Eliciting Sustainability Preferences[*]

Julia Meyer[†]   Michaela Tanner[‡]   Sugandhita Sugandhita [§]

December 1, 2025

Abstract

While regulation in several jurisdictions requires sustainability preferences to be formally integrated into financial advisory processes, little is known about how these preferences can be captured most effectively. Existing research suggests that current approaches are vulnerable to social desirability bias, which may allow advisors to exert substantial influence over their clients' choices. Moreover, the sustainability attributes of investment products cannot easily be disentangled from financial characteristics such as performance, liquidity, and fees. We address these challenges by developing a choice-based conjoint approach that integrates sustainability preferences with financial product features. Our aim is to reduce behavioral biases and elicit sustainability preferences under conditions that more closely resemble real-world decision-making.

Keywords: Sustainable Investing, Preferences

JEL Codes: D14, G11, G41, J32, Q56

1 Introduction

The growing awareness of sustainability challenges among financial market participants has fundamentally reshaped capital allocation processes worldwide. An increasing share of global assets under management is now invested according to sustainability criteria, reflecting heightened investor demand for products that align with environmental and social goals [GSIA, 2021]. A growing body of research shows that sustainability-related information can significantly affect investor preferences, although these preferences vary widely across individuals [Heeb et al., 2022, Riedl and Smeets, 2017, Hartzmark and Sussman, 2019, Bauer et al., 2021]. Such heterogeneity plays a critical role in shaping asset prices, as differences in tastes for sustainable attributes may translate into differences in expected returns, willingness to pay, and risk assessments [Fama and French, 2007]. Understanding sustainability preferences is therefore essential not only for explaining market outcomes but also for harnessing the financial system's potential to support sustainable development.

At the same time, regulatory frameworks increasingly require financial institutions to integrate sustainability preferences into advisory processes. This is particularly evident in the European Union's implementation of MiFID II sustainability preference requirements and similar regulatory developments in Switzerland. In practice, however, the effective integration of sustainability considerations into financial advice remains challenging. Many investors have limited awareness of their own sustainability preferences, and the advisory process often requires clients to express preferences using predefined categories – frequently aligned with regulatory templates rather than reflecting investor mental models or lived experience. As sustainability has become a complex and multifaceted concept, clients and advisors alike face

information overload, low sustainable finance literacy [Filippini et al., 2024], and limited familiarity with sustainable financial products. The combination of these factors increases the likelihood of suboptimal investment decisions and subsequent dissatisfaction with advisory outcomes.

Behavioral frictions further complicate the elicitation of sustainability preferences. Evidence suggests that stated preferences are highly sensitive to question framing, social desirability pressures, and the influence exerted by advisors during the advisory conversation. Similar discrepancies between stated and revealed preferences have long been documented in the context of risk profiling, and there is extensive literature discussing the advantages and disadvantages of a wide range of elicitation methods [Garagnani, 2023, Falk et al., 2023, Lönnqvist et al., 2015, Holt and Laury, 2002].

Furthermore, investors' preferences for risk depend on how they perceive risk – whether as variance, probability of loss, or other intuitive dimensions – leading to misalignment in communication and mismatches between investment choices and actual comfort levels [Zeisberger, 2022, Holzmeister et al., 2020]. In delegation settings, such miscommunication has been shown to produce dissatisfaction and accusations of mis-selling or greenwashing when advisor and client perceptions diverge [Kling et al., 2022, Stefan et al., 2023]. A parallel challenge exists for sustainability: because the concept is intrinsically broad and multidimensional, individuals hold varying understandings of what constitutes "sustainable investing." If these subjective perceptions differ between clients and advisors, elicitation errors and misaligned product recommendations are likely to follow. [Peters et al., 2025] provide first evidence of similar issues in terms of sustainability perception, reporting differences between finance professionals and the general population.

Despite these challenges, the tools used in practice to elicit sustainability preferences lag significantly behind those used to elicit risk preferences. Extensive evidence in behavioral finance and financial advice shows that structured, quantitative, and validated tools are essential to reliably measure risk preferences and reduce advisor-induced bias. In contrast, sustainability preferences are typically assessed through simplistic yes/no questions or coarse regulatory categories – most notably those prescribed under EU MiFID II. Such approaches oversimplify a complex preference structure that, according to the academic literature, involves multiple underlying motivations. Prior research distinguishes at least four types of motives driving sustainable investment decisions: financial (i.e., expectations of superior risk-adjusted performance), value-based (ethical or moral alignment), impact-oriented (desire to contribute to real-world outcomes), and expressive (identity signaling) [Chatterji et al., 2009, Riedl and Smeets, 2017]. Simple preference elicitation tools are fundamentally unable to capture this multidimensionality, let alone identify the relative importance of each motive for individual investors.

Furthermore, investors face economically meaningful trade-offs when choosing sustainable investments. Sustainability attributes often come at the cost of higher fees, lower liquidity, or deviations from optimal portfolio risk-return profiles. The extent to which sustainability-minded investors are willing to accept such trade-offs is a central empirical question, with direct implications for market equilibria, sustainable fund design, and regulatory expectations. Recent evidence also documents interactions between financial and nonfinancial preferences [Bachmann et al., 2024]: sustainability motives may influence performance beliefs, and conversely, (potentially biased) financial expectations may shape sustainability choices. These interactions further underscore the need for elicitation approaches capable of capturing preferences in a manner that combines sustainability dimensions wit potentially

confounding financial attributes.

The role of the advisor adds another important layer of complexity. Advisors are central intermediaries in financial decision-making, but research shows that their own sustainability literacy, preferences, and communication styles influence the client's expressed preferences and eventual investment behavior [Paetzold et al., 2015, Cauthorn et al., 2025]. In many cases, advisors report avoiding sustainability discussions due to their own lack of expertise and concerns about overwhelming clients with complex or ambiguous information. As a result, the elicitation of sustainability preferences often becomes a box-ticking exercise rather than an informative component of financial planning. Given the regulatory importance and market relevance of sustainability preferences, improving their elicitation is thus critical for consumer protection, advisory quality, and the credibility of sustainable finance more broadly.

Taken together, these developments highlight a substantial gap between the complexity of sustainability preferences documented in academic research and the simplistic tools currently used in financial advice. While the literature offers a nuanced understanding of the motivations behind sustainable investing, existing advisory practices fail to incorporate these insights into reliable preference elicitation mechanisms. This gap limits the ability of financial intermediaries to offer tailored advice, exacerbates the risk of preference misclassification, and may undermine investor trust in sustainable finance.

The present paper addresses this gap by developing a structured, choice-based conjoint approach to elicit sustainability preferences in a way that is robust to behavioral biases, minimizes advisor influence, and combines sustainability attributes with financial characteristics. Conjoint analysis has long been recognized as the gold standard for capturing heterogeneous

preferences in settings involving trade-offs across multiple attributes. Applying this method to sustainability preferences enables a systematic identification of the relative importance investors assign to different sustainability dimensions, and – crucially – their willingness to trade off sustainability attributes against financial performance, liquidity, and fees. This approach also offers a way to translate complex sustainability concepts into intuitive choice tasks that reduce reliance on abstract definitions and subjective perceptions.

By providing an elicitation tool that is theoretically grounded, empirically validated, and practically implementable, our work contributes to the literature on sustainable finance, financial advice, and behavioral household finance. It also provides guidance for regulators and market participants seeking to improve the integration of sustainability preferences into investment processes. More broadly, our approach strengthens the conceptual and methodological foundations needed to align investor intentions with real investment decisions, thereby supporting the financial sector's evolving role in fostering sustainable development.

