Does Proximity Internalize Environmental Externalities in Sustainable Finance?
Evidence from Hypothetical Municipal SDG Bonds in Japan

Draft: 2026-01-15 20:38:55 (JST)

Abstract

Sustainable finance may attract demand through the financial value of sustainability labels rather than non-financial sustainability profiles. We investigate whether such profiles change demand for projects with positive externalities but low profitability (biodiversity and natural disaster resilience) among institutional investors proximate to issuers. We ran online surveys about bids for hypothetical municipal SDG bonds whose allocation to UoP randomly changes between decarbonization, biodiversity, disaster resilience, and social equity. The estimations find that changes in allocation to UoPs do not change bids for the bonds. By contrast, heterogeneity by geographical proximity creates significant effects on bids. Proximate investors bid higher for greater allocation to disaster resilience compared to decarbonization. This suggests that proximate investors may not value local sustainability as much as financially valued projects like decarbonization.

Keywords: Sustainable finance; Municipal bonds; ESG investing; Geographical proximity; Use of proceeds

JEL Classification: G11; G12; H74; Q56

1 Introduction

Public sector GSSS (green, social, sustainability, sustainability-linked) bond issuance has grown gradually yet significantly as a supply engine of sustainable development in the 2020s. Public GSSS bonds finance projects with diffuse benefits (positive environmental externality) and low own profitability, which are difficult for private issuers to pursue given their profit-maximization objectives (Cingolani, 2022; Jackson and Petraki, 2021; Flammer et al., 2025; Oehmke and Opp, 2024). On the other hand, such a mechanism regarding externality also operates on the demand side. While retail investors may care about possible externality through their investment (Bonnefon et al., 2025), institutional investors cannot invest in positively external finance without expecting return (Berg et al., 2022). To this end, it remains unknown whether institutional investors value ESG finance that funds local sustainability projects—projects that could benefit nearby organizations—despite their low profitability.

We shed light on municipal SDG bonds in Japan to evaluate how the allocation to certain UoPs may change bond pricing and the role of geographical proximity in the pricing effect. Specifically, we evaluate bids for hypothetical municipal SDG bonds whose allocation consists of 4 UoPs—decarbonization, biodiversity, disaster resilience, and social equity. We treat biodiversity and disaster resilience as projects with positive local externalities despite low profitability, compared to decarbonization, which is financially better but lacks local externalities. We treat social equity as a low-profitable project without local externalities. We measure the effect of variation in allocation to UoP on bid (own effect). This reveals how SDG bonds with higher weight of certain low-profitable projects may be favored if the pre-issuance financial performance is identical.

We also account for a different possible channel of bidding through geographical proximity that may play a role in internalizing sustainable externalities for low-profit projects. For this, we account for geographical distance between the investor's organization and the issuing prefecture as a source of heterogeneity in own effect (proximity heterogeneity). Successful internalization of positive environmental benefits may appear in the form of lower bids for bonds with higher allocation to such projects.

This study is motivated by the previous findings that ESG finance attracts investors through better financial profiles of ESG labels (Hartzmark and Sussman, 2019) while sustainable impact change in SRI does not change the demand if the financial profile stays unchanged (Berg et al., 2022; Døskeland and Pedersen, 2016; Bonnefon et al., 2025). One possible reason for insignificant ESG impact is the lack of relatability (Fong and Luttmer, 2009) or perceived benefit. For example, carbon reduction amount is difficult to perceive as showcased in Døskeland and Pedersen (2016). Consequently, investors may be satisfied with a binary label of "Green" or "Social" (Hartzmark and Sussman, 2019; Heeb et al., 2022) or with warm-glow giving (Andreoni, 1990). To overcome this possible issue, we take UoPs that benefit locally in addition to climate mitigation projects (projects for carbon emission reduction).

This approach is also motivated by a possible identification problem in the premium of SDG bonds.

Previous studies might underestimate the premium of SDG bonds when matching them with conventional bonds conditional on observed pre-issuance characteristics. More sophisticated strategies are needed, such as the approaches taken by Ando et al. (2024) and Hartzmark and Sussman (2019), if SDG bond issuers have better prospects (Pástor et al., 2021, 2022). This study attempts to eliminate such unobserved differences by comparing across SDG bond issuers. We examine the impact of allocation weight to different sustainable projects on the bid at issuance.

This study finds that institutional investors do not change their bids based on allocation to UoP. This is consistent with previous studies showing that non-financial environmental profiles do not change demand. However, proximity creates positive heterogeneity for disaster resilience but not for biodiversity. This indicates that projects with positive environmental externalities are disfavored by proximate investors. Instead, proximate investors bid lower for SDG bonds whose allocation is weighted toward decarbonization. The results hold when investors in large cities are excluded, so proximity heterogeneity does not help mobilize low-profit yet externality-generating projects such as biodiversity and disaster resilience.

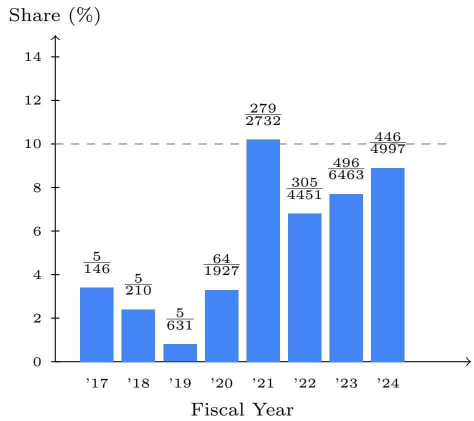
This study contributes to the literature on non-financial profiles in ESG finance. As shown by Heeb et al. (2022) and Døskeland and Pedersen (2016), UoP allocations alone have little pricing impact—investors appear indifferent to sustainability impact levels. Geographical proximity activates differentiated UoP preferences, suggesting non-financial profiles can matter when investors are proximate to the issuer. This study also contributes to literature on demand analyses of ESG finance based on the future performance of ESG profiles (Pástor et al., 2021, 2022). Our findings that decarbonization is demanded at a lower spread among proximate investors indicate that ESG finance is valued for its expected future financial performance rather than local sustainability benefits. Decarbonization projects are tied to Paris Agreement commitments, which provide stronger signals of policy support and regulatory stability compared to locally-oriented UoPs.

