482). Rather, it will focus on immediate emotions, seeing them as a critical factor that influences investor decision-making. As also concluded by Virlics (2013), "emotions do not only play a role in the decision-making process, but they also can be informative for the decision makers" (p.1012). That is, these emotions are evoked by certain important factors, which may contain additional information on companies that cannot be captured easily in financial statements. For this, imagery is considered to be closely related.

As shown by Kees et al. (2010) and Monarrez et al. (2014) for the smoking example, it is the imagery that evokes fear[1], and then causes the behaviour to change based on this. The bridge between the emotion being evoked and the action being made is however more complex, as elaborated on by Papies (2017), who refers to this as the 'intention-behaviour gap' (p. 2). The framework Papies (2017) uses can be found below in Figure 1. To briefly elaborate on this figure[2], situational cues can be seen as routines that have been learned by individuals and are stored in their memories as habits. Given the fact that these situations take place numerous times in daily life, people gain comprehensive representations of these experiences. This then leads to situated conceptualisation, which is the reactivation of such memories through internal (from within our own senses and mind) or external cues (through things that happen in the environment). As a result, this drives a certain behaviour based on the given context.

So how does this link to the presented research? Papies (2017) describes interventions that can be performed to steer behaviour by either cueing, or training people. Rademaker and Pearson (2012) conducted research on the potential of training interventions for visual imagery, and found that there was no overall effect of training on imagery strength, and merely higher metacognition of imagery. Hence, it can be assumed that training measures with regard to imagery perception and emotion evocation do not make much sense; for the KIID example, it will not matter much whether we show managers an image once or numerous times, as it will approximately have the same strength on their investment behaviour. However cue interventions, like the upstream intervention, may be very useful. An upstream intervention is a large scale intervention, such as use of law and policy to change situational cues in the decisional context (Papies, 2017). For the KIID example, this would represent the cue by imagery that evokes the different emotion (Smoking: fear) and thereby also changes the situational behaviour (investing more or less).

[1] Given that the definition of emotions won't be addressed to greater extent, it assumed that states like 'fear' represent emotions.
[2] Also see "1.2 | Situated conceptualizations in the intention-behaviour gap" in Papies (2017), p.3-4.

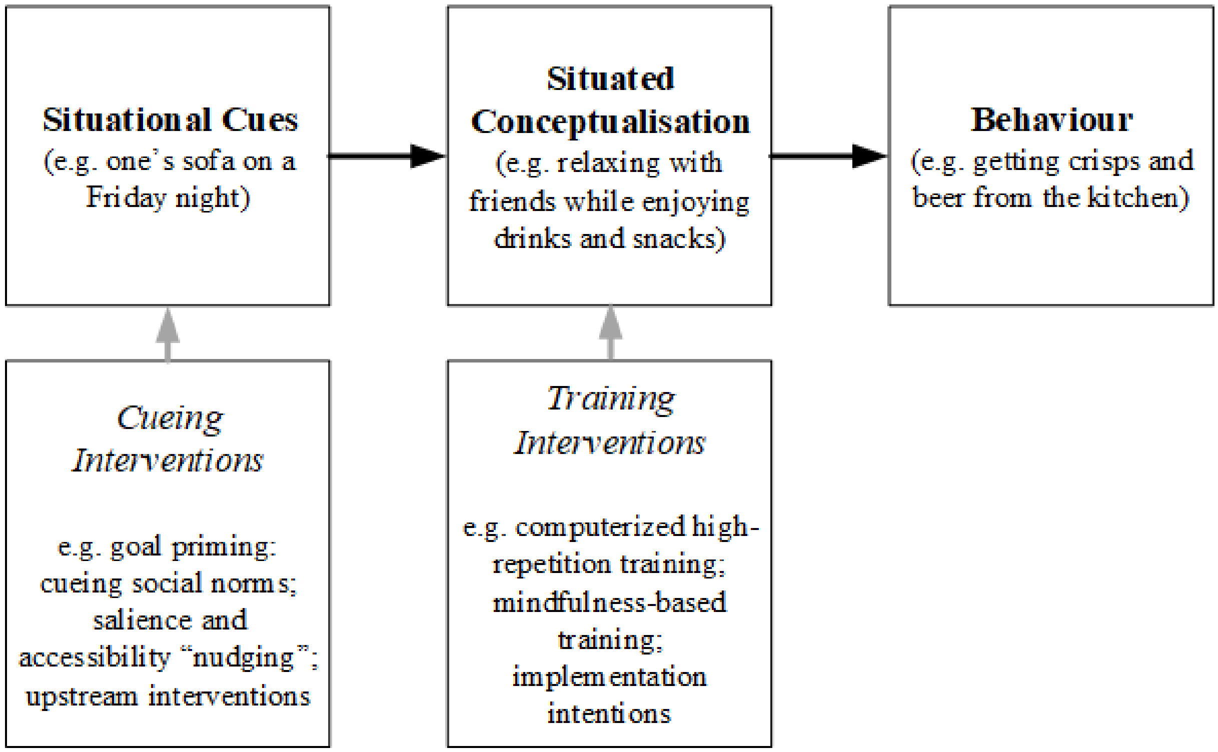


FIGURE 1. FRAMEWORK FOR SITUATED INTERVENTIONS THAT CHANGE THE EFFECTS OF SITUATIONAL CUES ON BEHAVIOUR (REPRINTED FROM PAPIES, 2017, P.3)

2.3. Imagery on sustainability

Elucidating why the change in this behaviour using imagery can be substantial, Leiserowitz (2005) can be considered. Leiserowitz (2005)[3] investigates affective imagery of global warming in a survey setting to measure the degree to which citizens of the Unites States 'feel' that global warming is a dangerous issue. It is found that "Americans as a whole perceive global climate change as a moderate risk" (Leiserowitz, 2005, p.1437), and "personally relevant affective images of climate change lack" (p.1438). This would indicate some difficulties for the presented paper, as it aims to affect behaviour using an imagery cue. At the same time, Leiserowitz (2005) presents opportunities for the research, namely that 'there was no association to temperature-related morbidity and mortality, health effects of extreme weather events, air-pollution… all of which are potential health consequences of global climate change" (p.1438). Hence, the effect of imagery may only be sufficiently strong when people are informed about the dangers. It should also be taken into

[3] Note that Leiserowitz' conclusions may not fully hold now, given that the paper was published in 2005, and awareness on climate change (thus global warming) has been increasing rapidly the last years (Iturriza et al., 2020).

consideration that Leiserowitz (2005) did not actually show the imagery, but gathered affective image "using the method of discrete or continued word associations" (p.1437). Hence, the study might lack the emotional evocation that actually comes from the physical imagery (Mykolas et al., 2019).

O'Neill and Smith (2014) elaborate that the literature on physical imagery around sustainability has been lacking, despite its importance and distinct properties from words. As O'Neill and Smith (2014) put it, physical imagery can "transcend linguistic and geographic barriers" (p.73). O'Neill and Smith also mention three important factors that make imagery distinct from text:

> First, images are analogical - that is images are interpreted based on similarity, whereas words rely on social convention…. Second, images lack an explicit propositional syntax (they use cues instead of precise syntactic devices)… Lastly, images in general are indexical - the come to be seen as a direct representation of reality, rather than viewed as a particular version of reality framed in a particular way (O'Neill & Smith, 2014, p.73-74)

O'Neill and Smith (2014) also provide some details on typical 'climate images' that they found in newspapers. These "climate images depict identifiable people, the causes of climate change, climate impacts at home and abroad, and graphical or scientific representations of climate change" (p.77). They elaborate that there is a certain personification of climate change; images of people dominated coverage (O'Neill & Smith, 2014, p. 77). They also mention the role of television news on visualizing climate change, to which Lester and Cottle (2009) look at two distinct dimensions. Firstly, visual scenes and spectacular images of nature, and people under threat; secondly, imagery of strategic relations of contention[4] (Lester & Cottle, 2009, p.922). They conclude that either form can "convey powerful symbolic messages" (Lester & Cottle, 2009, p. 933). The presented research will focus on the visual scenery; looking at both spectacular images of nature as a positive cue, and people, animals, or the world under threat as a negative cue. To see how this affects behaviour and asset pricing, the following hypotheses are formed.

[4] That is, the assessment of conflicting views and voices about climate change and its presentation.

2.4. Hypotheses

Firstly, positive and negative imagery are seen as policy interventions that affect situational cues (Papies, 2017) and thereby behaviour in positive and negative ways respectively:

H_1 = Exposure of individuals to positive (negative) imagery in investment decisions will lead to a higher (lower) propensity to invest compared to individuals exposed to neutral imagery investing in a similar company.

Given that there is support for the claim that sustainability imagery can carry strong emotional evocation (Lester & Cottle, 2009, p. 933; Mykolas et al., 2019), the effect of sustainable imagery should also be stronger for either positive or negative imagery:

H_2 = Positive (negative) imagery on sustainability will lead to a higher (lower) propensity to invest compared to a similar positive (negative) non-sustainability imagery company.

And to address the point of Leiserowitz (2005), that people are not yet informed enough to see it as something that affects them, the following will also be tested:

H_3 = Individuals that deem sustainability as more important will have a significantly higher (lower) propensity to invest in companies displaying positive (negative) sustainability imagery, compared to individuals that deem sustainability less important.

3. Methodology

3.1. Method choice and data acquisition

In order to test the stated hypotheses an experimental method is used. It is the most commonly used method in behavioural finance (De Bondt et al., 2008) and has large advantages. These advantages are the ability to personally customize design around one's research question and keep outside factors constant, while checking for only one treatment (Obergruber & Hrubcova, 2016). As such, the experimental method allows for convenient manipulation with regard to sustainability imagery and direct measurement of respondents' decision-making.

Qualtrics software has been used to design and conduct this experiment, as it is readily available to university students, easy to use, and offers thorough customisation. Respondents have been gathered by distributing the survey among friends, family, colleagues, and their extended community (i.e. friends of friends) through verbal and digital means. In addition, verified survey swap services[5] have been used, all with best efforts to acquire a diverse and representative sample. Three €10 giftcards (either for Amazon or Bol.com) were put up for a raffle, to be distributed to three participants randomly, in order to incentivise people to take part in the survey. There was no further monetary compensation, nor was it based on performance. The survey was made available in English and Dutch, and was completely optimized for both desktop and mobile devices.

3.2. Experimental method

Participants were shown neutral, negative, and positive imagery as a manipulation in their investment taking decisions. That is, the imagery forms the experimental treatments with neutral imagery as a control group and positive and negative imagery as the treatment groups. Hence, this would imply a between-subjects design. Nevertheless, as will be seen, there are also some within-subjects elements. This will be elaborated on in 3.3.3. Firstly, the method and measurement of imagery will be explained, followed by elaboration on its position within the investment decisions by discussing the financial context.

[5] The used service was SurveyCircle.com. One can find respondents here by also participating in others' surveys. It has strict rules and monitoring, as to insure survey participation is taken seriously by all (for instance, it is controlled whether participants use the approximate allocated time for any given survey. Persons who do not adhere can be reported to the site and have their surveys removed, and the max observations to be attained is capped at a hundred).

3.2.1. Experimental method: imagery

Imagery from OASIS database has been used. This database, developed by Kurdi, Lozano, & Banaji (2017), is an open-access dataset that measures affective standardized imagery based on valence (the degree of positive and negative emotion evoked) and arousal (the intensity of the given emotion's evocation). It is readily accessible[6], easy to use, and contains a substantial amount of around 900 images (Kurdi et al., 2017). The data on OASIS is divided into four different categories, being persons, animals, objects, and scenery.

Using both this standardization and categorization, the following approach is taken. Firstly, distinction is made between positive, neutral, and negative imagery. That is, imagery is taken with low, medium, and high valence. Secondly, distinction is made between low-, medium-, and high-intensity, captured by low, medium, and high arousal. Thirdly, using the categorization, distinction is made as to include imagery that reflects 'neutrality' (also referred to as 'control') using the objects category[7], and imagery that reflects 'nature' using the scenery category. The reason for choosing two sets, being 'neutrality' and 'nature' will be elaborated more thoroughly later on, but can be seen intuitively as a benchmark (neutral) and an effect to be measured (nature). Because there was one control group and two treatment groups (neutral, positive, and negative treatment), with three intensities, and two sets, a total of eighteen images were used from OASIS. The used imagery, together with their arousal and valence means (μ) and standard deviation (σ) can be found in Table 1 in the Appendix.

To justify the choice of imagery, one may first look at Figure 2, showing all possible images ranked by their respective arousal and valence scores. Green dots represent the 'animal' category, being quite divided over the grid, but often having relatively high arousal scores. This can be either with low valence (i.e. animals being hurt), or high valence (i.e. a playing puppy). The animal category was not used for this research, since there were better[8] alternatives for positive and neutral imagery. Additionally, the negative imagery on animals could be quite disturbing and was hence not included due to ethical considerations[9]. Blue dots represent the 'object' category and were used for most of the 'neutrality' imagery. Out of 9 total neutrality images, 7 were categorized as object. Only the low- and high-intensity positive imagery was obtained from the 'person category', which is represented by red dots in the grid. This was done as most object dots are cluttered in the medium-valence region, and there is hard distinction to make for higher-valence object dots (that is, their arousal scores do not differ substantially). Hence, the choice was made to include two 'person' images, reflecting a boy with a lollipop and two people getting married. This allowed

[6] The image set is open-access and can be found at http://www.benedekkurdi.com/#oasis.

[7] There was also made use of the category 'persons' for two of the imagery. Elaboration on this will follow.

[8] With regard to mean, standard deviation, and also the intuitive fit of imagery reflecting more 'sustainability' rather than just 'nature'.

[9] Another point is that survey distribution was primarily done on voluntarily base. Hence, disturbing image could greatly decrease completion rates.

for more distinct categories (the difference in arousal scores between low-, medium-, and high-intensity are larger), at the cost of not fully committing to one 'category'.

Finally, the yellow category reflects scenery, and offers both negative, neutral, and positive points at numerous arousal scores. This category was used for the 'nature' imagery.

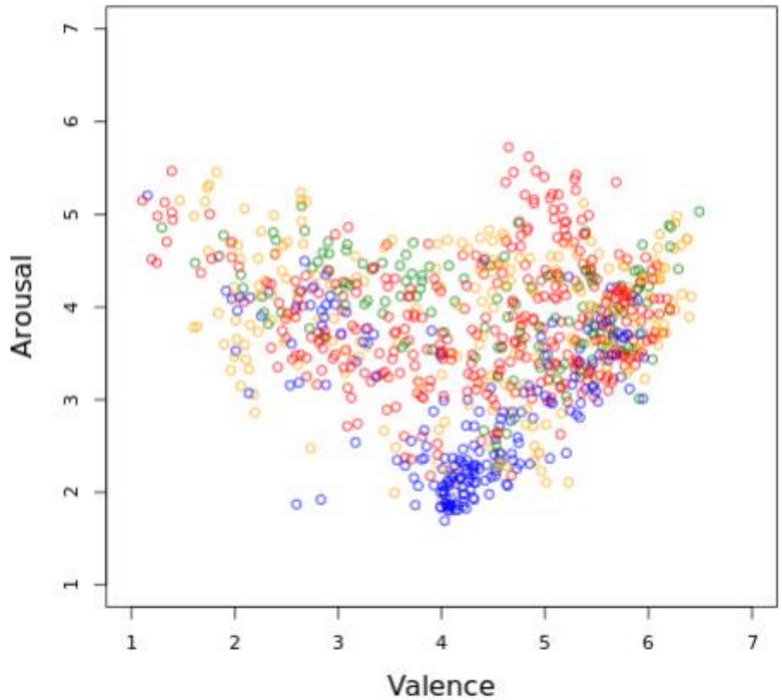


FIGURE 2. OASIS IMAGERY IN VALENCE-AROUSAL GRID (KURDI ET AL., 2017)
Notes: green = animal, blue = object, red = person, yellow = scenery

Figure 3 and Figure 4 show the valence-arousal grid for the nine 'neutrality' and the nine 'nature' images respectively[10]. Despite best attempts made to have approximate equal distances, some error remains due to a limited amount of (ethically suitable) pictures. This is especially true for the 'nature' group imagery, where imagery with low arousal was lacking, and negative low-intensity imagery was generally not very nature-related (rather, it was scenery such as buildings burning down by non-natural causes). The degree of nature-relatedness was mostly based on general consensus; i.e. environmental problems such as pollution, and forest fires (rather than buildings) are generally seen as unsustainable (Massard-Guilbaud & Mosley, 2011) and were hence used as negative imagery. Vice versa, more 'green' is overall seen as related to sustainability (Biggart, Hoffman, & Henn, 2013) and was hence used in the positive imagery.

[10] Linkages between image code (i.e. Neg high) and actual image can be found in Table 1.

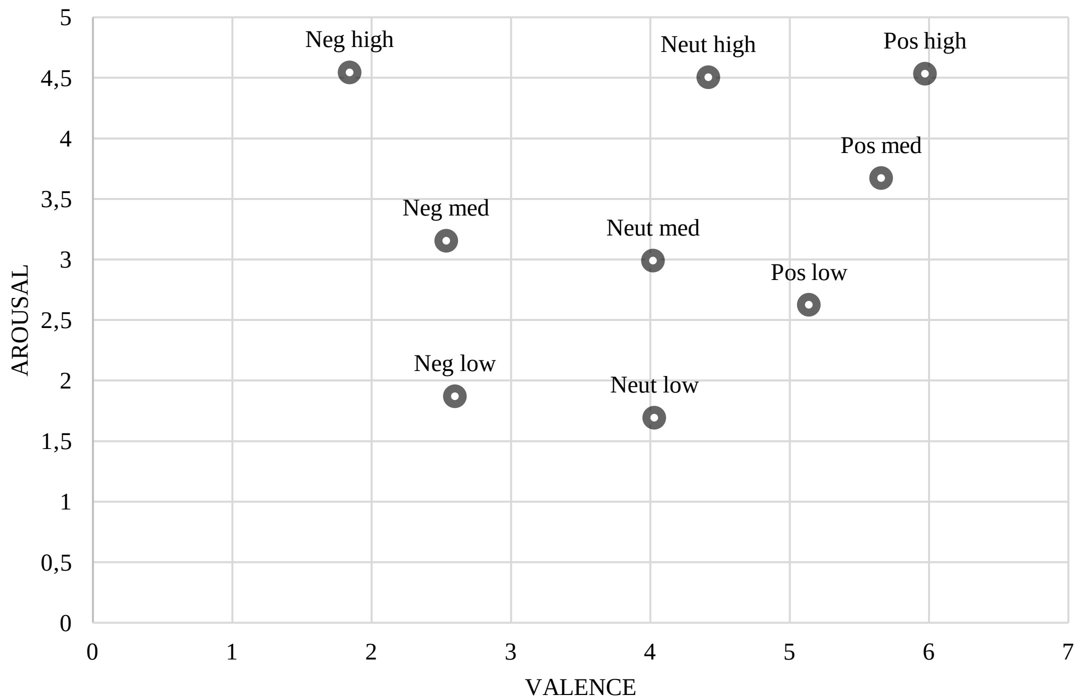


FIGURE 3. VALENCE-AROUSAL GRID FOR 'NEUTRALITY' IMAGERY

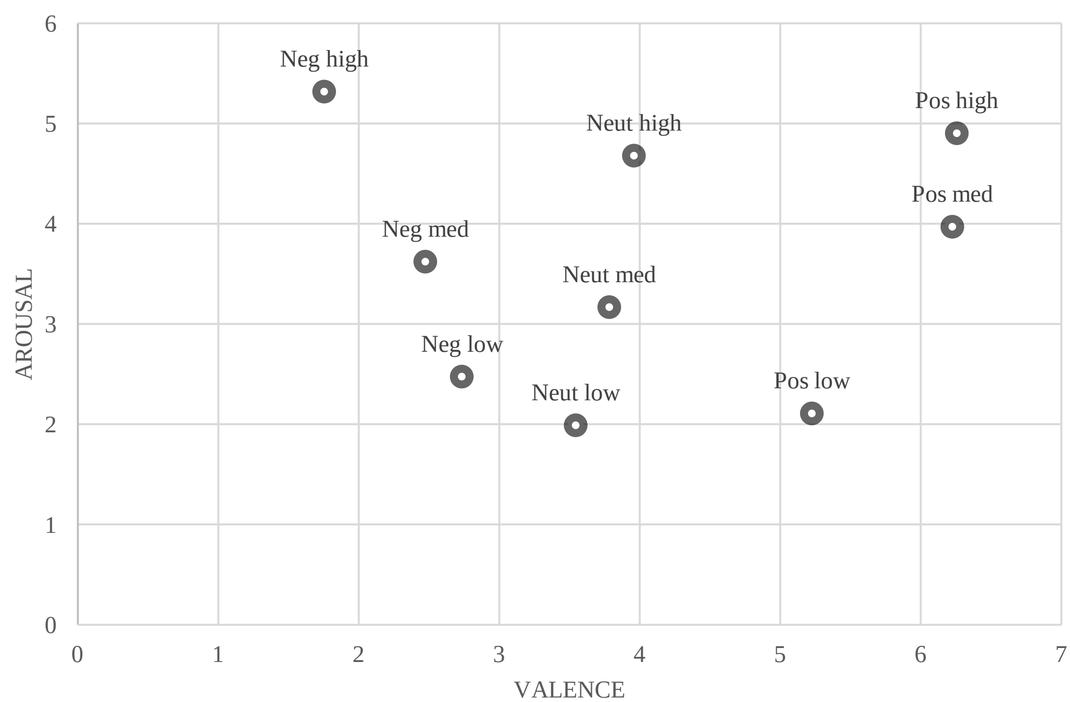


FIGURE 4. VALENCE-AROUSAL GRID FOR 'NATURE' IMAGERY

3.2.2. Experimental method: financial fundamentals

Given the context of KIIDs mentioned in former sections, merely showing the imagery for an investment decision would lack the significant portion of context around the company, and hence give incomplete conclusions. As such, financial statistics have been provided in the experiment as well, which will also be referred to as the 'fundamentals'. These fundamentals have been chosen based on two grounds. Firstly, real-world KIIDs themselves were used, as they display financial information in organised format for investors (Walther, 2015) and are therefore directly applicable in the experiment as well. Secondly, theoretical grounding on important factors in asset pricing has been used. Finally, given that these fundamentals are not part of the main research question, additional focus was put on making them easy to understand.