Our study contributes to the growing number of papers addressing investor preferences for sustainability. The literature differentiates motivations for investors to consider sustainability in their investment decision: financial, value-based, impact-oriented, and expressive considerations [Chatterji et al., 2009, Riedl and Smeets, 2017]. Previous studies suggest that the demand for sustainable investments is driven by a combination of both, financial and non-financial, motives [Riedl and Smeets, 2017, Hartzmark and Sussman, 2019, Bauer et al., 2021].

To evaluate whether non-financial or financial motives dominate, a large stream of the sustainable investment literature focuses (i) on the question of whether investors are willing to pay (WTP) for sustainability and (ii) on the link between the probability of holding

6

a sustainable asset and return expectations, i.e., financial beliefs. A number of empirical [Barber et al., 2021] and experimental [Heeb et al., 2023, Gutsche and Ziegler, 2019, Rossi et al., 2019, Apostolakis et al., 2018] studies find confirming evidence for the prevalence of a significant WTP by sustainable investors. These results thus point to the fact that investors gain non-financial utility from sustainable investments that leads them to accept lower financial returns, and as a consequence, "pay for sustainability." At the same time, a number of papers argue that sustainable investors hold optimistic return expectations and may thus be financially motivated to hold these investment products. Hartzmark and Sussman [2019], for example, show in an experimental setting that investors are more optimistic regarding the return potential of funds with a sustainability label. In confirmation and based on more recent survey data and portfolio holdings, Giglio et al. [2021] report that investors with larger shares of sustainable funds in their portfolios are, in general, more optimistic about the returns of these investments and Engler et al. [2023] find that individuals who expect higher returns on sustainable assets invest larger shares of their portfolio sustainably. Furthermore, Bachmann et al. [2024] show based on survey evidence using impact investors, that the two motives might be interlinked: Investors with very strong nonfinancial preferences exhibit significantly more optimistic risk/return expectations for impact investments.

This literature confirms the importance of gaining a more in-depth understanding of sustainability preferences, as well as the need to establish stronger links between the elicitation of financial and non-financial preferences. This paper provides a detailed introduction to a comprehensive choice-based conjoint approach for capturing sustainability preferences, risk/return preferences, and willingness to pay fees.

2 Methodology

Understanding individual preferences is an integral part of predicting decision-making behaviour of consumers. In consumer research, a fundamental distinction is made between two forms of decision data: revealed preferences and stated preferences. Both approaches aim to provide insights into consumer behavior. Revealed preferences are derived from the observation of actual market choices, that is, the effective behavior of consumers in real purchasing situations. In contrast, stated preferences are obtained through surveys in which consumers are presented with hypothetical decision scenarios and asked to indicate their preferred alternative Morikawa et al. [2002], Louviere et al. [2010] Although stated preference data are collected in hypothetical situations and therefore entail certain limitations regarding their realism, they are particularly suitable when the aim is to clearly identify consumer preferences based on product and service attributes. In real market contexts, attributes often cannot be varied sufficiently, or correlated product characteristics such as price and size cannot be separated. As a result, revealed preferences may not fully reflect the true and primary determinants of consumer decisions Morikawa et al. [2002], Hsiao [2018] For the study of consumer decision-making traditional demand theories, consider only constraints related to monetary aspects, such as the price of a product or service Maier and Weiss [1990]. This perspective originates from the era of the Industrial Revolution, when products with few distinguishing features were mass-produced Lancaster [1971]. But in the age of product customization and individualism this represents a substantial limitation as products are characterized by a range of differing attributes Maier and Weiss [1990]. The American economist Kelvin Lancaster addressed this shortcoming in his theory of consumer demand Lancaster [1966]. In his book Consumer Demand – A New Approach, he emphasized the following: when products and services differ in their attributes, their individual demand curves

should also behave differently, because each consumer evaluates and values these attributes personally Lancaster [1971]. This also implies that changes in product or service attributes will affect each consumer differently, resulting in distinct reactions in the form of altered demand curves. Lancaster accounted for this by formulating two key assumptions:

- All products and services possess objective attributes that are relevant to consumer decisions.

- Consumers react differently to the attributes of a product, but not in their fundamental assessment of them. It is the attributes and the utility they generate that matter to consumers. They are interested in the attributes of products and services, rather than in the product or service itself.

Conjoint analysis, a survey method, aims to measure how respondents trade-off between product attributes and respective levels Steiner and Meißner [2018]. Choice-based conjoint analysis (CBCA) is one such method, most frequently and widely used Steiner and Meißner [2018], where individuals indicate their preferences by making a choice among various product alternatives with differing combinations of attributes Asioli et al. [2016].

CBCA overcomes several limitations of general conjoint approaches Apostolakis et al. [2018]. As opposed to asking respondents to rate or rank alternatives in traditional conjoint analysis, CBCA allows respondents to choose a preferred alternative which is often assumed to better resemble decisions that individuals make in the actual world Cohen [1997]. Contrary to having respondents rate or rank options, making a choice is typically considered less mentally demanding having a straightforward interpretation Steiner and Meißner [2018]. Another advantage of CBCA is the "none" option, which can be picked by a respondent if none of the alternatives provided are attractive enough Cohen [1997].

The components of a CBCA can be arranged in different ways, as described below:

Attributes: Attributes refer to the features or characteristics of the product alternatives under consideration. Each product alternative can be associated with multiple attributes. Consumer make their choices for or against particular alternatives based on these attributes Street and Burgess [2007]. To identify the relevant attributes of a CBCA, it is advisable to conduct focus groups or to analyze quantitatively the available product landscape. This ensures that only relevant attributes are included in the CBCA. However, the list should not be too long, as this would increase the complexity of the CBCA Holmes et al. [2017]. Empirical studies have shown that between five and a maximum of nine attributes are suitable Auspurg and Liebe [2011].

Levels: Levels denote the different manifestations of each attribute. These cn be quantitative as well as qualitative in nature. By varying the levels, it becomes possible to observe which attributes, and which specific manifestation, generate utility for respondents Street and Burgess [2007].

Choice Sets: A CBCA consists of a series of choice sets. Each choice set contains the product alternatives available to the decision-maker described by the defined attributes and levels. The number of product alternative included determines the size of a choice set Street and Burgess [2007]. Empirical evidence suggests that choice sets comprising up to four product alternatives are perceived as easily manageable by the decision makers Auspurg and Liebe [2011]. The number of choice sets and consequently the number of choices required to measure the utilities or in case of our prototype the investment preferences depend on the number of attributes, the number of levels and the number of alternatives which are presented in one choice set. The higher the number of attributes or levels are, the more

choices are required to measure the utility for the individual product characteristics.

After the respondents have assessed different product choices, these assessments are then broken down to estimate the utility of each attribute-level of the products, also known as part-worth utilities Steiner and Meißner [2018], Amaya-Amaya et al. [2008]. As such, CBCA uses a decompositional approach. These part-worth utilities determine the significance that a respondent assigns to specific attributes or features Steiner and Meißner [2018]. The most common method to estimate these part-worth utilities at an aggregate level has been multinomial logistic (MNL) regression, and applying a hierarchical Bayes approach at an individual level Steiner and Meißner [2018].

Respondents assess several products within choice sets, but they usually only specify which product they would select and one does not gain insight into the relative preferences for the non-selected options Orme [2000]. Hence, we are left with sparse data for each respondent. Hierarchichal Bayes multinomial logistic (HB-MNL) models have been known to provide robust individual part-worth estimates, even when limited data was available from each respondent Sawtooth Software, Inc. [2021]. Basic MNL models suffer from the independence of irrelevant alternatives (IIA) assumption Cohen [1997]; Orme [2000]; Elshiewy et al. [2017], which suggests that the probability of choosing a particular option from a choice set remains unaffected by the availability or unavailability of other alternatives in the set Cohen [1997]. Such is not the case in reality, as the substitution rate among equally appealing choices, with different combination of attributes, cannot be assumed to be equal Orme [2000]. HB-MNL models overcome this assumption as a maximum-utility rule instead of a logit rule can be applied to individual-level estimates Orme [2000]. HB-MNL has the ability to "borrow" information from different respondents and model more accurate individual-level estimates

rather than calculating the "average" estimates for the whole sample, subsequently disassociating heterogeneity from noise Orme [2000].

