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ESG Fund Preferences of Chinese Individual Investors Based on Discrete Choice Experiment and Mixed Logit Modeling

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Abstract With the ongoing advancement of the global sustainable development agenda, ESG (Environmental, Social, and Governance) investing has emerged as a critical pathway for advancing green finance and responsible investment. However, systematic quantitative research remains scarce regarding the preference structures and willingness to pay (WTP) of Chinese individual investors toward ESG fund products. This study employs experimental economics methodology, utilizing Discrete Choice Experiments (DCE) to construct simulated investment scenarios. Combined with conditional logit and mixed logit (MXL) models, it systematically identifies key attributes influencing investor decision-making and their heterogeneous preference distributions at the individual level. The experimental design incorporates five core attributes: green certification methods, ESG screening strategies, return rates, and fee structures. Through structured choice-set surveys with 96 experienced investors, this study estimates marginal utility functions for fund characteristics. Empirical results indicate that investors generally prefer government-certified funds and exhibit a tendency toward negative screening strategies. Notably, they demonstrate atypical preferences for high-fee products, while the influence of return rates proves relatively weak. The mixed logit model further reveals significant individual preference heterogeneity, with pronounced divergences particularly in green certification and ESG strategy attributes. Although directional bias in attribute estimates precluded precise derivation of willingness to pay (WTP), this research validates the feasibility and explanatory power of the "DCE+MXL" framework for modeling ESG behaviors in China. It provides quantitative support for optimizing ESG fund design, guiding investor behavior, and informing policymaking, while contributing methodological insights for micro-behavioral modeling in green finance contexts.

Index Terms Sustainable Finance, ESG Investment, Discrete Choice Experiment, Conditional Logit Model, Mixed Logit Model.

I. Introduction

The global financial markets are rapidly transitioning into a new development paradigm centered on sustainability, transparency, and responsible governance. Against this backdrop, ESG (Environmental, Social, and Governance) investing has emerged as a representative pathway integrating green finance with fintech innovations. The UN's 2030 Sustainable Development Agenda explicitly advocates for global capital allocation toward green and low-carbon initiatives. As of 2024, over 6,000 institutions have signed the UN Principles for Responsible Investment (PRI), with assets under management exceeding $130 trillion. While China's market has entered a policy-driven favorable period, individual investors' understanding of ESG products remains immature, with significantly divergent investment behaviors. Crucially, the specific preference structures lack quantitative modeling support in the Chinese context.

While ESG research has become relatively systematic in mature Western markets, China still lacks rigorous quantitative studies based on behavioral experiments and micro-level modeling. The current Chinese market presents three core research questions: (1) How are preference structures distributed among Chinese individual investors when presented with fund products featuring different ESG characteristics? (2) Which product attributes (e.g., green certification, screening strategies, return levels) significantly drive investment selection probabilities? (3) Does substantial individual preference heterogeneity exist, and how can it be identified and measured through modeling frameworks?

This study innovatively employs a Discrete Choice Experiment (DCE) to construct simulated investment decision scenarios, integrating both Conditional Logit Model (CLM) and Mixed Logit Model (MXL) for parameter estimation, to systematically analyze investors' behavioral responses to key attributes of ESG funds. The Logit-class modeling framework not only estimates marginal utilities but also captures preference distribution heterogeneity through mixed modeling, accounting for variations in socio-demographic characteristics, behavioral preferences, and risk

attitudes.

This study makes significant theoretical contributions by filling the empirical gap in China's ESG investment research regarding individual investor preference identification, emphasizing a dual-support approach combining behavioral experiments and individual-level modeling. Methodologically, it pioneers the integration of DCE and MXL in China's green fund evaluation context, effectively mitigating revealed preference sampling biases. At the practical level, the findings provide quantitative support for ESG fund product design, marketing strategy optimization, and policy formulation. Furthermore, from a micro-behavioral decision-making perspective, this study bridges experimental economics with advanced random utility modeling methods to construct an identification framework for investor preference heterogeneity, ultimately aiming to optimize green financial product strategies and enable precise quantitative simulation.

II. Related Work

II. A.Investor Preference Driving Mechanism

Existing research categorizes investor preferences into two types: self-interested motives (pursuing financial returns) and altruistic motives (emphasizing social responsibility). On one hand, investors driven by self-interest tend to select stocks with strong ESG performance, as they believe these stocks can deliver higher financial returns and effectively mitigate risks [1]. On the other hand, investors motivated by altruism prioritize corporate social responsibility performance, aiming to promote environmental protection and social equity through their investments to align with personal values [2]. Further analysis reveals that social norms and signaling are key factors influencing investor choices. According to Riedl and Smeets [3], investors with a strong sense of social identity are more inclined to choose products that meet social responsibility standards. Meanwhile, Yucel et al. [4] suggest that individuals with higher sustainable financial literacy and those who perceive sustainable financial instruments as environmentally beneficial often exhibit positive investment stances, while higher-income individuals are more likely to show favorable attitudes toward such instruments. Berk and Van Binsbergen [5] demonstrate that despite the higher returns offered by so-called "sin stocks" (e.g., alcohol, tobacco, and gaming), many institutional and individual investors avoid them due to the influence of social norms.