To offer more elaboration on the first point, the document by Deloitte (2020) will be addressed, which offers a practical guide to Key Investor Information. Some of these matters will not be entirely relevant for the experimental companies, as they regard personalised information on the asset. This will be avoided, as to not complicate the investment decisions. One may think here about practical information about the company (i.e. where to obtain documents, information on specifics), charges on the fund, and its identification (i.e. ISIN codes). The relevant points of financial data in the KIID that remain are its past performance and its risk and reward profile.

Firstly to address past performance, does it actually say something about future performance? Though there have been studies documenting this phenomena over the last decades, and it can be found to still hold with numerous strategies (Jiang, Han, & Yin, 2019), there is also large discussion about it due to large outliers and support for efficient markets (Nayak, Misra, & Behera, 2019). For this reason, these types of diagrams may also contain warnings on interpretation, as can be seen in Figure 5 for a Vanguard fund KIID, stating its past performance is "not a reliable indication of future performance". As such, the graphs will not be included to avoid confusion among participants. The risk and reward profile provides a more interesting base. Namely, this has been a key component (if not, the only component) in traditional asset pricing models, such as the Capital Asset Pricing Model (Sharpe 1964; Treynor, 1962). Here, the risk-reward relationship is the only variable, being captured by ß, the exposure to the market. Moreover, the risk and reward profile can also be portrayed in an easy-to-understand table (See Figure 6). For this reason, it is seen as a good fit, and tables similar to the displayed examples will also be implemented in the experiment itself.

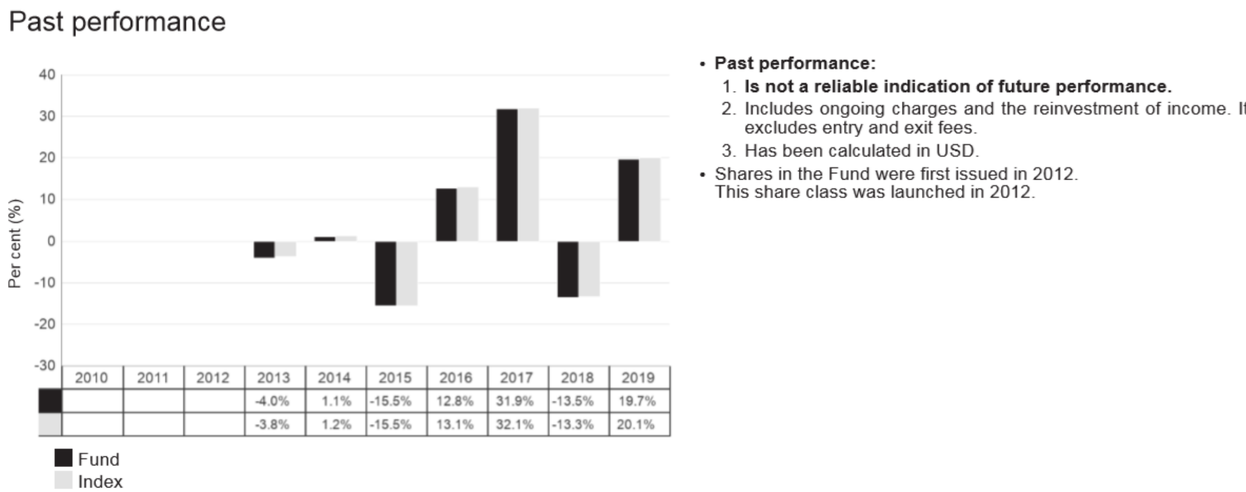


FIGURE 5. PAST PERFORMANCE INDICATION FROM VANGUARD SUB-FUND KIID (REPRINTED FROM VANGUARD GROUP, 2020)

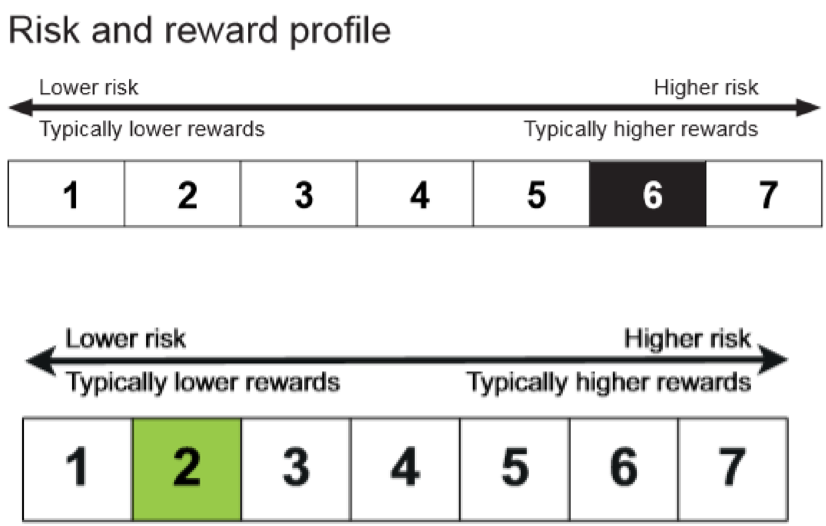


FIGURE 6. RISK AND REWARD PROFILES AS SEEN IN VANGUARD GROUP (2020) AND DELOITTE (2020) RESPECTIVELY (REPRINT)

However, as also mentioned in 2.1, the CAPM has been criticised heavily due to its lack of explanatory variables by streams such as behavioural finance (De Bondt et al, 2008). Though it provides a base, more financial fundamentals are required to simulate an investment decision. At the same time there exists a trade-off here, as too many variables will lead to the phenomenon of information overload (Pilli & Mazzon, 2016). For this reason, only one additional important variable was added, being company size.

The importance of company size was shown in the Fama-French (1993) three-factor model. This model substantially increased the explanatory power of the CAPM by adding the factors 'firm size' and 'book-to-market ratio', explaining large parts of expected return variance (Drew, 2003). Both could be suitable, but it can be argued that firm size is easier to understand than book-to-market ratio, as it is commonly measured by simply the number of employees (Ettlie & Rubenstein, 1987; Medrano-Adán, Salas-Fumás Sanchez-Asin, 2019). Moreover, it is commonly accepted in legislation. To illustrate this, under the European Union's *Commission Recommendation concerning the definition of micro, small and medium-sized enterprises* (2003), small and medium-sized enterprises (SMEs) are defined to have a maximum of 250 employees, small enterprises to have maximum of 50 employees, and microenterprises to have a maximum of 10 employees[11].

Yet, definitions do also differ slightly between countries (also see Table 2). For instance, under the United States' legislation[12], distinction between industries is made for companies' number of employees required to be defined a given size. Dilger (2018) simplifies this in a historical overview with a general rule that micro enterprises are defined as less than 6 employees, small- as 250 or lower, medium- at 500 or lower, and large enterprises at 1000 or higher. The most striking difference between the two is that for US legislation a medium size company is at 500 employees or lower, whereas for European legislation this is already at 250 employees or lower (which is deemed 'small' in the United States). Of course, this may also be different for many other countries' legislation that are not mentioned now.

To account for the given differences in the definitions, the experiment had a sufficient number of variance in the presented 'Company size' (also see Table 2). These could be either: 2, 10, 100, 250, 1000, or 5000 employees, where 2 and 10 captured microscale companies, 100 and 250 captured small/medium companies, and 1000 and 5000 captured large (multinational) enterprises[13].

It should be noted that it is not as important for these 'fundamentals' to contain all possible information for an informed investment decision. They should merely offer sufficient indication (that is, a context) such that participants can form an idea of the hypothetical companies; it is the treatment imagery which is most important as the research subject. As will also be shown in 3.3.3, the fundamental information will also drop out in actual calculations for mean comparison using t-tests, as the fundamentals are kept

[11] Additional definitions within the legislation document, such as annual turnover, will not be addressed.

[12] Also see Small Business Size Regulations (2020).

[13] Note that categorization of these values did not play a part in the experiment.

constant between companies per intensity. In further statistical (regression) analysis, the fundamentals will be controlled for.

TABLE 2. COMPANY SIZE DEFINITIONS IN EU/US LEGISLATION AND EXPERIMENT

Size definition	**EU legislation (# employees)**	**US Legislation (# employees)**	**Used in experiment (# employees)**
Micro	< 10	< 6	2, 10
Small	< 50	< 250	100, 250
Medium	< 250	< 500	100, 250
Large	< 1000	< 1000	1000, 5000

Notes: Legislation numbers based on 'Commission Recommendation concerning the definition of micro, small and medium-sized enterprises (2003)' for EU and 'Small business Regulation (2020) for US.

3.3. Experimental design

3.3.1. Experimental setup: overview

A general overview of the experimental setup can be found in Figure 7. Starting with an introductory page, participants were informed about the investment decisions they had to make, and were asked to consent with participation and anonymized data collection. They were then split into the three groups as mentioned in 3.2, being neutral, positive, and negative imagery. At this point, participants would be shown the investment decisions (see Figure 8 for an example). The fundamentals and order in which the companies are shown were randomized. Each participant was shown eight companies: low-, med-, and high-intensity control (='neutrality') imagery; low-, med- and high-intensity nature imagery, and two no-imagery companies (elaboration on randomization and no-imagery companies will follow later on). After this, all participants were shown the control questions. These included general demographics, such as age and gender, and a manipulation check to see if participants felt the 'right' (neutral/positive/negative) emotion equal to the treatment they were in. Other Likert-items were also shown to capture valuable properties of participants that may influence the investment decision, such as familiarity with financial concepts. (Ezzeddine, Soussi, Baccar, & Bouri, 2014). Lastly, participants could choose to enter a raffle for one of three 10€ (Bol.com or Amazon) gift cards.

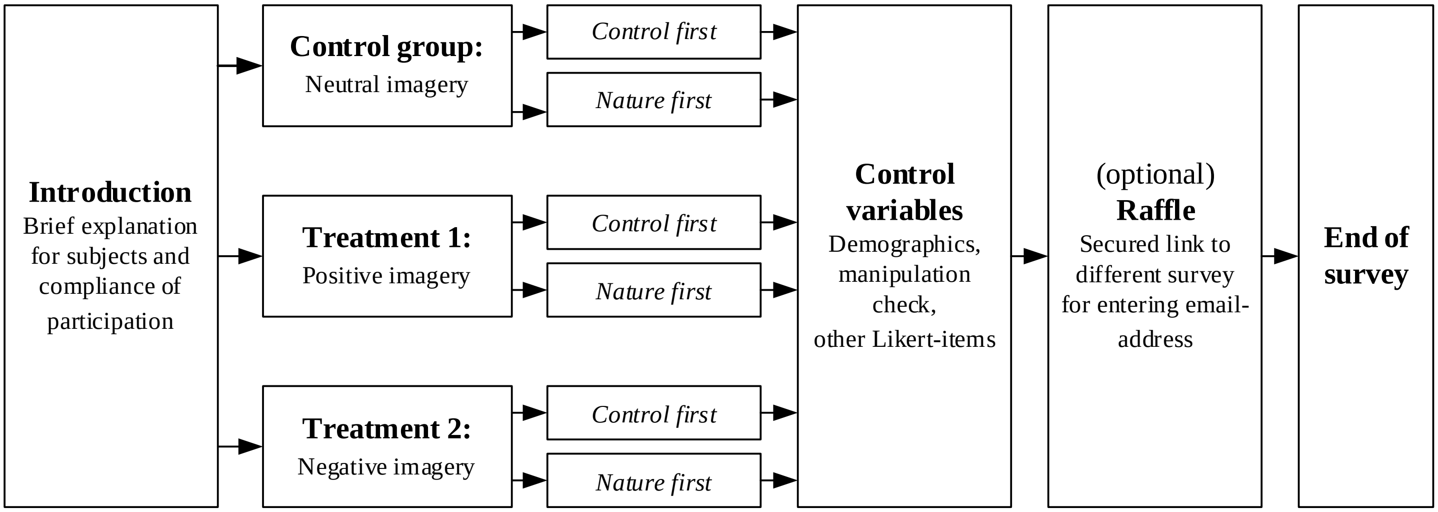


FIGURE 7. GENERAL OVERVIEW OF EXPERIMENTAL SETUP

3.3.2. Experimental setup: introduction

Given the former general overview, a more thorough elaboration will be offered for each of the survey's subparts (introduction, investment decision, and controls). The introduction screen was presented similarly for each participant as shown in Figure 9. Firstly, it proposes a hypothetical scenario, in which €10,000 is inherited, and can be invested in a given hypothetical company, or kept for a 0% return. Some 'story-telling' is done in order to avoid the hypothetical bias (Murph, Allen, Stevens, & Weatherhead, 2005), a phenomenon where subjects behave differently in hypothetical scenarios. By designing the experiment in a fashion in which people are more informed about context, one can partly adjust for this hypothetical bias (Murph et al., 2005). After this, an example risk and reward table is given (always depicting '6'), followed by an indication that participants will be offered statistics on company size. It is made clear that they will be shown eight companies, and additional emphasis is put on the fact that decisions should be made individually (this is also repeated at each investment decision; see Figure 8). That is, they should make their decisions as if they had the full amount of inheritance money each time. Only a short sentence is given stating: "At times, images may be shown in addition to the previously mentioned information. These images can be associated with the company". This is done to avoid an overly large attachment to the imagery and thereby to avoid a demand effect (De Bondt et al, 2008). Finally, a brief explanation on the raffle is offered, and a statement is made of anonymously recorded and fair-use data. Participants need to confirm that they have read the instruction and consent with data recording by ticking a box before they can continue the survey.

3.3.3. Experimental setup: investment decision

An example of an investment decision was shown in Figure 8. Figure 7 showed that order was dependent on another step called 'control first' or 'nature first'. To elaborate on this, it should firstly be stated that there were two sorts of randomization; a randomization in the fundamentals and a randomization in the order of displaying the companies. Naturally, this randomized order was important for both, as to generalize results (that is, all levels of risk, size and their combinations for companies were addressed) and to make sure that there is no influence of the order itself. However, to maintain the point valid of imagery being the only treatment, it should be made sure that the fundamentals presented were the same over two respective companies of the 'control' and 'nature' imagery group[14]. For instance, the company with 'control' neutral low-intensity imagery and the company with 'nature' neutral low-intensity imagery were required to have the same fundamentals presented, such that it was only the difference in imagery that formed the treatment.

Though randomization for the fundamentals was of no further issue[15] a small limitation revolved around randomization for the companies. Namely, within Qualtrics, full randomization of company order was not feasible due to the need for both 'nature' and 'control' companies to display similar fundamentals[16]. To maintain the randomization, participants were randomly assigned subgroups 'control first' or 'nature first', having all 'control' companies presented first or having all 'nature' companies presented first. This setup can be seen in Figure 10 and will be argued to have a near-identical effect of complete randomization.

Given that there were two times three different intensity companies, this would add up to six decisions for participants in total. However, as can be seen in Figure 10, an additional 'Standard no image company' and a 'no imagery with fundamentals of former medium intensity company' were also added, giving a total of 8 decisions to be made. These 'no image' companies were added to create a baseline in later analyses and as additional controls. These elements are also the reason that some parts of the experiment can also be classified as within-subjects design.

[14] This is for comparing means using t-tests. Naturally, in i.e. OLS regression, this can be controlled for.

[15] Other than being only able to have of one randomized subset in Qualtrics, hence requiring a 'ticked box' multiple-choice question for the secondary one (as also seen in Figure 8). This was never mentioned an issue in the comment box participants were given at the end of the survey, and is not addressed further as a limitation.

[16] Qualtrics' display logic requires the input to be known; hence it cannot be fully randomized due to display logic only functioning one-way.

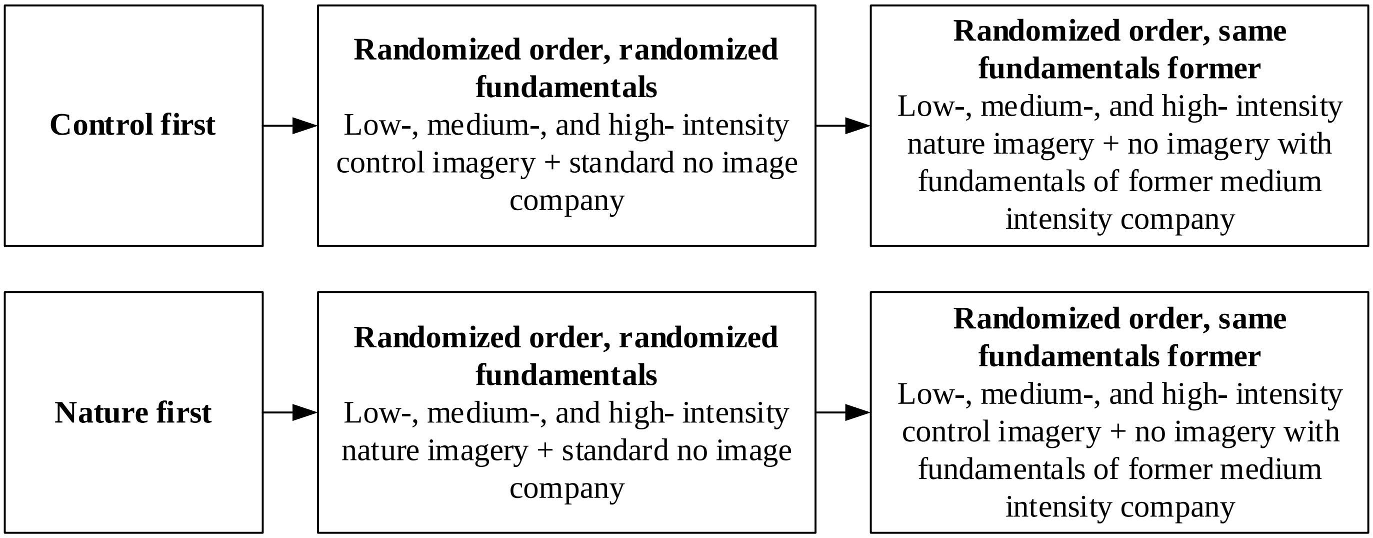


FIGURE 10. OVERVIEW OF COMPANY ORDER IN SURVEY

The 'standard no image company' was an investment decision that was similar for all participants, not depending on treatment group. It can be found in Figure 11, and contains a 'no image available'-image, a risk and reward table of 4, and a company size of 100 employees. These numbers were picked mostly arbitrary, but in a manner that avoided extreme situations (e.g. risk-reward of 1 or 7 score; 2 or 5000 employees). Given its similarity across all subjects, the investment percentages can give an indication about treatment affecting subsequent decisions[17] and a general willingness to invest of each participant.