2.1 Model

When an individual - n has to make a choice from K alternatives, each alternative offers a level of utility U_{nk} and the individual selects the alternative maximising U_{nk} Elshiewy et al. [2017]. As this utility is known only to the decision-maker Elshiewy et al. [2017], the random utility model follows the form:

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

where V_{nk} and ϵ_{nk} are the observable and respectively the unobservable part of utility derived from choosing an alternative. This random utility model forms the basis of MNL models Elshiewy et al. [2017]. Since the individual only chooses 1 alternative out of K alternatives, these K alternatives with different attribute levels act as explanatory variables defined under vector X_{nk}. According to Elshiewy et al. [2017] the observable part V_{nk} i.e., "proxy of the decision-maker's utility" is related to the explanatory or independent variables X_{nk} through $V_{nk} = f(X_{nk})$. Generally, this utility function assumed is linearly-additive Elshiewy et al. [2017], Steiner and Meißner [2018] :

$$V_{nk} = f(X_{nk}) = \sum_{k=1}^{K} \beta_{nk} * X_{nk} \tag{2}$$

where the vector of β_{nk} are the part-worth utility parameters. The vector of β in Equation 2 is estimated through the MNL model and explains the effect of explanatory variables X_{nk}

on the choice-probability of an individual.

$$P_{nj} = \frac{exp(V_{nj})}{\sum_{k=1}^{K} exp(V_{nk})} = \frac{exp(\beta'.X_{nj})}{\sum_{k=1}^{K} exp(\beta'.X_{nk})} \tag{3}$$

Choice probability P_{nj} , according to Equation 3 is the probability of an individual n choosing an alternative j out of K alternatives. Since HB-MNL model is a "Hierarchical" model, estimating the individual choice probabilities, given the individual part worth utilities (Ref Equation 2), is an integral part of the lower hierarchical layer Eggers et al. [2022]. At a higher layer in the hierarchy, to include heterogeneity among individuals in the model, it is assumed that a multivariate normal (MVN) distribution describes the individual part worth utilities Eggers et al. [2022], Natter and Feurstein [2002].

$$\beta_n = \text{MVN}\ (\alpha,\ W) \tag{4}$$

This heterogeneity MVN distribution of the part worth β_n of an n_{th} individual is defined by α, a vector of means of the individual part worth distribution and W, a matrix of variances and covariances of different individuals' part worth distribution.

2.2   Estimation Procedure

The iterative procedure of parameter estimation is described in Figure 1. In step (A.), after having defined our distribution function of the part-worth utilities β, we also define and assume the distribution function of our other parameters α and W. Supposedly the α is distributed normally with mean as average of betas and covariance matrix equal to W/n where n are the number of individuals. We also assign default values to these parameters to
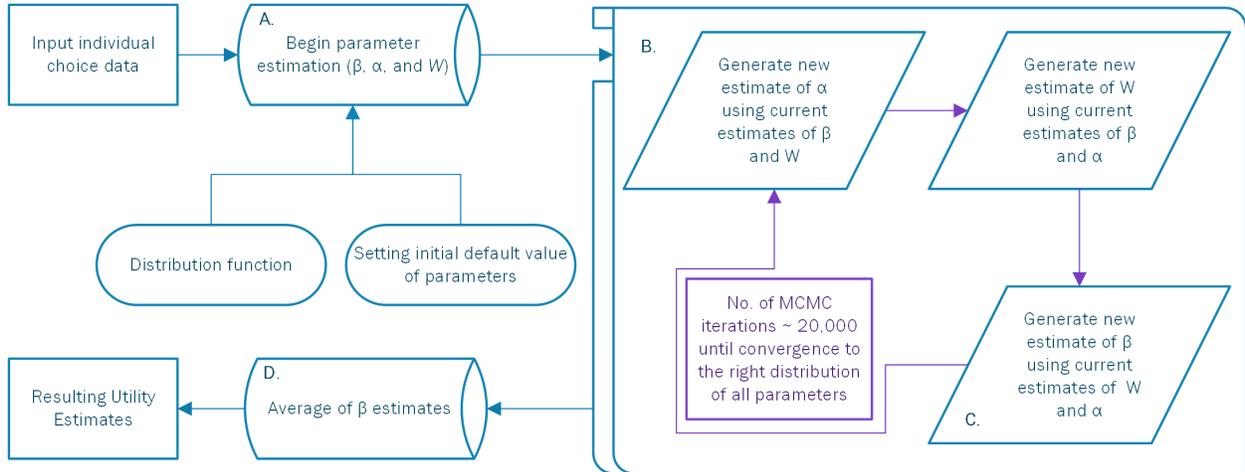
begin the optimization procedure.

Figure 1: Parameter estimation procedure of HB-MNL model

Note: Own illustration based on explanations from Elshiewy et al. [2017], Eggers et al. [2022], Sawtooth Software, Inc. [2021]

The iteration begins with a 3-step process, marked as (B.). Firstly, given the current estimate of β and W, estimate of α is obtained from the distribution as described earlier. Secondly, with the present estimates of α and β, new estimates of W are obtained from a prior defined matrix of covariance, i.e., inverse Wishart distribution Natter and Feurstein [2002]. Lastly, using the current estimates of α and W, the betas (β) are estimated through the "Metropolis Hastings Algorithm" under the step marked as (C.) in figure 1. This process ensures that the betas are drawn repeatedly to resulting in a better fit of the model when the iterative process has converged Eggers et al. [2022], Sawtooth Software, Inc. [2021].

These 3 steps in (B.) of figure 1 are repeatedly performed to re-estimate the parameters (α, W and β) conditionally until it converges to the right distributions for all these parameters. This estimation process is known as "Gibbs sampling technique" Sawtooth Software, Inc.

[2021].The Monte Carlo Markov Chain (MCMC) is also deployed in the step (B.), where each estimation iteration is based on the previous iteration performed in a chain-like structure. The convergence of the iterations are ensured by the Markov chain property Sawtooth Software, Inc. [2021]. For instance, figure 2 depicts the convergence of the mean distribution to the true posterior distribution over 20,000 iterations.
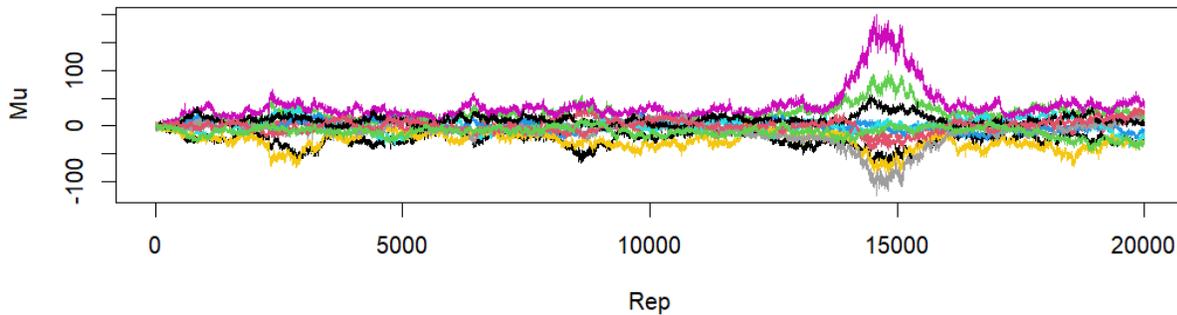

Figure 2: Convergence of MCMC iterations

Note: Graphical output from analysing an individual's choice dataset in ChoiceModelR (R programming)

As a result, the β estimates are averaged across the iterations in step (D.) and summarized as the individual part-worth utilities or individual preferences. This is presented as one of the key advantages of HB-MNL model Elshiewy et al. [2017]. Furthermore, the MCMC algorithm has the additional benefit of providing estimates of other model parameters in addition to the betas Allenby et al. [2005]. The whole estimation process is highly robust Elshiewy et al. [2017], and the resulting values exhibit independence from the initial values used at the beginning of the estimation process Sawtooth Software, Inc. [2021].