The remainder of the paper proceeds as follows. Section 2 describes the institutional context of municipal SDG bonds in Japan. Section 3 details our survey design and experimental variation. Section 4 presents the estimation framework. Section 5 summarizes data and descriptive statistics. Section 6 presents results, progressing from average spreads to whole-sample analyses. Section 7 discusses mechanisms, reconciles prior literature, and derives policy implications. Section 8 concludes.

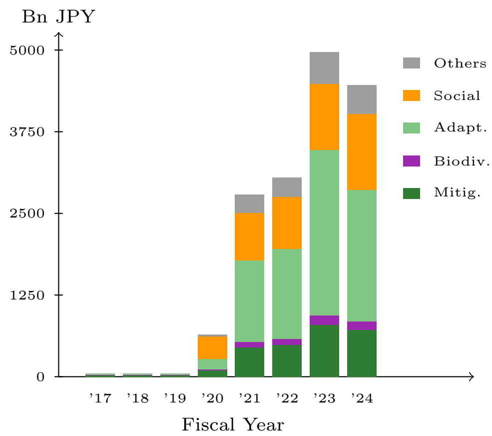
2 Municipal Bond Issuance in Japan

Municipalities in Japan have issued GSSS bonds and their share has increased since 2020, until which time Tokyo was the only municipal issuer, as shown in Figure 1a. The municipal GSSS bonds allocate various sustainability UoPs outside climate mitigation as shown in Figure 1b. The highest weight is placed on natural disaster prevention and mitigation as shown in Table 1. Large allocation goes to climate adaptation and social projects. Adaptation is a major UoP across the whole sample, whereas social projects are adopted heavily among less than half of the bonds. Mitigation and biodiversity are both minor yet common UoPs, both of which are distinct from corporate GSSS bonds.

These projects are not adopted by private GSSS bonds as they do not align with profit maximization. If UoP composition affects investor demand, this has direct implications for municipal borrowing costs and the efficiency of sustainable finance allocation.



(a) Municipal Share of GSSS Issuance



(b) UoP Allocation by Fiscal Year

Notes: (a) Municipal share (%) of total GSSS bond issuance in Japan. Values show municipal/total issuance in Bn JPY. (b) UoP allocation for 150 municipal GSSS bonds. Mitig.=Mitigation, Biodiv.=Biodiversity, Adapt.=Adaptation. Data source: Japan Exchange Group (2024).

Table 1: Summary Statistics of UoP Allocation in Municipal GSSS Bonds (%)

	Mitigation	Biodiversity	Adaptation	Social	Others
N	150	150	150	150	150
Mean	16.4	3.6	50.9	20.6	8.4
SD	10.6	2.4	28.8	35.2	6.3
25th Percentile	10.0	2.0	40.0	0.0	7.0
50th Percentile	19.0	5.0	59.0	0.0	8.0
75th Percentile	25.0	5.0	70.0	25.0	10.0

Notes: Statistics based on 150 municipal GSSS bond issuances from FY2017–2024 (excludes 3 SLBs with no specific UoP). Values represent % of proceeds allocated to each category.

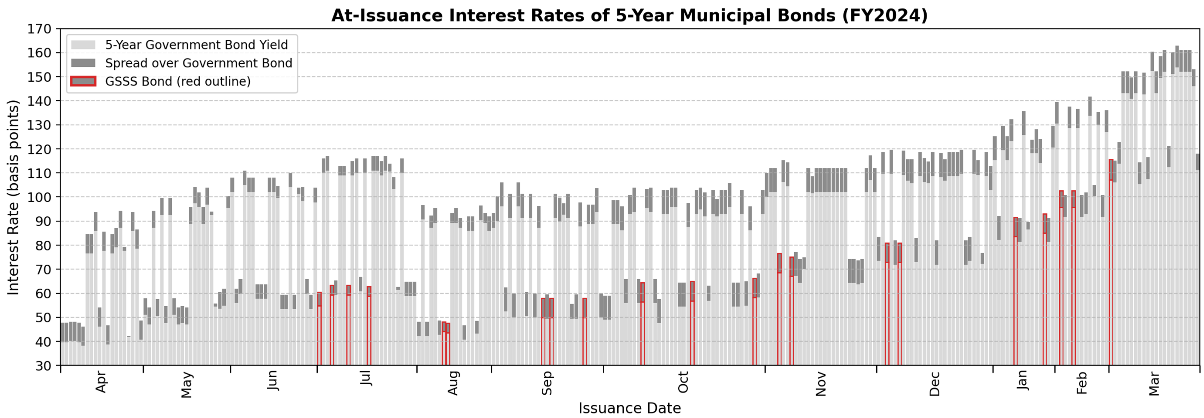


Figure 2: At-Issuance Interest Rates of 5-Year Municipal Bonds in Japan, FY2024

Notes: Each bar represents a municipal bond issuance, decomposed into the 5-year government bond yield (light gray) and the spread over government bonds (dark gray). GSSS bonds are highlighted with red outlines. Spreads typically range from 0 to 20 basis points. Data source: Japan Local Government Bond Association (2024).