The 'no imagery with fundamentals of former medium intensity company' was similar to the 'standard no image company', except that its fundamentals were not the same for all participants. Rather, it had the same fundamentals as the medium-intensity company first shown for each specific participant (either control or nature, depending on whether participants were in the 'control first' or 'nature first' group respectively). This company was added as it enabled general t-tests to be performed between means of this no imagery company and the medium intensity company (for either 'nature first' or 'control first'). Both no-image calculations will be addressed more thoroughly in 4.2.

[17] I.e. if the mean average investment for the no-imagery company was higher for positive, this would mean the imagery of previous decisions still had an influence on further decisions taken. This will be investigated later on in 4.2.1.

The investment decisions were made using a 0 to 100 slider, indicating the percentage of the €10,000 inheritance money to be invested in the company. This was done given the mobile-friendliness and ease-of-use that sliders offer. Qualtrics requires the slider to have a given starting point, so 50% was chosen to minimize anchoring effects (De Bondt et al, 2008). Furthermore, the explanation and the reminder that decisions should be made independently were restated each time. Responses were required to be given before participants could advance the survey.

Judging from data and the comment box at the end of the survey, participants seemed to understand the assignment well. Some participants were confused by the 'no imagery' decisions, as they believed it to be a technical error. This should however not influence the results, as it implies participants had still performed the investment task 'as if' there was simply no imagery available.

3.3.4. Experimental setup: controls

Finally, the control questions can be found in Figure 12. These consisted of general demographic questions (age, gender), a manipulation check to see if participants felt the emotions (positive, neutral, negative) as intended, and Likert-scale items to control for the extent that participants based their decision on the fundamentals, the degree to which they linked imagery to the company's practises, financial knowledge, and importance of climate change.

With regard to the manipulation check, it should be noted that this may be difficult for participants to answer, as i.e. 'neutral emotions' are difficult to define. Moreover, intensities may also influence the decision; the concepts of 'valence' and 'arousal' were not mentioned to participants to avoid complication. This means that i.e. high-intensity neutral imagery (A burning sun) might be affiliated with negative imagery more easily, especially if shown as the last company (recency effect; Baddeley & Hitch, 1993). To take into account these inaccuracies, it will be argued that if the majority (> 50%) of respondents answers the question correctly, the imagery was perceived as intended.

The Likert-scale items were chosen due to their ease in use and understanding (Arnold, McCroskey, & Prichard, 1967). That is, more extensive tests such as financial literacy questions (Van Rooij, Lusardi, & Alessie, 2011) could also be used, but make the survey significantly more extensive. Given that participants will be asked to participate on a voluntary base, this was therefore not used as it would increase the chance that respondents quit the survey early (the questions are also quite confronting for those not familiar with financial concepts). With regard to the climate change importance question, the climate-belief scale was taken into account (Kerr & Wilson, 2018; Lewandowsky, Gignac, & Oberaur, 2013) due to its common use in literature, but was also transformed to a simple Likert-scale question for the same reason.

3.4 Statistical method

As will follow in the next section, in addition to general t-tests, Ordinary Least Square (OLS) regression will be used for cross-sectional analyses of the data acquired through the experiment. OLS is widely used in numerous disciplines, including econometric theory, due to its ability to have the smallest variance of all linear estimation, given it satisfies the Gauss-Markov assumptions (Theil, 1971). It is also convenient due to its ability to show relationships in mathematical equations and allows for intuitive interpretations and claims to be made about magnitude (of coefficients) and significance. Adding to the intuitive and convenience argument, the OLS estimations in this paper can effectively model the investment decision made (with the constant becoming an 'average' investment and the 'additional' effect of other variables presented by their respective notation in the equations). Regression equations will be presented in 4.3, which will be preceded by data and descriptive analyses of the experiment itself.

4. Analyses

4.1. Dataset

Distribution of the experiment took place from 2 April 2020 to 26 April 2020. In this time, 323 total observations were recorded. However, 62 of these observations were only partial completions[18], and were dropped for this reason. Hence, this led to 261 completed observations. Though dropping any of these complete responses should be done very carefully, as to avoid an omission bias in the data, some of these completed observations were invalid. These were mostly people who filled in '0' or '1' for all investment decisions, because they would simply "always put their money on the bank" (remark, obs#168). If, and only if, all investment decisions were answered similarly with a 0 (or a 1), the observation was deleted[19]. All other observations were kept, leading to a total amount of 254 'valid' observations[20], which will be used for the analyses.

The most important variables with their descriptions can be found below in Table 3. With regard to dataset demographics, one may have look at Figure 14, which shows that a majority of the respondents (59.06%) was female, and that the mean age was 29.41 years old, containing a positive skew. The sample might not be fully representative of the actual population, given that it was distributed via friends and family. As such, there will be a relatively large number of students that have participated. Taken this into account, and considering that there was no deliberate selection of subjects, it is assumed to not be problem for the remainder of the paper.

With regard to treatment distribution, Table 5 shows that this was done relatively equally. Though an option in Qualtrics was used to ensure an equal spread, participants quitting the survey early may skew the treatment distribution. It is henceforth logical that the negative imagery group has the least amount of participants (31.50%), as seeing negative imagery (and assuming it evokes negative emotions) will make one less eager to participate in the survey. However, following this logic, it is unclear why the positive treatment also has a relative low amount of participants (32.67%). Nevertheless, the differences are small and therefore assumed to not be a problem; participants are equally distributed into the treatment groups.

[18] All of the partial observations quit the survey after the introduction, or after a small number of investment decisions. There were no partial observations that did the investment decisions but did not fill in control questions.

[19] Thus, if only one investment decision was made, the observation was still kept.

[20] Note that the 'valid' observations did include all persons that did not answer the verification question right. This will be elaborated on later.

TABLE 3. VARIABLE DESCRIPTIONS

Variable name (*shortened*)	Description
Investment ***(invest)***	Ratio variable that acts as the dependent variable and indicates the percentage (0 to 100%) that was invested in a given company. Can be the investment in the control imagery low intensity (***low***), medium intensity (***med***), or high intensity company (***high***). Alternatively can be investment in the nature imagery low intensity (***low_n*)**, medium intensity (***med_n***), or high intensity company (***high_n***). It may also be for the standardized no-image company (***noimage_standard***) or the no-image company with statistics based on the medium-intensity company (***noimage_based***). In the regression analyses, all investments are put under the invest variable, with dummy variables (of similar names: low, med, high) categorising the intensity and dummy variables categorising whether or not the imagery was nature or not (***control, nature***).
Treatment group ***(positive/negative)***	The independent treatment variable 'treatment group' contains categorisation of participants in neutral, positive and negative treatment. It will be displayed through dummy variables, being ***positive*** (where 0 is neutral or negative, 1 is positive imagery) and ***negative*** (where 0 is neutral or positive, 1 is negative imagery). Hence, if both are included in i.e. OLS regression, the baseline will contain neutral imagery treatment.
Risk	Ordinal variable that shows which risk-reward table was presented to the participant. Can range from 1 (low risk, typically low rewards) to 7 (high risk, typically high rewards). It is similar for both control and nature groups per each intensity (low/med/high). For no image companies, the value was either always equal to 4 or the same as the medium-intensity companies.
Size	Ratio variable[21] that shows the amount of employees presented to the participant. Can be 2, 10, 100, 250, 1000, or 5000. As with risk, the values are similar for both control and nature groups per each intensity. For no image companies, the value was either always equal to 100 or the same as the medium-intensity companies.
Familiarity with finance (*familiarity_finance*)	Ordinal variable capturing how the familiar participants were with financial concepts and investment decisions. It is based on a 5-point Likert item ('not at all' to 'completely'); hence this variable can range from 1 to 5.
Importance climate change ***(importance_climate)***	Ordinal variable capturing how the important participants deemed climate change as an issue. It is based on a 5-point Likert item ('barely any importance' to 'very important'); hence this variable can range from 1 to 5.
Affect for imagery ***(affect_imagery)***	Nominal/ordinal variable capturing the extent to which participants believed they took into account the imagery. The variable consists of responses "I only briefly took a look at them" = 1, "I took some time to look at them" = 2, "I started wondering how these images influenced the company's way of business" = 2, "They made me think of other firm characteristics, like corruption and social responsibility" = 4, other answer = 5.
Affect for fundamentals ***(affect_fundamentals)***	Ordinal variable capturing the extent to which participants believed they took into account the financial fundamentals (size or risk). It is calculated as the maximum value of their responses to what extent they took either the risk-reward table or the company size statistic into account. Both were based on 5-point Likert items ('not at all' to 'completely'); hence this variable can range from 1 to 5.

Notes: other variables that may be introduced as based on these given variables and will be elaborated on in their respective section. Shortened variable names (if existing) may be displayed and will be used in equations.

[21] Should be interpreted carefully, as only 6 possibilities were possible. Though the numbers are at the interval level, due to these few rounded categories, this may also be seen as an ordinal variable.

Table 4 also shows the outcome of the manipulation check question, which is of great important for the validity of the dataset and research. As can be seen, even when assuming the harshest criteria (where the response 'I do not know' is taken as an incorrect answer) the manipulation check percentage (52.36) exceeds the 50% mark mentioned in 3.3.4. Nevertheless, it only does so by a small margin, showing that the question may have been difficult to answer. Observations with incorrect answers will still be kept, as dropping them would result in a too low observation count for valid empirical analyses. Naturally, this forms a limitation and causes care to be taken in interpretation.

4.2. Descriptive statistics

4.2.1. Descriptive statistics: investment decisions

A comparison of means for the investment decisions, organised by treatment and intensity, can be found in Table 5. One can see that the average investment is around 32% if all observations are taken into account. When observed per treatment, it can be found that neutral treatment had an average investment of 32.80%, close to the overall average. Average investment for the positive imagery treatment was higher, at 40.04%, and average investment for the negative imagery treatment was lower, at 22.90%. Using t-tests, it can also be found that there is a significant difference between means at the 99% confidence level for neutral and negative ($t = 3.420$), and positive and negative ($t = 5.269$). There is a significant difference between means at the 95% confidence level for neutral and positive ($t = 2.14$). These findings are in accordance with hypotheses stated in 2.4, but require more thorough analysis. To do this, the no-imagery company with fundamentals based on the medium company will be used, as to exclude the fundamental component entirely (since it is constant over both; only the imagery has changed). In 4.3, regression analysis controlling for the fundamentals will also be used.

4.2.2. Descriptive statistics: differences whether or not imagery is used

The differences between medium company and (based) no image company can be calculated for using nature companies as a base or using the control companies as a base and can be found in Table 6 below.

TABLE 6. DIFFERENCES MEDIUM-INTENSITY AND BASED NO IMAGE COMPANY

Base	Treatment	Obs	Mean	Std. Dev.	Min	Max	|t-stat*|	p-stat*
Nature	Neutral	91	3.626	16.530	-31	68	2.093	0.039
	Positive	83	7.422	19.924	-47	75	3.394	0.001
	Negative	80	-6.013	28.784	-85	100	1.868	0.065
	Total	**254**	**1.831**	**22.703**	**-85**	**100**	**1.285**	**0.200**
Control	Neutral	91	0.582	16.980	-40	66	0.327	0.744
	Positive	83	6.325	25.519	-63	81	2.258	0.027
	Negative	80	-7.588	20.193	-85	53	3.361	0.001
	Total	**254**	**-0.114**	**21.734**	**-85**	**81**	**0.083**	**0.933**

**Notes: t-statistics and p-statistics are given for H_0: Mean(variable) = 0 (per treatment), two-tailed test.*

Given that both variables capture the nature/control company minus the no-image company, a positive mean would indicate a higher willingness to invest in the imagery company (thus, a lower willingness to invest in the no-imagery company) and a negative mean vice versa. Table 6 shows significantly (95% confidence) positive means when for participants that were in positive treatment, and significantly (99% confidence) negative means for participants in negative treatment. These differences are also quite substantial, at around 6 to 7 percent higher or lower investment for positive and negative treatment respectively. Furthermore, these result are also in accordance with the first hypothesis. Neutral imagery only seems to have a significant difference (95% confidence) when using nature image as a benchmark; even without looking at significance, the difference in means seems quite large (3.626 against 0.582). Finally,

Table 7 compares means per treatment, and shows that there is a significant difference (99% confidence) between using either negative or neutral, and using either positive or negative imagery. The latter also provides some lead in the same direction as the firstly stated hypothesis, though a significant difference would also be expected between positive and neutral imagery.

4.2.1. *Descriptive statistics: differences whether imagery is control or nature*

Something that has not been addressed so far, is the second hypothesis, which predicts that positive nature imagery will have higher investment than positive control imagery of equal intensity. Similarly, it is expected that negative nature imagery will have lower investment than negative control imagery of equal intensity. Looking at the data, Figure 15 shows a bar graph of mean investment decisions per treatment group, divided per intensity. From this figure, one may see that nature companies have higher percentages of investment for each given intensity given each respective treatment. Hence, this does not corroborate the second hypothesis.

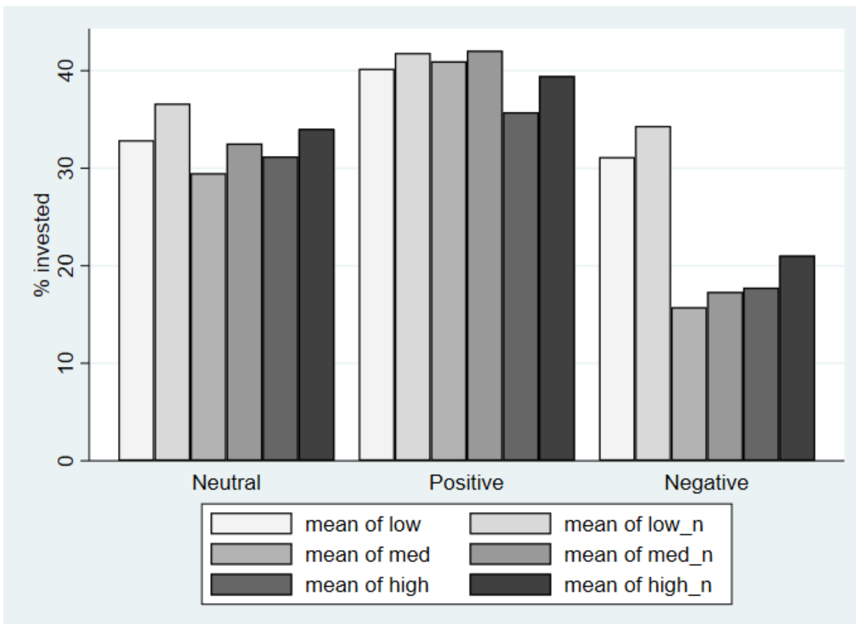
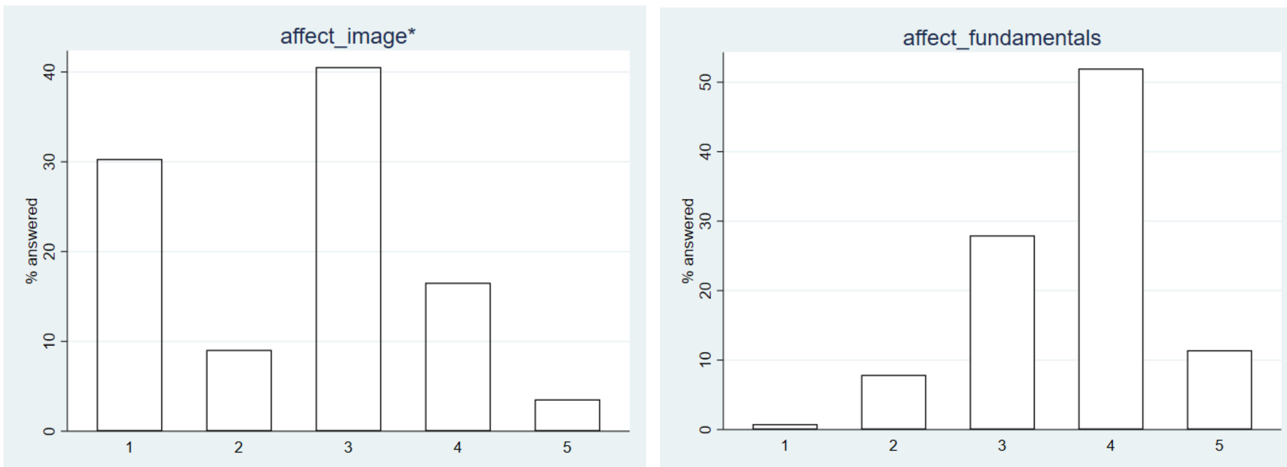


FIGURE 15. BAR CHART COMPARING CONTROL AND NATURE COMPANIES

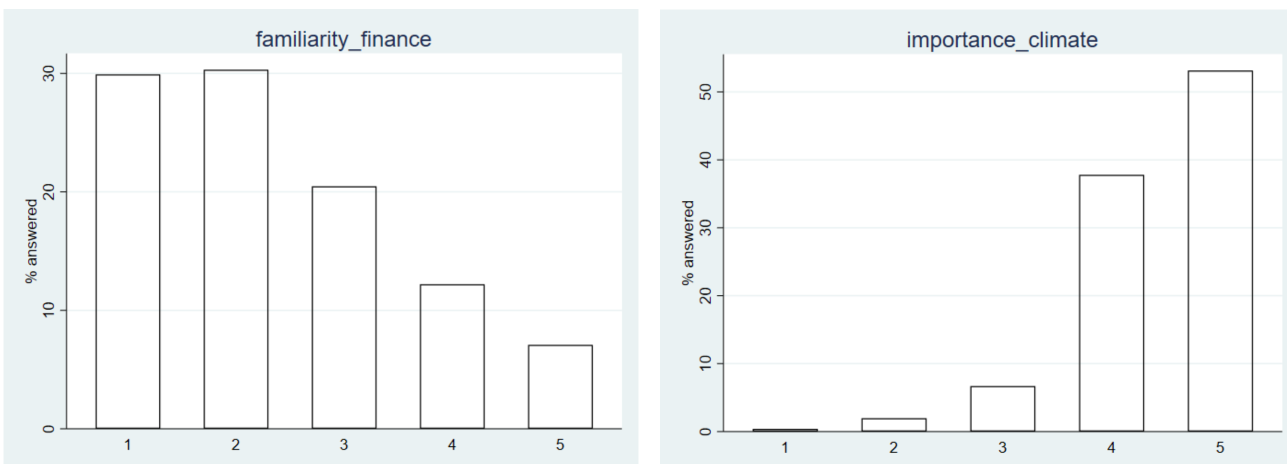
To investigate this further, the difference is taken between the nature and the control companies at each of the three intensities, after which t-tests are performed. These are displayed in Table 8 for each given intensity, most turning out insignificant, except for two: low intensity for the neutral treatment group (90% confidence) and high intensity for the positive treatment group at 90% confidence, close to 95% (p = 0.054). The latter may be interesting, as it relates to the point of 'spectacular imagery of nature' made by Lester & Cottle (2009, p.922), which creates certain personification of sustainability that might evoke exceptional emotions. This would suggest that a certain intensity is needed to see a difference between the control and nature companies, and the positive difference that is found is also expected in the second hypothesis. Nevertheless, this does not explain why a negative difference is not found for the opposite. More thorough empirical analysis is needed, controlling for other factors, which is what will be addressed next.

4.2.2. *Descriptive statistics: controls*

Namely, the sample can be furtherly identified by looking at responses for the control questions. This is given in Table 9 in the Appendix per treatment[22] or in Figure 16 below where frequencies can easily be compared.



