Sustainability Preferences of Index Fund Investors: A Discrete Choice Experiment

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Keywords: Socially Responsible Investment, ESG, Willingness-to-Pay, Discrete Choice Experiment

JEL Classifications: C90, G40, G50.

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1 Introduction

Assets under management (AUM) in socially responsible investments (SRI) have experienced remarkable growth over the last decade. Around one third of the total AUM in the US incorporate sustainability in some way or another.[1] Despite this trend, it is unclear how investors trade off financial performance for sustainability as financial institutions struggle to elicit their clients' sustainability preferences. Meanwhile, a parallel trend currently in financial markets is the rise of passive investments. According to the Investment Company Institute's 2020 Factbook, the total assets managed passively in the US surged from 11 billion USD in 1993 to 2.8 trillion USD in 2020 (e.g., Haddad et al., 2021). Therefore, it is a puzzle as to how retail investors reconcile these two seemingly contradictory trends as investing with a sustainable strategy usually involves sacrificing portfolio diversification. In this study, we tackle these issues by measuring how index fund investors trade off financial performance for sustainability by using a discrete choice experiment (DCE). Our results shed light on how sustainability preferences can be measured as well as how sustainability objectives can be effectively integrated into index funds (e.g., Fichtner et al., 2017; Chen and Scholtens, 2018).

Although SRI has become increasingly popular, more research is needed to better understand how investors trade off a portfolio's performance for sustainability, or ESG (environmental, social, and governance). The research indicates that social preferences play a pivotal role in driving the demand for SRI products and that investors are willing to accept lower returns and higher management fees for better ESG performance (e.g., Riedl and Smeets, 2017). In a separate natural experiment, Hartzmark and Sussman (2019) find that while non-monetary motives do influence investment decisions, investors also maintain a strong belief that higher sustainability predicts better future fund returns, despite the absence of empirical evidence for this pattern (e.g., Revelli and Viviani, 2015; Busch and Friede, 2018). Duchêne et al. (2022) observe that participants, finance professionals and students in a lab-in-the-field experiment, are willing to accept lower returns if their investments positively affect the environment but they will not bear increased risk in their portfolio decisions. Additionally, Bauer et al. (2021) find that pension beneficiaries have strong social preferences. However, when asked about return expectations of sustainable

[1] To put this into perspective, in 2020, the total sustainable AUM by professional investment managers in the U.S. surpassed that of Europe, reaching 17.1 trillion USD, compared to 3.07 trillion USD in 2010, as reported by USSIF. For details, see `https://www.ussif.org/currentandpast`. The EU has 12 trillion USD in sustainable AUM in 2021, as reported by EUROSIF. For details, see `https://www.eurosif.org/eurosif-reports/`.

portfolios, the majority of beneficiaries in their sample are optimistic about the effect of ESG factors on pension outcomes. Bauer et al. (2024) conduct a careful analysis of retail index investors' expectations for returns in an online survey and find that they do expect higher returns when they are shown a fund with a high ESG label. These studies collectively show that financial motives do play a crucial role in SRI. Investors implicitly balance sustainability, potentially due to their social preferences, with the financial attributes of assets.

The rising trend in SRI makes it imperative to have clear regulatory guidelines to assess investors' sustainability preferences; however, the assessment methods currently are lacking. In March 2020, the European Commission introduced the EU Taxonomy that is a detailed classification system aimed at identifying economic activities that are environmentally sustainable. Moreover, in the context of directing finance toward the European Green Deal, the EU Commission also introduced the assessment of clients' sustainability preferences in 2022.[2] Insurance and investment advisers are required to obtain information not only about the client's investment knowledge and experience, ability to bear losses, and risk tolerance as part of the suitability assessment but also about their sustainability preferences. However, what complicates matters in the implementation is the lack of a clear understanding of sustainability preferences. It most likely is jointly determined by a set of underlying preferences, such as social preferences, norm-following preferences, ambiguity preferences, as well as beliefs.

Our study contributes to the understanding of sustainability preferences by directly measuring investors' willingness-to-pay (WTP) for sustainability.[3] It provides a tool for financial institutions when they assess their clients' sustainability preferences, especially when it is not necessary to understand the detailed underlying preference or belief foundations. We are not the first to assess investors' WTP for sustainability. For example, Gutsche and Ziegler (2019) conduct stated choice experiments and discover that investors who derive a "warm glow" from sustainable investments have political affiliations with left-wing parties and possess strong environmental consciousness that demonstrate a significantly higher mean WTP for sustainable investment products at the cost of returns compared to their counterparts. In another study, Engler et al. (2024) use large-scale

[2] For details, see `https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32021R1253`.

[3] Willingness-to-pay is a conventional welfare measure for price changes that is typically represented by compensating and equivalent variations which correspond to the maximum amount an individual would be willing to pay to secure the change (e.g., Hanemann, 1991; Breidert et al., 2006). For brevity, we use the abbreviation "WTP" throughout the paper.

online experiments with individual investors across five European countries and find that social preferences significantly increase both the proportion of sustainable investments in portfolios and the WTP for these investments. However, these preferences do not significantly affect investors' sensitivity to fees. Instead, financially illiterate investors tend to pay higher fees due to their limited attention to them and their incorrect beliefs about the performance of high-expense funds. Similarly, Heeb et al. (2023) conduct a framed field experiment and observe that although investors have a substantial WTP for sustainable investments that is primarily driven by emotional rather than calculative impact evaluations, they do not pay significantly more for a greater effect. Through an IPO experiment, Brodback et al. (2021) find that individual investors are willing to pay a sizable premium only for significantly more responsible assets. Additionally, Baker et al. (2022) use a revealed preference approach to show that investors attribute a higher implicit value to ESG stocks, being willing to pay an increased annual premium for funds with an ESG mandate compared to equivalent funds without such a mandate. This premium was 0.09% in 2019 and had more than tripled to 0.28% in 2022. These studies collectively contribute to the understanding of how different factors influence investors' WTP for sustainability and the varying degrees of financial trade-offs they are willing to make.

Instead of directly asking investors, we use a DCE to calculate investors' WTP for sustainability. A DCE is grounded in random utility theory which posits that an individual's preferences among alternatives can be modeled by assigning a real-value score to each choice that is derived from a parameterized distribution. The alternatives are then ranked based on these scores to determine the most preferred option (e.g., de Bekker-Grob et al., 2012). Three other studies have used a DCE to assess investors' WTP for sustainability attributes. Bauer and Smeets (2015) find that investors who strongly identify with SRI allocate significantly more to sustainable investments. Their study, which surveyed clients from two banks exclusively offering SRI products, uses a conjoint analysis to arrive at this conclusion. Apostolakis et al. (2016) explore pension beneficiaries' WTP for various characteristics of responsible investment through a choice-based conjoint experiment. Participants in the study were asked to select their preferred investment portfolio from a range of options that combined attributes such as SRI, impact investments, and cost. Lagerkvist et al. (2020) conduct a choice experiment on equity fund savings among private investors in Sweden to estimate the WTP for sustainable and responsible investments by using conventional fund attributes such as cost, risk-return profile, sustainability selection strategies, and sustainability focus.

Compared to other studies, ours offers several novel contributions. First, we align our study with the Sustainable Finance Disclosure Regulation (SFDR), specifically Articles 6, 8, and 9, by examining investors' preferences across a spectrum of sustainability levels: "grey" (comparable to Article 6), "light green" (comparable to Article 8), and "dark green" (comparable to Article 9).[4] Second, we investigate investors' trade-offs between funds' ESG attributes and other characteristics by specifically addressing their preferences for ESG integration strategies. The consideration of sustainability criteria plays a crucial role in shaping investors' decision-making, with fund flows significantly influenced by the intensity of ESG screening activities (e.g., Borgers et al., 2015; Hartzmark and Sussman, 2019). Investors often rely on ESG ratings to guide their portfolio decisions, with more sustainable funds typically attracting larger net inflows (e.g., Bollen, 2007; Hartzmark and Sussman, 2019; Ferriani, 2023; Emiris et al., 2024). However, sustainability preferences may not monotonically increase with ESG scores. This lack of an increase might be especially true for index fund investors in our sample, who need to balance index tracking and ESG objectives. Thus, higher ESG integration may not necessarily be better for them. Additionally, concerns about greenwashing and the uncertainty about the ESG rating could deter investors from selecting the highest ESG category (e.g., Yu et al., 2020; Avramov et al., 2022). And ESG preferences may also depend on the particular ESG integration strategy adopted by the fund, as these strategies significantly affect funds' risk-adjusted returns and loadings on risk factors (e.g., Renneboog et al., 2008). Finally, our study contributes to the literature by demonstrating substantial heterogeneity in sustainability preferences among investors, which shows meaningful correlations with demographic factors, personal preferences, and financial status (e.g., Sandberg et al., 2009; Giglio et al., 2021, 2023). A novel feature of our study is that we validate the DCE results and investors' heterogeneous preferences for sustainability based on an incentivized decision on allocation.

We conducted our online field survey experiment in collaboration with Meesman Indexbeleggen, which is a prominent Dutch index fund that expanded its product range to include sustainable funds alongside traditional index fund options. Meesman clients receive an invitation to the experiment through a monthly newsletter. During the ex-

[4]SFDR Article 6, grey funds, addresses investments that do not promote environmental or social aspects and do not have sustainable investment as a goal. SFDR Article 8, light green funds, are products that promote investments or projects with positive environmental or social qualities, or a combination of such characteristics, as long as the investments are made in enterprises that adhere to sound governance practices. SFDR Article 9, dark green funds, outlines the disclosure requirements for funds with distinct sustainability objectives, where most of the portfolio consists of ESG-focused investments. For details, see `https://finance.ec.europa.eu/sustainable-finance/disclosures/sustainability-related-disclosure-financial-services-sector_en`.

periment, they work on the DCE task with 13 choice sets. In each choice set, they were asked to choose the most preferred option among three distinct hypothetical funds. These funds varied across multiple dimensions, including ESG score categories, ESG strategies, management fees, and risk-return profiles. The choice sets were designed carefully in collaboration with Meesman to somewhat reflect the nuances of real-world investment scenarios. At the end of the survey, participants make an incentivized decision on how to allocate a monetary budget between an ESG fund and a conventional index fund.

We find that the index fund investors in our sample have distinct preferences and varying levels of willingness to forgo financial returns or to pay higher management fees for different levels of and strategies for ESG. On average, these index investors show a preference for ESG integration with a negative screening strategy over either positive screening or active engagement strategies of which they are relatively indifferent. Specifically, investors are prepared to sacrifice 3.50% of annual returns or to accept an increased annual management fee of 1.47% for ESG integration that uses a negative screening strategy. By contrast, these numbers drop to 2.61% and 1.09% respectively for a positive screening strategy. For strategies involving active engagement, the numbers are 2.69% and 1.13% respectively. Participants slightly prefer light green over dark green funds, but the difference is not significant, so there is a lack of sensitivity to the degree of ESG intensity. In line with conventional wisdom, participants also favor higher risk-adjusted returns and lower management fees. These findings reflect the preferences of index fund investors who tend to prefer passive investment strategies and need to balance their concerns about sustainability with their goals for index investing. These are also consistent with the literature, underscoring investors' preferences for ESG, either due to social preferences or positive expectations towards financial performance (e.g., Riedl and Smeets, 2017; Bauer et al., 2021, 2024).

To further explore heterogeneity in sustainability preferences, we use a latent class analysis based on mixed logit models. This method allows us to probabilistically assign participants to distinct classes based on their choices in the DCE (e.g., Greene and Hensher, 2003). Consequently, we can estimate the WTP for sustainability for each investor class. We identify four classes with considerable differences in their sustainability preferences, investment strategies, and considerations of financial performance. Predominantly, 70% of our sample place substantial emphasis on ESG integration while also considering the financial performance of funds: among them, 57% prefer the negative screening strategy, while only 13% prioritize active engagement. Furthermore, 16% of our sample demonstrate a marked preference for ESG integration and negative screening strategies but largely overlook financial attributes. Finally, the remaining 13% focus primarily on financial attributes, showing minimal sensitivity to ESG integration and strategies.

To validate our classification, we analyze participants' demographics, preferences elicited in the survey, and their choices in an incentivized decision on portfolio allocation. In this analysis, we identify distinct classes of participants with significantly different characteristics. One class is predominantly female, has the highest average age, the least financial literacy and ESG knowledge, and the lowest investment amounts within our sample. This group shows the highest pro-social preferences and the greatest willingness to invest in ESG funds. Conversely, another class is predominantly male, possesses the most investing experience and ESG knowledge, and is in the most favorable financial situation. This group has the fewest pro-social preferences and the lowest willingness to invest in ESG funds. The remaining two classes of participants are mixed in their characteristics and have moderate preferences for sustainability and financial concerns. Overall, participants with strong pro-social preferences allocate significantly more to the ESG fund when making an incentivized decision on portfolio allocation.

Our study contributes to the body of knowledge on how investors deal with the trade-offs between sustainability attributes and financial considerations in their investments. We precisely measure investors' WTP for sustainability under various ESG selection strategies. Focusing on index fund investors also provides field evidence of how retail investors balance sustainability with an appetite for low-cost index investing. Moreover, another major contribution of our study is to generate a meaningful classification of investors according to how they balance sustainability and financial performance.

The remainder of the paper is organized as follows: In Section 2, we present the design of our survey experiment. Next, in Section 3, we introduce the results of the DCE and the latent class analysis. In Section 4, we conclude the paper and discuss the implications of our findings.

2 Study Design

To explore investors' WTP for the ESG attributes of funds, we conduct an online survey experiment that targets index fund investors at Meesman Indexbeleggen, which is a Dutch asset management firm. Established in 2005, Meesman has grown to manage over 1 billion

Euros in assets and to serve over 30,000 retail investors. The firm specializes in passive investing by offering an array of index funds, of which many prioritize ESG principles. For instance, the two Meesman funds that we use in this survey experiment are the "Aandelen Wereldwijd Totaal" (Equity Worldwide Total) and the"Aandelen Duurzame Toekomst" (Equity Sustainable Future). The first tracks a market-weighted combination of three MSCI indexes: the MSCI World Custom ESG Index, the MSCI Emerging Markets Custom ESG Index, and the MSCI World Small Cap Custom ESG Low Carbon Index. The second is designed for investors seeking an index fund with a stronger focus on sustainability as it invests globally in stocks aligned with various sustainable themes. Both funds were categorized within the same risk-return spectrum. The management fee for Equity Worldwide Total is 0.4%, which is slightly lower than the 0.5% fee for Equity Sustainable Future.