II. B.Preference Measurement Methods and Modeling Tools

Research on investors' ESG preferences primarily employs two methodological approaches: revealed preference data and stated preference data. Revealed preference data, derived from real-world investment decisions, captures actual market behavior but may suffer from issues such as information asymmetry, limited sample representativeness [6], and challenges like inconsistent ESG data quality, divergent rating criteria, and potential "greenwashing" risks. These factors could lead to misjudgments of true preferences [7], [8]. In contrast, stated preference data is collected through experiments or surveys, enabling researchers to simulate complex investment decision-making scenarios under controlled conditions. This approach better uncovers latent demand and preference patterns [3]. Among stated preference methods, the Discrete Choice Experiment (DCE) has gained prominence and been widely applied in fields such as transportation, energy, and environmental economics [9], [10]. In DCEs, respondents make selections among carefully designed hypothetical products or services (e.g., investment portfolio options), allowing quantification of their trade-offs between attributes (e.g., financial returns, risk, ESG performance) and willingness-to-pay [10].

II. C.Challenges and Gaps in China's ESG Market

Although ESG investment is rapidly developing globally, the Chinese market still faces multiple challenges. First, insufficient information disclosure and inconsistent evaluation standards hinder investors' understanding and trust in ESG products [11]. Moreover, voluntary or mandatory guidelines alone cannot serve as independent factors in improving a country's overall ESG performance [12]. Second, domestic individual investors' awareness of ESG investment remains at an early stage, and stable preference patterns have yet to form [13]. Empirical studies show that Chinese retail investors generally have a vague understanding of ESG concepts, and the weight of ESG factors in their investment decisions remains relatively low [14]. Finally, existing research primarily focuses on macro-level aspects such as financial institutions and products, with relatively few studies on individual investors—particularly empirical analyses in the context of developing countries [15], [16]. Additionally, research by Qu and Zhang [17] highlights that, in developing countries, the value relevance of ESG information may vary due to governance differences. This suggests that while ESG information may be highly decision-useful in developed markets, it may require more localized adaptation in developing economies.

II. D.Advancements based on existing research

Through a comprehensive review of existing research, this study identifies a notable gap in investor behavior modeling within China's ESG investment sector, which this study seeks to address through methodological innovation. Unlike prior studies that rely on explicit data for preference measurement, this study employs the Discrete Choice Experiment (DCE) approach to simulate latent decision-making processes. While existing literature has limited application of the Choice Modeling (CLM) framework, this study integrates DCE, CLM, and Mixed Logit (MXL) models to construct a more robust analytical framework. Shifting focus from the institutional and corporate investors predominantly examined in current research, this study innovatively concentrates on individual investors within the Chinese context. Methodologically, this study advances beyond conventional approaches that depend on secondary data or questionnaire scoring by implementing controlled experiments with randomized assignments and structured choice sets for data collection. Essentially, this research transcends traditional limitations in preference measurement by combining randomized experiments with heterogeneity modeling, marking the first attempt to delineate the behavioral drivers of ESG investment at the micro-investor level. The subsequent process design of this study is illustrated in Figure 1.

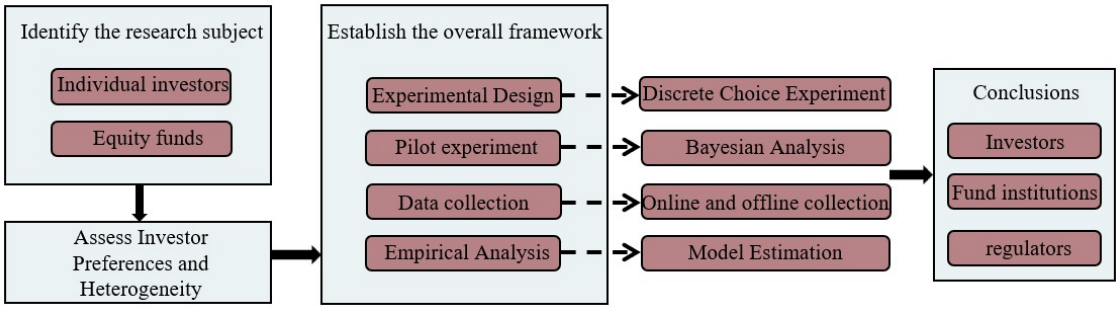

Figure 1: Process Flow Diagram

III. Methodology

III. A. Experimental Design

This study employs Discrete Choice Experiment (DCE) methodology to construct an investor behavior simulation environment, systematically evaluating investors' preference structures and selection probabilities for key attributes of ESG fund products through carefully designed investment option scenarios. The experimental design follows a core logic where each respondent completes 8 choice tasks, with each task presenting two fund product options (A and B) along with an "opt-out" alternative, thereby comprehensively capturing real-world decision-making processes when investors face different attribute combinations. All option combinations are generated using orthogonal experimental design principles to eliminate inter-attribute interference, ensuring each attribute level independently reflects its impact on choice behavior. To further optimize choice set design and enhance experimental efficiency, this study utilizes Ngene software to generate statistically efficient choice sets, achieving both scientific rigor and operational feasibility in the experimental framework [18].

The experimental design framework not emphasizes the scientific rigor and rationality of option configuration, but also carefully considers respondents' practical experience and data quality control. Following Bauer's [19] approach, this study structured the questionnaire into six main sections: basic information, investment experience, risk attitude, financial literacy, sustainable investment fund scale, and environmental attitude modules, to comprehensively collect respondents' personal characteristics and investment preference data. During implementation, the research team first conducted a pilot test with 40 potential respondents and refined the questionnaire based on feedback to ensure logical clarity and comprehensibility. Furthermore, to mitigate the impact of learning effects and respondent fatigue on experimental results, the formal survey reduced each participant's decision-making tasks from ten to eight choice sets while optimizing the design for greater clarity and conciseness.