Mean* = 2.448 | Std. Dev. = 1.106 **Mean = 3.654 | Std. Dev. = 0.814**



Mean = 2.362 | Std. Dev. = 1.227 **Mean = 4.413 | Std. Dev. = 0.737**

**Notes: The results of the affect_image variable should not be interpreted as a Likert-item; 1 = "I only briefly took a look at them", 2 = "I took some time to look at them", 3 = I started wondering how these images influenced the company's way of business, 4 = They made me think of other firm characteristics, like corruption and social responsibility, 5 = other (also see 3.3.4). For this reason, the 5th category is also left out in calculation of the mean and standard deviation, and interpretation of it is limited.*

FIGURE 16. BAR CHARTS OF FREQUENCY ANSWERS CONTROL VARIABLES

[22] These differences per treatment, however, did not seem very substantial. An interesting finding is that negative treatment answered 'greatly' more often on the affect_image question than the positive and neutral treatment (8.66% to 4.72 and 3.15%), but this is very minor and won't be addressed more extensively for this reason.

With regard to the extent people were affected by the image, choices 1 (= I only briefly took a look at them) and 3 (= I started wondering how these images influenced the company's way of business) seemed to be most picked, whereas 2 (= I took some time to look at them) was rarely chosen. This may mean that people think in relatively absolute terms, either completely not thinking about the imagery or thinking rather carefully about them. Financial fundamentals seemed to be quite important to people, with the mean of 3.654 leaning more towards higher Likert-item scores. With regard to familiarity with financial concepts and investment decisions, one may see that the sample is primarily unfamiliar. Climate change is deemed very important among sample participants, with 90.95% of participants choosing one of the higher two options.

The following paragraph will use the described control variables to create models with sufficiently explanatory power, as to avoid omission biases. All three hypotheses will be addressed one by one, of which equations are presented where regression estimates are based upon. The tables for the regression estimates can be found at the end of each subparagraph.

4.3. Empirical analyses

4.3.1. Empirical analyses: hypothesis 1

The first hypothesis concerns the positive and negative treatment imagery, and expects that positive imagery will lead to a higher propensity to invest, whereas negative imagery causes lower propensity to invest. This was already shown in Table 6 by significant differences in means, but can also be done by means of OLS regression analyses. Hence, a simple baseline estimation can be performed using Equation (1).

$$(1)\quad invest = \alpha_1 + \beta_1 positive + \beta_2 negative + \epsilon_1$$

The OLS estimation of the equation can be found in Table 10|[23]. It is estimated using 1880 observations, which is the total number of respondents times[24] eight investment decisions. It shows the hypothesized signs, as being in positive treatment significantly (99% confidence interval) increases average investment by 6.156%, while being in negative treatment significantly (99% confidence interval) decreases average investment by 8.358%. It can also be seen that the constant is significant at the 99% confidence interval, and shows an average investment percentage of 34.64%. This is close to the total average investment found for the investment decisions (also see Table 5). However, the explanatory power of the model is still quite low, as the R-squared shows that only 4.5% of the variance can be explained. To create a more thorough model, the controls should be added. This is done in Equation (2).

$$(2)\quad invest = \alpha_2 + \gamma_1 positive + \gamma_2 negative + \gamma_3 age + \gamma_4 female + \gamma_5 familiarity\_finance + \gamma_6 risk + \gamma_7 size + \epsilon_2$$

When age, gender, familiarity with financial concepts, and the fundamentals are added[25], the earlier found effects of positive and negative treatment do not change substantially[26]. Both are still significant at the 99% confidence level, but the size of the coefficients has altered. The positive treatment coefficient has gone up to 8.684%, whereas the negative treatment coefficient has decreased in absolute sense to -7.704%.

23 Table also contains estimations for following equations related to testing this hypothesis.

24 The total amount of respondents is 254. There were however missing values for gender and age (see Figure 14), which decreased this to 235 data points. 235 times 8 then gives the 1880 total observation count.

25 The variables age, familiarity with finance, risk, and size were all mean-centered to make interpretation of the constant more intuitive; it reflects the investment decision of an average participant.

26 At this point, a VIF-test and Breusch-Pagan / Cook-Weisberg test were also run to test for multicollinearity and heteroskedasticity problems respectively. The results of these can be found in Table 11 and Table 12. The VIF-test showed a mean VIF of 1.14, indicating no further multicollinearity problem. The Breusch-Pagan / Cook-Weisberg test did show there to be heteroskedasticity problem. Hence, all estimations (including the previous two) have been adjusted by means of robust standard errors.

Age plays a significant role (99% confidence), with a positive effect of 0.152%. Hence, for every year older a participant was, the higher their investment by 0.152%. Given that the sample size primarily consists of people under 30 (also see Figure 14), this should be interpreted as just slightly higher investment for the higher ages (around 30-35) and slightly lower investment for lower ages (around 25-30). Both fundamentals are significant at the 99% confidence level, and show expected signs. Namely, higher categories in the risk-reward table will generally be less invested in, at -1.203% per category, which can be explained by general risk-averse attitude of people (Veld & Veld-Merkoulova, 2008). Higher size companies can be imagined to be more successful, giving that they managed to grow to their given state, hence the size variable logically shows a positive sign of 0.00196% per employee added. The constant remains significant at the 99% confidence level, with a value of 31.59%, being similar to the former estimation. The R-squared statistic has increased due to the controls, explaining 8.4% of the variance. An R-squared statistic around 10% can be expected in this setup, due to the complexity of investment decisions and the simplification caused by the experimental setup.

So far, decisions have only been categorised into groups by whether they contained neutral, positive, or negative treatment. As shown in the methodology, another distinction can be made with regard to the imagery. Namely, imagery can be divided into low-, medium-, and high-intensity. This is done in Equation (3).

$$(3)\quad invest = \alpha_3 + \delta_1 low + \delta_2 med + \delta_3 high + \delta_4 age + \delta_5 female + \delta_6 familiarity\_finance + \delta_7 risk + \delta_8 size + \epsilon_3$$

It should be noted that is possible to include all intensities into the regression, as the 'no image' investment decisions are marked as neither of the intensities, and thereby form the baseline for interpretation. That is, if all intensity dummies equal 0, the equation reflects the outcome for a no-imagery investment decision. Low-intensity imagery has a positive coefficient of 2.586%, but is insignificant; there is no substantial difference between showing low-imagery or no-imagery. Medium- and high-intensity imagery do show significant effects (90% and 95% confidence respectively), both having a negative sign. Hence, higher intensity imagery would reduce the investments made. However, this is merely a result for aggregated intensity dummies. To further inspect this, there should be made distinction in treatments.

This can be done by simply adding the positive and negative variables to the former equation. It should be noted that no-imagery investment decisions were still categorized by the three treatments, as to avoid potential errors of treatment affecting them (despite order randomization). Hence for interpretation, a baseline regression (where all intensity dummies equal 0) would be no-imagery, and when positive and negative are included (where all treatment dummies equal 0) a neutral treatment. This is captured in Equation (4).

$$(4)\quad invest = \alpha_4 + \zeta_1 low + \zeta_2 med + \zeta_3 high + \zeta_4 positive + \zeta_5 negative + \zeta_6 age + \zeta_7 female + \zeta_8 familiarity\_finance + \zeta_9 risk + \zeta_{10} size + \epsilon_4$$

This estimation does not cause any substantial changes to the coefficients found in the former equation, and displays its expected signs as previously. One interesting note here is the increase in the R-squared statistic, which has increased from 3.6% to 9.3%. As such, this gives an indication that the treatment dummies have around 5.7% of explanatory power with regard to the investment decision. To truly capture the effect both intensities and treatments have, it makes sense to include interaction terms between the two. This way, it can be captured how the intensities influence the investment decision, while making distinction for the given treatment one was in. This is captured in Equation (5).

$$(5)\quad invest = \alpha_5 + \eta_1 low + \eta_2 med + \eta_3 high + \eta_4 positive + \eta_5 negative + \eta_{6[a,b,c]} positive\#(low, med, high) + \eta_{7[a,b,c]} negative\#(low, med, high) + \eta_8 age + \eta_9 female + \eta_{10} familiarity\_finance + \eta_{11} risk + \eta_{12} size + \epsilon_5$$

When interaction terms are added, their main effects all decrease in size (in absolute terms) and turn insignificant, except for the positive treatment, which is still significant at the 90% confidence level. This main effect is the coefficient where the other terms (that is, the intensity dummies) have the value 0, and thus reflects the no-imagery investments decisions. Hence, this means that on average no imagery decisions were made 5.526% higher for participants in positive treatment[27]. When looking at the interaction terms, significant effects can be found for positive medium-intensity imagery (95% confidence), and negative medium- and high-intensity imagery (99% and 95% confidence respectively). These coefficients have their expected sign, where positive medium-intensity imagery increases investment by 8.439% and negative medium- and high-intensity imagery decrease investment by -10.57% and -9.250% respectively.

The interaction term findings differ partly from expectations. Firstly, following this paper's theoretical grounding, higher-intensity positive imagery should evoke more positive emotion, further amplifying the investment percentages. Hence, it is interesting to see that only medium-intensity positive imagery has a significant effect, and higher-intensity does not. This may be due to the imagery for medium-

[27] Note that this does not contradict the findings discussed in 4.2.2, where it was found that positive treatment participants invest relatively less in no imagery companies than their imagery-containing counterparts, because they may still invest higher in absolute terms for no imagery companies when compared between treatments. That is, despite investing less in imagery companies, the percentage may still be higher than what a participant in neutral treatment would invest for a similar no-imagery company.

and high-imagery being very close to each other in their arousal scores, as seen in Figure 3 and Figure 4, but then one might also expect them to simply display similar size coefficients. A secondary explanation may lay in a trade-off of social practises and profitability, which will be discussed later in section 545. With regard to the negative imagery, it would then also be expected that the higher-intensity decreases investment even more substantially than the medium-intensity imagery. These differences in size are however rather small, which may also imply there to be a 'cap' on emotional attribute in investment decisions.

For both positive and negative imagery, it is supported that low-intensity imagery does not have a significant effect. As such, both treatments support a claim that there is a certain threshold of intensity to be attained before imagery influences investment decisions. When this degree is sufficient to a 'medium' level, both treatments have a significant effect in expected direction, supporting hypothesis 1: positive imagery increases investment percentages and negative imagery decreases investment percentages made. When this intensity becomes even larger, the effect remains for negative imagery with a similar magnitude, but disappears again for positive imagery.

These given effects for (medium-intensity) positive and negative imagery may serve several practical uses by means of guiding investment behaviour. For example, governments may implement legislation to include negative imagery in certain companies KIIDs, in order to reinforce their corporate governance, or punish companies that are ethically misbehaving. As such, following the negative effect on investment propensity, this will inevitably lower demand and consequently the companies' stock prices. Imagery may thus provide a relative simple solution, as when it is merely adapted in legislation, it can provide monetary incentives for companies to act in a socially responsible way. Naturally, the opposite could also be done using positive imagery, where socially responsible governance is rewarded with positive imagery in company documents, which will in similar manner increase the companies' stock prices.

TABLE 10. REGRESSION TABLE: HYPOTHESIS 1

Variables	(1) Investment	(2) Investment	(3) Investment	(4) Investment	(5) Investment
Low			2.586	2.575	1.166
			(1.744)	(1.744)	(2.814)
Med			-3.241*	-3.242*	-2.553
			(1.766)	(1.702)	(2.703)
High			-3.937**	-3.944**	-1.663
			(1.756)	(1.719)	(2.755)
Positive	6.156***	8.684***		8.679***	5.526*
	(1.490)	(1.560)		(1.567)	(2.925)
Negative	-8.358***	-7.704***		-7.708***	-3.283
	(1.382)	(1.424)		(1.409)	(2.798)
Positive#low					2.003
					(4.269)
Positive#med					8.439**
					(4.264)
Positive#high					2.151
					(4.243)
Negative#low					2.101
					(4.015)
Negative#med					-10.57***
					(3.827)
Negative#high					-9.250**
					(3.981)
Age		0.152***	0.178***	0.152***	0.152***
		(0.0579)	(0.0590)	(0.0575)	(0.0570)
Female		0.508	1.698	0.515	0.519
		(1.368)	(1.384)	(1.366)	(1.356)
Familiarity with finance		0.287	0.601	0.292	0.286
		(0.509)	(0.529)	(0.506)	(0.504)
Risk		-1.203***	-1.273***	-1.254***	-1.270***
		(0.338)	(0.349)	(0.337)	(0.336)
Size		0.00196***	0.00191***	0.00193***	0.00203***
		(0.000385)	(0.000399)	(0.000387)	(0.000384)
Constant	32.64***	31.59***	32.29***	32.74***	32.35***
	(0.954)	(1.225)	(1.458)	(1.596)	(2.041)
Observations	2,032	1,880	1,880	1,880	1,880
R-squared	0.045	0.084	0.036	0.093	0.108

*Notes: Robust standard errors in parentheses as follows: *** p<0.01, ** p<0.05, * p<0.1.*
Variables age, familiarity with finance, risk, and size are mean-centered.

4.3.2. Empirical analyses: hypothesis 2

The secondary hypothesis concerns the difference between control imagery and imagery on nature (representing sustainability). It expects that positive imagery on sustainability will lead to higher investment percentages than positive imagery not focused on sustainability, and the opposite direction to hold for negative imagery. To investigate this hypothesis, dummies that categorise control and nature imagery are added. This is shown in Equation (6).

$$(6)\quad invest = \alpha_6 + \theta_1 positive + \theta_2 negative + \theta_3 control + \theta_4 nature + \theta_5 age + \theta_6 female + \theta_7 familiarity\_finance + \theta_8 risk + \theta_9 size + \epsilon_6$$

The estimation of Equation (6) can be found in Table 13|[28]. This estimation can be compared to the former estimation of Equation (2), which was identical except for the newly added nature1 and control1 dummies. Doing this, one may see that the R-squared statistic only increased very marginally, around 0.2%. This gives indication that dividing into the control and nature group may not have substantial additional explanatory power. Observing the variables themselves, it is seen that only control1 has a marginally significant (90% confidence) effect, being -2.873%. Given that the baseline equation is for no-imagery investment decisions, it can be interpreted that being shown control imagery decreases investments made by 2.873%.

Naturally, this decrease only says something about the very aggregate, whereas this may differ substantially per given treatment or intensity. For this reason, interaction terms will be required again to investigate these relationships. Before this is done, an additional step should be made, where intensities are introduced into the equation as regular terms. This is done in Equation (7).

$$(7)\quad invest = \alpha_7 + \iota_1 low + \iota_2 med + \iota_3 high + \iota_4 positive + \iota_5 negative + \iota_6 nature + \iota_7 age + \iota_8 female + \iota_9 familiarity\_finance + \iota_{10} risk + \iota_{11} size + \epsilon_7$$

It is important to briefly describe this additional step, as it changes the former interpretations. Namely, the control dummy is excluded from the equation. This is done, as to avoid collinearity that would be caused by having both the intensity dummies and nature and control dummies. To elaborate this, imagine all intensity dummies are equal to 0. This would imply that the model describes a no-imagery investment decision. Hence, this means that if all intensity dummies are equal to 0, both the control and nature dummy must also be equal to 0 per definition (there is simply no imagery; so it cannot be control or nature depicting).

[28] Table also contains estimations for following equations related to testing this hypothesis.

This means that the original programming of the dummy (equal to 1 for its respective group, equal to 0 for the other group or no-imagery group) only requires one variable, as the 'no-imagery' group is already captured using the intensity dummies. Thus, the baseline of the estimation is still no-imagery investment decisions. However, the coefficients for the intensity groups reflect control-group imagery, and nature imagery is captured as the coefficient of the intensity plus an additional (intercept) value from the nature dummy variable.

This interpretation can also be seen by comparing the estimated coefficients of the intensities in Equation (7) $(\iota_1, \iota_2, \iota_3)$ with the estimated coefficient of intensities found in Equation (3) $(\delta_1, \delta_2, \delta_3)$. One may observe that, after inclusion of the nature dummy, there is an increase in confidence level for both medium (from 90% to 95%) and high (from 95% to 99%) intensity, and that all coefficients have increased quite substantially in (absolute) size (-3.241 to -4.528; -3.936 to -5.230). This may offer an initial indication of stronger effects of control imagery, but needs to be more carefully investigated with interactions terms as discussed earlier. This is displayed in Equation (8).

$$(8) \quad invest = \alpha_8 + \kappa_1 low + \kappa_2 med + \kappa_3 high + \kappa_4 positive + \kappa_5 negative + \kappa_6 nature + \kappa_{7[a_1,a_2,b_1,b_2,c_1,c_2]} positive\#(low, med, high)\#(control, nature) + \kappa_{8[a_1,a_2,b_1,b_2,c_1,c_2]} negative\#(low, med, high)\#(control, nature) + \kappa_9 age + \kappa_{10} female + \kappa_{11} familiarity\_finance + \kappa_{12} risk + \kappa_{13} size + \epsilon_8$$

Using these triple-interaction terms, an equation similar to Equation (5) is created, with the additional distinction between control and nature imagery. Similarly to results of Equation (5), the main effect of positive treatment is still marginally significant at the 90% confidence level. Significant effects can again be found for positive medium-intensity imagery, as well as negative medium- and high-intensity imagery. What can now be found however, is that the positive treatment medium-intensity effect is only significant for control imagery, at 90% confidence with a coefficient of 9.669%. This is slightly higher than the coefficient of Equation (5) (η_{6b}), being 8.439%. For the negative medium-intensity, it can be seen that the coefficient for control imagery is less substantial (-9.830) than for nature imagery (-11.31); though both are still of rather large magnitude, decreasing investment by around 10%. The finding for medium imagery also supports the hypothesis, as nature imagery decreases investment (even) more than control imagery. However, when looking at negative high-intensity imagery, the opposite is found, with control imagery decreasing investment (even) more than nature imagery. To investigate these differences, and see if control and nature are significantly different om one another, the margins of responses can be observed. That is, observing the derivatives of predictions of the model based on Equation (8), where the nature covariate will be used to as the term of interest (being a manipulation term).

TABLE 13. REGRESSION TABLE: HYPOTHESIS 2

Variables	(6) Investment	(7) Investment	(8) Investment	
Low		1.289	-0.399	
		(1.876)	(3.079)	
Med		-4.528**	-4.118	
		(1.821)	(2.930)	
High		-5.230***	-3.229	
		(1.849)	(2.952)	
Positive	8.683***	8.679***	5.526*	
	(1.562)	(1.567)	(2.931)	
Negative	-7.706***	-7.708***	-3.283	
	(1.420)	(1.408)	(2.803)	
Control	-2.873*			
	(1.557)			
Nature	-0.302	2.572*	3.130	
	(1.583)	(1.414)	(2.299)	
			#control	#nature
Positive#low			2.982	1.023
			(4.975)	(5.045)
Positive#med			9.669*	7.210
			(5.013)	(5.117)
Positive#high			2.571	1.731
			(4.967)	(5.009)
Negative#low			2.062	2.140
			(4.601)	(4.684)
Negative#med			-9.830**	-11.31**
			(4.199)	(4.549)
Negative#high			-9.990**	-8.510*
			(4.566)	(4.639)
Age	0.152***	0.152***	0.152***	
	(0.0579)	(0.0575)	(0.0571)	
Female	0.509	0.515	0.519	
	(1.369)	(1.366)	(1.358)	
Familiarity with finance	0.284	0.292	0.286	
	(0.509)	(0.507)	(0.504)	
Risk	-1.199***	-1.254***	-1.270***	
	(0.338)	(0.337)	(0.337)	
Size	0.00201***	0.00193***	0.00203***	
	(0.000389)	(0.000387)	(0.000385)	
Constant	32.78***	32.74***	32.35***	
	(1.599)	(1.595)	(2.045)	
Observations	1,880	1,880	1,880	
R-squared	0.086	0.094	0.110	

*Notes: Robust standard errors in parentheses as follows: *** p<0.01, ** p<0.05, * p<0.1.*
Variables age, familiarity with finance, risk, and size are mean-centered.
All coefficients in estimation of (8) were estimated in a singular equation, but displayed next to each other for ease in readability.

Firstly, the aggregate effect should be investigated. That is, identifying the margins between the nature and control group in general, not taking into account any treatments or intensities. This is shown in Table 14. As seen in the estimation of Equation (8) where the control imagery group displayed a negative coefficient, the control group also displays a lower margin. This difference, which is shown as 'contrast' in the table, can however be seen not to be significant.

TABLE 14. AGGREGATE MARGINS

Group (a)	Margin[b]	Std.	|t-stat|[d]	p-stat[d]
Control (705)	31.374	1.108		
Nature (705)	33.862	1.495		
Contrast (nature - control)	**2.487**	**2.265**	**1.10**	**0.272**

Notes: (a) Amount of observations in between brackets per respective group. (b) Margins are based on estimation of Equation (8). (c) Standard Errors are calculated using Delta-method. (d) t- and p-statistics are given for H_0: Margin = 0, two-tailed test.