2.1 Design Overview

In our invitation, we framed our survey as being general, not particularly about SRI, and comprised five main modules. It started with a consent form and a brief introduction to the survey's content as well as the associated incentives. We provided three types of rewards to encourage participation and careful decision-making. First, we randomly selected one participant from the first 100 who completed the survey to receive a cash reward of €200. Second, we randomly selected one participant from all who completed the survey to receive another cash reward of €200 plus any monetary incentives determined by their choices and luck: in particular, we randomly selected a participant and paid them according to their answer to one randomly drawn payoff-relevant question in the survey.[5] Third, from all participants who completed the survey, we randomly selected one to receive €400 in Meesman investment credits. These credits could only be allocated between the two previously mentioned Meesman products.

In the first module, we assessed investors' trade-offs between the ESG attributes of funds (ESG score category and ESG selection strategies) and other attributes (management fee and return-risk profile) using the DCE. Following this assessment, in modules 2-4 we obtained auxiliary measures, such as time preference, risk preference, and ambiguity attitudes. In the fifth module we administered a non-incentivized questionnaire about participants' demographics, preferences, and attitudes.

[5]Out of the five modules, two were payoff-relevant.

2.2 Module 1: Discrete Choice Experiment

The first module gauged participants' WTP for ESG investments. Initially, participants evaluated their own knowledge of ESG in comparison to other investors of Meesman using a Likert scale question.[6] Following this self-assessment, the concept of ESG was introduced without disclosing any information on the link between sustainability and financial performance. Participants were then shown a series of 13 choice sets, each containing three hypothetical funds (not real Meesman products) differentiated by four attributes: ESG score category, ESG selection strategies, management fee, and return-risk profile. For each choice set, participants were asked to select the fund they preferred. An option to review the definition of ESG was available through an "ESG explanation" button, enabling participants to refresh their memory if needed. To examine the consistency of participants' responses, we used the dominance test.[7] To alleviate the burden on participants from responding to 13 consecutive choice sets, we interspersed questions about their demographics, such as gender, age, education, occupation, income, and financial status, after every four choice sets.

The number of attributes and their respective levels in a DCE should be carefully limited to prevent participants' confusion. Current DCE studies typically feature between three and seven attributes (e.g., Johnson et al., 2013). Pearmain and Kroes (1990) recommends that the ideal maximum should be six or seven attributes while ensuring they are sufficiently influential on participants' decisions. To identify the most pivotal fund attributes, we got input from Meesman. This input was instrumental in defining meaningful attributes and their levels and combinations within the DCE. We recognized five essential attributes for fund selection: ESG score category, management fee, ESG selection strategy, return, and risk. To streamline the survey and to minimize participants' burden, we maintained a constant risk level while varying returns to signify the funds' financial performance. Specifically, we adopted the term "maximum drawdown" to explain risk that we defined as the maximum percentage loss an investment could experience from its peak to trough during a downturn. We used this terminology as it was used by Meesman when communicating risk to clients. Consequently, all funds in the DCE were presented

[6] Participants were asked to self-assess their knowledge about ESG in the investment context relative to other respondents. They were presented with the following statement: "I think that my knowledge about ESG—an English-language designation for investing with an eye for the environment, society, and good corporate governance in the investment context is better than ...% of the participants in this survey." They were instructed to choose a value between 0% and 100%.

[7] We conducted both a pilot experiment and a subsequent survey experiment that were identical in design and involved clients of Meesman as participants. In the pilot experiment, two participants failed the dominance test; however, no participants failed the test in the subsequent survey. In our analysis, we excluded the responses of those who failed the test.

with identical risk profiles (up to a 20% loss from peak to trough) but featured different returns. This was externally valid as the risk only referred to a category, while within the same risk category there could be variations in the expected returns. Practically this helped us achieve a DCE with a smaller reasonable number of choice sets.

Table 1 gives the details about the attributes and their levels used in the DCE. There are three levels of ESG-score category: grey, light green, and dark green. The ESG selection strategy encompasses four levels: none, negative screening, positive screening, and active engagement. Participants were shown explanations for each strategy. The management fee per year is presented at three fixed levels: 0.5%, 1.0%, and 1.5%. Regarding financial performance, annual returns are delineated into three brackets: 4%, 7%, and 10%. All brackets are paired with the same maximum drawdown (up to a 20% loss from peak to trough).

Table 1: Attributes and Attribute Levels

This table presents the attributes of the funds and their respective levels as used in the discrete choice experiment conducted in the survey.

Attribute	**Attribute Level**
ESG score Category	Grey, Light Green, Dark Green
Management Fee (per year)	0.5%, 1.0%, 1.5%
ESG Selection Strategy	**None**
	Negative Screening: The fund or index excludes sectors or companies that are not considered sustainable. Typical ones that may be excluded from the portfolio are tobacco, alcohol, pornography, controversial weapons and companies that violate international standards
	Positive Screening: The fund or index actively selects companies that work proactively with sustainability
	Active Engagement: The fund's managers exercise their right to vote at general meetings and can engage with management to influence the company's behavior in a sustainable direction
Return-Risk (Annual)	**Return:** 4% expected annual return **Risk:** Up to 20% loss from peak to trough
	Return: 7% expected annual return **Risk:** Up to 20% loss from peak to trough
	Return: 10% expected annual return **Risk:** Up to 20% loss from peak to trough

Combining the attributes with their respective levels yield a total of 108 unique combinations (calculated as $3^3 \times 4^1$). However, incorporating all 108 alternatives into the DCE is impractical. Therefore, a fractional factorial design becomes imperative (e.g., Rose and Bliemer, 2009). Numerous variants of this design exist of which the orthogonal design is the most recognized (e.g., Gunst and Mason, 2009). This design strives to minimize correlations between attribute levels. Another reason for not including all combinations is that some of them are not externally valid. We verified their validity with Meesman. Therefore, we set the following constraints when composing the hypothetical funds:

- A fund focusing on sustainability should not have lower management fees than a fund without such a focus;
- If a fund is categorized as in the grey category, then it should not use any ESG strategies.

At the same time, some studies advocate for efficient designs as gauged by an "efficiency error" metric (e.g., Kuhfeld et al., 1994; Chrzan and Orme, 2000). The most prevalent criterion for assessing design efficiency is the $D - error$ that is segmented into three categories: $D_z - error$ (assuming no prior information), $D_p - error$ (with exact prior information), and $D_b - error$ (with uncertain prior information). The design with the lowest $D - error$ is considered D-efficient and is fundamentally aimed at optimizing the informational yield of each choice set (e.g., Rose and Bliemer, 2009). An increase in the number of choice sets enhances the amount of data that are obtainable from each respondent, thereby boosting efficiency. However, too many choice sets might enhance the cognitive load on participants, potentially compromising the reliability of their choices (e.g., Koemle and Yu, 2020). Thus, it is crucial to strike a balance, ensuring a high level of statistical efficiency without overburdening the participants. The statistical efficiency of the DCE is optimized when the number of choice sets is a common multiple of the total number of alternatives and attribute levels, potentially reaching a statistical efficiency of 100% (e.g., Vanniyasingam et al., 2016).

In our design, we decided on three options within each choice set, and all choice sets contained a common status quo option. A status quo option typically represents either the baseline levels of attributes or the participant's current situation. In our design, the status quo option is characterized by a fund in the grey category, the lowest management fee (0.5% per year), no ESG selection strategy, and an expected annual return of 7% coupled with a 20% maximum drawdown risk. A design with a status quo option tends to yield more robust models (e.g., Rolfe and Bennett, 2009; Soekhai et al., 2019).

To accommodate these constraints, an efficient design generation is necessary. We used the modified Fedorov algorithm (e.g., Cook and Nachtrheim, 1980). This algorithm is particularly suited to our needs due to its versatility and ability to incorporate a wide range of flexible constraints within the design framework (e.g., Collins et al., 2014). Lacking prior information on our sample's preferences, we used the Ngene software to generate the choice set design, optimizing for $D_z - error$ minimization. With our design parameters and the above considerations, we optimally achieved statistical efficiency by selecting the quantities of choice sets that were common divisors of the levels of the attributes. Suitable quantities for our study are 12 and its multiples that ensure the experimental design is both robust and effective in measuring the desired outcomes. This approach enhances the reliability of our results, particularly in the context of the DCE. We also added one for a consistency check. To mitigate the order effect and to ensure reliable responses (e.g., Koemle and Yu, 2020), the order of the choice sets and the order of alternatives within each choice set were randomized between subjects.

The DCE was designed to elicit the stated preferences of participants who were expected to adhere to the principles of rational choice. To identify participants who deviated from rational choice behavior, a commonly used method is the dominance test. This test involves presenting a choice set where one option is unambiguously superior to other options across all attributes. Participants who failed to select this clearly dominant option were deemed to fail the consistency test. In our study, we incorporated one choice set to conduct this consistency check. This extra choice set featured one alternative with a lower management fee that stood out, while its other attributes were the same as other alternatives, ensuring it is the unequivocally superior choice.[8] Table 2 presents a sample choice set, while Figure A.2 in the Appendix A presents the original screenshot corresponding to the DCE in the survey.

2.3 Time and Risk Preference Elicitation

The second and third modules were designed to assess participants' time and risk preferences through survey questions, respectively. We adopted the methodology developed and validated by Falk et al. (2018). For each preference, we obtained both a qualitative and a quantitative measure. Questions in this module were not incentivized.[9]

The quantitative assessment of risk preferences was a "staircase" procedure, consisting

[8] No participant failed this dominance test in our experiment.

[9] Falk et al. (2018) demonstrate the validity of these questions in non-incentivized surveys.

Table 2: Exemplary Choice Set in the Discrete Choice Experiment

This table presents an example from the 13 choice sets used in the discrete choice experiment.

Choose your preferred investment fund from the three investment funds below.

Attribute	**Fund 1**	**Fund 2**	**Fund 3**
ESG-score Category	Light Green	Dark Green	Grey
Management Fee (per year)	1.5%	1.0%	0.5%
ESG Selection Strategy	**Active Engagement:** The fund's managers exercise their right to vote at general meetings and can engage with management to influence the company's behavior in a sustainable direction.	**Negative Screening:** The fund or index excludes sectors or companies that are not considered sustainable. Typical companies that may be excluded from the portfolio are tobacco, alcohol, pornography, and controversial weapons; and companies that violate international standards.	**None**
Return-Risk (Annual)	**Return:** 10% expected annual return **Risk:** Up to 20% loss from peak to trough	**Return:** 4% expected annual return **Risk:** Up to 20% loss from peak to trough	**Return:** 7% expected annual return **Risk:** Up to 20% loss from peak to trough
Which investment fund do you prefer?	☐	☐	☐

of a sequence of four binary choices. Participants had to choose between a fixed lottery, offering a chance to win either €300 or nothing, and varying guaranteed cash amounts:

"You can choose between a payment of a certain amount of money, OR a draw where you have equal chances of getting €300 or getting nothing. We present you with four different choice problems, each in the following format.

Which do you prefer:

- A 50:50 chance of receiving €300 or nothing;
- Guaranteed to receive y euros."

In all four choice problems, the lottery option stayed constant. Selecting the lottery option led to an increase in the sure amount presented in the subsequent question, and selecting the sure amount led to a decrease.

The quantitative assessment of time preferences was also a staircase procedure, consisting of four interrelated choices between immediate and delayed financial rewards within a survey question. In this choice series, participants were presented with four scenarios where they must choose between receiving a fixed sum (€100) immediately or a larger amount y (>€100) in 12 months. In particular, the choice problems were framed as the following:

"Suppose you were given the choice between receiving a payment today or receiving a payment 12 months from now. We will now present five situations to you. The payment today is the same in every choice problem (€100). The payment over 12 months is different in each choice problem (the payment varies). For each situation, we would like to know which one you would choose. Suppose there is no inflation, that is, future prices are the same as current prices.

Please consider the following two options:

- Receive €100 today;
- Receive y euros (>€100) over 12 months."

In all four subsequent choice problems, the immediate payment remained constant. The delayed amount was adjusted upwards if the respondent chose payment today in the previous question, and downwards if the delayed option was chosen.

The qualitative assessment of willingness to take risk was captured through respondents' self-assessment, using a 7-point Likert scale with the question: "In general, how willing are you to take risks?" The qualitative measure of time preferences was determined through the respondents' choice on a 7-point Likert scale for the question: "How willing are you to forego a benefit today in order to gain a greater benefit in the future?"

2.4 Elicitation of Ambiguity Attitude

The fourth module assessed participants' attitudes toward ambiguity; specifically, we used an adapted version of the Ellsberg urns (e.g., Ellsberg, 1961) as proposed by Dimmock et al. (2016). This module was incentivized.

As illustrated in Figure 1, (Figure A.3 presents the full screenshot of the task in the Appendix A) in which participants were tasked with choosing between two boxes, each containing exactly 100 balls. The balls were labeled with either a positive (purple balls) or a negative sign (orange balls). Their choices were between an unambiguous Box K in which the quantity of purple balls was clearly indicated, and an ambiguous Box U with an undisclosed number of purple balls. Participants were asked to choose between the two boxes, and if a random draw from the selected box came up with a purple ball (with plus sign), then there was a chance to win €100. The goal was to find the number of purple balls in Box K that makes a participant indifferent between the two boxes. We asked five incentivized questions in total, changing the number of purple balls in Box K each time. If Box K was chosen, then the number of purple balls in Box K decreased in the next question; if Box U was chosen, the number increased.