2.3   R Package - ChoiceModelR

There are numerous open source programming languages that could be utilized in estimation and statistical analysis. The R programming language offers the package `ChoiceModelR`, which facilitates the implementation of a HB-MNL model for estimating part-worth utilities. Sermas [2012] provides a sophisticated function `choicemodelr` which enables estimation of the betas using a range of parameter values discussed in section 2.1 and 2.2.

Initially, the input choice data has to be structured in a certain way such that choidemodelr can easily process the data. Table 5 shows an excerpt of an individual choice dataset where respID is the unique respondent ID and qID is the question number or choice set number.

AltID is the alternative number in the given choice set or question. In this choice set, there were three attributes where the first and the second attributes both had four levels, while the third attribute had three levels. Finally, the Choice column provides an individual's choice of the alternative within the choice set.

The parameters specified in modelling the choice data using the choicemodelr function are described in detail in table 6.

The `xcoding` argument of the choicemodelr function ensures that, when assigning 0 value, the choice data is effects coded i.e., the last level within every attribute is eliminated to avoid dependencies. The `mcmc` attribute allows us to specify values for total number of iterations and number of iterations to be used for estimation of the betas. The most important argument in the model is `prior` where one can specify the initial parameter values as per our discussion in section 2.1 with respect to equation 4. The α is assumed to be 0 (normal distribution), hence the `mubar` value is set at 0. The `v` sub-argument specificies the prior (initial) value of the variance and subsequent covariance matrix to be assumed, similar to

the explanation pertaining to equation 4 . The `df` value also assigns additional degrees of freedom (excluding the number of parameters estimated) to the covariance matrix.

Numerous combinations of iterations, the `df` and `v` were tested during analysis. High values of degrees of freedom or prior variance would lead to a high variation in the results, leading to less chances of convergence in the designated number of iterations. Also, if a high value for `df` is specified, there is a higher degree of influence of `v` and sufficient data is required to change that value Sawtooth Software, Inc. [2016]. Usually, a value of 1 is considered for `v` Sawtooth Software, Inc. [2016]. However, a higher value for the prior variance has the tendency to better fit individual data than focus on the borrowing ability from the population Sawtooth Software, Inc. [2016]. Accordingly, the default value of 2 for `v` in `choicemodelr` function is deemed more appropriate and aligns more closely with our objective of estimating individual utilities.

The convergence of the data was typically observed with 20,000 iterations in comparison to using 50,000 or 100,000 iterations. Furthermore, a higher number of iterations are computationally intensive and time consuming. On an average, the time taken to display the results ranged from 10 seconds (20,000 iterations) to 70 seconds (100,000 iterations).

2.4   Statistical Fit

As discussed earlier in section 2.1 through equation 3, we estimate the individual's probability of choosing an alternative in the choice set. The product of these probabilities is known as likelihood Sawtooth Software, Inc. [2021]. Root-likelihood (RLH) is considered as a goodness of fit measure which assesses how well a model fits the data. It is calculated by taking the nth root of the likelihood, where n is the number of choices made by the individual

Sawtooth Software, Inc. [2021]. In essence, RLH can be defined as the geometric mean of the probabilities. In a chance model, the expected RLH is inversely proportional to the number of options in the choice task. For instance, if a choice task comprises of four options, then the chance model has an RLH value of 0.25. Accordingly, an RLH value of 1 suggests that the predicted probabilities of an individual's choices align perfectly with the actual choices.

Sawtooth Software calculates the RLH value alongside the respondent utilities once the choice data has been processed. Using the same choice data collected via the Sawtooth survey, we estimated models using choicemodelr function and the resulting RLH values for some respondents ranged from 0.94 to 0.99, indicating a strong fit.

2.5 Experiment Design

The discrete choice experiment is designed in R using the `cbcTools` package. The full factorial profile (different combinations of attribute and levels) is generated with `cbc_profiles` after which the experiment designs are constructed with `cbc_design(method = "cea")`, which implements the Coordinate Exchange Algorithm (CEA) with attribute-by-attribute D-error optimisation for Bayesian D-efficient designs. The resulting comparison of choice sets are displayed in Figure 3, which reports several summary statistics for design quality.

Four experiment designs are evaluated, each with four alternatives, differing only in the number of choice tasks per respondent (4, 5, 6, and 7 tasks for Designs 1–4, respectively; see Figure 3). For each design, the D-error (Null and Prior), a balance metric, an overlap metric, and the proportion of distinct profiles used ("profile usage") is reported. D-error indicates how efficiently a design captures information from respondents in an experiment:

the smaller the D-error, the more informative (and thus better) the design. It decreases from 1.4 in Design 1 to 0.8 in Design 4. The balance metric, which reflects how evenly attribute levels are distributed across the design, ranges between 0.66 and 0.70, indicating a good spread of levels across choice sets. The overlap metric is equal to 0 for all four designs, implying that attribute levels do not coincide across alternatives within the same choice set and thus maintain discriminatory power. Profile usage is the highest in Design 3 to 88.9% (24/27 profiles), indicating maximum usage of the factorial profiles.

Taking into account the design metrics, Design 3 is selected as the final experimental design for the prototype. This design requires each respondent to answer six choice tasks with four alternatives each and combines a low D-error (0.93), high balance (0.70), zero within-set overlap, and the highest profile coverage (88.9%) among the evaluated designs.

```
Structure
=====================
   Design Method respondents questions
Design 1     cea             1            4
Design 2     cea             1            5
Design 3     cea             1            6
Design 4     cea             1            7
Alternatives Blocks Profile Usage
             4        1 (16/27) 59.3%
             4        1 (18/27) 66.7%
             4        1 (24/27) 88.9%
             4        1 (23/27) 85.2%
No Choice Labeled?
        No          No
        No          No
        No          No
        No          No

Design Metrics
=====================
   Design Method D-Error (Null) D-Error (Prior) Balance Overlap
Design 1     cea      1.412017        1.412017   0.656   0.000
Design 2     cea      1.113708        1.113708   0.683   0.000
Design 3     cea      0.928414        0.928414   0.699   0.000
Design 4     cea      0.792960        0.792960   0.680   0.000

Interpretation:
- D-Error: Lower is better (design efficiency)
- Balance: Higher is better (level distribution)
- Overlap: Lower is better (attribute variation)
- Profile Usage: Higher means more profiles used
```