3 Survey Design

Our survey design creates hypothetical SDG bonds based on actual municipal SDG bond issuances in Japan. The survey asks respondents about their bid for the respective SDG bond as organizational investment decisions. We set four issuers (Miyagi, Tokyo, Osaka, and Fukuoka) for SDG bonds. These prefectures were chosen because: (1) Tokyo and Osaka are central cities while Miyagi and Fukuoka are regional cities, and (2) their locations are geographically well-distributed across Japan for spatial analyses.

The bonds have a common set of 4 UoPs displayed in Table 2. The first UoP is decarbonization projects (climate mitigation) as a profitable environmental UoP for the Paris Agreement. The second UoP is biodiversity as an environmentally beneficial yet low-profit type of project. This UoP is common in Japanese municipal bonds with a small share in both central and regional municipalities. The third UoP is disaster resilience, which has the highest share among municipal bonds, mobilized for natural disaster prevention. The last UoP is social equity. We vary the allocation of four common UoPs across bonds shown to each investor. Table 2 details the four UoP categories.

In the survey, the allocation for each UoP changes randomly across the 4 different prefectural bonds shown to each respondent. The allocation to the UoPs is patterned such that each UoP allocation (UoP1, UoP2, UoP3, UoP4) takes either 6.25bn JPY (62.5%, heavily weighted), 3.75bn JPY (37.5%, highly weighted), or 1.25bn JPY (12.5%, baseline), with the total fixed at 10bn JPY. The experimental design yields 10 unique allocation patterns across the four UoP categories (see Appendix E for the complete distribution).

Table 2: Descriptions of UoPs and Allocations

UoPs	**Project Details**	**Label**
Decarbonization	• Solar power facilities in metropolitan facilities • Electrification of public vehicles and energy efficiency	UoP1
Biodiversity	• Water source conservation & disaster prevention forests • Greening parks and waterfront spaces	UoP2
Disaster Resilience	• Renovation of underground channels and floodgates • Landslide prevention facilities	UoP3
Social Equity	• Renovation of housing for low-income groups • Expansion of support education facilities	UoP4

In these settings, we ran online surveys asking respondents to state their preferred spread to Japan's government bond. Choices are $\{-21, -14, -7, 0, 7, 14, 21\}$[bps] as a plausible spread range based on actual municipal bond issuances in FY2024 (Figure 2). To ensure capital availability, investors are hypothetically assumed to have gained 20% additional capital from their existing investments. We asked them to allocate this capital between the SDG bond (at their chosen spread) and Japanese government bonds. We repeated these questions four times (once per issuer), with decisions treated independently each time.

4 Data and Descriptive Statistics

The data are collected via online survey on Freeasy (13–14 December 2024 and 16–17 January 2025). From 30,000 random respondents, we filtered down to 892 final respondents meeting institutional investor criteria (Appendix A). The summary statistics of sample organizational investors are in Table 3. Their geographical distribution is in Figure B.1.

The sample distribution of bids for the respective sustainability bond is displayed in Figure 3. It shows the most frequent spread is 7[bps] across the issuers with shares at nearly 40%. It is worth noting that the share of -21[bps] is large for each issuer. Figure 4 displays the distribution of spreads conditional on UoP allocation levels for each of the four UoPs. Each panel shows how the spread distribution varies across three allocation levels (12.5%, 37.5%, 62.5%), with separate curves for each issuer. The spread distributions exhibit notable heterogeneity across allocation levels and issuers. For instance, when decarbonization (UoP1) allocation is high (62.5%), spreads tend to concentrate at lower values, particularly for certain issuers, suggesting that investors value high decarbonization allocations. Conversely, higher allocations to biodiversity (UoP2), disaster resilience (UoP3), or social equity (UoP4) show different patterns depending on the issuer, with some issuers experiencing wider spread distributions or shifts toward higher spreads. These patterns provide preliminary visual evidence that UoP composition influences investor valuations differently depending on issuer identity, foreshadowing the issuer-specific proximity heterogeneity we uncover in the regression analysis.

Table 3: Summary Statistics: Respondent Characteristics (N = 892)

Panel A: Individual			**Panel B: Organizational**		
Variable	Count	%	Variable	Count	%
Age			*Firm Size*		
20–29	89	10.0	<10 employees	91	10.2
30–39	206	23.1	10–49	116	13.0
40–49	244	27.4	50–99	119	13.3
50–59	202	22.6	100–499	201	22.5
60+	151	16.9	≥500	365	40.9
Sex			*Investment Volume (JPY)*		
Male	698	78.3	>50M	303	34.0
Female	194	21.7	>100M	139	15.6
			>500M	161	18.0
Marital Status			>1B	136	15.2
Married	654	73.3	>5B	153	17.2
Unmarried	238	26.7			
			Industry		
Household Income (JPY)			Manufacturing	229	25.7
<5M	127	14.2	Services	109	12.2
5–8M	250	28.0	Trading/Retail	72	8.1
8–10M	169	18.9	Finance/Insurance	66	7.4
10–15M	216	24.2	Other	416	46.6
≥15M	130	14.6			
			Firm Type		
			Private	489	54.8
			Intermediate Corp.	166	18.6
			Public Interest Found.	195	21.9
			Public Organization	42	4.7
			Investor Type		
			Executive Officer	149	16.7
			Manager	337	37.8
			Asset Manager	360	40.4
			Public Representative	46	5.2
			Org. Pressures (High)		
			Regulatory	501	56.2
			Stakeholder	472	52.9
			Environmental Ops	459	51.5

Notes: Panel A reports individual characteristics. Panel B reports organizational characteristics. Firm Size categories: number of employees. Investment Volume categories in JPY. Organizational Pressures indicate respondents reporting high pressure levels.