III. B. Attributes & Levels

In the discrete choice experiment, this study selected five key attributes - including fund green certification, ESG screening strategies, three-year annualized return, and total expense ratio - to analyze investors' preferences and willingness to pay. Multiple levels were established for each attribute to reflect the diverse characteristics of fund products in the Chinese market. The details are shown in Table 1. The green certification attribute was divided into three forms: government certification, third-party certification, or no certification, allowing us to assess investors' trust in different certification sources. ESG screening strategies were further categorized into positive and negative

screening dimensions, each with three intensity levels (strict screening, moderate screening, and no screening) to provide deeper insights into how investors balance financial returns with social responsibility. For financial attributes, the three-year annualized return was set at five different levels (1%, 3%, 4%, 6%, 8%) to simulate various fund performance scenarios, while the total expense ratio incorporated seven levels (0.1%, 0.4%, 0.8%, 1.2%, 1.6%, 2.0%, 2.4%) representing different cost structures. These attributes not only directly influence investors' choice behaviors but also interact with non-monetary factors, creating complex decision-making trade-offs that reveal how investors reconcile social responsibility with economic returns. This carefully calibrated design enhances the experiment's ecological validity and offers a comprehensive framework for understanding the multifaceted nature of investor decision-making processes. The attribute configuration captures the essential trade-offs investors face when evaluating ESG investment products in real market conditions.

Table 1: Attributes and Levels in the Discrete Choice Experiment

Attributes	Levels
Fund Green Certification	Government Certification, Third - Party Certification, No Certification
ESG Positive Screening Strategy	Strict Screening, Moderate Screening, No Screening
ESG Negative Screening Strategy	Strict Screening, Moderate Screening, No Screening
Three - year Annualized Rate of Return	1%, 3%, 4%, 6%, 8%
Fund Comprehensive Fee Rate	0.1%, 0.4%, 0.8%, 1.2%, 1.6%, 2.0%, 2.4%

Note: Negative screening refers to excluding polluting or non-compliant companies, while positive screening indicates prioritizing companies with outstanding ESG performance.

III. C. Randomization Mechanism and Sample Allocation

In the design of discrete choice experiments, ensuring representative choice scenarios for respondents is crucial for enhancing experimental quality. This study adopted a systematic design based on attribute-level space, constructing choice sets following the D-efficient design principle to minimize attribute multicollinearity. Using Ngene software, this study generated an optimal design matrix and implemented random sampling to assign each respondent unique yet representative choice scenarios, balancing efficiency and randomness to improve statistical power and data reliability. Concurrently, the sample was randomly divided into multiple subgroups, each assigned different choice sets while maintaining consistent task structures and diverse option combinations. This approach facilitates the identification of preference heterogeneity and strengthens cross-group comparisons. During the experimental introduction phase, respondents were instructed to treat the simulated fund portfolios as actual purchasable products, enhancing situational immersion and reducing choice bias caused by hypothetical scenarios. This ensures the results more accurately reflect investors' true preference structures.

III. D. Modeling Methods

III. D. 1) Conditional Logit Model

The Conditional Logit Model (CLM) is a statistical model extensively applied in discrete choice analysis, originally developed by McFadden [20] based on Random Utility Theory (RUT). The model postulates that when presented with multiple alternatives, individuals make choices by maximizing the utility of each option. Utility consists of two components: a deterministic part derived from observable characteristics of the alternatives, and a stochastic component representing unobservable influencing factors.

Consider the choice scenario where individual i faces J alternatives. The utility U_{ij} of alternative j can be expressed as:

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

Here, V_{ij} represents the observable utility component, typically expressed as a linear function: $V_{ij} = \beta' X_{ij}$, where X_{ij} denotes the characteristic vector of alternative j and β is the parameter vector to be estimated; ε_{ij} is the random error term following an independently and identically distributed (IID) extreme value distribution.

The probability of an individual choosing a particular alternative can be expressed as:

$$P_{ij} = P(U_{ij} > U_{ik}, \forall k \neq j) = \frac{\exp(\beta' X_{ij})}{\sum_{k=1}^{J} \exp(\beta' X_{ij})} \tag{2}$$

The model is primarily used to analyze individuals' choice behaviors among different alternatives, particularly suited for situations where the characteristics of alternatives (rather than individual characteristics) influence the choice outcome. In discrete choice experiments, the Conditional Logit Model serves as the most fundamental model

for analyzing questionnaire data. However, it has limitations, including the Independence of Irrelevant Alternatives (IIA) assumption and its inability to account for heterogeneity in individual preferences.

III. D. 2) Mixed Logit Model

To address the aforementioned limitations of the Conditional Logit Model, this study further introduces the Mixed Logit Model (MXL). Proposed by Revelt and Train [21], MXL is an advanced discrete choice model based on Random Utility Theory. Compared to the traditional Multinomial Logit Model (MNL), the key improvement of MXL lies in allowing preference coefficients to follow specific probability distributions across individuals, thereby overcoming the constraints of the "Independence of Irrelevant Alternatives" (IIA) assumption.