Figure 3: Profile Selection Criteria

3 Specifications of the Tool and Videos

The financial and sustainable investment strategy related preferences of individual private investors are, as previously noted elicited using the CBCA method, which is embedded in the prototype workflow illustrated below. The whole decision workflow of the prototype can be divided in three phases: assessment instruction, investment preference assessment and risk capacity assessment. The following sections provide a detailed description of all three phases.
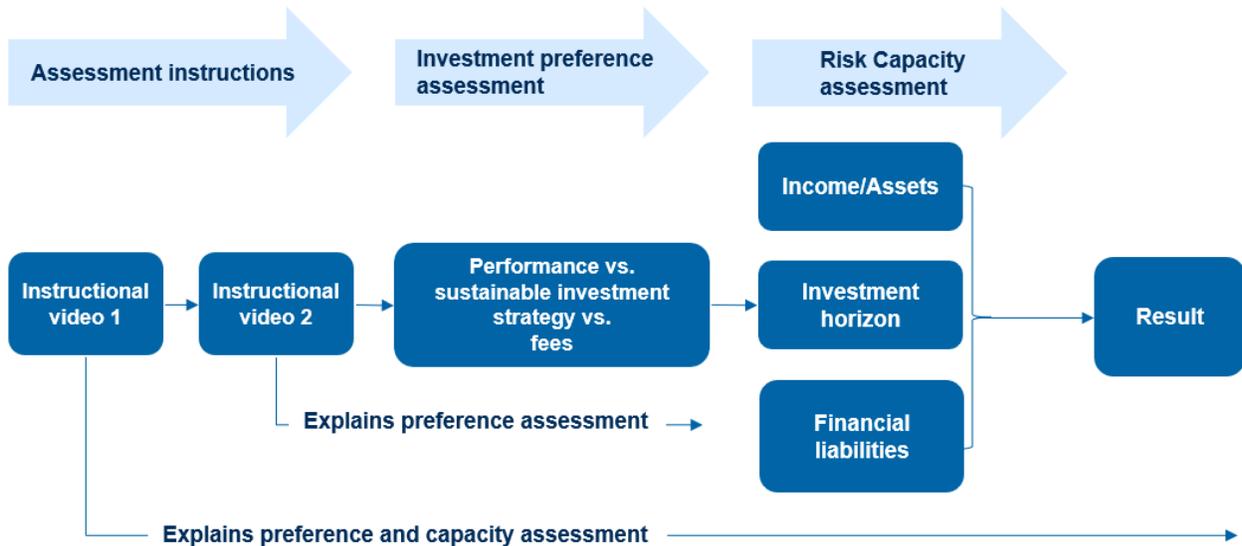
Figure 4: Prototype workflow

3.1 Assessment instructions

To convey the content of the CBCA to private investors as clearly as possible, two videos were produced and shown prior to the start of the assessment. The first instruction video presents the overall procedure of the assessment, while the second video explains the individual attributes and their respective levels, complemented by illustrative examples. Given the scope of information – which would otherwise have resulted in a substantial amount of text – the video format was chosen over a purely textual presentation. As part of a survey of 1,000 private French individuals, respondents were asked to evaluate the scope and length of the second video. The feedback was positive: more than 70% indicated that the total experiment (including the video) had an appropriate length and a large majority of close to 90% indicated that the content of the video was conveyed in a way that facilitated the execution of the CBCA. While nearly 60% answered the comprehension questions on sustainability investment strategies and fees correctly, distinguishing between high- and low-impact

strategies appeared to be challenging. Only 26% and 15% , respectively, were able to answer these two questions correctly. This finding led to the decision not to differentiate impact strategies by degree of impact, but rather to combine them into a single level within the CBCA (see below Chapter 4.2.2).

3.2 Investment preference assessment

To elicit investment preferences, the CBCA method introduced in Chapter 2 was employed. The determination of which attributes are relevant for the CBCA, and which are not, depends both on the research context and on the perceptions of private investors. The present prototype focuses for the assessment of the investment preferences on financial aspects (risk/return as well as fees) and sustainable investment strategies. All three dimensions were based on quantitative analysis of the existing market, complemented by the perception of private investors and client advisors, and are described in detail below.

3.2.1 Attribute: Risk tolerance/Return

For the financial attribute risk/return, three levels were selected, and their choice can be justified as follows. First, returns are inherently a consequence of the level of risk taken - higher risk entails greater return potential, and vice versa. As a result, return preferences cannot be measured independently of risk [Markowitz, 1952]. Consequently, the two dimensions are combined into a single attribute with varying manifestations, with risk expressed in terms of value fluctuations. Second, presenting only average returns would, over a longer period, inevitably suggest exclusively positive outcomes. It is, however, essential to make investors aware of both positive and negative fluctuations. For this reason, fluctuation ranges are presented in combination with the expected long-term annual return. Third, historical risk and

return figures from both 308 sustainable and 726 conventional investments sourced via LSEG and the fund data base of myfairmoney.ch. This broad data basis enhances the robustness of the three clustered return categories. Finally, while it would in principle be possible display qualitative labels such as "high risk" or "medium risk" instead of numerical values, such an approach presupposes a certain level of financial literacy. Moreover, qualitative categories such as high, medium, or low are highly subjective and may be interpreted differently by each respondent. Empirical research in the survey context has already confirmed these limitations [Borgers et al., 2003].

Attribute levels	Average return	Risk fluctuation
Attribute level 1: Low risk/return	1 percent	-6 percent to +8 percent
Attribute level 2: Medium risk/return	3 percent	-11 percent to +16 percent
Attribute level 3: High risk/return	6 percent	-21 percent to +33 percent

Table 1: Attribute levels: Risk/Return

To derive the figures reported in Table 1, historical performance data for the sample fund database described above are used. All funds with non-missing history of annualized performance (measurement period: last 10 years up to end of January 2025) and annualized standard deviation (SD) are ordered by their annualized standard deviation and split into three equally sized groups (terciles) representing low, medium, and high risk. For each tercile, the mean annualized return and mean standard deviation are calculated, and an approximate 90% fluctuation range is obtained under the assumption of normally distributed annual returns (Mean $\pm 1.64 \times$ SD). These ranges and corresponding mean returns are rounded to whole percentage values to improve comprehensibility for respondents, resulting in the three risk/return combinations shown in Table 1.

3.2.2 Attribute: Sustainable investment strategy

For the attribute of sustainable investment strategy three levels were initially selected, and their choice can be justified as follows. Sustainability objectives can be pursued through different sustainable investment strategies, each with distinct levels of effect on the environment. The effects targeted by these approached can, in turn, be linked to specific investor motives, which have been extensively documented in the academic literature [Chatterji et al., 2009, Busch et al., 2021, Edmans and Kacperczyk, 2022]. The manifestations used in the prototype were designed to reflect, on the one hand, the typical attitudes of two well-documented investor types - values-based and impact-oriented investors - while, on the other hand, also accounting for the actual product offerings available on the financial market. In addition, the option of pursuing no sustainability objectives was included. To capture the diversity of existing strategies, the fund database of the platform myfairmoney.ch was analyzed. This analysis suggested a threefold distinction: one category comprising values-based strategies, and two categories representing impact-oriented strategies that differ in the degree of impact. However, both a survey of private investors (see above Chapter 4.1) and an online interview in written format with client advisors indicated that private investors find it difficult to differentiate between varying degrees of impact. As a result, the final version of the prototype presents only two sustainable investment strategies as options, beside the option not pursuing any sustainability objectives. This modification also helped taking into account another feedback provided by the client advisors, who indicated that a survey requiring eight choices was too time-consuming. By reducing the number of levels for the sustainability strategies, the total number of required choices to measure utility or investment preference was lowered to six.

Attribute levels	Examples
Attribute level 1: Alignment	Such investments could be made in companies that are already contributing to sustainability goals or pursuing a clear reduction path.
Attribute level 2: Impact	Such an investment could involve a strategy of encouraging the invested companies to become more sustainable by exercising shareholder rights (voting rights or dialogue with the companies).
Attribute level 3: No sustainability	Such an investment does not take sustainability criteria into account.

Table 2: Attribute levels: Sustainability

The prototype deliberately refrained from using the technical classification of individual sustainable investment strategies as attribute levels. Such a distinction would require a considerable degree of financial and product knowledge. Instead, the wording of the options was kept concise and framed in such a way that investors - regardless of their level of expertise - could more easily identify with the statements and align them with their own motives.

3.2.3 Attribute: Fees

For the third financial attribute fees, three levels were selected as well. Fees not only differentiate between active and passive investment styles but also allow a distinction to be made between impact-oriented strategies. Strategies with a higher degree of impact can be distinguished from those with lower impact, as they typically involve higher fees. These elevated costs can be explained by the fact that such investment vehicles often manage relatively small volumes of assets, meaning that fixed cots are spread across smaller asset base. In addition, the analysis of the underlying investments is generally more complex and time-intensive, which further contributes to higher fees. This differentiation simultaneously reduces the complexity of the decision task for private investors.