Of course, insignificance in the aggregate margins was to be expected, given that the treatments greatly change the context of the imagery. As such, margins are investigated taking these treatments into account in Table 15. Here, the expected results are found, being a positive difference for positive treatment, and a negative difference for negative treatment. However, this difference is only marginally significant for positive treatment, at the 90% confidence level. It does seem rather substantial, as on average positive nature-imagery companies get an additional investment of 5.621% compared to their control-imagery counterparts.

TABLE 15. TREATMENT-SPECIFIC MARGINS

Treatment (a)	Group (a)	Margin[b]	Std.	|t-stat|[d]	p-stat[d]
Positive (608)	Control (228)	38.303	1.818		
	Nature (228)	43.492	2.121		
	Contrast (nature - control)	**5.621**	**3.128**	**1.80**	**0.073**
Negative (616)	Control (231)	25.153	1.688		
	Nature (231)	23.863	1.905		
	Contrast (nature - control)	**-1.290**	**2.959**	**0.44**	**0.663**

Notes: (a) Amount of observations in between brackets per respective group. (b) Margins are based on estimation of Equation (8). (c) Standard Errors are calculated using Delta-method. (d) t- and p-statistics are given for H_0: Margin = 0, two-tailed test.

To identify potential effects even more thoroughly, the treatments can also be categorised per intensity. This can be seen in Table 16.

TABLE 16. TREATMENT/INTENSITY-SPECIFIC MARGINS

Treatment (a)	**Intensity (a)**	**Group (a)**	**Margin**[b]	**Std. Error**[c]	**|t-stat|**[d]	**p-stat**[d]
Positive (608)	Low (152)	Control (76)	40.430	2.492		
		Nature (76)	44.583	4.211		
		Contrast **(**nature - control)	**4.153**	**5.089**	**0.82**	**0.415**
	Med (152)	Control (76)	38.679	2.505		
		Nature (76)	49.019	4.354		
		Contrast **(**nature - control)	**10.339**	**5.107**	**2.02**	**0.043**
	High (152)	Control (76)	36.859	2.487		
		Nature (76)	41.720	4.148		
		Contrast **(**nature - control)	**4.861**	**4.970**	**0.98**	**0.328**
Negative (616)	Low (154)	Control (77)	29.800	2.301		
		Nature (77)	35.070	3.746		
		Contrast **(**nature - control)	**5.270**	**4.730**	**1.11**	**0.265**
	Med (154)	Control (77)	20.889	2.101		
		Nature (77)	12.708	3.496		
		Contrast **(**nature - control)	**-8.181**	**4.539**	**1.80**	**0.072**
	High (154)	Control (77)	21.216	2.282		
		Nature (77)	15.836	3.656		
		Contrast **(**nature - control)	**-5.379**	**4.595**	**1.17**	**0.242**

Notes: (a) Amount of observations in between brackets per respective group. (b) Margins are based on estimation of Equation (8). (c) Standard Errors are calculated using Delta-method. (d) t- and p-statistics are given for H_0: Margin = 0, two-tailed test.

The table shows significant differences between nature and control imagery to exist, but only for medium-intensity imagery (95% confidence for positive, 90% confidence for negative). Both differences are in accordance to their hypothesized direction and are rather substantial, with positive medium-intensity nature companies attaining 10.339% more investment than their control imagery counterparts; and negative medium-intensity nature companies receiving 8.181% less investment compared to similar control imagery companies. Alternatively, one may compare the contrast of each given intensity between negative and positive treatment (rather than either negative or positive to the neutral benchmark). This can be done through a difference-in-difference method, which is shown in Table 16. Here, a significant difference (90% confidence) of 10.240% can be found for high intensity when positive and negative treatment are compared to each other. The difference is more substantial for medium intensity imagery at 18.520% (99% confidence), which displays the great dispersion between using negative or positive imagery as an effect on investment behaviour.

The data supports the claim that sustainability imagery can carry additionally strong emotional evocation by Lester & Cottle (2009, p. 933) and Mykolas et al. (2019). Thereby, it corroborates hypothesis 2 to certain extent. The 'strong emotional evocation', reflected in relatively higher investment for positive sustainability imagery and relatively lower investment for negative sustainability imagery, is only found for medium-intensity imagery. It may be possible to explain this intuitively; as also argued in the previous paragraph (4.3.1), low-intensity imagery can be seen as not to evoke emotion sufficiently to the point that it significantly affects investment decisions. Hence, this 'weak emotional evocation' may also not be strong enough to show a substantial difference between the control and nature imagery. Then, with regard to high-intensity imagery, one may find that the difference may be low due to both margins being very high already (caused by large degrees of emotional evocation). This was also seen in the previous paragraph, where coefficients for high-negative imagery were of large magnitude. However, this does not hold for positive imagery, which did not show a significant effect in previous hypothesis testing. This will be discussed more thoroughly in section 5. When looking at difference-in-differences, by comparing contrast of positive and negative treatment, a substantial difference is found for medium-intensity, but also a smaller significant difference for high intensity. This corroborates the earlier finding with respect to hypothesis 1 on the effect of positive and negative imagery.

Implications of these findings can also be used similarly as mentioned in 4.3.1 to guide investment behaviour; positive imagery can reward and negative imagery can punish companies as to guide their behaviour through monetary incentives. In addition to this, if (and only if) medium-intensity imagery is used, which was shown to have consistent expected effects for both positive and negative treatment in the previous section, this effect can be amplified by ensuring the imagery is nature-, and thereby sustainability-oriented.

4.3.3. Empirical analyses: hypothesis 3

The third and final hypothesis concerns the conclusions made by Leiserowitz (2005), who found that "Americans as a whole perceive global climate change as a moderate risk" (p.1437), and consequently that the effect of imagery may only be sufficiently strong when people are informed about the dangers (See 2.3). However, as also mentioned in 2.3, there has been a drastic increase in climate change awareness over the last decade (Iturriza et al., 2020). Moreover, the presented sample contained relatively young participants (mean of 29 years old), which is also to be seen in the distribution of the climate importance variable (Figure 16), as it is heavily negatively skewed. For this reason, a dummy will be created split at the median[29] to avoid high outliers, and maintain meaningful analyses. At the same time, the limits of these analyses should be clear and interpreted carefully, as both groups in the dummy are relatively well-aware about climate change.

To test the hypothesis, the climate importance variable should firstly be included in the model. This is shown in Equation (9), and its estimation can be found in Table 18.

$$(9) \quad invest = \alpha_9 + \lambda_1 positive + \lambda_2 negative + \lambda_3 control + \lambda_4 nature + \lambda_5 importance\_climate + \lambda_6 age + \lambda_7 female + \lambda_8 familiarity\_finance + \lambda_9 risk + \lambda_{10} size + \epsilon_9$$

This shows no significant effect nor additional explanatory power[30] offered by the climate importance variable. This may be, once again, due to the high skewness in the variable with both categories reflecting participants' rather high degree of importance dedicated to climate change, but it may also be because the terms are more interesting to look at through interactions.

One may note also that, in Equation (9), the intensity variables were left out[31]. This was done in preparation for the interaction terms. Though the intensity variable would be a valuable addition as an additional interactor-term, it would create a four-way interaction term if included. The data sample is too small to ensure statistical outcomes of such an estimation would be valid. Hence, the interaction estimation will only be specified per treatment, which can be seen in Equation (10). Its estimation can also be found in Table 18.

[29] This dummy would be equal to 0 if the response is a 4 or lower, and equal to 1 if the response is equal to 5.

[30] Compared to estimation of Equation (2).

[31] The 'control' variable was also able to be included again, because of this. (see interpretation in *Empirical analyses: hypothesis 2*4.3.2).

$$(10) \quad invest = \alpha_{10} + \mu_1 positive + \mu_2 negative + \mu_3 control + \mu_4 nature + \mu_5 importance\_climate + \mu_{6[a,b]} positive1\#(control1, nature1)\#importance\_climate + \mu_{7[a,b]} negative1\#(control1, nature1)\#importance\_climate + \mu_8 age + \mu_9 female + \mu_{10} familiarity\_finance + \mu_{11} risk + \mu_{12} size + \epsilon_{10}$$

TABLE 18. REGRESSION TABLE: HYPOTHESIS 3

Variables	(9) Investment	(10) Investment
Positive	8.670***	11.45***
	(1.563)	(1.853)
Negative	-7.704***	-4.372**
	(1.422)	(1.737)
Nature	-0.303	2.941
	(1.584)	(1.816)
Control	-2.875*	-0.955
	(1.557)	(1.789)
Importance climate change	-0.493	3.146*
	(1.240)	(1.609)
Positive#control#importance_climate		-4.545
		(3.599)
Positive#nature#importance_climate		-8.991**
		(3.703)
Negative#control#importance_climate		-6.490**
		(3.025)
Negative#nature#importance_climate		-9.663***
		(3.186)
Age	0.152***	0.165***
	(0.0579)	(0.0581)
Female	0.566	0.279
	(1.389)	(1.389)
Familiarity with finance	0.304	0.325
	(0.512)	(0.514)
Risk	-1.199***	-1.189***
	(0.338)	(0.336)
Size	0.00202***	0.00204***
	(0.000389)	(0.000389)
Constant	33.01***	29.26***
	(1.667)	(1.913)
Observations	1,880	1,880
R-squared	0.086	0.092

*Notes: Robust standard errors in parentheses as follows: *** p<0.01, ** p<0.05, * p<0.1. Variables age, familiarity with finance, risk, and size are mean-centered.*

The effects of Equation (10) are difficult to interpret due to the triple-interaction term, which causes an already existing interaction effect between two variables to depend on another factor[32]. Therefore, interpretation for this equation will again be given using the margins, with the covariate importance_climate as the manipulation term. The aggregate margins of climate change importance can be found in Table 19. As can be seen, the means are both around the same level (32.487% and 32.006%), and as such no significant difference caused by the climate importance variable can be found. However, as previously, the interpretation gains more meaning when split into its respective treatment groups, which can be seen in Table 20.

TABLE 20. TREATMENT-SPECIFIC MARGINS

Treatment (a)	**Climate change importance (a)**	**Margin[b]**	**Std. Error[c]**	**|t-stat|[d]**	**p-stat[d]**
Positive (608)	Relatively low (288)	41.748	1.476		
	Relatively high (320)	39.808	1.576		
	Contrast (high-low)	**-1.930**	**1.967**	**0.98**	**0.327**
Negative (616)	Relatively low (336)	25.704	1.432		
	Relatively high (280)	22.793	1.233		
	Contrast (high-low)	**-2.912**	**1.712**	**1.70**	**0.089**

Notes: (a) Amount of observations in between brackets per respective group. (b) Margins are based on estimation of Equation (8). (c) Standard Errors are calculated using Delta-method. (d) t- and p-statistics are given for H_0: Margin = 0, two-tailed test.

Negative margins can be found for both positive and negative treatment, of which only the negative margin is statistically significant (90% confidence). This entails that people who believe climate change to be (relatively) more important are less willing to invest in companies that display negative imagery, compared to people who believe climate change is (relatively) less important. The one distinction that is now yet to be made to test the hypothesis, is to split the companies into categories of control and nature, which is done in Table 21.

[32] Also, coefficients can get overwhelming. For example, the main effect of positive would increase investment substantially by 11.45%, but when interacted with nature and importance of climate change it would decrease again by 8.991%.

TABLE 21. TREATMENT/GROUP-SPECIFIC MARGINS

Treatment (a)	Group (a)	Climate Change importance (a)	Margin[b]	Std. Error[c]	|t-stat|[d]	p-stat[d]
Positive (608)	Control (228)	Relatively low (108)	40.403	1.789		
		Relatively high (120)	39.003	2.757		
		Contrast (high-low)	**-1.400**	**3.288**	**0.43**	**0.670**
	Nature (228)	Relatively low (108)	44.298	1.787		
		Relatively high (120)	38.453	2.879		
		Contrast (high-low)	**-5.845**	**3.391**	**1.72**	**0.085**
		Difference-in-Difference (contrast nature - contrast control)	**-4.445**	**4.336**	**1.03**	**0.305**
Negative (616)	Control (231)	Relatively low (105)	24.209	1.718		
		Relatively high (126)	20.864	2.085		
		Contrast (high-low)	**-3.344**	**2.706**	**1.24**	**0.217**
	Nature (231)	Relatively low (105)	28.104	1.771		
		Relatively high (126)	21.586	2.245		
		Contrast (high-low)	**-6.518**	**2.867**	**2.27**	**0.023**
		Difference-in-Difference (contrast nature - contrast control)	**-3.173**	**3.512**	**0.90**	**0.366**

Notes: (a) Amount of observations in between brackets per respective group. (b) Margins are based on estimation of Equation (8). (c) Standard Errors are calculated using Delta-method. (d) t- and p-statistics are given for H_0: Margin = 0, two-tailed test.

Following Table 21, it can be seen that differences in investment caused by the climate importance variable are only significant for nature decisions, respectively decreasing investment by -5.845% for positive imagery (90% confidence) and 6.518% for negative imagery (95% confidence). As done for hypothesis 2, the difference-in-difference method can also be used here, to compare the contrast from investing in nature and in control companies. However, the terms turns out to be insignificant, indicating no difference between contrasts.

Though it is in accordance with the hypothesis that there is a relationship between nature-related imagery and climate change importance, and that negative imagery should show a negative contrast term, this term was not to be expected for positive imagery. In both cases, people who deem climate change more important, will invest lower in the nature companies. The finding of this result may be attributed to an omitted variable bias, where people who deem climate change most importantly have certain characteristics that lead them to invest less, but these characteristics must also then be related to nature-imagery, given the insignificant effects found for control imagery. This will be discussed more thoroughly in section 5.

4.4. Robustness

Though in the previously performed empirical analyses section control variables were added to increase explanatory value, it would be extremely difficult to capture all factors relevant in investment decision-making. In this subsection, some additional tests will be done to identify how robust the empirical findings of this paper are, as well as elaborating on further limitations and potential for future research. This is done by addressing personal characteristics, followed by the experimental setup.

4.4.1. Robustness: Personal characteristics

Firstly, the amount of personal characteristics recorded for participants was rather limited, with demographic variables merely being age and gender, and two other Likert-items reflecting familiarity in financial concepts, and degree of importance of climate change as a societal problem (the latter only being relevant for hypothesis 3). It would be difficult to ask for much more information, as this lengthened the survey. Given the voluntarily base on which the survey was distributed, this would have greatly increased the chance of people not completing the survey. However, this does not imply that it might not be relevant to include more detailed personal characteristics and attitudes in future research. For example, looking at Ezzeddine et al. (2014), which mention familiarity with finance to be a very important control in investment decision-making (despite it being insignificant for all estimation in this paper), also mention the optimism and attitude of the investment decision maker to be extremely important (p.102). Naturally, attitudes will depend on a plethora of personal characteristics, on which much more thorough research can be conducted from within the psychological branch, with regard to investment decisions. In the experiment, an attempt was made to measure this 'attitude' in a very simplified manner; a 5-option multiple choice question was implemented asking to what extent people paid attention to imagery, as well as a 5-point Likert scale for the attention paid to the fundamentals (see Table 3 and Table 9). Though these measures are limited in elaborate explanation due to their simplicity, they may provide an initial idea of the role of attitude with regard to imagery in investment decisions.

Therefore, it is possible to add these 'affect' variables as interaction terms to their relevant groups. That is, interacting the imagery affect with the treatment group (positive/negative) and the fundamental affect with both fundamental variables (risk/size). Firstly, the imagery affect variable will be investigated, which can be seen in Equation (11). Note that the variable contains an 'other' category (where it equals 5). As such, the main effects are split per category (also due to the other 4 options not being in Likert-item style), and the interaction is run separately for the four options (treated ordinally) and for a dummy capturing the 'other' category.

$$(11) \quad invest = \alpha_{11} + v_1 positive + v_2 negative + v_{3[a,b,c,d,e]} affect\_image + v_{4[a,b]} positive\#affect\_image + v_{5[a,b]} negative\#affect\_image + v_6 age + v_7 female + v_8 familiarity\_finance + v_9 risk + v_{10} size + \epsilon_{11}$$

The estimation of Equation (11) can be found in Table 22|[33]. The main effects show that, without image affection, a significant effect can be found for only negative treatment (95% confidence), which is in its expected negative direction and quite substantial (-10.31). The main effect for affect_image can be observed to be significantly (99% confidence) negative for most categories, and decreasing more in size over categories 3 and 4. This would hence give a lead that a general higher affection for imagery decreases investment percentage. Note that the coefficients for the 'other' category (affect_image equals 5) are very difficult to interpret as responses varied greatly. As an example, one participant answered "I was looking primarily to what vision and mission would fit a given company, and how much I could associate with this" (obs#38, translated), whereas one other answered "I tried to ignore them as they did not provide relevant information" (obs#231).

If one then looks at the interaction terms themselves, a significant (99% confidence) positive effect can be found for the positive interaction term, but no significant effect for the negative interaction term. Though this should be interpreted carefully, the data thus points to a larger role of affect with regard to positive imagery, where more affect for imagery increases investments made as long as positive imagery is shown. When comparing this estimation with the estimation of Equation (2), it can be found that the imagery affect variable adds around 2% of explanatory power, not being very substantial.

[33] Table also contains estimations for following equations related to robustness testing.

The former equation measures effects of attitude with regard to imagery, but attitudes have also been measured with regard to fundamentals. This was done to provide insights on the financial side of the investment decision (though the fundamentals were not the key research topic) and can be seen in Equation (12)|[34].

$$(12)\quad invest = \alpha_{12} + \xi_1 positive1 + \xi_2 negative1 + \xi_3 age + \xi_4 female1 + \xi_5 familiarity\_finance + \xi_6 risk + \xi_7 size + \xi_8 affect\_fundamentals + \xi_9 affect\_fundamentals\#risk + \xi_{10} affect\_fundamentals\#size + \epsilon_{12}$$

The interpretation of main effect of the fundamental affect variable should be made where the secondary variable is at its average value, given that both risk and size were mean-centered. Hence, for an average risk or size response, there is no significant main effect of the fundamental affect variable. Both risk and size show significant (99% confidence) coefficients similar to previous estimations. However, the interaction term is only significant (99% confidence) between affect_fundamentals and risk, and shows a negative coefficient; that is, deeming to be affected by fundamentals more leads to lower investment, when the risk/reward category increases. This can be explained somewhat intuitive; risk-reward may be somewhat embraided into people, due to general risk perceptions people have (though mainly focused on 'loss aversion' as shown by Huber et al., 2017) and the concept having been central since the earliest of financial theories such as the Capital Asset Pricing Model (Treynor, 1962; Sharpe 1964). Size, despite its prominent explanatory role shown in the Fama-French (1993) model, may be a bit less intuitive. Hence, it plays no role directly with affect, as the affect variable is based on people's own interpretation on how much they took the fundamentals into account when making their investment decisions (which is also a general weakness of Likert-items; what is 'very high' for one person need not be similar for another person). For this reason, an additional robustness test with regard to personal characteristics can be done, which did not depend on Likert-items or participants having to rate themselves.

[34] Note that, the financial fundamentals were based on Likert-scale items, and hence do not need any sort of dummy adjustment as done in the imagery_affect estimation.

Namely, as mentioned in 3.3.3, one of the no-imagery decisions was 'standardized' for all participants, always displaying the same risk and size. Hence, the data acquired from this investment decision may be used to determine a 'willingness to invest' by looking at deviations from the mean investment decision (with higher percentages than average indicating a higher willingness to invest and vice versa). This would capture the participants' personal characteristics without participants being conscious of it. Being unaware of the measurement reduces potential biases that arise, such as the demand effect or the overconfidence bias (De Bondt et al, 2008). The approach also enables one to theoretically capture all personal characteristics as an attitude in one variable, making it convenient to be used in regression analyses.