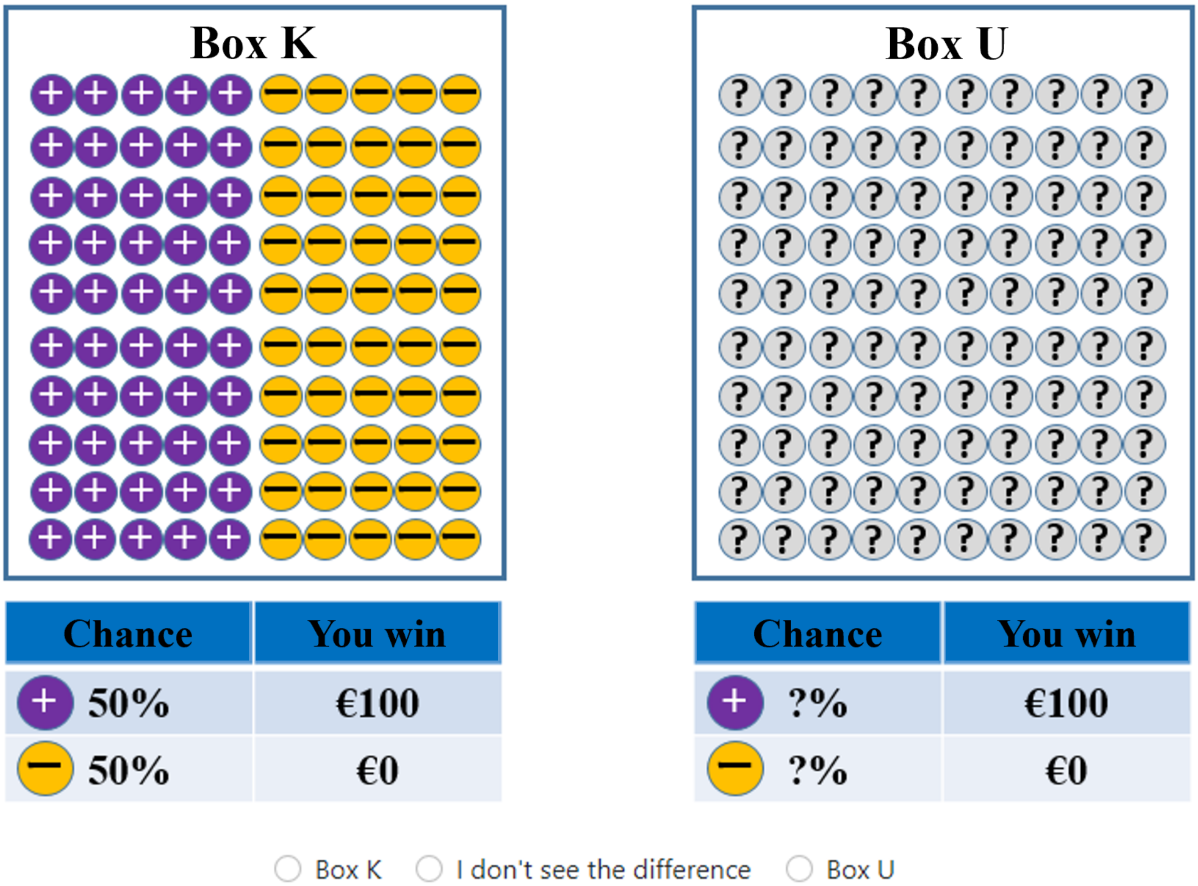

Figure 1: An Exemplary Elicitation of Ambiguity Attitude

Note: This figure displays an original screenshot depicting the elicitation of attitudes toward ambiguity.

2.5 Questionnaire

The fifth module consisted of a set of survey questions. It included non-incentivized Likert scale questions concerning the comparison of sustainable funds to conventional ones in terms of both return and risk (as in Riedl and Smeets, 2017). Additionally, participants were asked to express their perspectives on the impact of ESG investing, along with their preferences for passive versus active investment strategies. This module also included questions about participants' financial background and current financial situation. Notably, we assessed participants' financial literacy through an incentivized question (receiving €50 from a lottery for correctly answering the question) focusing on the calculation of expected returns based on Kuhnen (2015). Furthermore, participants were asked to provide further demographic information. The questions are detailed in Table B.1 in the Appendix B.

At the end of the experiment, participants were informed about a lottery incentive with the possibility of winning €400 Meesman investment credits. They were asked to make an investment allocation of the €400 between two Meesman funds assuming that they were to win the lottery. These two funds were: "Aandelen Wereldwijd Totaal" (Equity Worldwide Total) and "Aandelen Duurzame Toekomst" (Shares Sustainable Future). Both funds were categorized within the same risk-return spectrum. The experiment showed that the management fee for Equity Worldwide Total was slightly lower at 0.4% than the 0.5% fee for Shares Sustainable Future. Participants were provided detailed information about these two funds, including links for further explanations of their compositions and country allocations. Moreover, participants were also informed that their investment decisions would be implemented if they were selected to receive the credits.

2.6 Procedure

Survey invitations were sent to Meesman's clients along with the monthly Meesman newsletter. Since almost all clients were subscribed to the newsletter, they received the invitation, which included a link for easy access to the survey. Participants could start the survey with a simple click, and it was available online from May 8, 2023, to June 3, 2023. Figure A.1 in the Appendix A visually illustrates the daily number of responses. By June 3, a total of 963 participants started the survey, with 457 completing it. The survey took an average of approximately 24 minutes to complete. Furthermore, the announcement regarding the survey's reward was made on October 30, 2023.

2.7 Sample Characteristics

Table 3 provides a comprehensive overview of the demographic information, preferences, and beliefs of our survey participants. The sample had a higher proportion of males (70.24%) compared to the general Dutch population in 2022, where males constituted 49.75%. The average age of participants was 44.17 years, ranging from 21 to 90 years, that is slightly above the national average of 42.4 years in 2022. Educational attainment among participants was relatively high: 50.08% held a university degree (WO, university education in the Netherlands), and an additional 25.82% possessed a college degree

(HBO, higher vocational education in the Netherlands). This attainment contrasts with the general Dutch population in 2021, where 34% had attained degrees from either HBO or WO institutions. Employment in paid positions among participants was slightly lower, with 68.49% employed compared to approximately 79% of the working-age population (ages 15 to 64) in the Netherlands.[10] The average monthly income among participants was €3,750 and was higher than the national average gross monthly income of approximately €3,040. Regarding portfolio size, 57.99% of the participants had portfolios under €50,000. In terms of financial literacy, 42.23% of the participants correctly answered the question about calculating expected returns.[11]

When it comes to investment preferences, participants showed a higher inclination towards ESG index funds as compared to active ESG funds. On sustainability, there was a general skepticism toward the idea that less sustainable funds were riskier than sustainable ones. Participants generally believed that ESG funds positively impacted society. Concerning fund performance, there was a tendency to believe that index funds outperformed active funds financially, while ESG funds underperformed conventional funds.

Participants displayed altruistic tendencies, moderate levels of trust, and strong inclinations toward positive reciprocity. On average, participants were willing to donate 12.65% (€126.54) of a €1,000 windfall amount in a non-incentivized question. Additionally, their interest in investing in energy transition was moderate, and they strongly agreed that asset managers should actively engage in improving companies' energy efficiency. Table B.1 in Appendix B shows more definitions of the specific items outlined in Table 3.

3 Results

This section presents our main findings and is organized as follows: Subsection 3.1 presents the results from regressions using the DCE data and the estimations of the WTP for the sustainability attributes of the funds. Subsection 3.2 has the identification of the optimal number of participant classes, and subsection 3.3 uses latent class models to classify participants and to examine each class in detail. Subsection 3.4 provides verification

[10] The lower employment in paid positions among participants is likely attributable to retirement rather than unemployment, given the higher average age of our sample.

[11] All data on the Dutch population were derived from the latest reports by the Dutch Central Bureau of Statistics (Centraal Bureau voor de Statistiek, CBS) and the OECD.

Table 3: Summary Statistics

This table presents the summary statistics of the participants in the survey. Table B.1 has the definitions of the variables.

	Mean	Median	SD	Obs.
Demographics				
Gender				457
Male	70.24%			
Female	29.76%			
Age	44.17	40	14.02	457
Origin				457
Dutch	94.53%			
Others	5.47%			
Investing Experience (year)				457
1-3	36.76%			
4-10	38.07%			
Above 10	25.17%			
Education				457
University	52.08%			
College	25.82%			
Lower than College	21.66%			
Other	0.44%			
Occupation				457
Paid Work	68.49%			
Other	31.51%			
Monthly Income	€3,750	€4,250	€1,875.29	457
€0 to €3,000	19.47%			
€3,000 to €5,000	39.17%			
Above €5,000	41.36%			
Total Investment				457
€0 to €10K	28.01%			
€10K to €50K	29.98%			
Above €50K	42.01%			
Correct Expected Return Calculation	42.23%			457
Preferences				457
Altruism (1–7)	4.85	5	1.67	
Trust (1–7)	3.51	4	1.41	
Positive Reciprocity (1–7)	5.62	6	1.00	
Negative Reciprocity (Self) (1–7)	2.79	2	1.33	
Negative Reciprocity (Others) (1–7)	3.72	4	1.37	
Donation (0–1000)	126.54	56	167.27	
Energy Transition Preference (0–100)	47.28	50	30.66	
Energy Efficiency Engagement (1-7)	5.32	6	1.45	
Ambiguity Attitudes (0-1)	0.44	0.48	0.16	
Time Preference (Qualitative Self-assessment) (1-7)	5.81	6	0.96	
Time Preference (Quantitative "Staircase") (0-1)	0.91	0.94	0.15	
Beliefs				
ESG Return by Likert Scale (1–5)	2.76	3	0.92	450
Index (Vs. Active) Fund Return (1–5)	3.83	4	0.93	451
ESG Index Fund Preference (1–7)	4.63	5	1.46	457
Active ESG Fund Preference (1–7)	3.50	3	1.72	457
Sustainability Risk (1–7)	3.42	3	1.36	457
ESG Impact (1-7)	5.27	5	1.16	457

of the classification outcomes. Our results focus on the DCE analyses using investor characteristics as control variables. The detailed results of these characteristics are in the appendix: results for time and risk preferences are in subsection A.3 of Appendix A; those for ambiguity attitudes are in subsection A.5 of Appendix A.

3.1 DCE Results and WTP

We assess participants' trade-offs among three mutually exclusive alternative funds by using a multinomial discrete choice model that assumes a utility function for each option in a choice set of the DCE. The random utility model (RUM) provides the theoretical foundation for the DCEs that is fundamental to understanding how individuals make choices among discrete alternatives, such as selecting between different investment funds. According to the RUM, the utility U_{ij} that individual i derives from alternative j consists of two components: the observable component that is denoted as V_{ij} which is based on measurable attributes of the alternatives and the individual's characteristics and represents the systematic preferences that can be modeled and estimated; and the unobservable component that is denoted as ϵ_{ij} which captures the random factors affecting the utility that are unobserved or unknown during our survey, such as individuals' tastes, measurement errors, or omitted variables. The utility function can be expressed as:

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{1}$$

There are three main assumptions in the RUM model:

- Utility maximization: Individuals are assumed to choose the alternative that maximizes their utility.
- Randomness: Due to the unobserved component ϵ_{ij}, choices are probabilistic.
- Distribution of the error term: The stochastic component ϵ_{ij} is often assumed to follow a specific probability distribution, such as the Gumbel distribution in the case of multinomial logit models.

In our study, the utility function for participant i choosing alternative j is modeled as follows:

$$U_{ij} = \beta_1 X_{1,j} + \beta_2 X_{2,j} + \ldots + \beta_k X_{k,j} + \epsilon_{ij}, \tag{2}$$

where $X_{k,j}$ represents the levels of attribute k for alternative j, and β_k denotes the parameters representing the marginal utility or preference weight for each attribute.

The multinomial logit (MNL) model is a widely used model for analyzing choice data where individuals select one option from a set of mutually exclusive alternatives. It is based on the random utility theory, where the utility U_{ijt} that individual i derives from alternative j in choice set t is:

$$U_{ijt} = \beta' X_{ijt} + \epsilon_{ijt}, \tag{3}$$

where β is a vector of fixed coefficients (assumed to be the same across all individuals), X_{ijt} is a vector of observed attributes of the alternatives, and ϵ_{ijt} is an error term.

The probability that individual i chooses alternative j in choice set t is given by:

$$P_{ijt} = \frac{\beta' X_{ijt}}{\sum_{k=1}^{J} \exp(\beta' X_{ijt})}. \tag{4}$$

By analyzing the choices made by participants based on Equation (3), the coefficients β' can be estimated to indicate the importance of each attribute. This estimation allows us to assess how changes in attributes affect the probability of an alternative fund being chosen and to quantify trade-offs among different attributes (e.g., willingness to pay higher management fees for better ESG performance) by using Equation (4).

However, the MNL model has several limitations. First, it is based on the assumption that all individuals have the same preferences, ignoring unobserved heterogeneity among tastes. Second, it imposes the independence of irrelevant alternatives (IIA) property, meaning that the relative odds of choosing between any two alternatives are unaffected by the attributes of other alternatives. Finally, it follows the assumption of independence across observations which is violated when the same individual makes multiple choices (panel data), leading to correlated error terms.

Given the substantial heterogeneity in investors' preferences and beliefs, especially concerning ESG investments (e.g., Sandberg et al., 2009; Giglio et al., 2021, 2023; Bauer et al., 2024), we use the more flexible mixed logit model over the conventional MNL model. The mixed logit model accommodates unobserved heterogeneity in tastes and accounts for correlations due to the panel nature of our data, as each participant faces several choice sets (e.g., Adamowicz et al., 2011). The mixed logit model allows for variations in tastes among participants, enabling us to capture correlations between the choice alternatives (e.g., McFadden and Train, 2000; Greene and Hensher, 2003; Gutsche and Ziegler, 2019).

The utility function in the mixed logit model is specified as:

$$U_{ijt} = \beta_i' X_{ijt} + \epsilon_{ijt}, \tag{5}$$

where $\beta_i = \beta + \eta_i$. Here, β is the mean parameter vector, η_i is a vector of individual-specific deviations, and ϵ_{ijt} remains an IID extreme value. The probability that individual i chooses alternative j in choice set t is:

$$P_{nj} = \int \prod_{t=1}^{T_i} \left(\frac{\exp(\beta_i' X_{ijt})}{\sum_{k=1}^{J} \exp(\beta_i' X_{ikt})} \right) f(\beta_i|\theta)\, d\beta_i, \tag{6}$$

where T_i is the number of choice sets faced by individual i, the product over t accounts for the panel nature (multiple observations per individual), X_{ijt} represents the observed attributes of alternative j in choice set t, $f(\beta_i)$ is the individual-specific parameter vector, and $f(\beta_i|\theta)$ is the individual-specific probability density function of β_i parameterized by θ. Since this integral often has no closed-form solution, numerical methods like the simulated maximum likelihood estimation are used. For our simulated maximum likelihood estimation of the mixed logit model, we use the Stata command "mixlogit" (e.g., Hole, 2007), with R = 1000 Halton draws (e.g., Gutsche and Ziegler, 2019).