In the Mixed Logit Model, the utility function takes a form similar to that of the Conditional Logit Model, but with preference coefficients β treated as random variables following certain probability distributions (e.g., normal or log-normal distributions). Specifically, the utility function can be expressed as:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \beta' X_{ij} + \varepsilon_{ij} \tag{3}$$

Here, β is a random vector whose distribution can be specified according to practical research needs. The probability of an individual choosing a particular alternative can be expressed as:

$$P_{ij} = \int \prod_{k=1}^{J} \left[\frac{\exp(\beta' X_{ij})}{\sum_{k=1}^{J} \exp(\beta' X_{ij})} \right]^{y_{ik}} f(\beta|\theta) d\beta \tag{4}$$

Here, y_{ik} is an indicator variable where $y_{ik} = 1$ if individual i chooses alternative k, otherwise $y_{ik} = 0$; $f(\beta|\theta)$ is the probability density function of β, with parameter θ describing the distribution's characteristics (e.g., mean and variance).

By incorporating random parameters, the Mixed Logit Model can capture heterogeneity in preferences among individuals. In this study, various socio-demographic characteristics (such as gender, age, education level, and asset size) may significantly influence investors' preferences for ESG fund products. Using the MXL model, this study can identify these heterogeneous preferences and further explore their underlying drivers.

III. E. Parameter Interpretation and Derivation Logic

In this study, all attribute coefficients can be interpreted as marginal utility increments relative to the baseline. Specifically, if a cost attribute (such as the fund's total expense ratio) is included, the willingness-to-pay (WTP) can be calculated as the ratio of the attribute coefficient to the cost coefficient:

$$WTP_k = -\frac{\beta_k}{\beta_{cost}} \tag{5}$$

Here, β_k represents the coefficient of the k-th attribute, while β_{cost} denotes the coefficient of the cost attribute (fund expense ratio). This formula allows us to quantify investors' relative valuation of different attributes.

Although this study ultimately failed to estimate valid WTP due to directional bias, the model structure fully satisfies the estimation requirements. This implies that, based on the existing data and model framework, this study can further explore investors' attention to various attributes and their willingness to pay when selecting sustainable investment funds. By analyzing these parameters, this study can gain deeper insights into how investors weigh returns, costs, and social responsibilities, thereby providing a scientific foundation for developing more effective sustainable investment strategies.

IV. Experimental Design and Results Analysis

IV. A. Sample Overview and Data Structure

The data for this study were sourced from finance majors at universities and employees/clients of Galaxy Securities' Chengdu branch. Prior to the formal experiment, researchers conducted a small-scale pilot survey among finance students and some securities industry practitioners, primarily aimed at validating research hypotheses and optimizing questionnaire design. Building upon the pilot study, researchers collaborated with Galaxy Securities' Chengdu branch to distribute formal questionnaires to its individual investors. To ensure sample representativeness, this study rigorously screened eligible respondents, requiring them to have purchased at least one equity-oriented stock fund product in the past year and possess certain financial investment experience. The questionnaires were distributed both online and offline to cover investor groups of different age demographics and technological literacy levels. Ultimately, 107 questionnaires were collected, with 96 being valid, yielding an effective response rate of 89.71%. To guarantee data quality, the research team conducted strict verification of all returned questionnaires, eliminating invalid ones that were incomplete, contained logical inconsistencies, or exhibited abnormal response

patterns.

The sample in this study demonstrates strong representativeness, covering middle-aged and young groups with high education levels and financial literacy, making it an ideal sample for micro-level ESG behavior research. As shown in Table 2 regarding demographic distribution characteristics, females account for approximately 56.25%, with a standard deviation of 0.4987, indicating balanced gender distribution and avoiding biases caused by gender differences. In terms of educational background, as high as 96.88% of respondents hold a bachelor's degree or higher, with a standard deviation of only 0.1749, reflecting the overall high education level of the sample. This not only suggests that respondents possess strong cognitive and information processing abilities but also implies they may approach the understanding and evaluation of ESG fund products more rationally and comprehensively. Additionally, about 69.79% of the sample are married, with a standard deviation of 0.4616, and the diversity in marital status further enhances the sample's representativeness.

For the two key variables of age and assets, the sample data also exhibit good coverage and dispersion. The median age is 37 years, with a standard deviation of 7.8351, indicating a relatively concentrated age distribution primarily within the middle-aged and young range. Investors in this age group typically have stronger financial capabilities and investment willingness, along with higher acceptance of emerging investment concepts such as ESG funds. The median asset value is 1,179,688 yuan, with a high standard deviation of 1,283,113 yuan, and the maximum and minimum values are 5 million yuan and 80,000 yuan, respectively. This reflects significant wealth disparities among respondents while also ensuring broad representation in terms of financial status. In summary, the sample structure is reasonable and diverse in characteristics, effectively capturing the behavioral traits and preference differences of investors with varying backgrounds in ESG investment decisions, thereby providing a solid foundation for subsequent in-depth analysis.

Table 2: Descriptive Statistics of Individual Characteristics

	Obs	Mean	Std.Dev.	Max	Min
gender	96	0.5625	0.4987	1	0
Education level	96	0.9688	0.1749	1	0
Marital status	96	0.6979	0.4616	1	0
Age (years)	96	37	7.8351	58	25
Assets (ten thousand yuan)	96	117.9688	128.3113	500	8

IV. B. Conditional Logit Model Results

This study first employed the Conditional Logit Model (CLM) to conduct empirical analysis of choice behavior. Based on Random Utility Theory (RUT), the model aims to examine the direction and significance of overall attributes' impact on selection probabilities. The model fit results show that the Wald chi-square test is significant (Wald chi2(12) = 227.13, p = 0.0000), with a pseudo R^2 of 0.1736, indicating good explanatory power of the model.