Naturally, the use of this variable comes at a cost, and some conditions need be met for it to be viable too. Firstly to address these conditions, one may argue that the placement of the investment decision may have an effect (being either the first, second, third, or fourth decision participants saw). However, given that the order was randomized, and sample size was reasonably large to filter this out, this is assumed not to be a further problem. A secondary issue would be the effect of the treatment group on no-imagery decisions. Though this cannot be completely filtered out, and one may have observed treatment to play a role even for no-imagery decisions in previous estimations[35], the average investment was shown to be somewhat equal across treatments in Table 5 (Neutral being 35.385, positive being 35.458, and negative being somewhat lower at 33.525). For this reason, it will also be assumed that the treatment does not provide a substantial issue for using this variable. Hence, it is included in Equation (13). It should be noted that inclusion of the variable does come at another cost, being that simply including it as both an investment and as a separate variable would, obviously, cause collinearity. Hence, including the variable as a control means that the no-imagery standardized investment decisions should be dropped from the dependent variable[36]. This, in turn, means that the estimations is done with a lower amount of observations, decreasing from 1880 to 1410.

$$(13)\quad invest = \alpha_{13} + \pi_1 positive + \pi_2 negative + \pi_3 will\_to\_invest + \pi_4 positive\#will\_to\_invest + \pi_5 negative\#will\_to\_invest + \pi_6 age + \pi_7 female + \pi_8 familiarity\_finance + \pi_9 risk + \pi_{10} size + \epsilon_{13}$$

35 That is, a marginally significant main effect for positive treatment; see estimation of Equation (5) and (8).

36 After this is done there is no further multicollinearity problem with the variable, as can be seen from a VIF-test presented in Table 23.

The first thing one may notice is the substantial increase in explanatory power of the model from 10.9% to 34.7%, when compared to its previous 'affect' variant. This is somewhat logical, due to the 'catch-all' nature of the willingness to invest variable mentioned earlier. In addition, the controls that showed insignificant effects in previous estimations now do show significant effects: gender shows a negative effect (95% confidence) of -2.928%, corroborating a large body of literature concluding that on average females invest less than males (Charness & Gneezy, 2012), and higher familiarity with finance decreases (95% confidence) investment by 1.194% per category up. Age, which was a significant predictor in all former estimations, does no longer display a significant effect.

Secondly, one may observe the main effect of the willingness to invest variable, being significantly (99% confidence) positive at 0.600%. This is to be expected, as it entails a higher willingness to invest will also cause higher actual investment[37]. More interestingly is the interaction term between it and negative treatment, which is significantly (99% confidence) negative with a coefficient of -0.194%. This means that, given one is in negative treatment, higher willingness to invest will actually cause lower investments to be made. This has practical applications, as those more willing to trade (which one may assume to be more sophisticated traders) will be more affected by the negative imagery, thus potentially increasing its strength in policy making decisions where unethical behaviour can be 'punished' (also see 4.3.1).

The same willingness to invest variable may also be used instead of the affect for fundamentals displayed in Equation (12). This results in the new Equation (14).

$$(14)\quad invest = \alpha_{14} + \rho_1 positive + \rho_2 negative + \rho_3 age + \rho_4 female + \rho_5 familiarity\_finance + \rho_6 risk + \rho_7 size + \rho_8 willingness\_to\_invest + \rho_9 willingness\_to\_invest\#risk + \rho_{10} willingness\_to\_invest\#size + \epsilon_{14}$$

Estimation of this equation does however not show any significant interaction terms. Hence, there is no additional effect of an 'attitude' when looking at the effect of fundamentals on investment percentages made.

[37] Note that this is measured by a deviation within the no-imagery standardized investment decision. As such, a 1% deviation from the mean investment results in a 0.6% increase/decrease in investment percentages made.

All in all, these robustness equations may point to an advantage in using negative imagery for policy use. Namely, when using an 'affect' variable that captures a question asked to participants on how severely they took either imagery or fundamentals into account, there can only be found a significant positive effect for positive imagery. This would imply that people need to be perceptive for positive imagery to a certain extent, before investment percentages would increase when the positive imagery is used. This may not be ideal in policy use which may likely tend to target an aggregation of investors, rather than only 'sensitive' ones. Given that there is no significant effect found for negative imagery[38], there may be less of a role of 'sensitivity', and investors may be affected by it rather equally, which may be beneficial when intending policy to be targeted at an aggregated group. Moreover, using the unconscious 'will to invest' approach for measuring investment attitudes, it is found that those with higher willingness to invest are affected additionally by negative imagery, but not by positive imagery. This may again have practical applications, if assuming those that have higher willingness to invest are sophisticated traders. As such, policy can be targeted at certain groups, and negative imagery will show an additional negative effect for these that have higher willingness to invest.

Naturally, as mentioned before, interpretations and potential for policy use should be approached carefully, as the given variables are very simplified for ease in use. Psychological research may specify what the real factors are that drive investment behaviour (rather than an aggregate 'affect' or 'willingness' variable), and give more detailed conclusions on use of imagery. Physiological research may be very useful, due to its ability to directly measure factors produced in imagery scenarios (i.e. through eye-tracking, or by measuring heart-rates). Finally, neurological research may give more meaning than what is now called 'emotion evocation', and specify parts in the brain that activate in investment decisions, plus changes caused by imagery treatments, or differences in what the imagery reflects (i.e. control and nature). Of course, this is than all about measuring individual characteristics, but also the experimental environment may be adjusted.

[38] Which again, merely points to a possibility of a stronger effect for positive imagery. The possibility of finding a significant effect with another (larger) sample is, of course, not ruled out.

TABLE 22. REGRESSION TABLE: ROBUSTNESS

Variables	(11) Investment				(12) Investment	(13) Investment	(14) Investment
Positive	-2.802				8.357***	8.890***	9.199***
	(3.952)				(1.564)	(1.559)	(1.556)
Negative	-10.31***				-7.638***	-8.288***	-8.129***
	(3.957)				(1.435)	(1.443)	(1.430)
Affect for imagery	= 2	= 3	= 4	= 5			
	2.409	-6.323***	-14.56***	-9.132**			
	(2.486)	(2.486)	(2.807)	(3.975)			
Positive#affect_image		4.441***		23.08***			
		(1.525)		(8.270)			
Negative#affect_image		1.700		-5.056			
		(1.344)		(6.635)			
Affect for fundamentals					1.268		
					(0.832)		
Risk	-1.249***				-1.155***	-1.532***	-1.533***
	(0.332)				(0.336)	(0.323)	(0.321)
Size	0.00193***				0.00181***	0.00219***	0.00209***
	(0.000381)				(0.000384)	(0.000348)	(0.000352)
Affect_fundamentals#risk					-1.388***		
					(0.468)		
Affect_fundamentals#size					0.000565		
					(0.000490)		
Willingness to invest						0.600***	0.539***
						(0.0368)	(0.0257)
Positive#will_to_invest						0.0355	
						(0.0582)	
Negative#will_to_invest						-0.194***	
						(0.0625)	
Will_to_invest#risk							0.00999
							(0.0138)
Will_to_invest#size							1.64e-05
							(1.46e-05)
Age	0.168***				0.146**	0.0935	0.104*
	(0.0578)				(0.0580)	(0.0581)	(0.0578)
Female	0.548				0.648	-2.928**	-3.135**
	(1.441)				(1.363)	(1.364)	(1.373)
Familiarity with finance	0.194				0.0449	-1.194**	-1.119**
	(0.510)				(0.514)	(0.499)	(0.505)
Constant	36.42***				31.48***	32.93***	33.05***
	(1.973)				(1.211)	(1.207)	(1.215)
Observations	1,880				1,880	1,410	1,410
R-squared	0.109				0.091	0.347	0.340

*Notes: Robust standard errors in parentheses as follows: *** p<0.01, ** p<0.05, * p<0.1.*
Variables age, familiarity with finance, risk, size, affect for fundamentals, and willingness to invest are mean-centered.
All coefficients in estimation of (11) were estimated in a singular equation, but displayed next to each other for ease in readability. The coefficients for(positive,negative)#affect_image are estimated separately for either affect_image = (1 to 4) and = 5 respectively.

4.4.2. Robustness: Investment decision

The presented experimental setup and environment had advantages and disadvantages. As argued by Vinogradov & Shadrin (2013), online experiments may be advantageous due their "natural decision-making environment" (p. 306). That is, participants feel less stress making their decisions, increasing accuracy of data and thereby the predictions made in models. Online experiments also allow for quick access to a large amount of data (Vinogradov & Shadrin, 2013). However, the main disadvantage with these online experiments, without real monetary incentive[39], is the inaccuracies and biases that may be found in data acquired from it (Vinogradov & Shadrin, 2013).

To elaborate on this, one may take the example of the data on climate change importance in this paper. Though it is possible that the used sample simply contained a group of climate change aware subjects (something that may of course also be improved by using i.e. a research survey distribution agency, that guarantees a representative sample), there is also a chance that people 'overestimated' their own importance. When this would be linked to monetary incentive (i.e. for each point you rate climate change importance higher, your own end payment will be deducted and handed to a climate charity), the results may show a much larger gap: something that would have been useful to test hypothesis 3 shown in this paper.

More extensive research (such as through decision labs or using monetary incentives) may also allow for more careful measurement of other variables. For instance, the treatment variable was based on the OASIS dataset (Kurdi et al., 2017) due to it being readily available. However, the focus of OASIS' creation was a "standardized, open-access, and widely available stimulus set with corresponding normative affective ratings" (Kurdi et al, 2017, p.458). The experiment may therefore be repeated using different imagery databases, such as the International Affective Picture System (IAPS) by Lang, Bradley, and Cuthbert (2008). The IAPS is "one of the most frequently used stimulus sets in behavioural research today. Its contribution to advancing research cannot be overstated" (Kurdi et el., 2017, p.458). Repetition of the experiment with different imagery datasets may give indication about its generalizability and validity. More precise categorisation (rather than low, medium, and high intensity) to the point of interval level may also be obtained using repetition and other imagery databases.

[39] Despite the gift cards that were offered, there was also no performance-bound monetary incentive.

Of course, the investment decision itself and its fundamentals may also be adjusted. Though a standard 10,000 euro payment with a small “story’ about inheritance was used in this paper to avoid hypothetical bias (Murph et al., 2005), this may be put differently when wanting to observe the behaviour of sophisticated investors (who may do this as a profession, and do not rely on inheritance money). The investment percentage may be replaced altogether by similar (yet different) terms, such as asking participants to rate investment attractiveness. The fundamentals may of course also be presented differently. In the presented experiment, it was simplified to two important factors, but other important factors exist in literature. An example would be the book-to-market value in the Fama-French (1993) also mentioned in 3.2.2. Another potential well-establish important financial factor to be investigated is the ‘winner and loser’ stocks; the phenomenon that former performance may bring indication about future performance. This was thoroughly described by Carhart (1997), who builds on the Fama-French (1993) model with this ‘momentum’ factor. In addition to the factor being theoretically grounded, it is also something that is currently also put in KIIDs (past performance), as was seen in Figure 5 for the Vanguard Group (2020).

A final point should be made in general about the experimental setup. Experimental research is commonly seen as strong in causal identifications, being internal validity. However, it is also seen as weaker on generalizability and applications to real-world phenomena, being external validity (Garcia & Wantchekon, 2010). Naturally, the external validity of the presented results is also relatively low, as it makes large assumptions about company documents (i.e. KIIDs) to an extent that it influences the investment decision-making. Given the criticisms that exist on KIIDs in the first place (Oehler et al., 2017; Walther, 2015) about the lack in their practical applications, there is also much research to be done in the field. For instance, imagery may be shown through internet brokerage services to see how this affects investment behaviour. Results of such a research may be more closely related to reality than those of the performed experiment.

5. Discussion

When observing the found results and made assumptions in this paper, the imagery forms a main discussion point. Firstly, as stated in 3.2.1, the OASIS database is put into four categories, being persons, animals, objects, and scenery. Though the same paragraph also elaborates on these and their relation to the selected imagery, it should be noted that Kurdi et al. (2017) used these categories "merely to facilitate the use of the stimulus set" (p.459). Hence, OASIS does not provide substantial support for the tests on hypothesis 2 and 3, which investigate the difference between 'nature' and 'control' imagery companies; any 'additional' emotional evocation should already have been captured in the arousal and valence scores.

However, it is then interesting that for hypothesis 2 significant differences are found between the two; and for hypothesis 3, persons with high climate change importance invest lower in nature companies. If it is assumed that the categories do not have an influence, an obvious explanation would then be that it is the non-exact equality of arousal and valence scores as seen in Figure 3 and Figure 4 that causes dispersions. At the same time, one may argue that these differences in scores were not very substantial, and should not cause a significant effect.

Even when assuming the categorisation to be correct, there is another key assumption within the 'nature' and 'control imagery. Namely, Lester and Cottle (2009) speak of climate change being represented by 'visual scenes and spectacular images of nature' (p.922). In the experiment, climate change is not mentioned until in the control questions. Hence, rather than climate change being represented by visual scenes and spectacular images of nature; it is spectacular images of nature that are shown with hopes of representing climate change, and thereby sustainability. This may be a connection not made by participants; they may not relate nature imagery to sustainability at all. Leiserowitz (2005) also mentions that "personally relevant affective images of climate change lack" (p.1438), further emphasizing the difficulties in making these connections[40].

These 'connections'[41] that can be made with regard to imagery may form another obstruction. Namely, in the methodology of Kurdi et al. (2017), participants were asked to rate imagery (either on arousal or on valence) as a standalone task. In the presented paper, the imagery is not a standalone subject; it relates to a certain aspect of a company. Though the paper did control for this by means of the affect variables, and the purpose of the study was to see how imagery related to investment behaviour, it implicitly assumes the valence and arousal scores documented by Kurdi et al. (2017) to be robust. To briefly elaborate on this, one

[40] Note that simply mentioning 'climate change' or 'sustainability' beforehand would likely lead to anchoring and demand effects (De Bondt et al, 2008) and may be surpassed using monetary incentives based on performance.

[41] Be it by thinking of 'climate change' when seeing nature imagery or any other thought process involved after seeing the imagery.

may look at the high-intensity negative control imagery, representing a knife covered in blood. Though this may already attain low valence and high arousal scores in observations by Kurdi et al. (2017), this may be further amplified by the fact that the image is relating to a company. That is, not only may a knife represent a crime, but relating it to a company may represent a criminal organisation, which may very much skew the actual arousal and valence scores. Naturally, if these differences are substantial from their theoretical values by Kurdi et al. (2017), this may have influenced results. Hence, this difference between standalone imagery and imagery relation to a company may also provide an interesting field for future research.

A final point is to be made on some of the findings that seemed unusual. With regard to hypothesis 1 it was found that only medium-intensity imagery consistently displays the hypothesized effects. For low intensity, it can be argued that there is no sufficient evocation of emotion to display a significant effect. For higher intensities, a similar argument would not hold, as a significant effect was found for negative imagery. A potential theory to explain this can be found in the environmental social governance (ESG) literature; assuming that high positive imagery is related to a high degree of investments of these ESG-factors, it may hurt the profitability of the company[42] (Capucci, 2018). This may however seem quite sophisticated, and is a statement that is still being discussed within the ESG literature (Capucci, 2018).

With regard to hypothesis 3, it may have seemed unusual that individuals that deem climate change more important will invest less in nature companies, independent of whether imagery was positive or negative. A potential explanation for this lies in an omitted variable bias; given that the sample in its entirety claimed to be relatively climate change aware, the highest score may be related to some type of 'idealist' behaviour. Moreover, pro-environmental attitudes can be associated with many determinants, including political beliefs and scientific knowledge (Weaver, 2016). It may hence also include some type of preventive investing behaviour, though this would still not explain why the effect was only found for nature companies.

A statistical limitation that may have played a prominent role in the paper may explain both the above mentioned results better. Namely, due to the large amount of subgroups used (through treatments, intensities, climate change awareness), chances of committing a family-wise error become larger. That is, when performing multiple analyses on the same data, one becomes more prone to making false discoveries (Type I errors). As such, some of the seemingly unusual (or any of the other) results may have also likely been a consequence of this family-wise error rate. This was explicitly not controlled for however, as the ways to control for this error rate (such as by Bonferonni correction) may greatly increase the probability of not rejecting a false null hypothesis (Type 2 error) and reduces statistical power (Olejnik, Supattathum, and Huberty, 1997). Because of this, controlling for it may do more harm than it brings benefit.

6. Conclusion

Using a between-subjects experimental setting, with some within-subject design elements, cross-sectional analyses were performed to show the influence of imagery on investment behaviour through emotion evocation. With imagery being the treatment, and financial fundamentals being equal in investment decisions, it can be found that positive imagery increases investment and negative imagery decreases investment. Using OLS regression estimations, this is also found when controlling for numerous factors and demographics. When differentiating the intensity of imagery, consistent effects can be found for medium intensity, which are also quite substantial; increasing positive imagery investments by around 8.5% and decreasing negative imagery investments by around 10%. This is in accordance with the hypothesis that imagery can be used as a type of upstream intervention to affect situational cues (Papies, 2017). When controlling for a degree to which subjects were affected by imagery, it is found to play a higher role in positive imagery, increasing investment with higher rates of affect. In addition, a willingness to invest variable shows a significant negative interaction term only for negative imagery; those with high willingness to invest will invest additionally less when negative imagery is displayed.

Distinction was also made between imagery that contained 'nature' imagery and those that did not ('control' imagery). When calculating differences made in investments, consistent effects were again found for medium imagery; for positive imagery, nature companies received around 10% higher investment than their control counterparts. For negative imagery, nature companies received around 8% lower investment than their control counterparts. This supports the hypothesis based on the fact that sustainability imagery can carry strong emotional evocation (Lester & Cottle, 2009, p. 933; Mykolas et al., 2019), amplifying the already positive and negative effects. When controlling for a degree to which participants deemed climate change important, it is found that those regarding climate change extremely important will always invest less in 'nature' companies, independent of imagery treatment. This finding does not support the hypothesis, which was based on Leiserowitz (2005), stating that people should be informed enough to see nature imagery as something that affects them, due to a the negative effect displayed for positive imagery.

The given results may serve practical uses in guiding investment behaviour. Governments may implement legislation to include imagery in company documents (such as Key Investor Information Documents). As an example, companies with a well-reinforced corporate governance or high ethical standards may be granted positive imagery in their documents, increasing investors' propensity to invest in them, thereby increasing demand and stock pricing. Vice versa, companies that are i.e. ethically misbehaving may be punished using negative imagery. This effect may be amplified by using sustainability-related nature imagery, causing even higher investment percentages for positive imagery, and even lower investment percentages for negative imagery. Medium-intensity imagery is most consistent to be used for these goals, and negative imagery may be preferred, due to it being more robust and able to target more sophisticated investors. That is, positive imagery is influenced more substantially by a certain affection for imagery than negative imagery is, making negative imagery able to target a generalized audience. Moreover, negative imagery will have an additional negative effect for those with higher willingness to invest, which may be a preferred target group.

7. Bibliography

Arnold, W., McCroskey, J., & Prichard, S. (1967). The likert-type scale. *Today's Speech, 15*(2), 31-33.

Baddeley, A.D., & Hitch, G. (1993). The recency effect: implicit learning with explicit retrieval? *Memory & Cognition, 21*(2), 146–155

Banerjee, S., & Green, B. (2015). Signal or noise? uncertainty and learning about whether other traders are informed. *Journal of Financial Economics, 117*(2), 398-423.

Barberis, N., & Thaler, R. (2003) A Survey of Behavioral Finance, in G.M. Constandinides, M. Harris and R. Stulz (Eds.), *Handbook of the Economics of Finance*. Elsevier.

Biggart, N. W., Hoffman, A.J, & Henn, R.L. (2013). Constructing green : the social structures of sustainability, in R. L. Henn & A. J. Hoffman (E.ds), *Urban and industrial environments.* MIT Press.

Cappucci, M. (2018). The ESG integration paradox. *Journal of Applied Corporate Finance, 30*(2), 22-28.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance, 52*(1), 57-82.

Carruthers, P. (2014). On central cognition. *Philosophical Studies : An International Journal for Philosophy in the Analytic Tradition, 170*(1), 143-162.

Charness, G., & Gneezy, U. (2012). Strong evidence for gender differences in risk taking. *Journal of Economic Behavior and Organization, 83*(1), 50–58.

Commission Recommendation concerning the definition of micro, small and medium-sized enterprises (2003). Document number C(2003) 1422, Official Journal L 124, 0036-0041. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32003H0361

De Bondt, W., Muradoglu, G., Shefrin, H., & Staikouras, S. (2008). Behavioral finance: Quo vadis? *Journal of Applied Finance, 18*(2), 7-21.