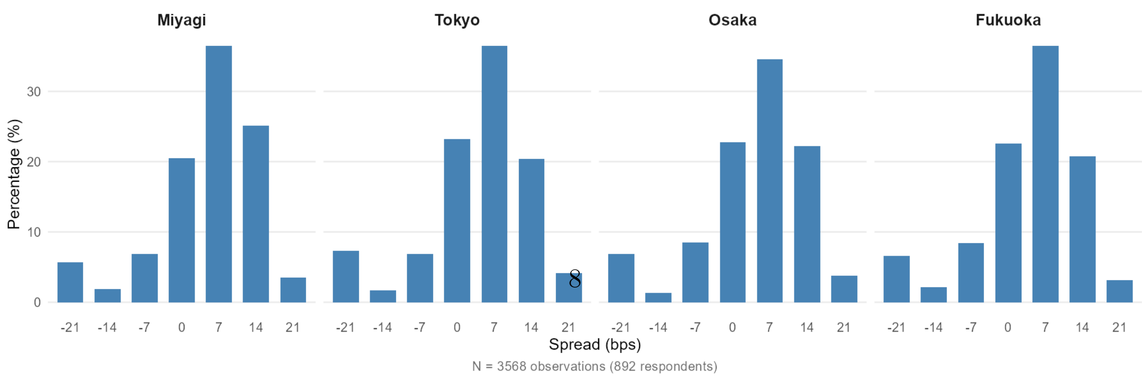


Figure 3: Distribution of Bid Spreads by Issuer

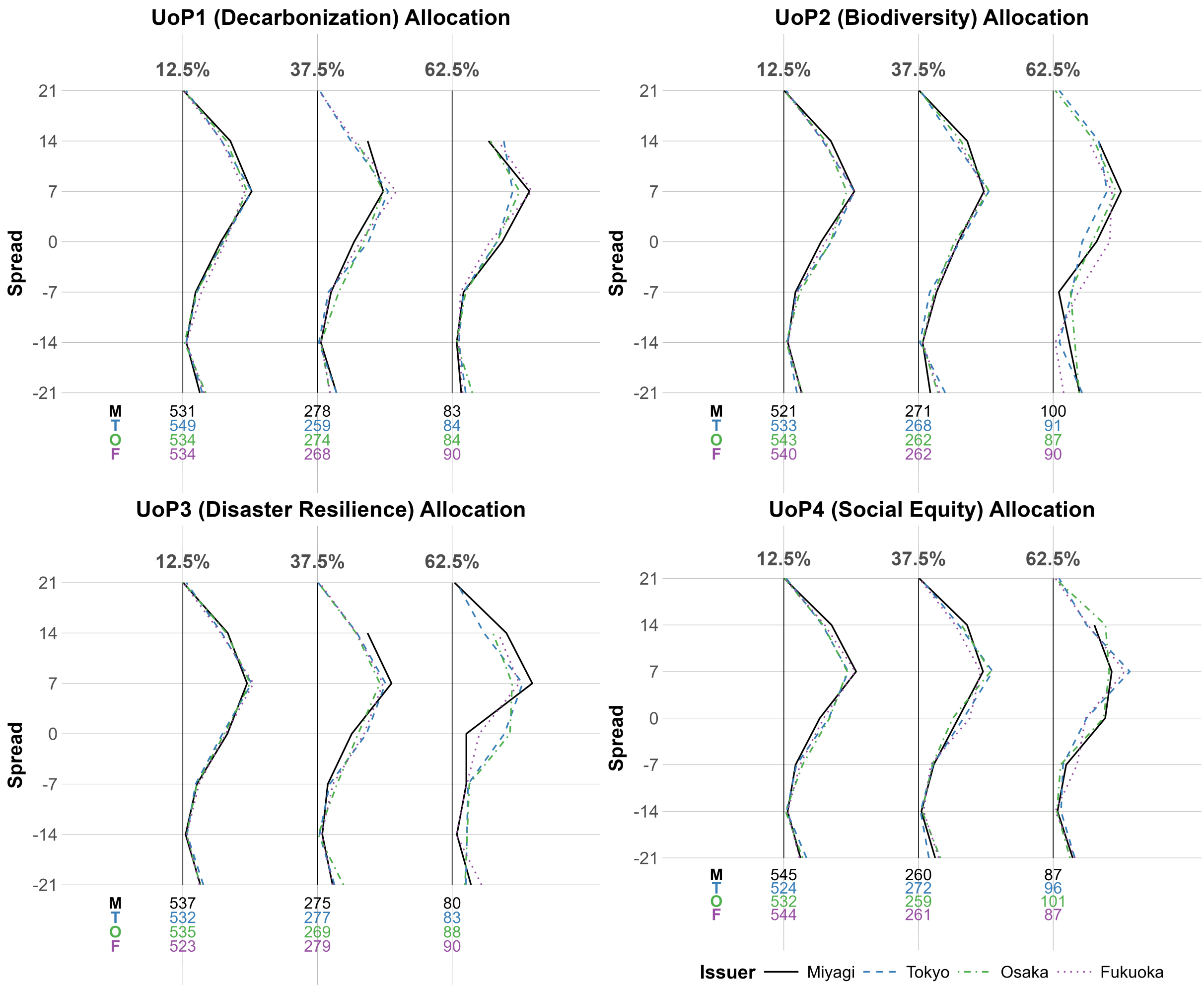


Figure 4: Distribution of Spreads by UoP Allocation Levels

Notes: Each panel shows the distribution of spreads for one UoP at three allocation levels (12.5%, 37.5%, 62.5%). The vertical black lines mark the zero-reference point for each allocation level. Distribution curves extend horizontally from these baseline positions, with the width indicating the proportion of observations at each spread value. Different line styles and colors represent different issuers (see legend in the Social Equity panel).