Based on the mixed logit model specified in Equations (5) and (6), we first estimate investors' preferences for ESG integration without distinguishing between light green and dark green. Subsequently, we delve deeper by exploring detailed ESG score categories, also interacting them with the ESG selection strategies. Both estimations are conducted using the mixed logit model based on data from 457 participants, yielding a total of 16452 observations (457 participants $\times$ 12 choice sets per participant $\times$ 3 fund options).

In our mixed logit model, we interact the ESG score category with the ESG selection strategy, using the combination of "grey" and "No ESG selection strategy" as the reference category. For the estimation of investors' ESG integration preferences, we define ESG integration as equal to one when the ESG score category is either light green or dark green, and zero otherwise. Its interaction with the three possible ESG selection strategies results in three variables: $X_{ESG\ Integration\_Negative\ Screening}$, $X_{ESG\ Integration\_Positive\ Screening}$, and $X_{ESG\ Integration\_Active\ Engagement}$. For the estimation of participants' preferences for specific ESG score categories, we interact the light green and dark green separately with the three ESG selection strategies, resulting in six variables: $X_{Light\ Green\_Negative\ Screening}$, $X_{Light\ Green\_Positive\ Screening}$, $X_{Light\ Green\_Active\ Engagement}$, $X_{Dark\ Green\_Negative\ Screening}$, $X_{Dark\ Green\_Positive\ Screening}$, and $X_{Dark\ Green\_Active\ Engagement}$. This approach avoids the issue of multicollinearity among independent variables, as the grey score only occurs with the "No ESG selection strategy". Additionally, $X_{Management\_Fee}$ represents the management fee category of the selected fund, and X_{Return} denotes the expected return category of the selected fund, assuming a fixed level of risk (20% maximum drawdown).

Direct comparisons of coefficient magnitudes in the mixed logit models can be misleading due to scale discrepancies. Therefore, we calculate the WTP that is the ratio of two marginal utility parameters. Specifically, we use the marginal utility of a monetary attribute (such as return or management fee) in the denominator and the marginal utility of the ESG attribute in the numerator. This calculation yields the necessary adjustment to the return or management fee to maintain constant utility when marginal changes occur in the ESG attributes. The resulting WTP reflects the amount participants are willing to trade off in monetary terms to obtain the ESG attribute.

Mathematically, a WTP is computed as -1 multiplied by the ratio of the parameter estimate for the attribute of interest to the parameter estimate of the monetary attribute:

$$WTP = -\frac{\beta_{attribute}}{\beta_{monetary}}, \tag{7}$$

where $\beta_{attribute}$ is the coefficient of the attribute for which WTP is being calculated, and $\beta_{monetary}$ is the coefficient of the monetary cost (or price) attribute in the model. In our study, we provide detailed mean WTP estimates for both the ESG score category and the ESG selection strategy.

The use of mixed logit models enables us to account for potential variation in tastes across participants. Specifically, in our analysis, these models presume that the parameters for nonfinancial explanatory variables, including ESG score category and ESG selection strategy, follow an independent normal distribution. This distribution is characterized by a mean of zero and a standard deviation of one across all participants. Table 4 presents the results of estimating participants' preferences for ESG integration combining with the ESG selection strategy and their WTPs. The table is divided into two panels. The upper panel provides the parameter estimates obtained from the models. The lower panel presents the calculated average WTP values. These values are derived from the coefficients estimated through the mixed logit models that focus on the interaction of the ESG score category (light green and dark green) with the ESG selection strategies.

In the upper panel of Table 4, Column (1) highlights a significantly positive coefficient for ESG integration interacted with the ESG selection strategy, indicating a strong preference for ESG-integrated funds. A negative coefficient for management fee indicates an aversion to higher management fees, while a positive coefficient for return indicates a preference for financially well-performing funds. Specifically, the Wald test results in-

Table 4: ESG Preference Estimation and WTP

The upper panel of this table presents the parameter estimates for each explanatory variable related to fund attributes in the survey's discrete choice experiment. The experiment uses mixed logit models for selecting one of the three funds. It includes mean and standard deviation coefficients for random parameters such as various ESG levels, ESG selection strategy, management fees, and return. Additionally, robust z-statistics, calculated from the estimated standard deviations (SD) of the parameters, are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels. The lower panel of this table presents the mean WTP estimates for each nonfinancial attribute, using 1000 Halton draws for MSL estimations, based on data from 12 choice sets.

	Dependent variable: Respondent's Choice among Three Funds			
	ESG×Strategy		*Light/Dark×Strategy*	
	Coefficient	SD Coefficient	Coefficient	SD Coefficient
Fund Attribute	(1)	(2)	(3)	(4)
Management Fee	-2.791^{***}	2.730^{***}	-2.828^{***}	2.811^{***}
	(−14.20)	(14.34)	(−13.28)	(14.48)
Return	1.132^{***}	0.684^{***}	1.062^{***}	0.690^{***}
	(19.58)	(17.41)	(20.65)	(16.81)
ESG Integration×Negative Screening	3.630^{***}	3.399^{***}		
	(16.23)	(14.25)		
ESG Integration×Positive Screening	2.949^{***}	2.720^{***}		
	(13.60)	(11.08)		
ESG Integration×Active Engagement	2.972^{***}	2.935^{***}		
	(15.13)	(14.05)		
Light Green×Negative Screening			3.797^{***}	0.275
			(9.93)	(0.55)
Light Green×Positive Screening			2.426^{***}	1.444^{***}
			(8.65)	(2.80)
Light Green×Active Engagement			2.906^{***}	2.883^{***}
			(14.03)	(13.00)
Dark Green×Negative Screening			3.401^{***}	3.145^{***}
			(15.55)	(13.14)
Dark Green×Positive Screening			2.706^{***}	2.740^{***}
			(11.21)	(−9.38)
Dark Green×Active Engagement			2.292^{***}	2.659^{***}
			(11.07)	(11.95)

	Mean WTP Estimates			
	ESG×Strategy		*Light/Dark×Strategy*	
	Based on Return	Based on Management Fee	Based on Return	Based on Management Fee
Fund Attribute	(1)	(2)	(3)	(4)
ESG Integration×Negative Screening	−3.208	1.301		
ESG Integration×Positive Screening	−2.606	1.057		
ESG Integration×Active Engagement	−2.627	1.065		
Light Green×Negative Screening			−3.575	1.343
Light Green×Positive Screening			−2.284	0.857
Light Green×Active Engagement			−2.737	1.028
Dark Green×Negative Screening			−3.202	1.203
Dark Green×Positive Screening			−2.548	0.957
Dark Green×Active Engagement			−2.158	0.811
Observations	16452 (457×36)		16452 (457×36)	
Log likelihood	−2612.860		−2690.364	

dicate that participants significantly prefer negative screening over other strategies, with p-values of 0.0116 and 0.0055 respectively for comparisons with positive screening and active engagement.[12] Column (2) shows the variability in the coefficient estimates that indicatethe diverse attitudes of participants toward ESG integration in combination with various investment strategies.

An examination of the detailed ESG score categories, as presented in Columns (3) and (4), identifies a significant preference for the negative screening strategy. For light green funds, the coefficient for the negative screening strategy is significantly larger than those for the positive screening ($p = 0.0009$) and active engagement ($p = 0.0202$) strategies, with no significant difference between the coefficients for the positive screening and active engagement strategies ($p = 0.1103$). Similarly, for the dark green funds, the coefficient for the negative screening strategy is significantly larger than those for the positive screening ($p = 0.0253$) and active engagement ($p = 0.0001$) strategies, and there is no significant difference between the coefficients for the positive screening and active engagement strategies ($p = 0.1586$). When comparing the light and dark green funds for each strategy, the coefficients are not significantly different for the negative ($p = 0.3014$) and positive screening ($p = 0.4311$) strategies. However, for the active engagement strategy, the coefficient for the light green funds is significantly larger than that for the dark green funds ($p = 0.0227$). Overall, the analysis indicates a strong preference for ESG integration, particularly through the negative screening strategy. Participants did not demonstrate significant sensitivity to the degree of ESG intensity between light and dark green funds.

The lower panel of Table 4 presents the participants' WTPs for the ESG attributes. Columns (1) and (2) show the details of the mean WTPs based on return and management fee, considering ESG integration in combination with various investment strategies. Column (1) shows that participants are willing to pursue ESG integration at a cost of 4.426%, 3.570%, or 3.389% of the annual return for negative and positive screening, or active engagement, respectively. Putting it another way, Column (2) shows that they are willing to pursue ESG integration at a cost of 1.766%, 1.424%, or 1.352% higher annual management fees for negative and positive screening, or active engagement, respectively. These percentages indicate a readiness to incur a cost for ESG integration. The WTPs of the detailed ESG score categories are provided in Columns (3) and (4).

[12] Note that negative screening may align more closely with (enhanced) index strategies (e.g., Auer, 2016; Trinks and Scholtens, 2017).

3.2 The Latent Class Logit Model

In this subsection, we further investigate heterogeneity in the sustainability preferences of our participants by conducting a latent class analysis. The latent class logit model (also known as the finite mixture logit model) is an extension of the standard multinomial logit model used to analyze DCE data (e.g., Boxall and Adamowicz, 2002; Greene and Hensher, 2003). It allows for the identification of unobserved heterogeneity in preferences by classifying individuals into distinct latent (unobserved) classes based on their choice behavior. Each class has its own set of parameter estimates, capturing different preference patterns within the sample.

In our DCE, the utility U_{ijt}^c that individual i in class c derives from alternative j in choice set t is specified as:

$$U_{ijt}^c = \beta_c^{'} X_{ijt} + \epsilon_{ijt}^c, \tag{8}$$

where $\beta_c^{'}$ is the class-specific parameter vector for class c, X_{ijt} is a vector of observed attributes for alternative j faced by individual i, and ϵ_{ijt}^c is an error term that is assumed to be an IID extreme value type I (Gumbel distribution).

Given that individual i belongs to class c, the probability that they choose alternative j in choice set t is:

$$P_{ijt|c} = \frac{\exp(\beta_c^{'} X_{ijt})}{\sum_{k=1}^{J} \exp(\beta_c^{'} X_{ikt})}, \tag{9}$$

where $\beta_c^{'}$ is the class-specific coefficient vector and reflects the importance of attributes for class c, $\exp(\beta_c^{'} X_{ijt})$ represents the exponential of the utility for alternative j in choice set t, and $\sum_{k=1}^{J} \exp(\beta_c^{'} X_{ikt})$ is the sum of exponentiated utilities over all J alternatives in choice set t.

Participants are probabilistically assigned to the c different classes using a membership model specified as a multinomial logit:

$$P_i^c = \frac{\exp(\gamma_c^{'} Z_i)}{\sum_{r=1}^{C} \exp(\gamma_r Z_i)}, \tag{10}$$

where $\gamma_c^{'}$ is the parameter vector associated with class c for the membership model; Z_i is a vector of individual-specific characteristics such as participants' demographics, preferences, and beliefs from our survey—that may influence class membership; and C is the total number of latent classes.

Following Train (2009), we use the expectation-maximization (EM) algorithm to ensure numerical stability and to facilitate the convergence of the log-likelihood function to its maximum when estimating the membership probabilities in Equation (10). The corresponding EM algorithm for maximum likelihood estimation is implemented in a Stata module (e.g., Pacifico and Yoo, 2013). As shown in Table A.4 in the Appendix A, we categorize participants into four classes. The rationale for this classification is validated and further elaborated upon in the following sections.

3.3 Characteristics of Classes

Table 5 presents the estimation results from the latent class logit model with the four classes identified. Panel 1 presents the WTP that members of each class assign to ESG integration, combined with ESG selection strategies, based on the return and management fee attributes of the funds. The coefficients are estimated using class-specific datasets from the DCE. By comparing the corresponding class coefficients for the return and management fee attributes, we assess participants' concerns regarding these two factors.

The following are descriptions of how each class of our participants deals with the trade-off between sustainability and the attributes:

- Class 1 participants (13.0% of the sample) show the strongest preference for ESG integration (either light green or dark green over grey) combined with the active engagement strategy. Among the four classes, these participants show the least concern for the risk-adjusted return and demonstrated comparatively less concern for the management fee compared to classes 2 and 4, but more than class 3.

- Class 2 participants (57.5%, the majority of the sample) also display a strong preference for ESG integration but favored the negative screening strategy. They care comparatively more about the risk-adjusted return and the management fee (less than class 4, but more than classes 1 and 3).

- Class 3 participants (16.0% of the sample) show the strongest preference for ESG integration in combination with the negative screening strategy, which is even more important to them than to class 2. Among the four classes, this group placed the least importance on the management fee and assigned less importance to the risk-adjusted return than classes 2 and 4, but more than class 1.

Table 5: Four-class Specification Coefficient Estimation Results

This table presents the results of the parameter estimation of the latent class logit model with highlighting of four distinct investor classes and an evaluation of model efficiency. The Class-specific Coefficient Estimates panel presents the estimated mean coefficients for random parameters, including ESG integration in combination with various ESG selection strategies, management fees, and risk-adjusted returns. It also includes the WTP for ESG integration combined with different ESG selection strategies, expressed as a percentage. Robust z-statistics, based on the estimated standard deviations of the coefficients, are provided in parentheses, with ***, **, and * denoting significance at the 1%, 5%, and 10% levels, respectively. The Model Efficiency Examination panel shows the assessments of the model's performance by examining posterior probabilities and prediction accuracy. The findings are based on data from 12 choice sets in the DCE.