Deloitte (2020) *A practical guide to KII*. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/lu/Documents/financial-services/lu-kiid-practical-guide.pdf

Dilger, R.J (2018) *Small Business Size Standards: A Historical Analysis of Contempory Issues*. Washington DC: Congressional Research Service, CRS Report R41523.

Dixon, T. (2012). Emotion: One word, many concepts. *Emotion Review, 4*(4), 387-388.

Drew, M. (2003). Beta, firm size, book-to-market equity and stock returns. *Journal of the Asia Pacific Economy*, *8*(3), 354–379.

Ettlie, J. E., & Rubenstein, A. H. (1987). Firm size and product innovation. *The Journal of Product Innovation Management*, *4*(2), 89–108.

Ezzeddine, B. M., Soussi, M.N., Baccar, A.., & Bouri, A.. (2014). CEO's personal characteristics, ownership and investment cash flow sensitivity: Evidence from NYSE panel data firms. *Journal of Economics, Finance and Administrative Science, 19*(37), 98–103.

Fama, E.F., & French, K.R. (1993). Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics 33*, 3–56.

Family Smoking Prevention and Tobacco Control Act, H.R.1256 - 111th Congress. Retrieved from: https://www.congress.gov/bill/111th-congress/house-bill/1256

Huber, J., Palan, S., & Zeisberger, S. (2017). *Does Investor Risk Perception Drive Asset Prices in Markets? Experimental Evidence* (SSRN Electronical Journal Working Paper 2017-05). Retrieved on 15 March from SSRN Electronic Journal.

Garcia, F.M., & Wantchekon, L. (2010). Theory, external validity, and experimental inference: some conjectures. *The Annals of the American Academy of Political and Social Science, 628*(1), 132–147.

Ibrahim, H., & Al-Ajlouni, M. (2018). Sustainable consumption. *Management Decision, 56*(3), 610-633.

Iturriza, M., Labaka, L., Ormazabal, M., & Borges, M. (2020). Awareness-development in the context of climate change resilience. *Urban Climate, 32*, 1-15.

Jiang, X., Han, L., & Yin, L. (2019). Currency strategies based on momentum, carry trade and skewness. *Physica A: Statistical Mechanics and Its Applications*, *517*, 121–131.

Kapor, P. (2014). Behavioral finance. *Megatrend Review, 11*(2), 73-94.

Kees, J., Burton, S., Andrews, J., & Kozup, J. (2010). Understanding how graphic pictorial warnings work on cigarette packaging. *Journal of Public Policy & Marketing, 29*(2), 265-276.

Kerr, J., R., & Wilson, M. S. (2018). Changes in perceived scientific consensus shift beliefs about climate change and GM food safety. *PLoS ONE, 13*(7), 1-17.

Kurdi, B., Lozano S., Banaji M.R. (2017) Introducing the Open Affective Standardized Image Set (OASIS). *Behavioral Research Methods*,*49*(2):457–470.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (2008). *International Affective Picture System (IAPS): Affective ratings of pictures and instruction manual (Technical Report A-8).* Gainesville: University of Florida, Center for Research in Psychophysiology.

Leiserowitz, A. (2005). American risk perceptions: Is climate change dangerous? *Risk Analysis, 25*(6), 1433-1442.

Lester, L., & Cottle, S. (2009) Visualizing climate change: television news and ecological citizenship. *International Journal of Communication, 3*, 920–936.

Lewandowsky, S., Gignac, G. E., & Oberauer, K. (2013). The role of conspiracist ideation and worldviews in predicting rejection of science. *PLoS ONE, 8*(10), 1-17.

Liesen, A. (2015). Climate change and financial market efficiency. *Business & Society, 54*(4), 511-539.

Loewenstein, G. (2000). Emotions in economic theory and economic behavior. *The American Economic Review, 90*(2), 426-432.

Massard-Guilbaud, G. & Mosley, S. (2011). *Common Ground : Integrating the Social and Environmental in History*. Newcastle upon Tyne: Cambridge Scholars Publishing.

Medrano-Adán L., Salas-Fumás V., & Sanchez-Asin, J. (2019). Firm size and productivity from occupational choices. *Small Business Economics, 53*(1), 243–267.

Mendel, B., & Shleifer, A. (2012). Chasing noise. *Journal of Financial Economics, 104*(2), 303-320.

Monarrez-Espino, J., Liu, B., Greiner, F., Bremberg, S., & Galanti, R. (2014) Systematic review of the effect of pictorial warnings on cigarette packages in smoking behavior. *American Journal of Public Health, 104*(10), 11-30.

Murphy, J., Allen, P., Stevens, T., & Weatherhead, D. (2005). A meta-analysis of hypothetical bias in stated preference valuation. *Environmental and Resource Economics, 30*(3), 313-325.

Mykolas, S., Rasa, P., & Arvydas, K. (2019). The effects of descriptive imagery and appeals on emotions and intentions related to pro-environmental behavior. *Sustainability, 11*(19).

Nayak, S. C., Misra, B. B., & Behera, H. S. (2019). Efficient financial time series prediction with evolutionary virtual data position exploration. *Neural Computing and Applications, 31*(2), 1053–1074.

Nelson, T. (2018). ESG, climate change risk and disclosure. *Governance Directions, 70*(11), 705-709.

Obergruber, P., & Hrubcova, G. (2016). Experiments in economics. *Procedia Economics and Finance, 39*, 482-492.

Oehler, A., Hofer, A., & Wendt, S. (2014). Do key investor information documents enhance retail investors' understanding of financial products? Empirical evidence. *Journal of Financial Regulation and Compliance, 22*(2), 115-127.

Olejnik,S., Li, J., Supattathum, S., and Huberty, C.J. (1997). Multiple testing and statistical power with modified Bonferroni procedures. *Journal of educational and behavioral statistics, 22,* 389-406.

O'Neill, S., & Smith, N. (2014). Climate change and visual imagery. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(1), 73-87.

Papies, E. (2017). Situating interventions to bridge the intention-behaviour gap: A framework for recruiting nonconscious processes for behaviour change. *Social and Personality Psychology Compass, 11*(7).

Pilli, E.D., & Mazzon, J.A. (2016). Information overload, choice deferral, and moderating role of need for cognition: Empirical evidence. *Revista De Administração, 51*(1), 36–55.

Pixley, J. (2002). Emotions and economics. *The Sociological Review, 50*(S2), 69-89.

Rademaker, R.L., & Pearson, J. (2012). Training visual imagery: Improvements of metacognition, but not imagery strength. *Frontiers in Psychology*, *3*, 224-224.

Schulze, P. (1994). Cost-benefit analyses and environmental policy. *Ecological Economics*, *9*(3), 197-199.

Sharpe, W.F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *Journal of Finance, September*, 425-42.

Shefrin, H. (2001). Behavioral corporate finance. *Journal of Applied Corporate Finance, 14*(3), 113-126.

Small Business Size Regulations,13 Code of Federal Regulations § 121 (2020). Retrieved from: https://www.ecfr.gov/cgi-bin/text-idx?SID=b919ec8f32159d9edaaa36a7eaf6b695&mc=true&node=pt13.1.121&rgn=div5#se13.1.121_1101

Theil, H. (1971). Best Linear Unbiased Estimation and Prediction. *Principles of Econometrics*. New York: John Wiley & Sons. pp. 119–124.

Treynor, J.L. (1962). Toward a Theory of Market Value of Risky Assets. *Asset pricing and Portfolio Performance, 7*(2), 15-22.

Vanguard Group (2020). *Key Investor Information Vanguard FTSE*. Retrieved from https://global.vanguard.com/portal/site/loadPDF?country=nl&docId=6015

Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics, 101*(2), 449-472.

Veld, C., & Veld-Merkoulova, Y. (2008). The risk perceptions of individual investors. *Journal of Economic Psychology, 29*(2), 226-252.

Vinogradov, D., & Shadrina, E. (2013). Non-monetary incentives in online experiments. *Economics Letters, 119*(3), 306–310.

Virlics, A. (2013). Emotions in economic decision-making: A multidisciplinary approach. *Procedia - Social and Behavioral Sciences, 92*, 1011-1015.

Walther, T. (2015). Key investor documents and their consequences on investor behavior. *Journal of Business Economics, 85*(2), 129-156.

Weaver, A. A. (2002). Determinants of environmental attitudes: A five-country comparison. *International Journal of Sociology, 32*(1), 77-108.

Williams, J., Cofield, A., Ellison, H., Jansen, F., McKessar, M., O'Rourke, S., & Seybert, E. (2010). Sustainable return on investment. *Sustainability, 3*(4), 235-240.

8. Appendix

TABLE 1. IMAGERY USED IN THE EXPERIMENT (ACQUIRED FROM KURDI ET AL., 2017)

Name	Image	µ valence	σ valence	µ arousal	σ arousal
Negative (control)					
Low intensity (Yarn 1)		2.598	1.471	1.871	1.262
Medium intensity (Toilet 4)		2.535	1.213	3.155	1.764
High intensity (Bloody Knife 1)		1.843	1.06	4.545	1.937
Negative (nature)					
Low intensity (Garbage Dump 7)		2.735	1.177	2.475	1.604
Medium intensity (Pollution 1)		2.475	1.331	3.621	1.853
High intensity (Fire 11)		1.755	1.112	5.317	1.897

Neutral (control)					
Low intensity (Wall 2)		4.029	0.497	1.693	1.239
Medium intensity (Bed 1)		4.02	0.916	2.99	1.729
High intensity (Sun 1)		4.416	1.358	4.505	1.852
Neutral (nature)					
Low intensity (Dirt 5)		3.545	0.831	1.99	1.376
Medium intensity (Woods 1)		3.784	1.271	3.168	1.504
High intensity (Thunderstorm 3)		3.96	1.326	4.68	1.745

Positive (control)					
Low intensity (Eating 3)		5.138	1.048	2.625	1.463
Medium intensity (Food 6)		5.657	0.990	3.673	1.744
High intensity (Couple 4)		5.971	1.238	4.535	1.453
Positive Nature					
Low intensity (Grass 4)		5.225	1.160	2.109	1.509
Medium intensity (Lake 1)		6.225	0.898	3.970	1.962
High intensity (Rainbow 2)		6.257	0.956	4.903	1.701

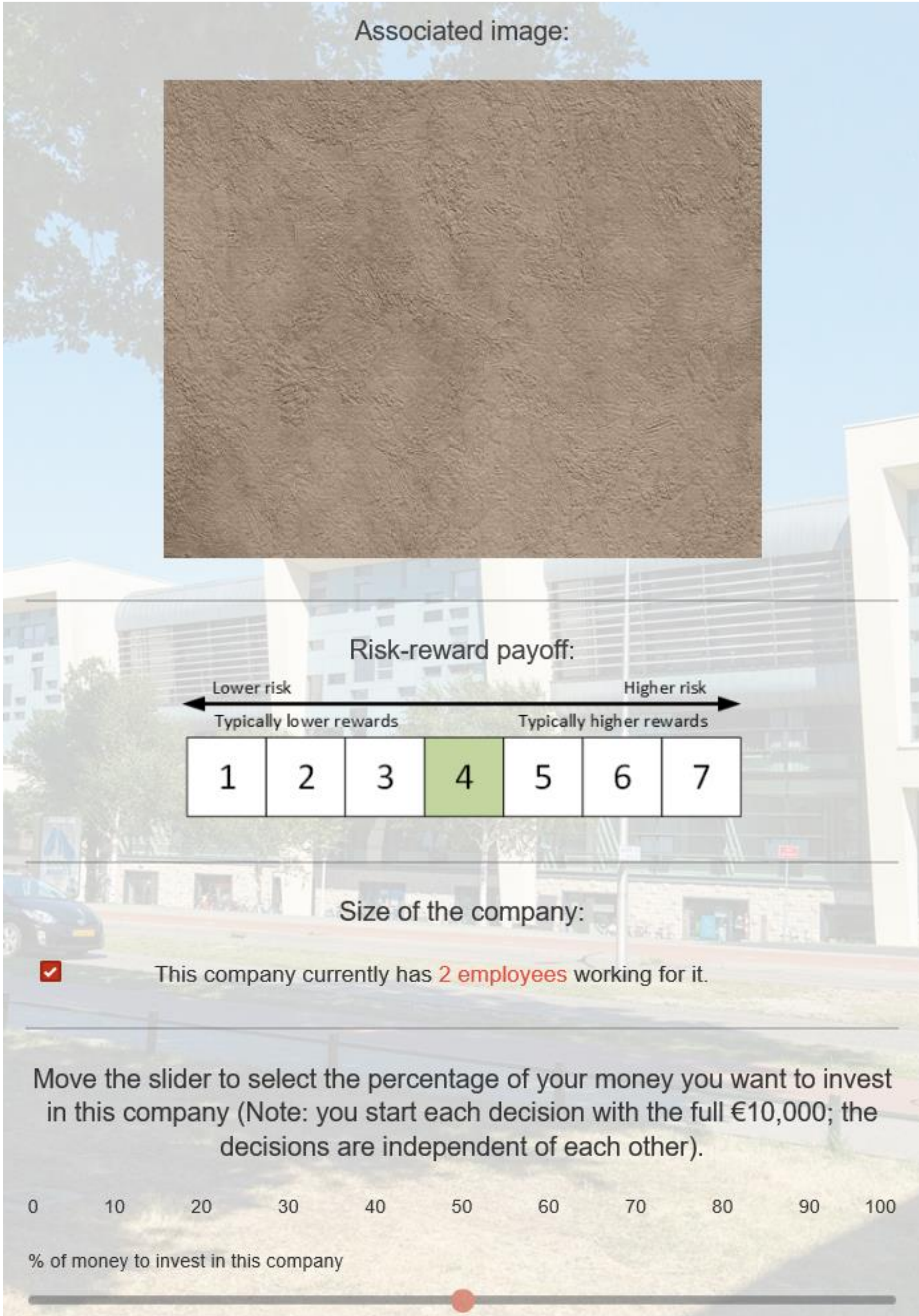
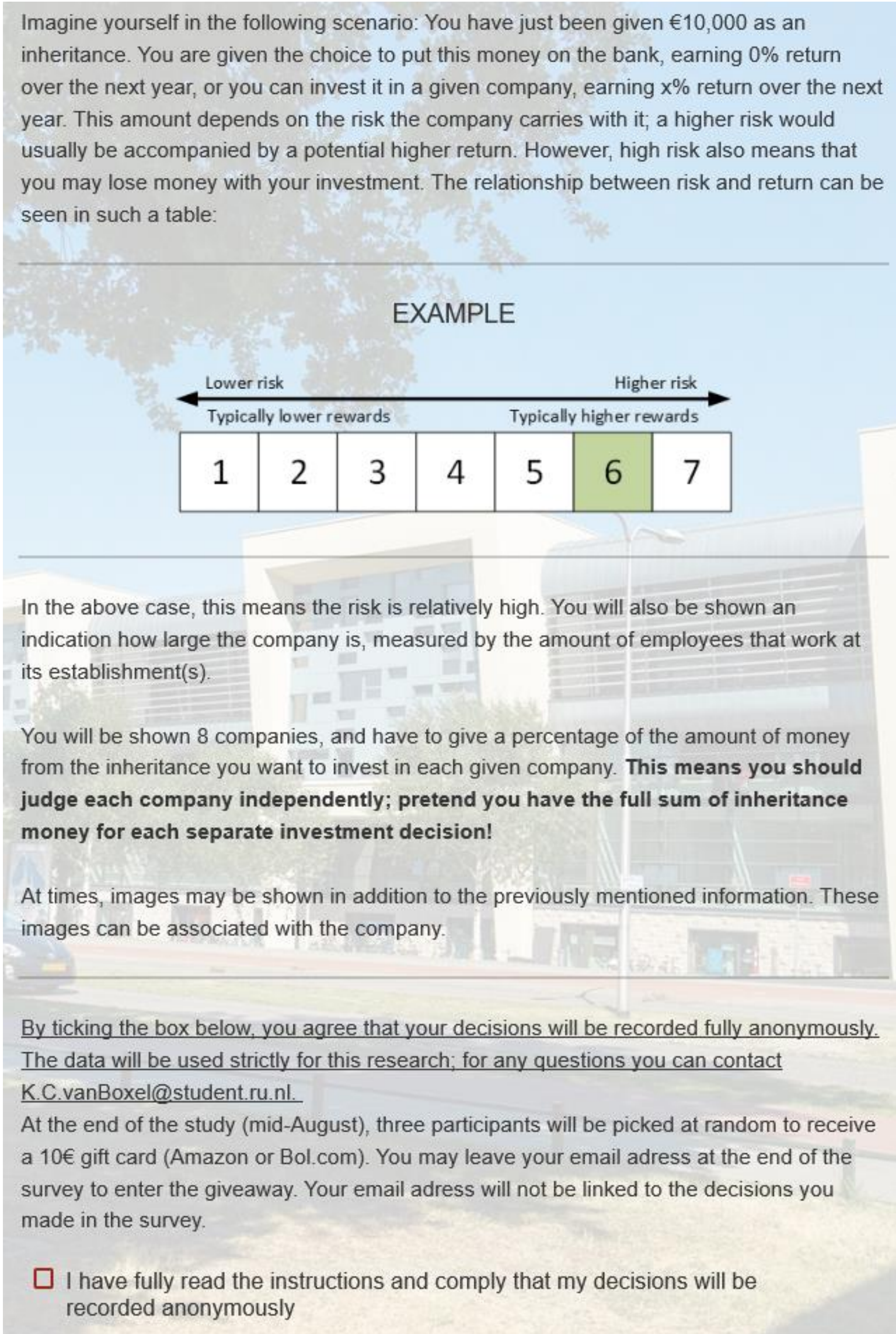


FIGURE 8. EXAMPLE INVESTMENT DECISION
(CONTROL LOW INTENSITY IMAGE; RISK = 4, SIZE COMPANY = 2)



Imagine yourself in the following scenario: You have just been given €10,000 as an inheritance. You are given the choice to put this money on the bank, earning 0% return over the next year, or you can invest it in a given company, earning x% return over the next year. This amount depends on the risk the company carries with it; a higher risk would usually be accompanied by a potential higher return. However, high risk also means that you may lose money with your investment. The relationship between risk and return can be seen in such a table:

EXAMPLE

Lower risk ← → Higher risk

Typically lower rewards — Typically higher rewards

1	2	3	4	5	6	7

In the above case, this means the risk is relatively high. You will also be shown an indication how large the company is, measured by the amount of employees that work at its establishment(s).

You will be shown 8 companies, and have to give a percentage of the amount of money from the inheritance you want to invest in each given company. **This means you should judge each company independently; pretend you have the full sum of inheritance money for each separate investment decision!**

At times, images may be shown in addition to the previously mentioned information. These images can be associated with the company.

By ticking the box below, you agree that your decisions will be recorded fully anonymously. The data will be used strictly for this research; for any questions you can contact K.C.vanBoxel@student.ru.nl.
At the end of the study (mid-August), three participants will be picked at random to receive a 10€ gift card (Amazon or Bol.com). You may leave your email adress at the end of the survey to enter the giveaway. Your email adress will not be linked to the decisions you made in the survey.