Specific regression results (as shown in Table 3) reveal that in fund green certification, "government certification" significantly and positively affects selection probability (coefficient = 0.6556, $p < 0.001$), while the impact of "third-party certification" is insignificant and slightly negative (coefficient = -0.3176, p = 0.059). Regarding ESG screening strategies, both "strict" and "moderate" positive screening significantly reduce selection probability (coefficients = -0.7516 and -1.2482, respectively, $p < 0.001$), whereas "strict" and "moderate" negative exclusion strategies significantly increase selection probability (coefficients = 0.4347 and 0.8362, respectively, $p < 0.05$). Regarding yield rates, this study found that the options with annualized yields of "1%", "3%", and "4%" had no significant impact on selection probability ($p>0.05$), indicating that lower yield levels did not significantly influence investors' choice preferences. However, when yields reached "6%" and "8%", the selection probability decreased significantly (coefficients=-0.6059 and -1.8547, $p<0.05$). This may reflect investors' cautious attitude toward excessively high yield expectations or their concerns about potential risks. Among fee variables, "cost" significantly and positively affects selection probability (coefficient = 0.8771, $p < 0.001$), suggesting investors may perceive higher fees as indicative of higher-quality services. Additionally, the "none" option significantly and positively influences selection probability (coefficient = 1.8547, $p < 0.001$), indicating that when other options lack clear appeal, investors tend to choose the baseline option without additional conditions.

The empirical findings reveal that investors do not simply pursue profits but make more complex preference trade-offs between ESG attributes and certification types. Government certification can effectively enhance investors' trust and preference, while insufficient credibility or low market awareness of third-party certifications may reduce their attractiveness. Regarding ESG screening strategies, excessive positive information may trigger investor skepticism or caution, whereas moderate negative information is perceived as a reflection of transparency, thereby increasing

its appeal. The attractiveness of high fee rates suggests the possible existence of non-linear cognitive factors such as brand perception and quality perception, further revealing multiple considerations in investors' decision-making processes. These findings not only enrich the understanding of ESG investment behavior but also provide important references for related product design and policy formulation.

Table 3: Results of the Conditional Logit Model

Explanatory Variables	Coefficient	Standard Error	z-value	p-value	[95% Confidence Interval]
cer_gov	0.6556	0.1678	3.91	0.000	[0.3267, 0.9845]
cer_th	-0.3176	0.1680	-1.89	0.059	[-0.6469, 0.0118]
pos_str	-0.7516	0.1573	-4.78	0.000	[-1.0599, -0.4432]
pos_med	-1.2482	0.1943	-6.42	0.000	[-1.6292, -0.8672]
neg_str	0.43470	0.1928	2.26	0.024	[0.0569, 0.8125]
neg_med	0.8362	0.2200	3.80	0.000	[0.4051, 1.2673]
rate_1%	0.0733	0.2225	0.33	0.742	[-0.3628, 0.5094]
rate_3%	0.0541	0.1994	0.27	0.786	[-0.3368, 0.4449]
rate_4%	0.0769	0.2185	0.35	0.725	[-0.3515, 0.5052]
rate_6%	-0.6059	0.2856	-2.12	0.034	[-1.1657, -0.0461]
rate_8%	-1.854655	0.3226753	-5.75	0.000	[-2.4871,-1.2222]
cost	0.8771	0.1148	7.64	0.000	[0.6521, 1.1021]
1.none	1.8547	0.3227	5.75	0.000	[1.2222, 2.4871]

Note: The standard error indicates the standard deviation of the estimated coefficient, measuring the precision of parameter estimation; the z-value tests whether the coefficient is significantly different from zero; when the p-value is less than 0.05, it indicates statistical significance of the coefficient; the 95% confidence interval represents the possible range of the true parameter value. In the table, "annualized return" is expressed in percentage terms. The same applies below.

To better visualize the impact of different attributes on investors' choices of ESG fund products, this study incorporated box plots to graphically present the results of the conditional logit model. Figure 2 reveals significant differences in the coefficient distributions between government green certification (*cer_gov*) and third-party certification (*cer_th*). The coefficients for government green certification are concentrated in the positive range, indicating a consistently positive influence on investor decisions, with a relatively tight distribution suggesting broad trust in government-certified ESG funds. In contrast, third-party certification coefficients predominantly fall in the negative range, reflecting investor skepticism—a finding consistent with the mixed logit model results. Additionally, positive screening strategies (*pos_str* and *pos_med*) show mainly negative coefficients, implying limited appeal to investors, possibly due to their greater focus on transparency in negative information and risk control.

Further analysis shows distinct patterns for negative screening strategies (*neg_str* and *neg_med*). Strict negative screening (*neg_str*) exhibits tightly clustered positive coefficients, demonstrating strong investor confidence in its ability to mitigate risks. Moderate negative screening (*neg_med*) also shows positive coefficients but with wider dispersion, indicating divergent investor views on this approach. Regarding yield, all annualized return levels except 8% (*rate_8*) concentrate in negative territory, suggesting general disfavor toward low-yield products. However, the *rate_8%* coefficients display anomalously high variability with predominantly negative values, likely due to model instability caused by this option. Consequently, it was excluded from subsequent analyses to ensure model robustness.