Attribute levels	Characteristics
Attribute level 1: Low fees	0.5 percent
Attribute level 2: Average fees	1.5 percent
Attribute level 3: High fees	2 percent

Table 3: Attribute levels: Fees

The fee levels presented are based on investment products currently available on the market and were derived from an analysis of 1034 investment products downloaded from LSEG. The fund sample is segregated into 3 equal parts (terciles) based on non-missing total expense ratios (TER). For each tercile, the mean TER is calculated and reported as respective attribute levels (see Table 3). While passive investment products charge on average around 0.4 percent, the costs of actively managed products amount to approximately 0.8 percent. Fees of about two percent were reported for investment products associated with high-impact investing strategies, which are among the most expensive form of investment.

3.3 Risk capacity assessment

In addition to eliciting preferences regarding sustainability objectives, fees, and risk tolerance, it is essential to assess an investor's risk capacity when determining an appropriate financial product. Risk capacity refers to an investor's objective financial ability to bear financial risks. It is determined by the investor's economic circumstances, such as existing wealth or the ability to accumulate wealth, investment horizon, and liquidity needs. While a high savings rate and a long investment horizon increase risk capacity and enable an investor to take on greater risks, a short investment horizon and a low savings rate tend to constrain it.

Under the Swiss Financial Services Act (FIDLEG), both financial capacity and investment

preferences must be assessed before providing an investment recommendation, and the recommendation must be consistent with the outcome of this assessment. However, the legislator does not prescribe how these factors should be measured, resulting in a variety of approaches across providers of investment advisory and discretionary portfolio management services.

For the present prototype, the following four questions were selected:

Question	Response options
1. Are you able to save at the end of the month?	Yes; No
2. What percentage of your wealth would you like to invest?	5-10 percent; 11-20 percent; 21-30 percent; 31-40 percent; more than 41 percent
3. What is your investment horizon?	less than 3 years; 3-8 years; more than 8 years
4. Which financial instruments have you already used?	Saving accounts; Bonds/Equities, Bond/Equity Funds; Options/Structured Products

Table 4: Attribute levels: Fees

The above listed questions are intended to capture the investor's financial flexibility (Question 3), the ability to save and thereby build reserves (Question 1), and related to that the likelihood that investments will not need to be liquidated prematurely to cover unforeseen expenses. The question on savings ability was deliberately not linked to a specific monetary amount or percentage, as individuals' financial circumstances vary substantially. Using broad ranges for saving amounts would therefore have yielded little meaningful information at the individual level. Moreover, calculating one's personal savings rate can be challenging for some respondents, and the overall assessment was designed to be as simple and low-threshold as possible.

Finally, Question 2 has a specific methodological purpose: it introduces information about

the proportion of total wealth the investor intends to invest, which can qualify the interpretation of risk capacity derived from the other items. Risk capacity constitutes the upper bound for admissible risk; the level of risk taken must never exceed it. However, when an investor expresses a high risk preference but intends to invest only a small share of their total wealth (e.g., 5–10%), the effective risk capacity for that specific investment may be higher because the exposure represents only a minor fraction of overall assets. Conversely, when the intended investment proportion is large, the measured risk capacity must be applied strictly. In this sense, Question 2 helps determine whether the investor's intended allocation leaves room for higher-risk impact investments that align with their preferences, or whether the objective financial constraints should override these preferences.

3.4   Final evaluation

The results section of the prototype produces an individualized results report summarizing the outcome of the preference elicitation. Figure 5 presents a bar chart that displays the relative importance of each product attribute in percentage terms (risk/return, sustainability goals, and fees). Next to the chart, the respondent's preferred level for each attribute is illustrated, for example a specific risk/return combination (average annual return and fluctuation band), a preferred sustainability orientation, and a fee level.

In addition to the graphical summary, the report contains two complementary narrative elements: a *recommendation* and a *product-based recommendation* as depicted in Figure 6). The recommendation summarizes, the combination of attribute levels that best matches the respondent's answers in plain language. The product-based recommendation then goes one step further by translating this general preference profile into an indicative product category. In the prototype, this takes the form of a short text suggesting a suitable type of investment

Relevanz der Produkteigenschaft für Ihr Finanzprodukt	Ihre bevorzugte Ausprägung der Produkteigenschaft

Risiko/Rendite

Ø Jahresgewinn 6%;
Renditeschwankung: −21% bis +33%

47%

Nachhaltigkeitsziele

Ich investiere mein Geld nur in Unternehmen, die bereits erste Schritte zu nachhaltigem Handeln unternommen haben.
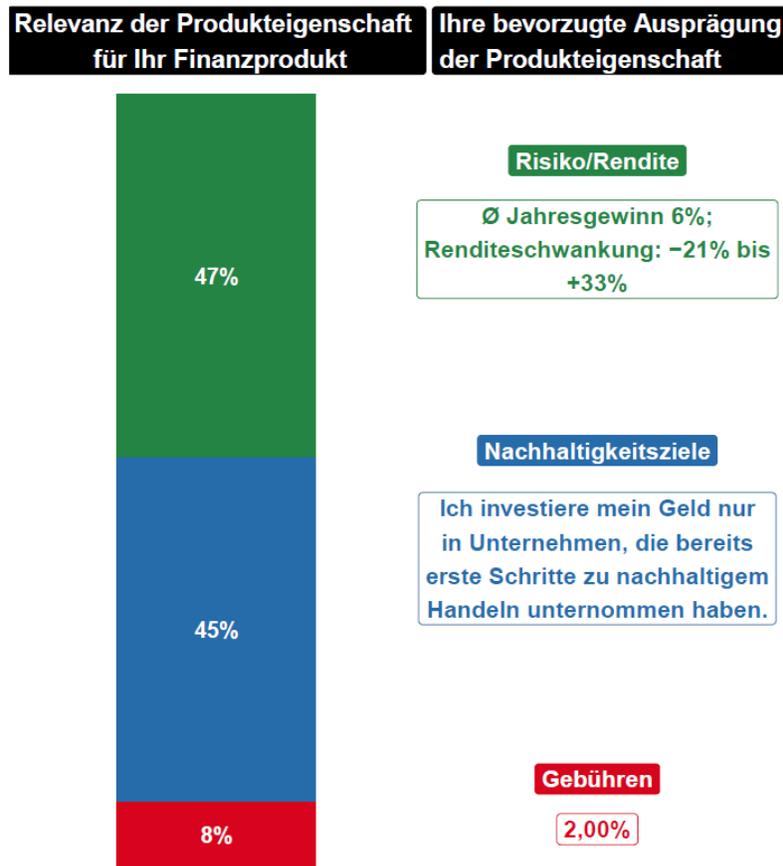
45%

Gebühren

2,00%

8%

Figure 5: Result figure

product, such as an actively managed fund with an exclusions-based, best-in-class, climate or thematic sustainability approach and a medium overall risk level, as in this example.

Empfehlung: Aufgrund Ihrer Antworten ist das Finanzprodukt, das Ihren Präferenzen am besten entspricht, ein Produkt mit mittlerem Risiko und einer langfristigen durchschnittlichen Rendite von 3 % pro Jahr. Das Finanzprodukt richtet sich an Unternehmen, die bereits erste Schritte auf dem Weg zu Nachhaltigkeitszielen unternommen haben. Das ideale Finanzprodukt würde auch hohe Gebühren von etwa 2,0 % pro Jahr mit sich bringen.

Produktbasierte Empfehlung: Basierend auf Ihren Antworten wäre ein aktiv verwaltetes Anlageprodukt mit einem ausschlussbasierten, Best-in-Class-, Klima- oder thematischen Ansatz und einem mittleren Risikoniveau eine optimale Wahl.