5 Estimation Framework

5.1 Interval Regression for Censored Bid Data

Our dependent variable—the bid spread—is interval-censored: respondents select among seven discrete spread categories rather than stating a continuous value. We therefore employ interval regression, which models the latent continuous spread underlying the observed categorical choice.

Let y_i denote respondent i's latent (unobserved) true bid spread:

$$y_i = \mathbf{x}_i'\boldsymbol{\beta} + u_i, \tag{1}$$

where $\mathbf{x}_i$ includes UoP allocations, proximity measures, and controls; $\boldsymbol{\beta}$ is the parameter vector; and $u_i \sim N(0, \sigma^2)$. The observed outcome is a category $j \in \{0, \ldots, 8\}$, corresponding to interval thresholds:

$$-\infty = \alpha_0 < \alpha_1 = -0.21 < \alpha_2 = -0.14 < \cdots < \alpha_7 = 0.21 < \alpha_8 = \infty.$$

The probability of observing category j is:

$$\Pr(\text{category } j) = \Phi\left(\frac{\alpha_j - \mathbf{x}_i'\boldsymbol{\beta}}{\sigma}\right) - \Phi\left(\frac{\alpha_{j-1} - \mathbf{x}_i'\boldsymbol{\beta}}{\sigma}\right),$$

where $\Phi(\cdot)$ is the standard normal CDF. Parameters are estimated by maximum likelihood.

5.2 Specification: UoP Allocations and Proximity Interactions

Our cross-sectional specification for interval regression allows for quadratic UoP effects:

$$y_i = \underbrace{\sum_{k=2}^{4} \beta_k \, \text{UoP}_{ik} + \sum_{k=2}^{4} \beta_{kk} \, \text{UoP}_{ik}^2}_{\text{own effects}} + \gamma p_i + \underbrace{\sum_{k=2}^{4} \delta_k \big(\text{UoP}_{ik} \cdot p_i\big)}_{\text{proximity heterogeneity}} + \mathbf{z}_i'\boldsymbol{\theta} + u_i, \tag{2}$$

where UoP_{ik} is the allocation to UoP k expressed as the difference from UoP1 (decarbonization), which takes 12.5, 37.5, or 62.5 with UoP1 as baseline because the sum is always 100. Thus, coefficients on UoP_k ($k = 2, 3, 4$) capture the effect of reallocating from decarbonization to the respective UoP category. UoP_{ik}^2 captures non-linear effects, $p_i \in [0, 1]$ is proximity measured by the geographical distance between investor i and the issuer. We specify $p_i = \exp(-\lambda d_i)$ where d_i denotes the distance and λ governs decay speed (λ is set for proximity to halve at 150 km for our baseline estimations).[1] For the estimators, β_k and β_{kk} capture baseline linear and quadratic effects, δ_k captures proximity amplification, and $\mathbf{z}_i$ includes investor controls.

[1]Appendix D uses λ for 100km and 200km to halve p_i. The functional graph of $p_i = \exp(-\lambda d_i)$ is visualized in Figure B.2.

For the panel fixed effects specification, we pool all four bond bids from respondent i:

$$\begin{aligned} y_{ij} = & \underbrace{\sum_{k=2}^{4}(\beta_k + \phi_{kj})\,\mathrm{UoP}_{ik} + \sum_{k=2}^{4}(\beta_{kk} + \phi_{kkj})\,\mathrm{UoP}_{ik}^2}_{\text{own effects}} + \gamma p_{ij} \\ & + \underbrace{\sum_{k=2}^{4}(\delta_k + \omega_{kj})\big(\mathrm{UoP}_{ik}\cdot p_{ij}\big)}_{\text{proximity heterogeneity}} + c_i + \varepsilon_{ij}, \end{aligned} \tag{3}$$

where j indexes issuer (Miyagi, Tokyo, Osaka, Fukuoka), so $y_{ij} = \alpha_{ij}$, which is α_i for issuer j. c_i is the individual fixed effect controlling for all time-invariant investor characteristics, ϕ_{kj} and ϕ_{kkj} capture issuer-specific deviations in baseline linear and quadratic effects, ω_{kj} captures issuer-specific deviations in proximity-interaction effects, and ε_{ij} is the idiosyncratic error. This specification exploits within-person variation across the four bonds, allowing us to identify UoP preferences net of unobserved investor heterogeneity. Proximity p_{ij} now varies by both investor i and issuer j, calculated as $p_{ij} = \exp(-\lambda d_{ij})$.

5.3 Alternative Specification: Dummy Variables for Discrete Levels

For easier interpretation, we also estimate specifications using dummy variables for discrete UoP levels. Let $\mathrm{UoP}_{ik}^M = 1(\mathrm{UoP}_{ik} = 37.5\%)$ and $\mathrm{UoP}_{ik}^H = 1(\mathrm{UoP}_{ik} = 62.5\%)$ denote Medium and High levels, with $\mathrm{UoP}_{ik} = 12.5\%$ as the reference category.

The cross-sectional dummy specification for interval regression is:

$$y_i = \underbrace{\sum_{k=2}^{4}\beta_k^M\,\mathrm{UoP}_{ik}^M + \sum_{k=2}^{4}\beta_k^H\,\mathrm{UoP}_{ik}^H}_{\text{own effects}} + \gamma p_i + \underbrace{\sum_{k=2}^{4}\delta_k^M\big(\mathrm{UoP}_{ik}^M\cdot p_i\big) + \sum_{k=2}^{4}\delta_k^H\big(\mathrm{UoP}_{ik}^H\cdot p_i\big)}_{\text{proximity heterogeneity}} + \mathbf{z}_i'\boldsymbol{\theta} + u_i, \tag{4}$$

where β_k^M and β_k^H capture the effects of Medium and High levels relative to Low, δ_k^M and δ_k^H capture proximity amplification for each level.