Panel 1: Class-specific Coefficient Estimates

	Class 1			Class 2			Class 3			Class 4		
		WTP Based on			WTP Based on			WTP Based on			WTP Based on	
Variable	Coefficient	Return	Management	Coefficient	Return	Management	Coefficient	Return	Management	Coefficient	Return	Management
Management Fee	−1.603***			−2.523***			−1.144***			−8.399***		
	(−5.87)			(−10.63)			(−5.64)			(−6.89)		
Return	0.134***			1,119***			0.185***			1.627***		
	(5.28)			(15.06)			(6.65)			(6.75)		
ESG Integration×	1.950***	−14.573	1.217	4.435***	−3.963	1.758	6.184***	−33.386	5.405	−0.273		
Negative Screening	(7.83)			(14.92)			(13.77)			(−0.54)		
ESG Integration×	2.686***	−20.067	1.676	3.591***	−3.209	1.424	3.650***	−19.704	3.190	−1.612***	0.991	−0.192
Positive Screening	(8.19)			(12.78)			(9.17)			(−2.86)		
ESG Integration×	3.287***	−24.559	2.051	3.623***	−3.237	1.436	2.797***	−15.098	2.444	−2.290***	1.408	−0.273
Active Engagement	(11.27)			(15.49)			(8.13)			(−4.44)		
Class Share	0.130			0.575			0.160			0.135		

Panel 2: Model Efficiency Examination

1. Posterior Probability

Number of obs	Mean	Std. Dev.	Min	Max
457	0.971	0.081	0.471	1

2. In-sample Predictions of the Actual Choice Outcomes

Number of obs	Class	Unconditional Probability	Conditional Probability
684	1	0.493	0.570
3180	2	0.721	0.876
876	3	0.530	0.720
744	4	0.402	0.707

- Class 4 participants (13.5% of the sample) prioritized the risk-adjusted return above all, showing the least interest in ESG integration regardless of the accompanying investment strategy. And they placed the highest emphasis on the management fee compared to other classes.

To quantitatively assess how effectively the this model discriminates between the four distinct classes, we calculate the average highest posterior probability of class membership across participants. Panel 2 of Table 5 displays the outcomes of this analysis. With a mean highest posterior probability of 0.971, the model demonstrates excellent ability to distinguish among diverse underlying preference patterns of participant types that correspond to the observed choice behaviors. We further evaluate the model's capacity for within-sample prediction of actual choice outcomes. We assign participants to class C if it yields the highest posterior membership probability for them. Subsequently, we classify each subgroup of participants classified as follows: we forecast both the unconditional probability and the conditional probability of the actual choice given class C membership. A simplistic random choice model yields an average unconditional probability of 0.33, because there are three options in each choice set. Our average unconditional choice probability clearly exceeds 0.33 in each class. The average conditional probability surpasses 0.5, indicating superior predictive performance. This analysis confirms the model's robustness in accurately classifying the observed participants' choice behavior.

To check whether the class identification makes sense, we also explore the preference patterns of participants by analyzing their trade-offs and WTPs for the fund attributes for each of the four classes respectively by using the DCE data and mixed logit models. Table A.5, Table A.6, Table A.7, and Table A.8 in the Appendix A present the parameter estimates. The results show that the four classes indeed make meaningful distinctions among their choices in the DCE.

3.4 Verification of Classes

In Table 6, we report how the four classes are different in their demographics, preferences, beliefs, and incentivized allocation decisions in the fifth Module. This module provides a validation of our DCE analyses and the classification results.

- Class 1 participants: This group demonstrates the strongest preference for ESG integration combined with active engagement, placed the least importance on the

Table 6: Class-Based Analysis of Sample Characteristics, Preferences, and Beliefs

This table presents a summary of the sample characteristics, preferences, and beliefs, categorized by classes as determined in the survey. The highest values are highlighted in bold black, while the lowest values are accentuated in bold blue for easy identification and comparison. Table B.1 has the definitions of the variables.

	Class 1 n=57; 12.47%		Class 2 n=265; 57.99%		Class 3 n=73; 15.97%		Class 4 n=62; 13.57%	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Characteristics								
Age	45.895	14.755	**42.506**	12.831	**49.233**	16.936	43.742	13.114
Male	0.825	0.685	0.811	0.539	**0.589**	0.642	**0.887**	0.546
Investing Experience (1-5)	**3.053**	1.315	3.208	1.270	3.192	1.440	**3.323**	1.156
Education (1-9)	**6.877**	1.377	**7.268**	1.044	7.137	1.097	7.113	0.977
Income (1-14)	**8.982**	4.262	10.034	3.849	9.890	3.277	**10.677**	3.202
Total Investment (1-8)	4.105	2.127	4.566	2.103	**4.014**	2.098	**4.823**	1.833
Monthly Investment (1-13)	4.772	2.260	4.902	2.471	**4.260**	2.404	**5.774**	2.802
Correct Expected Return Calculation (0-1)	0.333	0.476	**0.491**	0.501	**0.288**	0.456	0.371	0.487
ESG Knowledge (0-100)	39.596	25.642	37.879	24.276	**33.123**	23.280	**43.194**	24.886
Preferences								
Time Preference (0-1)	**0.844**	0.219	**0.927**	0.117	0.878	0.184	0.906	0.138
Risk Preference (0-1)	**0.451**	0.190	0.424	0.149	**0.384**	0.190	0.395	0.185
Ambiguity Attitude (0-1)	**0.398**	0.206	**0.456**	0.138	0.434	0.185	0.434	0.166
Altruism (1-7) base = Very Low	5.211	1.688	4.706	1.623	**5.575**	1.423	**4.290**	1.787
Trust (1-7) base = Very Low	**3.632**	1.472	3.513	1.441	3.507	1.355	**3.419**	1.300
Positive Reciprocity (1-7) base = Very Low	**5.333**	1.456	5.675	0.884	**5.753**	0.940	5.468	1.020
Negative Reciprocity (Self) (1-7) base = Very Low	**3.070**	1.474	2.804	1.299	**2.479**	1.292	2.855	1.341
Negative Reciprocity (Others) (1-7) base = Very Low	**3.175**	1.241	**3.955**	1.322	3.479	1.501	3.516	1.315
ESG Return by Likert Scale (1-5) base = Very Low	2.719	0.978	2.694	0.909	**3.068**	1.097	**2.419**	0.967
Index (Vs. Active) Fund Return (1-5) base = Very Low	**3.509**	1.167	3.864	0.911	3.616	1.186	**3.887**	1.103
Sustainability Risk (1-7) base = Very High	3.456	1.269	3.430	1.307	**3.781**	1.609	**2.935**	1.240
ESG Impact (1-7) base = Very Low	5.228	1.363	5.358	1.006	**5.521**	1.180	**4.645**	1.332
Willingness to Invest in ESG Index Fund (1-7) base = Very Low	4.965	1.362	4.525	1.282	**5.726**	1.357	**3.484**	1.457
Willingness to Invest in ESG Active Fund (1-7) base = Very Low	3.965	1.647	3.426	1.558	**4.575**	1.900	**2.113**	1.175
Willingness to Invest in Energy Transition (0-100)	47.193	30.885	47.208	29.562	**63.288**	28.856	**28.790**	27.065
Importance of Energy Efficiency Engagement (1-7) base = Very Low	5.807	1.246	5.302	1.334	**5.877**	1.178	**4.258**	1.774
Donation (0-1000)	175.105	191.953	111.834	153.268	**183.110**	195.684	**78.177**	138.283
Allocation to ESG Fund								
Sustainable Fund (0-400)	206.930	156.464	159.400	156.058	**255.014**	145.184	**81.532**	122.910

risk-adjusted return, and assigned comparatively less importance to the management fee. They possess the lowest levels of investing experience, income, and educational background. They are the most risk-averse and ambiguity-averse, and show the least tolerance for time delays. Additionally, they have the lowest levels of reciprocity, the highest levels of trust in others, and expect the lowest returns from index funds compared to active funds.

- Class 2 participants: These individuals show a strong appreciation for ESG integration combined with negative screening and place relatively greater emphasis on the risk-adjusted return and management fee attributes. They are the youngest on average and possess the highest levels of educational background and financial literacy. They show minimal tolerance for time delays and are the least ambiguity-averse. Notably, they are the most concerned about the negative impacts on others' benefits (negative reciprocity).[13]

- Class 3 participants: This group has the strongest preference for ESG integration combined with negative screening, placed the least importance on the management fee, and assigned less importance to the risk-adjusted return. They are the oldest on average and include the fewest male participants. They have the smallest investment amounts, the lowest levels of financial literacy, and minimal self-assessed ESG knowledge. They are the least risk-averse and least concerned about personal negative impacts. Notably, they have the strongest pro-social preferences, such as altruism and reciprocity, and are the most generous in making donations. They expect the highest returns from ESG investments, perceive the least sustainability risk, and recognize the most significant ESG impact. Demonstrating the strongest commitment to sustainable investing, they show the greatest willingness to invest in ESG index and active funds, place the highest importance on engaging in energy transition, and are the most inclined to invest in such initiatives.

- Class 4 participants: These participants prioritize the risk-adjusted return and the management fee above all, while showing the least appreciation for ESG integration. They are predominantly male with the most investing experience, highest income, largest investment amounts, and the highest self-assessed ESG knowledge. They have the weakest pro-social preferences, such as altruism and reciprocity, and expect

[13] Based on their response to the statement: "I am willing to punish someone who treats others unfairly, even if it may come at a cost to myself."

the lowest returns from ESG investments. Conversely, they expect the highest returns from index funds compared to active funds. Unlike class 3, they perceive the highest sustainability risks and the least significant ESG impact. Additionally, they show the lowest willingness to invest in ESG index and active funds, place the least importance on engaging in energy transitions, and demonstrate minimal willingness to participate in such initiatives. They also contribute the least in donations.

Overall, the above indicates that the characteristics of our distinct classes have meaningful connections with their choice patterns in the DCE. Participants' characteristics, especially social preferences and socio-demographic backgrounds, as elicited through the survey items, align well with the class-specific investment preferences and how they trade off sustainability for other attributes. Given the nature of our sample as index investors, all four classes show higher return expectations toward index funds compared to active funds. Notably, class 1 also have the lowest expectations for the returns of index funds among the four classes. This finding is in line with Goetzmann and Kumar (2008), who argue that lower-income, less-educated, and less-experienced investors are more prone to under-diversification and are more likely to opt for positive screening or active engagement strategies to seek higher returns. Moreover, the majority of our sample in class 2 hold a more balanced consideration between ESG and financial performance and prefer the negative screening strategy. This is in line with their identity as index fund investors.

We next validate our class identification by using participants' incentivized allocations to the ESG fund at the end of the experiment. Among the four classes identified, participants in class 3 allocate the highest amount on average (€255.01) to the ESG fund, representing 63.75% of the total budget. This allocation closely aligns with their strong pro-social and ESG preferences as well as potentially their belief in the superior performance of ESG investments in terms of returns and risks. In contrast, participants in class 4 allocate the smallest amount on average, €81.53, or 20.38% of the total budget, to the ESG fund. This allocation potentially stems from their expectations of the lowest returns from ESG investments, perceptions of the highest sustainability risks, minimal impact of ESG initiatives, and weakest pro-social and ESG preferences. Meanwhile, participants in class 1 and class 2 allocate an average of €206.93 and €159.40, respectively, or 51.73% and 39.85% of the total investment budget to the ESG fund. These findings demonstrate distinct investment behaviors across different classes, highlighting the influence of pro-social preferences and return-risk perceptions on investment decisions. They also indicate the complex dynamics within sustainable investing and underscore the importance of investor segmentation regarding sustainability preferences.

Participants' characteristics were closely aligned with the classification results in meaningful ways, which is complementary to the literature. For instance, in a separate online experiment using index fund investors, Bauer et al. (2024) find that younger, employed, and less-educated participants who have lower investment amounts, less investment experience, and demonstrate lower financial literacy through inaccurate return expectation calculations are more inclined to expect that a fund with a high ESG label will financially outperform the same fund without ESG rating information. Similarly, Giglio et al. (2021) highlight that older individuals tend to hold more optimistic beliefs about returns, while wealthier ones tend to be more pessimistic. Rossi et al. (2019) discover that individuals who perceive themselves as financially literate show less interest in SRI compared to their peers. Furthermore, Nilsson (2008) find that women and better-educated investors are more likely to allocate a larger proportion of their investment portfolios to SRI. In section A.6 of Appendix A, we further examine the effects of participants' individual characteristics, preferences, perceptions, and beliefs on their fund choices by interacting each of these factors with ESG attributes in the mixed logit models. Our findings contribute to a deeper understanding of how demographic factors, preferences, perceptions, and beliefs influence investment decisions related to SRI.

4 Conclusion

In this study, we examine how index fund investors trade off sustainability for performance. This trade-off reconciles the parallel rising trends of sustainable finance and passive index investing. Through a discrete choice experiment, we directly estimate participants' WTP for ESG characteristics of funds, such as ESG score categories (light green and dark green) according to the SFDR as well as ESG integration strategies (negative screening, positive screening, and active engagement).

In our sample, the majority of participants (around 70% in our sample) prioritize sustainability and place relatively less weight on the financial attributes of funds in their SRI decisions. Their average WTP for sustainability amounts to an annual return of 2.2% to 3.8%, depending on the ESG selection strategy. This range indicates that they are willing to forego some financial performance to pursue sustainability. This willingness could be due to their preferences or beliefs, or a result of their financial status or education. However, the majority of our participants prefer sustainable funds with a light green rather than a dark green ESG score category and the most conservative negative screening ESG strategy rather than more aggressive strategies. These are consistent with their index investing behavior. We further identify four distinct classes of sustainability preferences among them and validate our class identification using preferences, beliefs, socio-demographic information, and an incentivized allocation task. The results show that our classification is meaningful, which could have practical implications.

Our study identifies four important implications regarding investors' sustainability preferences. First, while social preferences are a determinant of SRI decisions, financial performance also plays an important role. Therefore, sustainability preferences should be assessed from both nonfinancial and financial perspectives. Second, ESG intensity and the corresponding sustainability investment strategy significantly affect investors' WTP for sustainability and thus their SRI decisions. The literature on sustainability preference has not extensively explored ESG intensity and its integration strategy. We demonstrate investors' preferences for ESG intensity by analyzing their WTP in the context of specific investment strategies. Third, in practice, given the substantial heterogeneity among investors, classifying them using our proposed method could be a potential solution for catering to various investment preferences. Finally, around 90% of participants place the most weight on funds' sustainability attributes when selecting a fund, indicating that they could overvalue funds' sustainability performance; this over-weighting could potentially lead to a market distortion.