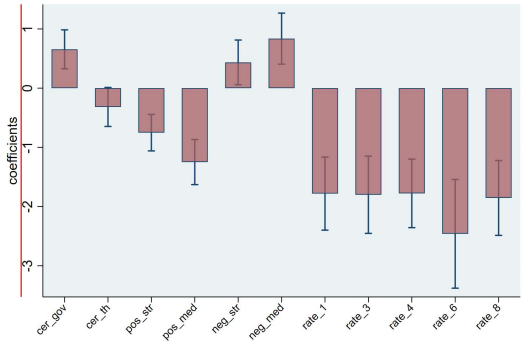

Figure 2: Conditional Logit Results

IV. C. Mixed Logit Model Results

In this study, the mixed logit model was employed to analyze preference differences among various investor groups regarding ESG fund products and to reveal the impact of individual heterogeneity on choice behavior. To ensure model identifiability, this study designated the 8% yield rate as the baseline level and excluded it, subsequently employing a mixed logit model to examine the heterogeneity in investors' preferences for ESG fund attributes.

The model results (as shown in Table 4) indicate that the coefficient for the cost variable is 0.3429, but its significance level is relatively low (p=0.361), suggesting that cost factors did not significantly influence investors' choice decisions in the current sample. Regarding green certification methods, the results indicate that government certification exhibited a statistically significant standard deviation (p<0.05). This suggests considerable divergence in investor attitudes towards government certification, with some investors placing strong trust in it while others express less approval. Concerning ESG screening strategies, the impact of positive screening on investor choice appears limited. In contrast, the coefficients for negative exclusion strategies (-1.2314 and -1.1917, respectively) were both significant (p<0.05). This implies that excessive negative information may raise investor concerns, whereas a *moderate* level of negative information can be perceived as a sign of transparency, thereby enhancing attractiveness. The standard deviations for *strict* and *moderate* negative screening were 4.4103 and 3.9138 (p<0.001), respectively, revealing significant differences in investor sensitivity to negative information. Some investors are notably more sensitive to such information, while others are more receptive to screening approaches characterized by higher transparency. Regarding returns, although the option with an 8% annualized return was excluded in the experimental design, it was found that the random effects for the 1% and 4% annualized return options were also significant (p<0.05). This reflects a widespread, yet variably intense, aversion among investors towards low-return products. For instance, the standard deviation for the 1% annualized return was 2.6675 (p<0.001), indicating that while some investors exhibit extreme disinterest in low-return products, others may be willing to accept such lower-risk portfolios. These findings not only enrich the understanding of ESG investment behavior but also provide valuable insights for designing related products and informing policy decisions.

The mixed logit model helps us capture significant divergence in investors' green preferences, which holds substantial implications for product customization and market segmentation. Specifically, the significant standard deviations for attributes such as government certification, negative screening, and return rates indicate considerable variation in individual preferences. For example, some individuals strongly trust government certifications, while others do not trust them at all; investors generally exhibit strong aversion to low-return products, but the intensity varies by individual. These findings not only reflect the diversity of investor preferences in the market but also provide guidance for financial institutions on how to better meet different needs.

Table 4: Results of the Mixed Logit Model

Explanatory Variables	Coefficient	Standard Error	z-value	p-value	[95% Confidence Interval]
Mean					
cost	0.3429	0.3753	0.91	0.361	[-0.3927, 1.0786]
none	0.3140	0.5956	0.53	0.598	[-0.8534, 1.4813]
cer_gov	-0.9442	0.3691	-2.56	0.011	[-1.6677, -0.2209]
cer_th	-1.0068	0.4281	-2.35	0.019	[-1.8460, -0.1677]
pos_str	-0.7344	0.4856	-1.51	0.130	[-1.6861, 0.2175]
pos_med	-1.0166	0.5688	-1.79	0.074	[-2.1314, 0.0982]
neg_str	-1.2314	0.6485	-1.90	0.058	[-2.5023, 0.0396]
neg_med	-1.1917	0.7315	-1.63	0.103	[-2.6255, 0.2421]
rate_1%	-1.8581	0.8105	-2.29	0.022	[-3.4468, -0.2696]
rate_3%	-0.0071	0.3500	-0.02	0.984	[-0.6932, 0.6788]
rate_4%	0.5609	0.4718	1.19	0.235	[-0.3639, 1.486]
rate_6%	0.2636	0.3979	0.66	0.508	[-0.5162, 1.0434]
Standard Deviation					
cer_gov	3.0530	0.9472	3.22	0.001	[1.1965, 4.9095]
cer_th	2.3338	1.2376	1.89	0.059	[-0.0919, 4.7595]
pos_str	0.4503	0.5245	0.86	0.391	[-0.5778, 1.4784]
pos_med	1.2493	0.8648	1.44	0.149	[-0.4457, 2.9443]
neg_str	4.4103	0.6186	6.48	0.000	[3.0755, 5.7452]
neg_med	3.9138	0.6519	6.00	0.000	[2.6360, 5.1916]
rate_1%	2.6675	0.6128	4.35	0.000	[1.4664, 3.8687]
rate_3%	0.4598	0.4116	1.12	0.264	[-0.3470, 1.2666]
rate_4%	0.5413	0.1229	4.44	0.000	[0.3008, 0.7819]
rate_6%	0.8599	0.8209	1.05	0.295	[-0.7492, 2.4689]

To gain a more comprehensive understanding of how different attributes influence investor choice regarding ESG fund products, this study incorporated box plots from the mixed logit model to visually depict the distribution of coefficients for each variable. As shown in Figure 3, the coefficient distributions for cost and no-ESG-attribute (none) exhibit a clear positive trend, aligning with the results from the conditional logit model. This suggests that products offering better cost efficiency hold greater appeal for investors. However, compared to the conditional logit model, the mixed logit model provides a finer-grained capture of heterogeneity among individuals. For instance, regarding green certification, while government green certification (cer_gov) still demonstrates an overall positive influence, its coefficient distribution spans a wide range. This indicates significant divergence in trust levels among investors towards this certification. Notably, the coefficients for third-party certification (cer_th) are predominantly concentrated in the negative range, reflecting widespread investor skepticism about its credibility – a finding not adequately captured by the conditional logit model.