The panel fixed effects dummy specification is:

$$\begin{aligned} y_{ij} = & \underbrace{\sum_{k=2}^{4}(\beta_k^M + \phi_{kj}^M)\,\mathrm{UoP}_{ik}^M + \sum_{k=2}^{4}(\beta_k^H + \phi_{kj}^H)\,\mathrm{UoP}_{ik}^H}_{\text{own effects}} + \gamma p_{ij} \\ & + \underbrace{\sum_{k=2}^{4}(\delta_k^M + \omega_{kj}^M)\big(\mathrm{UoP}_{ik}^M \cdot p_{ij}\big) + \sum_{k=2}^{4}(\delta_k^H + \omega_{kj}^H)\big(\mathrm{UoP}_{ik}^H \cdot p_{ij}\big)}_{\text{proximity heterogeneity}} + c_i + \varepsilon_{ij}, \end{aligned} \tag{5}$$

where ϕ_{kj}^M, ϕ_{kj}^H capture issuer-specific deviations in level effects, and ω_{kj}^M, ω_{kj}^H capture issuer-specific deviations in proximity interactions.

This dummy specification has the same flexibility as the quadratic specification (2 parameters per UoP: Medium and High vs quadratic and squared terms) but offers more intuitive interpretation as discrete pricing effects.

5.4 Parameter Structure for Marginal Effects

Table 4 summarizes how marginal effects decompose into baseline and proximity-heterogeneity components across all specifications. Note that proximity (p) is an observed characteristic (distance between investor and issuer), not experimentally varied, allowing us to measure heterogeneity in UoP effects.

Interval regression (equation 2) is run separately for each issuer, exploiting cross-sectional variation in proximity between investors evaluating the respective issuer of SDG bond. The fixed effects panel model (equation 3) pools each respondent's four bond evaluations with individual fixed effects, exploiting within-investor variation across issuers.

Intreg and FE estimate related but distinct parameters using different sources of variation. Intreg uses *between-investor* (cross-sectional) variation: for Tokyo bonds, we compare how investors at different proximities respond to different UoP allocations, capturing the total market effect including all investor heterogeneity (environmental preferences, local knowledge, etc.). Critically, Intreg does *not* use within-investor variation because each investor sees only one random UoP allocation per issuer. FE uses *within-investor* variation: we observe how the *same* investor changes their bid across issuers with different proximities and UoP allocations. The individual fixed effect α_i removes all time-invariant characteristics, isolating the within-person causal effect net of selection.

Table 4: Parameter Structure for Marginal Effects Across Models

Model	**Own Effect**	**Proximity Heterogeneity**
A. Continuous Quadratic Specification		
Intreg	$\beta_k + 2\beta_{kk} \cdot \text{UoP}_k$	δ_k
FE Panel	$(\beta_k + \phi_{kj}) + 2(\beta_{kk} + \phi_{kkj}) \cdot \text{UoP}_k$	$\delta_k + \omega_{kj}$
B. Dummy Specification (Reference: Low = 12.5%)		
Low→Medium		
Intreg	β_k^M	δ_k^M
FE Panel	$\beta_k^M + \phi_{kj}^M$	$\delta_k^M + \omega_{kj}^M$
Low→High		
Intreg	β_k^H	δ_k^H
FE Panel	$\beta_k^H + \phi_{kj}^H$	$\delta_k^H + \omega_{kj}^H$

Notes: Marginal effect formulas for all models:

- **Continuous Quadratic - Intreg:** $\frac{\partial y_i}{\partial \text{UoP}_{ik}} = \beta_k + 2\beta_{kk} \cdot \text{UoP}_{ik} + \delta_k \cdot p_i$
- **Continuous Quadratic - FE:** $\frac{\partial y_{ij}}{\partial \text{UoP}_{ikj}} = (\beta_k + \phi_{kj}) + 2(\beta_{kk} + \phi_{kkj}) \cdot \text{UoP}_{ikj} + (\delta_k + \omega_{kj}) \cdot p_{ij}$
- **Dummy - Intreg:** $\Delta y_i(\text{Low} \to \text{Medium}) = \beta_k^M + \delta_k^M \cdot p_i$; $\Delta y_i(\text{Low} \to \text{High}) = \beta_k^H + \delta_k^H \cdot p_i$
- **Dummy - FE:** $\Delta y_{ij}(\text{Low} \to \text{Medium}) = (\beta_k^M + \phi_{kj}^M) + (\delta_k^M + \omega_{kj}^M) \cdot p_{ij}$; $\Delta y_{ij}(\text{Low} \to \text{High}) = (\beta_k^H + \phi_{kj}^H) + (\delta_k^H + \omega_{kj}^H) \cdot p_{ij}$

For FE Panel, β and δ are pooled coefficients (Miyagi is reference), while ϕ and ω are issuer-specific deviations (zero for Miyagi).