Admittedly, in our DCE setting, we do not incentivize participants for their fund selection. Therefore, this shortcoming could potentially induce participants to place more weight on funds' sustainability attributes due to a concern about image (e.g., Bénabou and Tirole, 2010; Bauer and Smeets, 2015; Riedl and Smeets, 2017). But we still observe that more than 13% of participants place the most weight on funds' returns. Moreover, the latent class analysis generates meaningful classifications that are validated by an incentivized allocation. These results give us some confidence that a concern about image was not a main driver in our experiment. Additionally, the participants in our sample are index investors – compared with active or equity investors, they value more diversification and low management fees that may explain their stronger preferences for the negative screening investment strategy. Future research could explore sustainability preferences using our methodology among other investor groups, such as active or equity investors.

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A Appendix A

A.1 Participant Number

Between May 8 and June 3, 2023, we collected survey responses from participants. By June 3, 2023, a total of 963 participants had started the survey, with 457 successfully completing it. The average time taken to complete the survey was approximately 24 minutes.

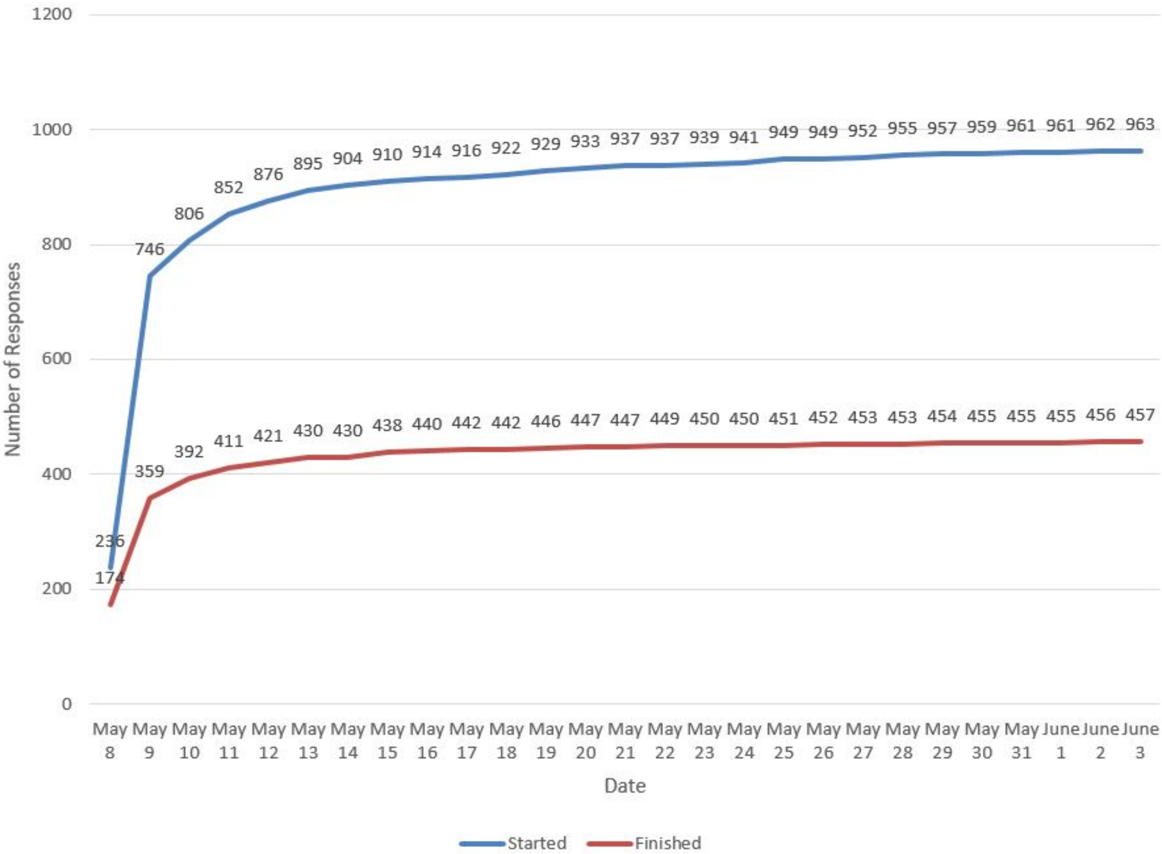


Figure A.1: Respondent Number

Note: The figure presents the count of respondents who initiated and completed our survey, respectively, over the period from May 8 to June 3, 2023.

A.2 An Exemplary Choice Set

Figure A.2 presents the screenshot corresponding to the DCE in the survey.

A.3 Time and Risk Preference

We elicit participants' time and risk preferences with the qualitative self-assessment method and the quantitative "staircase" method. In the Study Design Section 2, we

Click here if you would like to read the explanation about the ESG score again.

Show ESG score explanation

Choose your preferred investment fund from the three investment funds below.

Choice Question 1

Attribute	Investment fund 2	Investment fund 3	Investment fund 1
ESG Score Category	***Light green***	***Dark green***	***Gray***
Management fee	**1.5%** per year	**1.0%** per year	**0.5%** per year
ESG Selection Strategies	**Active involvement** : The investment fund managers use their voting rights at general meetings and can engage with management to influence corporate behavior in a sustainable direction	**Negative screening** : The investment fund or index excludes sectors or companies that are not considered sustainable. Typical companies that can be excluded from the portfolio are tobacco, alcohol, pornography, controversial weapons and companies that violate international standards	**No**
Return-Risk (Annual)	**Return: 4%** expected annual return; **Risk:** Up to **20%** loss from peak to trough (**max drawdown***)	**Return: 10%** expected annual return; **Risk:** Up to **20%** loss from peak to trough (**max drawdown***)	**Return: 7%** expected annual return; **Risk:** Up to **20%** loss from peak to trough (**max drawdown***)
Which investment fund do you prefer?	○	○	○

* Maximum drawdown is the maximum percentage loss from peak to trough (i.e., from high to low) of an investment in a period of falling stock prices.

Figure A.2: An Exemplary Choice Set

Note: This figure illustrates a screenshot from the discrete choice experiment conducted in the survey, an example choice set of three funds.

detail the methods used in Subsection 2.3. In our sample, on average, participants' time tolerance for investment elicited via the quantitative "staircase" method is higher than that elicited via self-assessment. Furthermore, they are risk-averse according to the quantitative "staircase" method but risk-seeking according to the qualitative self-assessment.

In our analysis, we use the participants' time and risk preferences elicited by the quantitative "staircase" method due to its greater accuracy and reliability.

Table A.1: Participants' Time and Risk Preferences

This table presents the results of measuring participants' time and risk preferences using qualitative self-assessment and quantitative "staircase" elicitation methods. In the qualitative self-assessment method, the range is from 1 to 7, with 1 representing the lowest perception and 7 representing the highest perception. In the quantitative "staircase" method, the range is from 1 to 16, with 1 indicating the lowest perception and 16 indicating the highest perception. We standardize the results to a range between 0 and 1. The original results are displayed in parentheses.

Preference	Qualitative Self-assessment	SD	Quantitative "Staircase"	SD
Time	0.829	0.138	0.906	0.150
	(5.805)		(14.497)	
Risk	0.714	0.160	0.417	0.167
	(5.000)		(6.672)	

A.4 An Exemplary Ambiguity Attitude Elicitation Task

Figure A.3 presents the screenshot corresponding to the ambiguity attitude elicitation task in the survey.

A.5 Ambiguity Attitude

We elicited participants' ambiguity attitudes using the adapted Ellsberg urns method (e.g., Ellsberg, 1961), with the specific methods detailed in the subsection 2.4 of the Study Design Section. In our sample, the average ambiguity attitude score among participants is 0.442 (on a scale from 0 to 1), which is below 0.5, indicating that participants are generally ambiguity-averse. The standard deviation of participants' ambiguity attitudes is 0.160.

A.6 Interaction of Individual Characteristics, Preferences, Perceptions, and Beliefs with ESG Attributes

We investigate the effect of participants' characteristics, preferences, perceptions, and beliefs on their fund choices by interacting them, one at a time, with the ESG attributes in the mixed logit models. Table A.2 presents the estimated parameters (with robust z-statistics in parentheses). The table shows the results of individual characteristics (such as ESG knowledge, investment experience, total investment, monthly income, correct calculation, education background, gender, and age), individual preferences (such as altruism, You now have a chance to win **€100** with the guessing game below.

Your task is to choose between Box K and Box U, both of which contain 100 balls with either a positive sign ("+") or a negative sign ("—"). The computer will randomly select a ball from the box you choose. You win 100 euros if a positive ("+") ball is selected.

What is the difference between the two boxes?

Box K contains a precise mix of 100 positive ("+") and negative ("—") balls. For example, Box K below contains 50 positive ("+") and 50 negative ("—") balls. Note: The mix in Box K may be different for different questions (e.g. 60 positive ("+") and 40 negative ("—") balls).

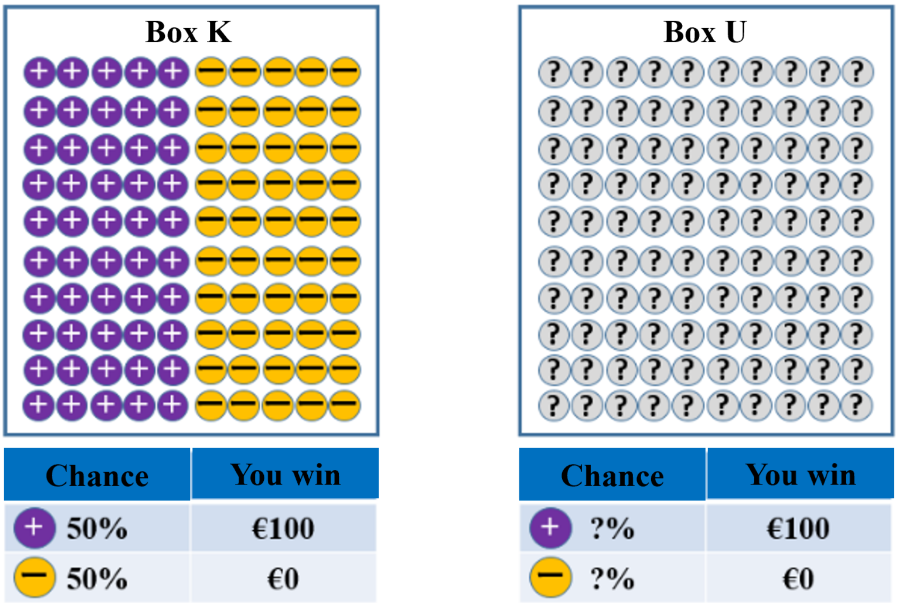
Box U contains an unknown mix of positive ("+") and negative ("—") balls.

How do you choose?

Please indicate below which box you prefer and we will then randomly select a ball from the box of your choice.

If you find both boxes equally attractive, you may choose the option "I don't see the difference". Then the computer will randomly choose a box for you and select a ball from it.

Remember: You win 100 euros if a positive ("+") ball is selected. Think carefully about your choice.



○ Box K ○ I don't see the difference ○ Box U

Figure A.3: An Exemplary Ambiguity Attitude Elicitation Task

Note: This figure displays a screenshot depicting the task designed to elicit attitudes towards ambiguity.

trust, reciprocity, time preference, risk preference, and ambiguity attitude), individual perceptions (such as ESG impact and sustainability risk), and individual beliefs (such as index fund return), and ESG fund preferences (such as ESG index fund versus active ESG fund), as defined in Table B.1. These are respectively interacted with variables for ESG integration and investment strategies.

Table A.2: ESG Preference Estimation with Interaction Terms

This table presents the parameter estimates for interaction terms. The dependent variable is the respondent's choice among three funds within the choice sets. All interaction terms consistently have an observation count of 16,452 (457×36). Column (1) presents the coefficients of the interaction terms with ESG×Negative Screening. Column (2) presents the coefficients of the interaction terms with ESG×Positive Screening. Column (3) presents the coefficients of the interaction terms with ESG×Active Engagement. Column (4) presents the mean coefficients for Return, and Column (5) presents the mean coefficients for Management Fee. Column (6) presents the estimation Log likelihood. Robust z-statistics, calculated from the estimated standard deviations (SD) of the parameters, are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

	Dependent Variable: Probability of Choosing the Fund					
	ESG (Negative)	ESG (Positive)	ESG (Active)	Return	Management Fee	Log likelihood
Interaction With	(1)	(2)	(3)	(4)	(5)	(6)
Altruism	4.513***	3.459***	3.878***	1.131***	−2.836***	−2585.178
	(5.22)	(4.52)	(5.73)	(17.41)	(14.97)	
Trust	0.198	1.746*	2.886***	1.124***	−2.769***	−2607.6399
	(0.19)	(1.82)	(3.03)	(20.01)	(−14.33)	
Reciprocity	5.388***	2.394*	5.263***	1.146***	−2.983***	−2599.290
	(5.23)	(1.84)	(5.68)	(19.55)	(−14.57)	
ESG Knowledge	−2.113***	−0.966	1.179*	1.082***	−2.727***	−2609.223
	(−2.91)	(−1.28)	(1.90)	(20.26)	(−14.53)	
ESG Impact	9.951***	8.113***	7.572***	1.077***	−2.768***	−2529.724
	(9.72)	(8.47)	(9.20)	(20.32)	(−13.96)	
Sustainability Risk	4.194***	4.489***	3.794***	1.038***	−2.941***	−2593.614
	(4.20)	(4.48)	(4.41)	(20.69)	(−14.43)	
Investment Experience	0.057	−1.517**	−0.516	1.132***	−2.816***	−2610.292
	(0.08)	(−2.16)	(−0.78)	(19.40)	(−14.19)	
Total Investment	−2.367***	−3.471***	−1.070*	1.039***	−2.718***	−2601.808
	(−2.69)	(−4.52)	(−1.68)	(20.30)	(−13.97)	
Monthly Income	−1.373*	−0.673	−1.173**	1.055***	−2.728***	−2612.744
	(−1.90)	(−1.02)	(−2.10)	(20.46)	(−13.92)	
Correct Calculation	0.747*	0.936**	0.714**	1.062***	−2.942***	−2609.222
	(1.85)	(2.33)	(2.20)	(20.69)	(−14.57)	
Education	4.30413***	1.193	1.109	1.080***	−2.699***	−2613.885
	(3.71)	(0.75)	(1.20)	(20.12)	(−14.19)	
Time Preference	1.869*	−1.362	−0.695	1.072***	−2.972***	−2610.246
	(1.81)	(−1.24)	(−0.77)	(20.09)	(−14.70)	
Risk Preference	−0.996	−2.374**	0.335	1.064***	−2.679***	−2613.242
	(−0.96)	(−2.16)	(0.38)	(20.41)	(−13.96)	
Ambiguity Attitude	−0.134	−0.228	0.270	1.055***	−2.710***	−2616.270
	(−0.10)	(−0.21)	(0.31)	(20.18)	(−13.97)	
Male	−0.923***	−1.006***	−0.203	1.059***	−2.660***	−2607.797
	(−3.12)	(−3.24)	(−0.78)	(20.51)	(−13.76)	
Age	1.833	−1.422	−0.792	1.059***	−2.660***	−2613.909
	(1.40)	(−1.19)	(−0.89)	(20.17)	(−13.83)	
Index Fund Return	−1.658	−1.452	0.540	1.052***	−2.647***	−2613.884
	(−1.40)	(−1.44)	(0.57)	(20.43)	(−−13.93)	
ESG Index Fund	11.632***	8.891***	7.495***	1.052***	−2.647***	−2473.888
	(12.87)	(9.91)	(9.63)	(20.27)	(−14.19)	
Active ESG Fund	8.044***	7.160***	5.392***	1.014***	−2.566***	−2522.510
	(10.17)	(9.24)	(8.04)	(20.90)	(−13.77)	

The estimated parameters for the interaction terms show that several factors positively influence ESG integration: investors' pro-social preferences (such as altruism and reciprocity), preference for ESG investing, perception of ESG's positive impact and sustainability risks, financial literacy, education, and time preference. Conversely, factors such as higher levels of ESG knowledge, larger total investment amounts, higher monthly income, male gender, and older age tend to negatively influence ESG integration. Notably, time and risk preferences as well as ambiguity attitudes do not significantly influence the decision to incorporate ESG integration in fund choices. Table A.3 presents the WTP estimates for ESG integration when combined with various investment strategies and specific terms of interaction.