Concerning ESG screening strategies, the mixed logit model reveals a marked difference in the coefficient distributions between strict negative screening (neg_str) and moderate negative screening (neg_med): the former skews towards the negative range, while the latter is more clustered in the positive range. This indicates that a moderate negative screening strategy is more attractive to investors. Furthermore, regarding the impact of return rates, although both models concur that low-return products are unpopular, the mixed logit model further reveals that an annualized return of 4% (rate_4) may serve as an acceptance threshold for some investors. This finding contrasts with the conditional logit model's implication that only high-return products are attractive. These results not only provide novel insights for understanding investor behavior but also offer robust support for financial institutions seeking to optimize product design, particularly in developing more precise strategies tailored to the needs of different market segments. By identifying key influencing factors and their heterogeneity, institutions can better address the diverse needs of investors, thereby promoting the adoption and development of ESG investment principles.

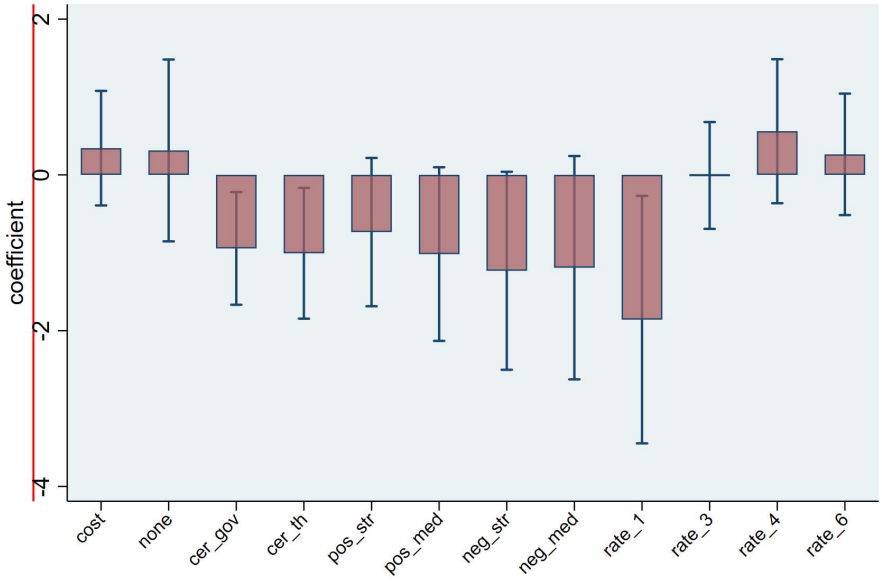

Figure 3: Mix Logit Results

As mentioned above, the differences in empirical results between the conditional logit model and the mixed logit model primarily lie in their respective capabilities to characterize individual heterogeneity. The conditional logit model assumes homogeneous preferences among all investors regarding fund attributes, and thus its estimation results can only reflect overall trends, such as the average positive impact of government green certification and negative exclusion strategies on choice behavior. However, this specification overlooks potential significant preference differences among individuals. In contrast, the mixed logit model effectively reveals the heterogeneous structure of investor preferences by introducing individual-level parameter disturbances. This model not only provides representative average preference values (i.e., coefficients) but also reflects the degree of individual preference variation through the standard deviations of parameters, thereby more comprehensively capturing the complex behavioral logic underlying investment decisions.

Leveraging this methodological advantage, the mixed logit model further identifies the moderating effects of

sociodemographic characteristics on preferences. For instance, high-asset investors exhibit a stronger trust tendency toward government certification compared to low-asset investors, while younger groups prefer stricter negative screening strategies—these differentiated preferences cannot be identified in the conditional logit model. Moreover, regarding the influence of return and cost attributes, the results from the conditional logit model present a relatively simple linear relationship, whereas the mixed logit model reveals significant divergence in investors' sensitivity to these two types of attributes due to factors such as risk attitudes and financial conditions. This finding not only deepens the understanding of ESG investment behavior mechanisms but also provides more targeted policy recommendations for financial institutions in product design and market segmentation strategies.

IV. D. Explanation of Willingness-to-Pay (WTP) Calculation Failure

Willingness-to-Pay (WTP) refers to the maximum price consumers are willing to pay when purchasing goods or services [9]. This concept reflects consumers' valuation of a particular good or service and the cost they can bear to obtain it. In economics and market research, WTP is typically calculated by converting the utility of non-monetary attributes into monetary equivalents, thereby helping to understand consumers' trade-off behaviors among different attributes [22]. For instance, in fund products, the maximum cost investors pay usually manifests as the fund's total expense ratio. Therefore, by examining the proportional relationship between attribute coefficients and the expense ratio coefficient in model estimation, investors' WTP for specific attributes can be calculated[10], [23].