Figure 6: Recommendation

The report provides a glossary at the bottom of the results that explains all attribute levels in non-technical language. For each attribute, the glossary lists the possible manifestations (e.g. low, medium and high risk/return profiles, with their corresponding average returns and fluctuation ranges, different sustainability goal orientations and fee levels) and illustrates these with brief descriptions or examples (see Figure 7). This structure ensures that respondents can see their personalized recommendation and understand the underlying building blocks of the decision transparently.

Glossar

Risiko/Rendite Merkmale	Beschreibung
Ø Jahresgewinn 1%; Renditeschwankung: −6% bis +8%	Niedriges Risiko-Rendite-Profil
Ø Jahresgewinn 3%; Renditeschwankung: −11% bis +16%	Mittleres Risiko-Rendite-Profil
Ø Jahresgewinn 6%; Renditeschwankung: −21% bis +33%	Hohes Risiko-Rendite-Profil

Nachhaltigkeitsziele Merkmale	Beispiel
Ich investiere mein Geld nur in Unternehmen, die bereits erste Schritte zu nachhaltigem Handeln unternommen haben.	Investment in Firmen, die bereits zu Nachhaltigkeitszielen beitragen oder einen klaren Absenkpfad verfolgen.
Ich investiere mein Geld um Unternehmen zukünftig zu nachhaltigem Handeln zu bewegen.	Einsatz von Aktionärsrechten (Stimmrechte/Engagement), um Firmen zu mehr Nachhaltigkeit zu bewegen.
Ich investiere mein Geld nicht zwingend nachhaltig.	Investment ohne Berücksichtigung von Nachhaltigkeitskriterien.

Gebühren Merkmale	Beschreibung
0,50% pro Jahr	Niedrige Gebühren
1,50% pro Jahr	Mittlere Gebühren
2,00% pro Jahr	Hohe Gebühren

Figure 7: Glossary

4   Further applications of the CBCA method

The prototype presented, along with the attributes and levels used to measure investment preferences, is based, as outlined, on a broad universe of investment products. In this form, the prototype can be adopted by independent platforms such as myfairmoney.ch without further modifications. For application within financial institutions, however, it is advisable - where necessary - to adapt the attributes and levels to the respective product range and to link the recommendation to a specific product that matches the result of the assessment.

The CBCA method presented here can not only be applied to identify the individual preferences of private investors but, in the financial context, can also be employed in line with its original purpose - namely, to measure the preferences of entire groups and to integrate these insights into the design of products and services. In doing so, offerings can be tailored to specific target groups, thereby reducing the risk of failure in terms of market acceptance. This approach may also be applied to the development of new financial products. Hypothetical attributes of financial products could be presented as product options in order to assess the extent to which target investors value these attributes. In addition to preferences fo such hypothetical attributes, it is particularly important to simultaneously assess the associated fees in order to determine investors' willingness to pay for them.

5   Conclusion

This paper introduces a straightforward and efficient approach to capturing sustainability preferences in detail. The main advantages of the suggested tool, which employs a choice-based conjoint approach, are the integrated elicitation of preferences concerning the financial and non-financial attributes of investment products, and the fact that the tool has a game-like

character, which aligns closely with well-established risk preference elicitation methodologies.

The tool has been extensively tested and optimized using large-scale survey evidence and feedback from participants in various undergraduate, postgraduate and executive education programs. It has also been developed through discussions with financial institutions and academics. The next step is to conduct further in-depth experimental analyses to assess how this innovative approach captures real sustainability preferences compared to other survey-based approaches. Furthermore, the practicability of the tool will be further evaluated and discussed with financial institutions.

The project's main objective is to provide open access to the tool for individuals and the option to integrate it into existing processes at financial institutions.

References

Greg M. Allenby, Peter E. Rossi, and Robert E. McCulloch. Hierarchical Bayes Models: A Practitioners Guide, January 2005.

M. Amaya-Amaya, K. Gerard, and M. Ryan. Discrete choice experiments in a nutshell. In M. Ryan, K. Gerard, and M. Amaya-Amaya, editors, *Using Discrete Choice Experiments to Value Health and Health Care*, pages 13–46. Springer, Dordrecht, 2008.

George Apostolakis, Gert van Dijk, Frido Kraanen, and Robert J. Blomme. Examining socially responsible investment preferences: A discrete choice conjoint experiment. *Journal of Behavioral and Experimental Finance*, 17:83–96, 2018.

D. Asioli, T. Næs, A. Øvrum, and V. L. Almli. Comparison of rating-based and choice-based conjoint analysis models. A case study based on preferences for iced coffee in Norway. *Food Quality and Preference*, 48:174–184, March 2016. ISSN 0950-3293.

K. Auspurg and U. Liebe. Choice-experimente und die messung von handlungsentscheidungen in der soziologie. *Kölner Zeitschrift für Soziologie und Sozialpsychologie*, pages 301–314, 2011.

Kremena Bachmann, Julia Meyer, and Annette Krauss. Investment motives and performance expectations of impact investors. *Journal of Behavioral and Experimental Finance*, 42: 100911, June 2024. ISSN 2214-6350. doi: 10.1016/j.jbef.2024.100911.

Brad M. Barber, Adair Morse, and Ayako Yasuda. Impact investing. *Journal of Financial Economics*, 139(1):162–185, 2021.

Rob Bauer, Tobias Ruof, and Paul Smeets. Get Real! Individuals Prefer More Sustainable Investments. *The Review of Financial Studies*, 34(8):3976–4043, July 2021.

N. Borgers, J. Hox, and D. Sikkel. Response quality in survey research with children and adolescents: The effect of labeled response options and vague quantifiers. *International Journal of Public Opinion Research*, 15(1):83–94, 2003.

Timo Busch, Peter Bruce-Clark, Jeroen Derwall, Robert Eccles, Tessa Hebb, Andreas Hoepner, Christian Klein, Philipp Krueger, Falko Paetzold, Bert Scholtens, and Olaf Weber. Impact investments: a call for (re)orientation. *SN Business & Economics*, 1(2):33, January 2021. ISSN 2662-9399.

Thomas Cauthorn, Julia Eckert, Anne Kellers, Christian Klein, and Bernhard Zwergel. Do Advisors Respond to Investors' Sustainability Preferences? 2025.

Aaron Chatterji, David Levine, and Michael Toffel. How Well Do Social Ratings Actually Measure Corporate Social Responsibility? *Journal of Economics & Management Strategy*, Volume 18:125–169, 2009.

Steven H. Cohen. Perfect union. *Marketing Research*, 9(1):12–17, 1997. ISSN 10408460.

Alex Edmans and Marcin Kacperczyk. Sustainable finance. *Review of Finance*, 26(6):1309–1313, 2022. doi: 10.1093/rof/rfac069.

Felix Eggers, Henrik Sattler, Thorsten Teichert, and Franziska Völckner. Choice-Based Conjoint Analysis. In Christian Homburg, Martin Klarmann, and Arnd Vomberg, editors, *Handbook of Market Research*, pages 781–819. Springer International Publishing, Cham, 2022.

Ossama Elshiewy, Daniel Guhl, and Yasemin Boztug. Multinomial Logit Models in Marketing - From Fundamentals to State-of-the-Art. *MAR*, 39(3):32–49, 2017. ISSN 0344-1369.

Daniel Engler, Gunnar Gutsche, and Paul Smeets. Why do investors pay higher fees for sustainable investments? an experiment in five european countries. *SSRN Working Paper*, 2023.

Armin Falk, Anke Becker, Thomas Dohmen, David Huffman, and Uwe Sunde. The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences. *Management Science*, 69(4):1935–1950, April 2023. ISSN 0025-1909. Publisher: INFORMS.