Table A.3: ESG Preference Estimation with Interaction Terms

This table presents the interaction terms' WTP values. Columns (1), (2), and (3) present the WTP values for ESG×Negative Screening, ESG×Positive Screening, and ESG×Active Engagement, respectively, reflecting the interaction effect based on Return. Columns (4), (5) and (6) present the WTP values for ESG×Negative Screening, ESG×Positive Screening, and ESG×Active Engagement, respectively, considering the interaction effect based on Management Fee.

	Mean WTP Estimates					
	Based on Return			*Based on Management Fee*		
	ESG (Negative)	ESG (Positive)	ESG (Active)	ESG (Negative)	ESG (Positive)	ESG (Active)
Interaction With	(1)	(2)	(3)	(4)	(5)	(6)
Altruism	−6.491	−4.974	−5.577	1.591	1.220	1.368
Trust		−1.553	−2.567		0.631	1.042
Reciprocity	−4.703	−2.090	−4.594	1.806	0.803	1.765
ESG Knowledge	1.953		−1.089	−0.775		0.432
ESG Impact	−9.239	−7.533	−7.031	3.595	2.931	2.736
Sustainability Risk	−4.041	−4.325	−3.655	1.426	1.526	1.290
Investment Experience		1.340			−0.539	
Total Investment	2.277	3.339	1.029	−0.871	−1.277	−0.394
Monthly Income	1.301		1.112	−0.503		−0.430
Correct Calculation	−0.704	−0.882	−0.672	0.254	0.318	0.243
Education	−3.987			1.595		
Time Preference	−1.743			0.629		
Risk Preference		2.230			−0.886	
Male	0.872	0.950			−0.347	−0.378
Age	0.872	0.950			−0.347	−0.378
ESG Index Fund	−11.055	−8.450	−7.123	4.395	3.359	2.832
Active ESG Fund	−7.934	−7.062	−5.318	3.135	2.791	2.102

A.7 Latent Classes by Examining BIC and CAIC

To identify the optimal number of latent classes, we assess various information criteria, such as the Consistent Akaike Information Criterion (CAIC) (e.g., Cavanaugh and Neath, 2019) and the Bayesian Information Criterion (BIC) (e.g., Neath and Cavanaugh, 2012). We systematically estimate ten latent class logit model specifications to ascertain the relevant information criteria. As indicated in Table A.4, both CAIC and BIC values show an insignificant decrease beyond four classes, indicating diminishing returns for models with more than four classes. Moreover, the determination of the number of classes should not rely solely on statistical indicators like CAIC and BIC but should also consider content-related motivations. Consequently, we select four classes, and demonstrate that this is a reasonable classification.

Table A.4: Latent Classes by Examining BIC and CAIC

This table presents the results of evaluating the Bayesian Information Criterion (BIC) and the Consistent Akaike Information Criterion (CAIC) to determine the optimal number of latent classes. It involves repeatedly estimating 10 latent class logit models and obtaining the corresponding information criteria for each.

Classes	LLF	Nparam	CAIC	BIC
2	−3134.919	12	6355.335	6343.335
3	−2742.524	19	5620.416	5601.416
4	−2581.668	26	5348.578	5322.578
5	−2534.936	33	5304.987	5271.987
6	−2462.767	40	5210.522	5170.522
7	−2425.407	47	5185.675	5138.675
8	−2416.829	54	5218.391	5164.391
9	−2384.35	61	5203.306	5142.306
10	−2343.069	68	5170.615	5102.615

A.8 Class-specific Analysis

Table A.5, Table A.6, Table A.7, and Table A.8 present class-specific parameter estimates from using the mixed logit models. In the upper panels of these tables, Column (1) reports the coefficients for ESG integration in combination with the ESG selection strategy, while Column (2) highlights the variability in these coefficient estimates. Columns (3) and (4) provide a detailed analysis of specific ESG score categories. The lower panels of these tables detail the participants' WTP for ESG attributes. Columns (1) and (2) focus on the mean WTPs based on returns and management fees, accounting for ESG integration alongside various investment strategies, while Columns (3) and (4) offer insights into the WTPs for specific ESG score categories.

In Class 1, as presented in Table A.5, Column (1) in the upper panel and Columns (1) and (2) in the lower panel show that participants demonstrate the strongest preference and highest WTP for ESG integration combined with Active Engagement funds. Additionally, Column (3) in the upper panel and Columns (3) and (4) in the lower panel show a stronger preference and higher WTP for "Dark Green" over "Light Green" when paired with Active Engagement. Notably, there was an insignificant preference for "Light Green" combined with Negative Screening. Overall, Class 1 participants favored higher ESG levels, particularly with Active Engagement strategies.

Table A.5: ESG Preference Estimation and WTP in Class 1

The upper panel of this table presents the parameter estimates for each explanatory variable related to fund attributes in the survey's discrete choice experiment, utilizing mixed logit models for selecting among three funds, specifically for investors classified in Class 1. It includes mean and standard deviation coefficients for random parameters such as various ESG levels, ESG selection strategy, management fees, and return. Additionally, robust z-statistics, calculated from the estimated standard deviations (SD) of the parameters, are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level. The lower panel of this table reports the mean WTP estimates for each non-financial attribute, using 1000 Halton draws for MSL estimations, based on data from 12 choice sets.

	Dependent variable: Respondent's Choice among Three Funds			
	ESG×Strategy		*Light/Dark×Strategy*	
	Coefficient	SD Coefficient	Coefficient	SD Coefficient
Fund Attribute	(1)	(2)	(3)	(4)
Management Fee	−1.483***	1.575***	−1.764***	1.620***
	(−5.46)	(5.89)	(−5.36)	(5.62)
Return	0.148***	0.111***	0.171***	0.119***
	(5.25)	(3.27)	(5.38)	(3.30)
ESG Integration×Negative Screening	1.771***	0.521		
	(7.28)	(−1.21)		
ESG Integration×Positive Screening	2.480***	1.325***		
	(7.59)	(−3.30)		
ESG Integration×Active Engagement	3.291***	1.347***		
	(11.32)	(5.40)		
Light Green×Negative Screening			1.407	3.148*
			(0.74)	(−1.67)
Light Green×Positive Screening			3.062***	1.738
			(4.24)	(−1.13)
Light Green×Active Engagement			3.353***	1.355***
			(10.51)	(5.29)
Dark Green×Negative Screening			1.789***	0.416***
			(6.77)	(−0.51)
Dark Green×Positive Screening			2.496***	1.486***
			(6.44)	(−2.65)
Dark Green×Active Engagement			3.861***	1.837***
			(8.42)	(4.27)
	Mean WTP Estimates			
	ESG×Strategy		*Light/Dark×Strategy*	
	Based on Return	Based on Management Fee	Based on Return	Based on Management Fee
Fund Attribute	(1)	(2)	(3)	(4)
ESG Integration×Negative Screening	−11.994	1.194		
ESG Integration×Positive Screening	−16.798	1.673		
ESG Integration×Active Engagement	−22.293	2.220		
Light Green×Negative Screening				
Light Green×Positive Screening			−17.875	1.736
Light Green×Active Engagement			−19.570	1.901
Dark Green×Negative Screening			−10.445	1.015
Dark Green×Positive Screening			−14.569	1.415
Dark Green×Active Engagement			−22.540	2.189
Observations	2052		2052	
Log likelihood	−460.512		−460.076	

Table A.6: ESG Preference Estimation and WTP in Class 2

The upper panel of this table presents the parameter estimates for each explanatory variable related to fund attributes in the survey's discrete choice experiment, utilizing mixed logit models for selecting among three funds, specifically for investors classified in Class 2. It includes mean and standard deviation coefficients for random parameters such as various ESG levels, ESG selection strategy, management fees, and return. Additionally, robust z-statistics, calculated from the estimated standard deviations (SD) of the parameters, are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level. The lower panel of this table reports the mean WTP estimates for each non-financial attribute, using 1000 Halton draws for MSL estimations, based on data from 12 choice sets.

	Dependent variable: Respondent's Choice among Three Funds			
	ESG×Strategy		*Light/Dark×Strategy*	
	Coefficient	SD Coefficient	Coefficient	SD Coefficient
Fund Attribute	(1)	(2)	(3)	(4)
Management Fee	−2.495***	1.111***	−2.482***	1.199***
	(−9.64)	(5.09)	(−8.57)	(5.15)
Return	1.136***	0.209***	1.147***	0.231***
	(14.37)	(4.90)	(13.21)	(5.21)
ESG Integration×Negative Screening	4.271***	1.342***		
	(13.69)	(5.06)		
ESG Integration×Positive Screening	3.485***	1.459***		
	(11.72)	(4.57)		
ESG Integration×Active Engagement	3.546***	0.969***		
	(14.57)	(4.53)		
Light Green×Negative Screening			−17.208	0.112
			(−0.00)	(0.00)
Light Green×Positive Screening			7.154	−4.864
			(1.46)	(−1.20)
Light Green×Active Engagement			3.588***	0.965***
			(13.21)	(4.08)
Dark Green×Negative Screening			4.300***	1.287***
			(12.56)	(4.58)
Dark Green×Positive Screening			3.937***	0.437
			(8.43)	(0.45)
Dark Green×Active Engagement			3.694***	1.402**
			(7.03)	(2.22)
	Mean WTP Estimates			
	ESG×Strategy		*Light/Dark×Strategy*	
	Based on Return	Based on Management Fee	Based on Return	Based on Management Fee
Fund Attribute	(1)	(2)	(3)	(4)
ESG Integration×Negative Screening	−3.759	1.712		
ESG Integration×Positive Screening	−3.068	1.397		
ESG Integration×Active Engagement	−3.137	1.429		
Light Green×Negative Screening				
Light Green×Positive Screening				
Light Green×Active Engagement			−3.129	1.446
Dark Green×Negative Screening			−3.750	1.733
Dark Green×Positive Screening			−3.433	1.586
Dark Green×Active Engagement			−3.221	1.488
Observations	9540		9540	
Log likelihood	−766.335		−765.614	

In Class 2, as presented in Table A.6, Column (1) in the upper panel and Columns (1) and (2) in the lower panel indicate a balance between preference and WTP for ESG integration with Negative Screening funds. When assessing ESG level-specific strategies in Column (3) in the upper panel and Columns (3) and (4) in the lower panel, there was a stronger preference and higher WTP for “Dark Green” compared to “Light Green” when combined with Negative Screening, though the preference for “Light Green” under Negative Screening was insignificant. Overall, Class 2 participants demonstrate rational trade-offs among ESG levels, investment strategies, and financial attributes such as risk-adjusted return and management fees.

In Class 3, as presented in Table A.7, Column (1) in the upper panel and Columns (1) and (2) in the lower panel show the strongest preference and highest WTP for ESG integration with Negative Screening funds. Column (3) in the upper panel and Columns (3) and (4) in the lower panel indicate a stronger overall preference and higher WTP for “Dark Green” across investment strategies. Participants in Class 3 display the most pronounced and somewhat irrational preference for “Dark Green,” especially with Negative Screening.

In Class 4, as presented in Table A.8, Column (1) in the upper panel and Columns (1) and (2) in the lower panel indicate significant resistance to ESG-integrated funds, with the highest sensitivity to risk-adjusted return and management fees among all classes. Participants prioritize the financial performance of funds and show a notable aversion to Positive Screening and Active Engagement strategies. Overall, Class 4 participants demonstrate a significant “anti-ESG” stance.

Table A.7: ESG Preference Estimation and WTP in Class 3

The upper panel of this table presents the parameter estimates for each explanatory variable related to fund attributes in the survey's discrete choice experiment, utilizing mixed logit models for selecting among three funds, specifically for investors classified in Class 3. It includes mean and standard deviation coefficients for random parameters such as various ESG levels, ESG selection strategy, management fees, and return. Additionally, robust z-statistics, calculated from the estimated standard deviations (SD) of the parameters, are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level. The lower panel of this table reports the mean WTP estimates for each non-financial attribute, using 1000 Halton draws for MSL estimations, based on data from 12 choice sets.