Although the logit model structure supports WTP estimation, investors' irrational interpretation of fees and returns renders the WTP metric ineffective. Specifically, regression results show that: investors tend to prefer funds with higher expense ratios while paying less attention to fund returns; compared to uncertified products, government certification significantly enhances product utility, whereas third-party certification reduces utility; moreover, investors exhibit aversion to positive ESG screening strategies but prefer stricter negative ESG exclusion strategies. These findings not only deviate from conventional wisdom but also make WTP calculations based on model estimation difficult to achieve.

Several factors may explain these results: First, the "cost" attribute in the experimental design might not accurately reflect investors' true perceptions. For example, some respondents may view higher expense ratios as indicative of superior management capabilities or premium services rather than purely as an economic burden. Second, respondents' decision-making behavior may contain a degree of randomness, particularly when faced with complex information, potentially leading to choice patterns that deviate from rational expectations. Finally, the option settings might be inappropriate, failing to adequately exclude other potential factors influencing the cost attribute. For instance, the experiment did not explicitly emphasize that all fund products were managed by the same team or employed identical investment strategies, which could lead respondents to conflate the total expense ratio with implicit characteristics, such as management quality or brand reputation.

To address this issue, future research could focus on the following improvements: First, optimize experimental design to ensure all options are as consistent as possible in non-monetary attributes—for example, explicitly stating that all fund products are managed by the same team using identical investment strategies—to reduce potential implicit meanings embedded in the total expense ratio. Second, simplify information presentation to lower respondents' cognitive load and avoid random choice behaviors caused by information overload. Finally, expand the sample scope and incorporate heterogeneity analysis to more comprehensively capture preference characteristics across different groups. Through these refinements, future studies may more accurately reveal investors' WTP for ESG fund products and the underlying behavioral mechanisms.

IV. E. Summary of Key Model Findings

This study employed conditional logit and mixed logit models to conduct an in-depth analysis of investor preference patterns when selecting ESG fund products. The findings reveal that investors exhibit a high level of trust in government certification, considering it a crucial guarantee of fund quality, whereas third-party certification failed to garner the same level of recognition. Furthermore, regarding ESG screening strategies, investors demonstrated a clear preference for negative screening strategies over positive screening. This preference may stem from the perception that negative screening conveys greater transparency and risk control information, thereby enhancing investors' perception of its reliability. Notably, contrary to conventional wisdom, the study also found that some investors are willing to accept higher fees, potentially associating them with higher-quality services or brand reputation.

The mixed logit model uncovered significant heterogeneity in investor preferences. For instance, substantial differences exist in preferences for green certifications and ESG screening strategies. While some investors strongly trust government certification, others remain entirely unconvinced. Similarly, attitudes towards low-return products vary significantly, with some investors exhibiting strong aversion, albeit to varying degrees. These results

underscore the importance of understanding preferences at the individual level and provide valuable insights for financial institutions seeking to tailor products to different market segments.

Although this study yielded valuable insights through both models, challenges arose when attempting to calculate willingness to pay (WTP). Specifically, the preference direction for the cost attribute contradicted theoretical expectations, preventing accurate WTP estimation based on the available data. This issue highlights the need for future research to optimize experimental design. Ensuring greater consistency across non-monetary attributes—such as explicitly stating that all funds are managed by the same team using identical strategies—could reduce potential confounding interpretations embedded within the overall fee structure. Additionally, simplifying information presentation and reducing respondents' cognitive burden are critical steps towards enhancing research reliability. Implementing these improvements should enable future studies to more accurately capture investors' true valuation of ESG fund products and the complex behavioral mechanisms underlying it.

V. Conclusions

This study employs discrete choice experiments with conditional and mixed logit models to analyze Chinese retail investors' preferences and decision-making mechanisms regarding ESG funds. Results show strong investor preference for ESG attributes, particularly government green certification, which serves as a trusted authoritative endorsement. Contrary to international literature, negative exclusion strategies are favored over positive screening, as they signal stronger transparency and risk control. Notably, some investors misinterpret high fees as markers of superior service quality, while returns exhibit weaker-than-expected influence, even displaying counterintuitive patterns. The combined methodology effectively captures heterogeneous preferences: the conditional logit model identifies overarching trends—investors prioritize credible green labels and risk filtering over mere returns or costs—while the mixed logit model reveals significant individual heterogeneity, with statistically diverse choice behaviors. However, unstable willingness-to-pay (WTP) estimates due to anomalous preferences suggest future research should optimize experimental design by improving attribute consistency and simplifying information to reduce cognitive load.

Based on these findings, this study offers several practical implications for fund institutions and regulators. First, in product design, emphasis should be placed on "government certification" attributes to enhance investor trust, with priority given to launching funds based on "negative exclusion" strategies. Simultaneously, clear explanations of services corresponding to higher fees should be provided to avoid misunderstandings caused by information asymmetry. Second, in marketing strategies, increased efforts should be made to popularize ESG knowledge, reduce information asymmetry, and target specific demographics including highly educated, younger, and high-net-worth individuals. At the policy level, recommendations include promoting integration between government and third-party certification standards to enhance credibility, and encouraging transparent disclosure of ESG funds' investment strategies and screening criteria.

While this study has certain limitations—including a relatively small sample size, uncontrolled brand/management team variables, and a narrow focus on ESG funds without covering other green financial instruments—it nevertheless offers valuable new perspectives for understanding ESG investment behavior in the Chinese market. Future research could expand the sample size and explore a broader range of ESG-related financial products to further advance the development of sustainable finance.

Declaration of Conflicting Interests

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Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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