6 Results

6.1 Pooled Specification Results

Table 5 presents results without issuer-specific components as results of the simplest model. This reveals that the pricing effects of UoP allocations are insignificant, indicating that allocation composition does not affect investor bids. The coefficient on proximity alone is significant in interval regression, while its significance and magnitude are both largely suppressed after controlling for individual fixed effects. This indicates that the association between proximity and bid is explained by organization-specific characteristics, and proximity does not have a causal effect independent of these characteristics. Proximity heterogeneity shifts UoP pricing in the positive direction for UoP_k $(k = 2, 3, 4)$. Yet again, the effects are weakened after controlling for individual fixed effects. Only UoP3 remains positively significant in the fixed effects model, and UoP3 amplifies the positive pricing effects with proximity. This indicates that unobserved individual-specific characteristics favor UoP1 further by lowering bids. UoP3 remains positively significant, with a magnitude indicating that investors bid $0.5p$ [bps] higher for every 10 percentage point increase in allocation to UoP3.

Table 5: Pooled Regression Results: Effect of UoP Allocation on Bid Spread

	Interval Regression		**Fixed Effects Panel**	
	Coef.	SE	Coef.	SE
Own Effects				
UoP2 (Biodiversity)	-1.345	(1.155)	0.002	(1.092)
UoP3 (Disaster Resilience)	-1.540	(1.178)	-0.789	(1.156)
UoP4 (Social Equity)	-1.590	(1.156)	-0.779	(1.050)
Proximity Effects				
UoP2 × p	4.857*	(2.491)	1.238	(2.372)
UoP3 × p	7.145***	(2.528)	5.000**	(2.501)
UoP4 × p	5.407**	(2.500)	2.265	(2.452)
Proximity Main Effect				
p	-4.263***	(1.566)	-1.363	(1.536)
N	3568		3568	
Respondents	892		892	
Individual FE	—		Yes	
Controls	Yes		Absorbed	

Notes: This table presents pooled regression results where UoP effects are constrained to be equal across issuers. Spread is in bps; UoP variables are scaled 0–1 (0.125, 0.375, 0.625). **Intreg:** Interval regression with issuer dummy variables and controls (investor/firm characteristics). **FE Panel:** Individual fixed effects absorb all time-invariant investor characteristics. **Own effect:** Baseline marginal effect of UoP allocation. **Proximity effect:** How proximity amplifies the UoP effect; total effect = own + proximity × p. Mid exponential proximity (halves at 150km). Significance: ***, **, *, † for $p < 0.01, 0.05, 0.10, 0.15$. SEs: robust (Intreg), clustered by individual (FE).

6.2 Average Bid Spreads

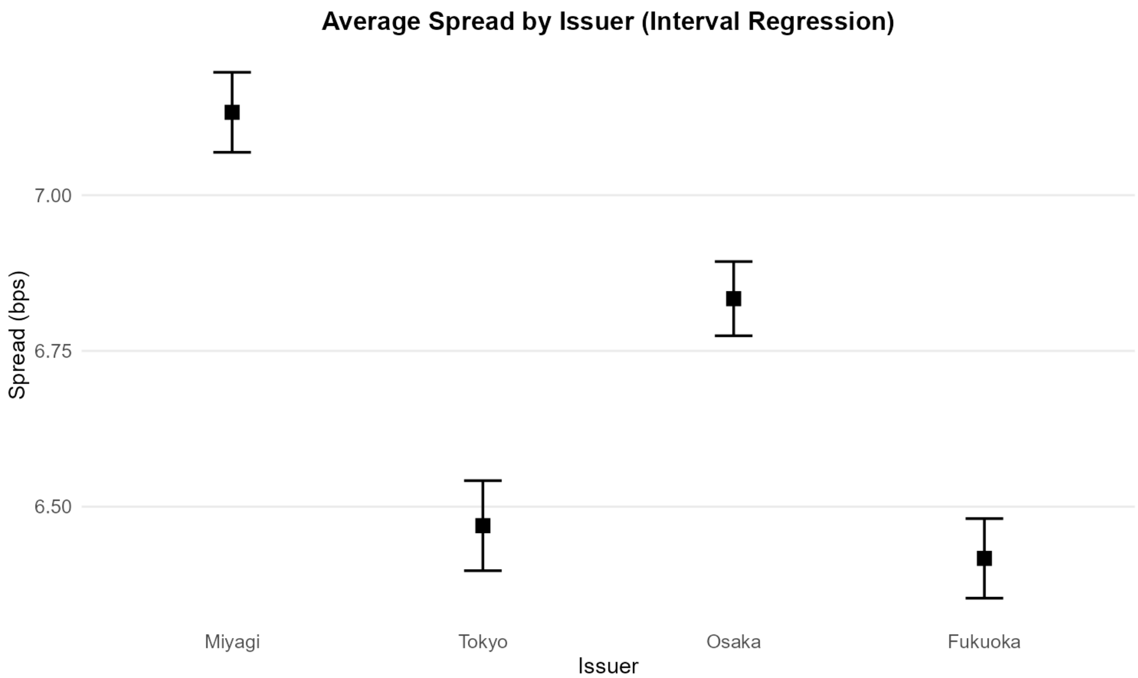


Figure 5: Average Spread of Each SDGs Bond

Notes: Predicted spreads from interval regression (Intreg) model with quadratic UoP specification.

6.3 Issuer-specific UoP pricing effects and proximity heterogeneity

We turn to examine the impacts by issuer. The estimated average bid differs across issuers, as Figure 5 shows. The interval regression estimates include organization-specific effects, and Miyagi has the highest spread at 7.25[bps]. Tokyo and Fukuoka have the lowest averages at 6.45[bps] and 6.40[bps]. The range of estimated spreads aligns with the market spread of GSSS bonds in late FY2024 displayed in Figure 2.

The estimation results of own effects and proximity heterogeneity are displayed in Table 6. The own effect is weak for both UoP_2 and UoP_3 while proximity heterogeneity effects are positively significant in UoP_3 (except for Osaka). This positive heterogeneity indicates that proximate investors bid higher for SDG bonds with greater allocation to climate adaptation.