☐ I have fully read the instructions and comply that my decisions will be recorded anonymously

FIGURE 9. INTRODUCTION SCREEN

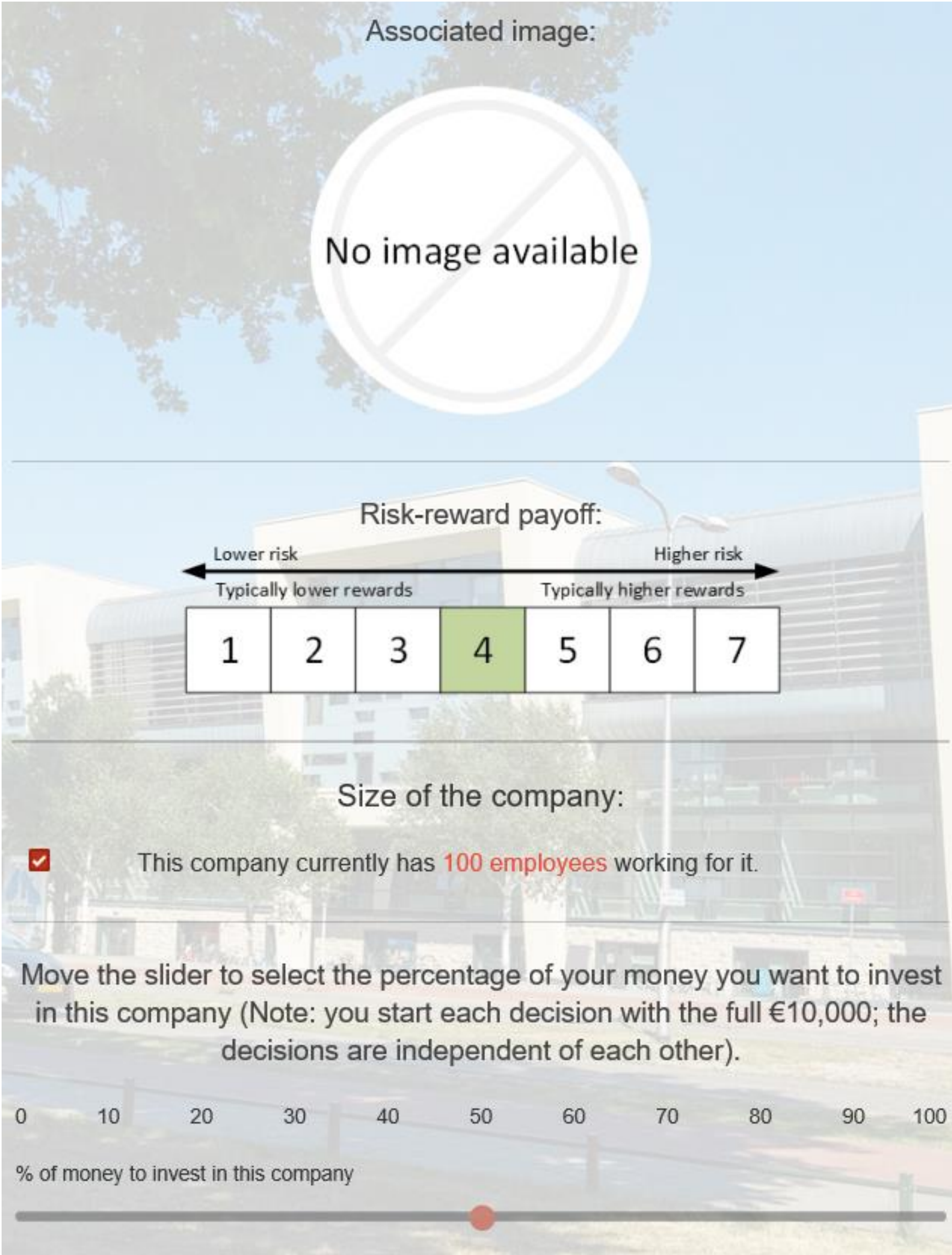
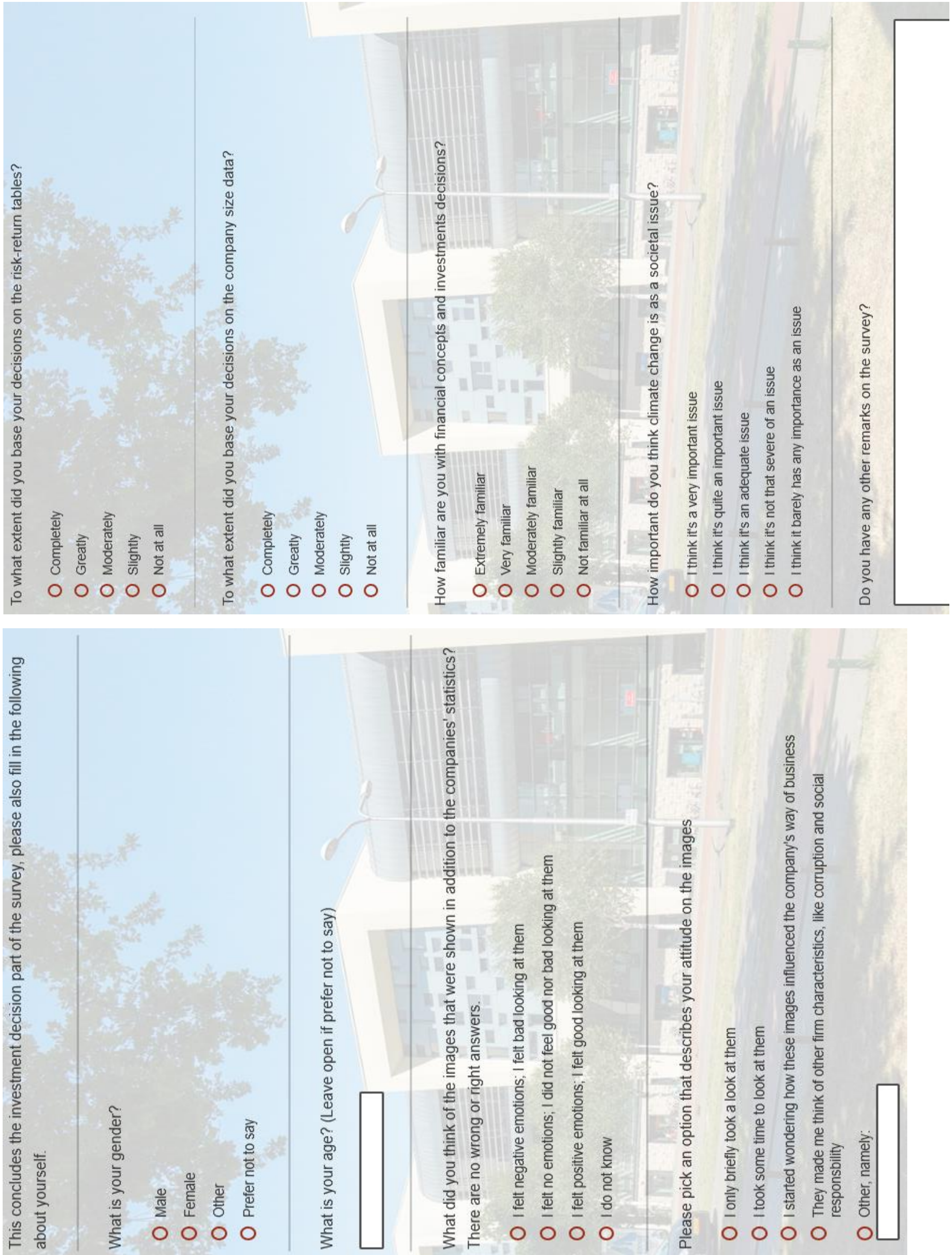


FIGURE 11. STANDARD NO-IMAGE COMPANY INVESTMENT DECISION


This concludes the investment decision part of the survey, please also fill in the following about yourself.

What is your gender?

- Male
- Female
- Other
- Prefer not to say

What is your age? (Leave open if prefer not to say)

What did you think of the images that were shown in addition to the companies' statistics? There are no wrong or right answers.

- I felt negative emotions; I felt bad looking at them
- I felt no emotions; I did not feel good nor bad looking at them
- I felt positive emotions; I felt good looking at them
- I do not know

Please pick an option that describes your attitude on the images

- I only briefly took a look at them
- I took some time to look at them
- I started wondering how these images influenced the company's way of business
- They made me think of other firm characteristics, like corruption and social responsbility
- Other, namely:

To what extent did you base your decisions on the risk-return tables?

- Completely
- Greatly
- Moderately
- Slightly
- Not at all

To what extent did you base your decisions on the company size data?

- Completely
- Greatly
- Moderately
- Slightly
- Not at all

How familiar are you with financial concepts and investments decisions?

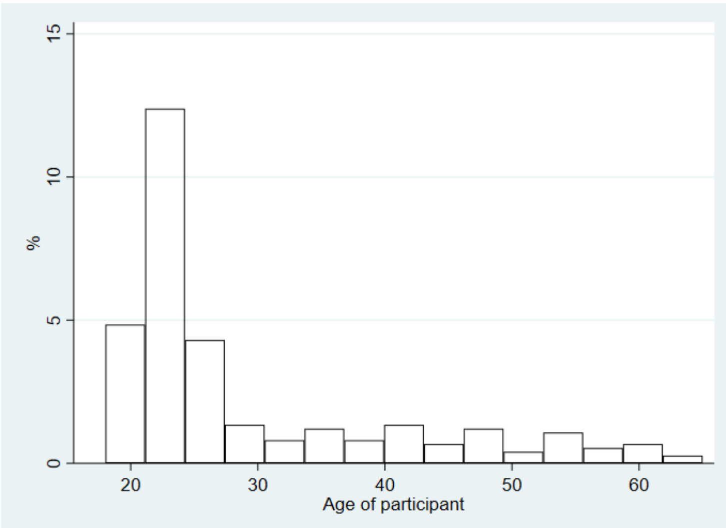
- Extremely familiar
- Very familiar
- Moderately familiar
- Slightly familiar
- Not familiar at all

How important do you think climate change is as a societal issue?

- I think it's a very important issue
- I think it's quite an important issue
- I think it's an adequate issue
- I think it's not that severe of an issue
- I think it barely has any importance as an issue

Do you have any other remarks on the survey?

FIGURE 12. CONTROL QUESTIONS



Gender	Percent	Frequency
Male	39.37	100
Female	59.06	150
Unknown	1.57	4
Total	100.00	254

Gender	Mean Age	Std. dev.	Frequency
Male	30.23	11.55	92
Female	28.86	11.20	143
Unknown	31.00	9.90	2
Total	29.41	11.30	237

FIGURE 14. DEMOGRAPHIC INFORMATION: AGE AND GENDER

TABLE 4. TREATMENT DISTRIBUTION AND MANIPULATION CHECK

Treatment	Incorrectly answered	Correctly answered	Answered 'Do not know'	Correct % (Don't know = incorrect)	Correct % (Don't know = missing)	Total in treatment	Treatment %
Neutral	32	47	12	51.65	59.49	**91**	**35.83**
Positive	41	35	7	42.17	46.05	**83**	**32.67**
Negative	27	51	2	63.75	65.38	**80**	**31.50**
Total	100	133	21	52.36	57.08	**254**	**100.00**

TABLE 5. INVESTMENT DECISION OUTCOMES

Group	Treatment	Obs.	Mean	Std. Dev.	Min	Max
low	Neutral	91	32.879	27.467	0	90
	Positive	83	40.205	29.005	0	100
	Negative	80	31.150	24.936	0	100
	Total	**254**	**34.728**	**27.467**	**0**	**100**
med	Neutral	91	29.495	24.726	0	100
	Positive	83	40.964	30.835	0	100
	Negative	80	15.750	19.789	0	100
	Total	**254**	**28.913**	**27.395**	**0**	**100**
high	Neutral	91	31.209	26.681	0	100
	Positive	83	35.747	29.992	0	100
	Negative	80	17.763	25.366	0	82
	Total	**254**	**28.457**	**28.320**	**0**	**100**
low_n	Neutral	91	36.637	27.166	0	100
	Positive	83	41.819	30.272	0	100
	Negative	80	34.606	28.143	0	100
	Total	**254**	**37.606**	**28.143**	**0**	**100**
med_n	Neutral	91	32.538	24.081	0	98
	Positive	83	42.060	31.698	0	100
	Negative	80	17.325	23.824	0	100
	Total	**254**	**30.858**	**28.448**	**0**	**100**
high_n	Neutral	91	34.044	27.265	0	100
	Positive	83	39.458	29.390	0	100
	Negative	80	21.050	24.573	0	100
	Total	**254**	**31.720**	**28.116**	**0**	**100**
noimage_standard	Neutral	91	35.385	25.075	0	82
	Positive	83	35.458	24.587	0	100
	Negative	80	33.525	25.834	0	100
	Total	**254**	**34.823**	**25.075**	**0**	**100**
noimage_based	Neutral	91	28.912	22.701	0	90
	Positive	83	34.639	29.759	0	100
	Negative	80	23.337	23.745	0	85
	Total	**254**	**29.028**	**25.826**	**0**	**100**
Average*	***Neutral***	**91**	**32.800**	**20.544**	**0**	**100**
	Positive	**83**	**40.042**	**24.069**	**0**	**100**
	Negative	**80**	**22.896**	**16.664**	**0**	**100**
	Total	**254**	**32.017**	**20.750**	**0**	**100**

[*]Notes: The 'Average' numbers are based on the average of all image presented investment decisions. That is, they do not include the no imagery investment decisions.

TABLE 7. T-TESTS COMPARING TREATMENT DIFFERENCE MEANS

Difference	Comparing (1	2)	Obs.	Difference of means (1-2)	Std. Error	|t-stat*|	p-stat*
Medium-intensity **nature** minus no-imagery based company	Neutral	Positive	174	-3.795	2.766	1.372	0.172
	Neutral	Negative	171	9.639	3.538	2.725	0.007
	Positive	Negative	163	13.434	3.866	3.475	0.001
Medium-intensity **control** minus no-imagery based company	Neutral	Positive	174	-5.743	3.260	1.762	0.080
	Neutral	Negative	171	8.170	2.843	2.874	0.005
	Positive	Negative	163	13.913	3.613	3.851	0.000

**Notes: t-statistics and p-statistics are given for H_0: difference in means(treatment) = 0, two tailed test.*

TABLE 8. DIFFERENCES CONTROL AND NATURE COMPANY PER INTENSITY

Intensity	Treatment	Obs	Mean	Std. Dev.	Min	Max	|t-stat*|	p-stat*
Low intensity	Neutral	91	3.758	21.054	-69	80	1.703	0.092
	Positive	83	1.614	18.038	-64	65	0.815	0.417
	Negative	80	3.188	17.410	-50	43	1.638	0.106
	Total	**254**	**2.878**	**18.937**	**69**	**80**	**2.422**	**0.016**
Medium intensity	Neutral	91	3.044	20.181	-67	53	1.439	0.154
	Positive	83	1.096	22.365	-75	60	0.447	0.656
	Negative	80	1.575	25.011	-74	100	0.563	0.575
	Total	**254**	**1.945**	**22.429**	**-75**	**100**	**1.382**	**0.168**
High intensity	Neutral	91	2.835	18.774	-64	72	1.441	0.153
	Positive	83	3.711	17.255	-56	65	1.959	0.054
	Negative	80	3.288	25.557	-87	100	1.151	0.253
	Total	**254**	**3.264**	**20.639**	**-87**	**100**	**2.520**	**0.012**

**Notes: t-statistics and p-statistics are given for H_0: Mean(variable) = 0 (per treatment), two-tailed test*

TABLE 9. FREQUENCY ANSWERS CONTROL VARIABLES

Chosen option	Treatment	Affect for imagery*	Affect for fundamentals	Familiarity with finance	Importance climate change
1 (Not at all)	Neutral	30 (11.81%)	2 (0.79%)	25 (9.84%)	0 (0.00%)
	Positive	27 (10.63%)	0 (0.00%)	24 (9.45%)	0 (0.00%)
	Negative	20 (7.87%)	0 (0.00%)	27 (10.63%)	1 (0.39%)
	Total	**77 (30.31%)**	**2 (0.79%)**	**76 (29.92%)**	**1 (0.39%)**
2 (Slightly)	Neutral	8 (3.15%)	6 (2.34%)	27 (10.63%)	1 (0.39%)
	Positive	9 (3.54%)	4 (1.57%)	25 (9.84%)	2 (0.79%)
	Negative	6 (2.36%)	10 (3.94%)	25 (9.84%)	2 (0.79%)
	Total	**23 (9.06%)**	**20 (7.87%)**	**77 (30.31%)**	**5 (1.97%)**
3 (Moderately)	Neutral	38 (14.96%)	28 (11.02%)	23 (9.06%)	7 (2.76%)
	Positive	36 (14.17%)	19 (7.48%)	15 (5.91%)	5 (1.97%)
	Negative	29 (11.42%)	24 (9.45%)	14 (5.51%)	5 (1.97%)
	Total	**103 (40.55%)**	**71 (27.95%)**	**52 (20.47%)**	**17 (6.69%)**
4 (Greatly)	Neutral	12 (4.72%)	43 (16.93%)	10 (3.94%)	36 (14.17%)
	Positive	8 (3.15%)	48 (18.90%)	13 (5.12%)	32 (12.60%)
	Negative	22 (8.66%)	41 (16.14%)	8 (3.15%)	28 (11.02%)
	Total	**42 (16.54%)**	**132 (51.97%)**	**31 (12.20%)**	**96 (37.80%)**
5 (Completely)	Neutral	3 (1.18%)	12 (4.72%)	6 (2.36%)	47 (18.50%)
	Positive	3 (1.18%)	12 (4.72%)	6 (2.36%)	44 (17.32%)
	Negative	3 (1.18%)	5 (1.97%)	6 (2.36%)	44 (17.32%)
	Total	**9 (3.54%)**	**29 (11.42%)**	**18 (7.09%)**	**135 (53.15%)**
Average	***Neutral***	***91 (35.83%)***	***91 (35.83%)***	***91 (35.83%)***	***91 (35.83%)***
	Positive	***83 (32.68%)***	***83 (32.68%)***	***83 (32.68%)***	***83 (32.68%)***
	Negative	***80 (31.50%)***	***80 (31.50%)***	***80 (31.50%)***	***80 (31.50%)***
	Total	***254 (100.00%)***	***254 (100.00%)***	***254 (100.00%)***	***254 (100.00%)***

**Notes: The results of the affect for imagery variable should not be interpreted as a Likert-item; 1 = "I only briefly took a look at them", 2 = "I took some time to look at them", 3 = I started wondering how these images influenced the company's way of business, 4 = They made me think of other firm characteristics, like corruption and social responsibility, 5 = other (also see 3.3.4).*

TABLE 11. VIF TEST

Variable	VIF
Positive	1.34
Negative	1.32
Age	1.02
Female	1.16
Familiarity with finance	1.14
Risk	1.00
Size	1.00
Mean VIF	1.14

Notes: H_0: VIF test based on Equation (2).

TABLE 12. BREUSCH-PAGAN / COOK-WEISBERG TEST FOR HETEROSKEDASTICITY

Variable	
χ^2	29.32
Prob > χ^2	0.000

Notes: H_0: Constant variance, variables are fitted values of invest in Equation (2).

TABLE 16. DIFFERENCE-IN-DIFFERENCE: POSITIVE-NEGATIVE MARGINS

Intensity (a)	Group (a)	Margin[b]	Std. Error[c]	|t-stat|[d]	p-stat[d]
Low (470)	Contrast positive (76)	4.153	5.089	0.82	0.415
	Contrast negative (77)	5.270	4.730	1.11	0.265
	Contrast **(**Contrast positive - contrast negative)	**-1.117**	**5.422**	**0.21**	**0.837**
Med (470)	Contrast positive (76)	10.339	5.107	2.02	0.043
	Contrast negative (77)	-8.181	4.539	1.80	0.072
	Contrast **(**Contrast positive - contrast negative)	**18.520**	**5.439**	**3.41**	**0.001**
High (470)	Contrast positive (76)	4.861	4.970	0.98	0.328
	Contrast negative (77)	-5.379	4.595	1.17	0.242
	Contrast **(**Contrast positive - contrast negative)	**10.240**	**5.420**	**1.93**	**0.054**

Notes: (a) Amount of observations in between brackets per respective group. (b) Margins are based on estimation of Equation (8), and reflect the difference-in-difference of negative-positive treatment group. (c) Standard Errors are calculated using Delta-method. (d) t- and p-statistics are given for H_0: Margin = 0, two-tailed test.

TABLE 19. AGGREGATE MARGINS OF CLIMATE_IMPORTANCE

Climate change importance (a)	**Margin[b]**	**Std. Error[c]**	**|t-stat|[d]**	**p-stat[d]**
Relatively low (872)	32.487	0.872		
Relatively high (1008)	32.006	0.864		
Contrast (high - low)	**-0.481**	**1.124**	**0.39**	**0.698**

Notes: (a) Amount of observations in between brackets per respective group. (b) Margins are based on estimation of Equation (8). (c) Standard Errors are calculated using Delta-method. (d) p-statistics are given for H_0: Margin = 0, two-tailed test.

TABLE 23. VIF TEST - WILLINGNESS TO INVEST

Variable	**VIF**
Positive	1.34
Negative	1.32
Female	1.17
Familiarity with finance	1.15
Age	1.02
Willingness to invest	1.02
Risk	1.00
Size	1.00
Mean VIF	1.14

Notes: H_0: VIF test based on Equation (13).