	Dependent variable: Respondent's Choice among Three Funds			
	ESG×Strategy		*Light/Dark×Strategy*	
	Coefficient	SD Coefficient	Coefficient	SD Coefficient
Fund Attribute	(1)	(2)	(3)	(4)
Management Fee	−1.435***	0.965***	−0.809***	1.178***
	(−6.99)	(4.67)	(−2.94)	(4.45)
Return	0.210***	0.068	0.262***	0.099**
	(8.01)	(1.41)	(6.74)	(2.00)
ESG Integration×Negative Screening	6.457***	0.509		
	(14.54)	(1.00)		
ESG Integration×Positive Screening	4.315***	1.157***		
	(10.17)	(2.64)		
ESG Integration×Active Engagement	3.269***	0.904***		
	(9.51)	(3.56)		
Light Green×Negative Screening			5.485***	1.263
			(7.72)	(0.76)
Light Green×Positive Screening			4.358***	4.994
			(3.52)	(−1.47)
Light Green×Active Engagement			2.663***	0.782
			(5.80)	(1.53)
Dark Green×Negative Screening			6.301***	1.018*
			(10.36)	(−1.80)
Dark Green×Positive Screening			5.783***	1.733*
			(6.70)	(1.79)
Dark Green×Active Engagement			4.144***	2.005***
			(6.62)	(4.03)
	Mean WTP Estimates			
	ESG×Strategy		*Light/Dark×Strategy*	
	Based on Return	Based on Management Fee	Based on Return	Based on Management Fee
Fund Attribute	(1)	(2)	(3)	(4)
ESG Integration×Negative Screening	−30.744	4.500		
ESG Integration×Positive Screening	−20.545	3.007		
ESG Integration×Active Engagement	−15.568	2.279		
Light Green×Negative Screening			−20.919	6.779
Light Green×Positive Screening			−16.620	5.386
Light Green×Active Engagement			−10.156	3.291
Dark Green×Negative Screening			−24.031	7.788
Dark Green×Positive Screening			−22.058	7.149
Dark Green×Active Engagement			−15.806	5.122
Observations	2628		2628	
Log likelihood	−398.898		−376.058	

Table A.8: ESG Preference Estimation and WTP in Class 4

The upper panel of this table presents the parameter estimates for each explanatory variable related to fund attributes in the survey's discrete choice experiment, utilizing mixed logit models for selecting among three funds, specifically for investors classified in Class 4. It includes mean and standard deviation coefficients for random parameters such as various ESG levels, ESG selection strategy, management fees, and return. Additionally, robust z-statistics, calculated from the estimated standard deviations (SD) of the parameters, are presented in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level. The lower panel of this table reports the mean WTP estimates for each non-financial attribute, using 1000 Halton draws for MSL estimations, based on data from 12 choice sets.

	Dependent variable: Respondent's Choice among Three Funds			
	ESG×Strategy		*Light/Dark×Strategy*	
	Coefficient	SD Coefficient	Coefficient	SD Coefficient
Fund Attribute	(1)	(2)	(3)	(4)
Management Fee	−8.387***	2.579***	−8.437***	2.641***
	(−7.34)	(−5.17)	(−6.97)	(−4.06)
Return	1.500***	0.593***	1.436***	0.695***
	(7.60)	(4.91)	(7.41)	(4.63)
ESG Integration×Negative Screening	0.047	0.924		
	(0.11)	(1.38)		
ESG Integration×Positive Screening	−1.326***	−2.513***		
	(−2.57)	(−2.513)		
ESG Integration×Active Engagement	−2.114***	−2.837***		
	(−4.27)	(−5.20)		
Light Green×Negative Screening			−13.579	0.379
			(−0.00)	(0.00)
Light Green×Positive Screening			−1.219	3.695*
			(−0.62)	(1.73)
Light Green×Active Engagement			−1.582***	2.161***
			(−3.50)	(−3.16)
Dark Green×Negative Screening			0.151	0.973*
			(0.33)	(−1.71)
Dark Green×Positive Screening			−2.029***	1.091
			(−3.94)	(−1.08)
Dark Green×Active Engagement			−1.923***	−2.553***
			(−3.34)	(−3.81)
	Mean WTP Estimates			
	ESG×Strategy		*Light/Dark×Strategy*	
	Based on Return	Based on Management Fee	Based on Return	Based on Management Fee
Fund Attribute	(1)	(2)	(3)	(4)
ESG Integration×Negative Screening				
ESG Integration×Positive Screening	0.884	−0.158		
ESG Integration×Active Engagement	1.409	−0.252		
Light Green×Negative Screening				
Light Green×Positive Screening				
Light Green×Active Engagement			1.102	−0.188
Dark Green×Negative Screening				
Dark Green×Positive Screening			1.413	−0.240
Dark Green×Active Engagement			1.339	−0.228
Observations	2232		2232	
Log likelihood	−294.260		−304.907	

B Appendix B

Table B.1: Definitions of Variables

Variable	***Description***	***Measurement***
High ESG Rating Info	High ESG rating information treatment	In the ESG condition, High ESG rating information about the fund is provided, while in the non-ESG condition, no ESG-related information about the fund is offered
ESG Return Belief	The participant's response to the question "I expect that the returns of index mutual funds that exclude companies with a low ESG score compared to those that do not exclude companies with a low ESG score will be?":	0, I do not know; 1, Much lower; 2, A bit lower; 3, The same; 4, A bit higher; 5, Much higher.
Male	Dummy variable for participant's gender	Equal to one if the participant reports being a man.
Age	The participant's self-reported age	
Origin	The participant's response to the question "What is your origin?":	0, Dutch background; 1, First generation foreign, Western background; 2, First generation foreign, non-Western background; 3, Second generation foreign, Western background; 4, Second generation foreign, non-Western background; 5, Origin unknown, or part of the information unknown (missing values).
Investing Experience	The participant's response to the question "How many years of experience do you have in investing?":	0, no or less than 1 year; 1, 1 year − 3 years; 2, 4 years − 6 years; 3, 7 years − 10 years; 4, more than 10 years.
Income	The participant's response to the question "What is your personal gross monthly income in categories?":	0, No income; 1, 500 euros or less; 2, 501 euros to 1000 euros; 3, 1001 euros to 1500 euros.

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Variable	***Description***	***Measurement***
Education	The participant's response to the question "What is your highest level of education?":	0, Primary school; 1, VMBO (Preparatory secondary vocational education, US: Junior High School); 2, HAVO/VWO (Higher General Secondary Education/Preparatory Scientific Education, US: Senior High School); 3, MBO (secondary vocational education, US: Junior College); 4, HBO (Higher Vocational Education, US: College); 5, WO (University); 6, Other; 7, Not (yet) completed education; 8, No education started yet.
ESG Knowledge	The participant's response to the question "What do you think your level of knowledge about ESG (Environment, Social, Governance: an English-language designation for investing with an eye for the environment, society and good corporate governance) in the investment context is relative to the respondents to this survey?":	A value between 0% and 100%.
Total Investment	The participant's response to the question "How much money do you currently invest (in shares/mutual funds)?":	0, I'd rather not say; 1, 4999 euros or less; 2, 5000 euros to 9999 euros; 3, 10000 euros to 24999 euros; 4, 25000 euros to 49999 euros; 5, 50000 euros to 99999 euros; 6, 100000 euros to 249999 euros; 7, More than 250,000 euros.
Monthly Investment	The participant's response to the question "How much do you invest on a monthly basis?":	0, 0; 1, 100 euros or less; 2, 101 euros to 300 euros; 3, 301 euros to 500 euros; 4, 501 euros to 1000 euros; 5, 1001 euros to 1500 euros; 6, 1501 euros to 2000 euros; 7, 2001 euros to 2500 euros; 8, 2501 euros to 3000 euros; 9, 3001 euros to 4000 euros; 10, 4001 euros to 5000 euros; 11, More than 5000 euros; 12, I'd rather not say;

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Variable	***Description***	***Measurement***
Occupation	The participant's response to the question "What is your main occupation?":	1, Paid work; 2, Works or assists in the family business; 3, Independent professional, freelancer, or independent; 4, Job seeker due to loss of job; 5, New jobseeker; 6, Except for searching for work as a result of loss of job; 7, Goes to school or study; 8, Takes care of the household; 9, Is retired (voluntary), early pension, pension scheme; 10, Has (partial) incapacity for work; 11, Does unpaid work while using unemployment benefits; 12, Does volunteer work; 13, Does something else; 14, Is too young to have a job;
Investing Amount in Index Fund	The participant's response to the question "Suppose you have 10,000 euros in a savings account. You can leave this money in the savings account for the coming year and will then receive 5% interest with certainty. You will then receive 500 euros. Or you can invest the amount in an investment fund that tracks the performance of the stock market based on a stock index, with a 50% chance of a return of +40% (+4,000 euros) and a 50% chance of a return of −20% (-2,000 euros). Given this information, how much of the 10,000 euros will you invest in this equity investment fund?":	Investment Amount in the Index Fund.

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Variable	***Description***	***Measurement***
ESG Return by Likert Scale	The participant's response to the question "What level do you expect the returns of sustainable investment funds compared to less sustainable investment funds to be?":	0, I do not know; 1, Much lower; 2, A bit lower; 3, The same; 4, A bit higher; 5, Much higher.
Index Fund Return	The participant's response to the question "In general, do you expect the returns of index mutual funds compared to active mutual funds to be?":	0, I do not know; 1, Much lower; 2, A bit lower; 3, The same; 4, A bit higher; 5, Much higher.
Trust	The participant's response to the question "Do you believe that people only have the best intentions?":	1, Totally disagree; 2, Disagree; 3, Fairly disagree; 4, Average; 5, Fairly agree; 6, Agree; 7, Totally agree.
Sustainability Risk	The participant's response to the question "Do less sustainable investment funds carry more risk than sustainable investment funds?":	1, Totally disagree; 2, Disagree; 3, Fairly disagree; 4, Average; 5, Fairly agree; 6, Agree; 7, Totally agree.
ESG Impact	The participant's response to the question "Do investment funds with ESG integration (environmental, social, governance) have a positive impact on society?":	1, Totally disagree; 2, Disagree; 3, Fairly disagree; 4, Average; 5, Fairly agree; 6, Agree; 7, Totally agree.
Positive Reciprocity	The participant's response to the question "When someone does me a favor, are you willing to return the favor?":	1, Totally disagree; 2, Disagree; 3, Fairly disagree; 4, Average; 5, Fairly agree; 6, Agree; 7, Totally agree.
Negative Reciprocity (Self)	The participant's response to the question "If you are treated very unfairly, will you take revenge at the first opportunity even if there are costs involved?":	1, Totally disagree; 2, Disagree; 3, Fairly disagree; 4, Average; 5, Fairly agree; 6, Agree; 7, Totally agree.

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Variable	***Description***	***Measurement***
Negative Reciprocity (Others)	The participant's response to the question "Are you willing to punish someone who treat others unfairly even if it may come at a cost to yourself?":	1, Totally disagree; 2, Disagree; 3, Fairly disagree; 4, Average; 5, Fairly agree; 6, Agree; 7, Totally agree.
ESG Index Fund Preference	The participant's response to the question "Would you like to invest in an index investment fund that excludes companies that do not sufficiently take into account the environment, society, and corporate governance even if this investment strategy is at the expense of the financial performance of the investment fund?":	1, Totally disagree; 2, Disagree; 3, Fairly disagree; 4, Average; 5, Fairly agree; 6, Agree; 7, Totally agree.
Active ESG Fund Preference	The participant's response to the question "Would you like to invest in an actively managed investment fund that excludes companies that do not sufficiently take into account the environment, society, and corporate governance even if this investment strategy is at the expense of the financial performance of the investment fund?":	1, Totally disagree; 2, Disagree; 3, Fairly disagree; 4, Average; 5, Fairly agree; 6, Agree; 7, Totally agree.

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Variable	***Description***	***Measurement***
Energy Transition Preference	The participant's response to the question "To what extent are you prepared to invest part of your invested capital in an investment fund that focuses purely on companies that directly contribute to the energy transition (for example by devising solutions that lead to higher energy efficiency or the development of renewable energy)?":	A value between 0 and 100.
Energy Efficiency Engagement	The participant's response to the question "To what extent do you think it is important that asset managers address companies in their voting policy (voting at remote shareholder meetings) or their engagement policy (private dialogue with companies) on their energy efficiency and contribution to the energy transition?":	A value between 0 (Not important) and 6 (Very important).
Donation	The participant's response to the question "Imagine the following situation: You have unexpectedly received 1000 euros today. How much of this amount would you donate to charity? (Values between 0 and 1000 are allowed.)":	A value between 0 and 1000.

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Variable	***Description***	***Measurement***
ESG Investment Amount	The participant's response to the following: "Meesman has two types of investment funds: Equity investment funds for the growth of your assets and Worldwide Total Shares is the ultimate share index investment fund for passive investors and Shares Sustainable Future is suitable for investors looking for an index investment fund with a more pronounced sustainable character. Please indicate how much you would like to invest in Worldwide Total Shares using your Meesman credits. The rest will be automatically invested in Shares Sustainable Future."	A value between 0 and 400.
Altruism	The participant's response to the question "How willing are you to give to charities without expecting anything in return?":	A value between 1 (Definitely not willing) and 7 (Very willing)

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Table B.1 – *Continued from previous page*

Variable	***Description***	***Measurement***
Correct Expected Return Calculation	The participant's response to the question "Suppose that when answering the previous question you decided to invest X euros of the amount of €10000 in the stock index investment fund and you are one of the selected winners and therefore you have 10,000. Remember that the return of the stock index mutual fund in the coming year will be either +40% or −20% with equal probability. The return for the savings account is guaranteed at 5%. How much money do you expect to have at the end of this one-year investment period? Please choose one of the answers below. If you choose the correct answer, you will receive a bonus of €50 on top of your payout for this experiment.":	0, $0.5\times(0.4X\text{-}0.2X)+0.05\times(10000\text{-}X)$; 1, $1.4X+0.8X+1.05\times(10000\text{-}X)$; 2, $0.4\times(10.000\text{-}X)\text{-}0.2\times(10.000\text{-}X)+0.05X$; 3, $0.5\times[0.4\times(10000\text{-}X)\text{-}0.2\times(10000\text{-}X)]+0.05X$; 4, $0.4X\text{-}0.2X+0.05\times(10000\text{-}X)$; 5, $0.5\times(1.4X+0.8X)+1.05\times(10000\text{-}X)$; 6, $1.4\times(10000\text{-}X)+0.8\times(10000\text{-}X)+1.05X$; 7, $0.5\times[1.4\times(10000\text{-}X)+0.8\times(10000\text{-}X)]+1.05X$; 8, I'd rather not answer that.

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