Eugene F. Fama and Kenneth R. French. Disagreement, tastes, and asset prices. *Journal of Financial Economics*, 83(3):667–689, 2007.

Massimo Filippini, Markus Leippold, and Tobias Wekhof. Sustainable finance literacy and the determinants of sustainable investing. *Journal of Banking and Finance*, 163:107167, 2024.

Michele Garagnani. The predictive power of risk elicitation tasks. *Journal of Risk and Uncertainty*, 67(2):165–192, October 2023. ISSN 1573-0476.

Stefano Giglio, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus. Five Facts about Beliefs and Portfolios. *American Economic Review*, 111(5):1481–1522, 2021.

GSIA. Global sustainable investment review 2020, 2021. URL http://www.gsi-alliance.org/#.

Gunnar Gutsche and Andreas Ziegler. Which private investors are willing to pay for sustainable investments? Empirical evidence from stated choice experiments. *Journal of Banking and Finance*, 102:193–214, 2019.

Samuel M. Hartzmark and Abigail B. Sussman. Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows. *Journal of Finance*, 74(6):2789–2837, 2019.

Florian Heeb, Julian F Kölbel, Falko Paetzold, and Stefan Zeisberger. Do Investors Care About Impact? *The Review of Financial Studies*, 2022.

Florian Heeb, Julian F Kölbel, Falko Paetzold, and Stefan Zeisberger. Do Investors Care about Impact? *The Review of Financial Studies*, 36(5):1737–1787, 2023.

T. Holmes, W. Adamowicz, and F. Carlsson. Choice experiments. In P. Champ, K. Boyle, and T. Brown, editors, *A Primer on Nonmarket Valuation*, pages 133–186. Springer, 2017.

Charles A. Holt and Susan K. Laury. Risk Aversion and Incentive Effects. *American Economic Review*, 92(5):1644–1655, December 2002. ISSN 0002-8282.

Felix Holzmeister, Jürgen Huber, Michael Kirchler, Florian Lindner, Utz Weitzel, and Stefan Zeisberger. What drives risk perception? a global survey with financial professionals and laypeople. *Management Science*, 66(9):3977–4002, 2020.

M.-H. Hsiao. *Towards an approach for monetary valuation of services*. Emerald Publishing Limited, 2018.

L. Kling, C. König-Kersting, and S. T. Trautmann. Investment preferences and risk per-

ception: Financial agents versus clients. *Journal of Banking and Finance*, page 106489, 2022.

K. Lancaster. A new approach to consumer theory. *The Journal of Political Economy*, 74: 132–157, 1966.

K. Lancaster. *Consumer Demand – A new approach*. Columbia University Press, New York and London, 1971.

J. Louviere, T. Flynn, and R. Carson. Discrete choice experiments are not conjoint analysis. *Journal of Choice Modelling*, 3:57–72, 2010.

Jan Erik Lönnqvist, Markku Verkasalo, Gari Walkowitz, and Philipp C. Wichardt. Measuring individual risk attitudes in the lab: Task or ask? An empirical comparison. *Journal of Economic Behavior and Organization*, 119, 2015. doi: 10.1016/j.jebo.2015.08.003.

G. Maier and P. Weiss. *Modelle diskreter Entscheidungen*. Springer, Wien, 1990.

H. M. Markowitz. Portfolio selection. *The Journal of Finance*, 7(60):77–91, 1952. ISSN 1557861080.

T. Morikawa, M. Ben-Akiva, and D. McFadden. Discrete choice models incorporating revealed preferences and psychometric data. *Econometric Models in Marketing*, 16:29–55, 2002.

Martin Natter and Markus Feurstein. Real world performance of choice-based conjoint models. *European Journal of Operational Research*, 137(2):448–458, March 2002. ISSN 0377-2217.

Bryan Orme. Hierarchical Bayes: Why All the Attention. *Sawtooth Software Research Paper Series*, 2000.

Falko Paetzold, Timo Busch, and Marc Chesney. More than money: exploring the role of investment advisors for sustainable investing. *Annals in Social Responsibility*, 1(1): 195–223, 2015. ISSN 2056-3515.

Sebastian M. Peters, Julia Meyer, and Matthias Stefan. Perception of Sustainable Investing: A Survey Experiment among the General Population and Financial Advisors, 2025.

Arno Riedl and Paul Smeets. Why Do Investors Hold Socially Responsible Mutual Funds? *Journal of Finance*, 72(6):2505–2550, 2017.

Mariacristina Rossi, Dario Sansone, Arthur van Soest, and Costanza Torricelli. Household preferences for socially responsible investments. *Journal of Banking and Finance*, 105: 107–120, 2019.

Sawtooth Software, Inc. CBC/HB v5, Software for Hierarchical Bayes Estimation for CBC Data. August 2016. URL `https://content.sawtoothsoftware.com/assets/276545e9-0445-474c-b01c-f5b24c3eba6d`.

Sawtooth Software, Inc. The CBC/HB System Technical Paper V5.6. *Sawtooth Software Technical Paper Series*, 2021.

Ryan Sermas. ChoiceModelR: Choice Modeling in R, January 2012. URL `https://CRAN.R-project.org/package=ChoiceModelR`. Institution: Comprehensive R Archive Network Pages: 1.3.0.

Matthias Stefan, Martin Holmén, Felix Holzmeister, Michael Kirchler, and Erik Wengström. You can't always get what you want: An experiment on finance professionals' decisions for others. *Working Paper*, 2023.

Michael Steiner and Martin Meißner. A User's Guide to the Galaxy of Conjoint Analysis and Compositional Preference Measurement. *Marketing ZFP - Journal of Research and Management*, 40(2):3–25, 2018. ISSN 0344-1369. doi: 10.15358/0344-1369-2018-2-3.

D. Street and L. Burgess. *The construction of optimal stated choice experiments.* John Wiley & Sons, Inc., Hoboken, New Jersey, 2007.

Stefan Zeisberger. Do people care about loss probabilities? *Journal of Risk and Uncertainty*, 65:185–213, 2022.

6 Appendix

respID	qID	altID	Attribute1	Attribute2	Attribute3	Choice
669deac	1	1	1	1	2	0
669deac	1	2	4	2	1	2
669deac	1	3	3	3	2	0
669deac	1	4	2	4	3	0
669deac	2	1	4	2	3	1
669deac	2	2	2	3	1	0
669deac	2	3	1	4	1	0
669deac	2	4	3	3	3	0
669deac	3	1	4	1	2	0
669deac	3	2	1	4	1	0
669deac	3	3	1	2	3	0
669deac	3	4	2	2	2	4

Table 5: Choice dataset structure

Arguments	Sub-options	Values	Explanation
data	-	-	The individual choice data as per table 5
xcoding	-	0	When 0, the choice data is effects coded and assumed to be categorical. If 1 is specified, the data is assumed continuous.
mcmc	R	20,000	No. of 'MCMC' iterations performed.
	use	10,000	The number of iterations used for estimating the betas. In this case, the initial 10,000 iterations are discarded and not used for estimation of betas.
	s	0.1	This is the default value and keeps the target acceptance rate of random draws of parameters at 30%.
options	none	FALSE	When the choice set has a "none" alternative, this option is set to TRUE, else FALSE.
	keep	1	This value indicates that every draw out of 10,000 iterations is saved for estimating the average beta at the end of the analysis. For instance, if this value was 2, then draws of beta for only half, i.e., 5000 iterations would be saved.
	save	TRUE	This function saves the betas for easier utility estimation.
prior	mubar	0	This is the default value and the mean of the (normal) distribution is assumed 0. This is analogous to α in equation 4
	v	2	This is the default value for prior variance and should be greater than or equal to 0.
	df	5	This is the default value for prior additional degrees of freedom for the covariance matrix and can range between 2 and 100,000.

Table 6: ChoiceModelR Model Specifications