The proximity heterogeneity in UoP_3 elevates bids. The magnitudes of the coefficients δ_k are around 7–17 in the continuous specification and 3–6 in the categorical specification for the medium level. In other words, allocation to natural disaster resilience is not valued by proximate institutional investors compared to decarbonization projects consistently across the issuers (except for Osaka). Such effects are not seen in UoP_2, demonstrating that biodiversity is evaluated similarly to decarbonization.

Lastly, UoP_4 shows mixed results in the sign of proximity heterogeneity when decomposing into the issuers. Tokyo has negatively significant proximity heterogeneity ($\delta_k = -14.4$[bps] in continuous, $\delta_H = -9.0$[bps] in categorical) while Osaka has positively significant proximity heterogeneity ($\delta_k = 6.2$[bps] in continuous, $\delta_H = 3.4$[bps] in categorical). This suggests heterogeneous effects of UoP_4 among proximate investors. Furthermore, motivations other than internalizing externalities may play a significant role, given the lack of positive externalities from social equity projects from a profit-maximization perspective.

These results are robust when we use different speeds of decay for the proximity function p_i for it to reduce by half at the distance of 100km (fast decay) and 200km (slow decay) (see Appendix D). We conduct another type of robustness check with the same estimations without investors in large cities. We exclude observations whose organizations lie in Miyagi, Tokyo, Osaka, and Fukuoka to see how investors in central and regional cities may affect the proximity heterogeneity. The results remain after the exclusion (see Appendix C). Therefore, bids for low-profit environmental projects are not favored even among proximate institutional investors outside those large cities.

Table 6: Fixed Effects Panel: Continuous vs Categorical Specification

	Continuous					Categorical			
	Miy	Tok	Osa	Fuk		Miy	Tok	Osa	Fuk
UoP2 (Biodiversity)									
β_k	3.171*	-3.108	0.732	-0.652	β_M	0.402	-0.497	0.152	0.020
	(1.795)	(2.222)	(1.770)	(1.313)		(0.871)	(0.921)	(0.781)	(0.617)
					β_H	2.371**	-1.877	0.593	-0.576
						(1.056)	(1.511)	(1.197)	(0.850)
δ_k	-2.597	13.111†	1.989	-3.262	δ_M	-0.872	4.102	0.121	1.045
	(2.878)	(9.008)	(3.717)	(4.895)		(1.224)	(4.326)	(1.524)	(2.071)
					δ_H	-1.693	5.034	1.315	-3.613
						(1.616)	(5.924)	(2.336)	(3.328)
UoP3 (Disaster Resilience)									
β_k	-1.627	-1.818	-0.464	-1.025	β_M	-0.729	-0.674	-0.142	-0.503
	(2.208)	(2.064)	(1.701)	(1.548)		(0.880)	(0.804)	(0.723)	(0.545)
					β_H	0.029	-0.797	-0.243	-0.311
						(1.640)	(1.463)	(1.083)	(1.082)
δ_k	6.992**	16.637**	-0.633	7.425*	δ_M	3.326**	5.729†	-0.048	2.230
	(3.215)	(8.320)	(3.724)	(4.280)		(1.364)	(3.713)	(1.486)	(2.192)
					δ_H	1.356	5.572	-0.233	3.213
						(2.032)	(5.441)	(2.298)	(2.525)
UoP4 (Social Equity)									
β_k	-1.542	1.272	-1.219	-0.792	β_M	0.910	-0.306	0.088	-0.404
	(2.140)	(1.739)	(1.531)	(1.443)		(0.937)	(0.813)	(0.701)	(0.619)
					β_H	-1.843	0.933	-0.808	-0.114
						(1.548)	(1.052)	(0.928)	(0.927)
δ_k	3.114	-14.407**	6.181*	5.929	δ_M	-0.903	-1.325	1.249	2.141
	(3.383)	(6.198)	(3.242)	(5.363)		(1.351)	(3.296)	(1.470)	(2.406)
					δ_H	3.035	-9.037**	3.420*	-0.314
						(2.137)	(3.588)	(2.038)	(3.725)
N	3568					3568			
Respondents	892					892			
Individual FE	Yes					Yes			

Notes: Spread in bps; UoP scaled 0–1. Estimates are issuer-specific: $\beta_k + \phi_{kj}$ (baseline) and $\delta_k + \omega_{kj}$ (proximity) per Eq. 3. **Continuous:** β_k = linear UoP effect; δ_k = proximity heterogeneity. **Categorical:** β_M, β_H = Medium/High vs Low (0.125); δ_M, δ_H = proximity heterogeneity. Proximity p = mid exponential (halves at 150km). ***, **, *, †: $p < 0.01, 0.05, 0.10, 0.15$. Clustered SEs.

7 Discussion

7.1 Key Findings

This study demonstrates that the pricing effect of UoP is weak, indicating that non-financial environmental profiles do not incentivize investors toward sustainability investing. Furthermore, the proximity heterogeneity effects on bids are occasionally significant but tend to be positive, so proximate organizations do not favor local sustainability projects. This suggests that local investors want to invest in SDG bonds for economic performance rather than for environmental externalities. In line with this, the observation of high demand for municipal SDG bonds is not due to the effect of proximity, as the significance of proximity alone is explained by individual fixed effects.

Considering the actual allocation in Japanese municipal bonds shown in Figure 1b, natural disaster resilience may not be an appealing UoP despite having the largest share as a distinctive municipal role. Therefore, to localize financial demand, municipalities may need to identify other projects with more favorable profiles among proximate investors. Capturing demand from proximate investors may matter for municipal sustainable finance, since proximity is at least associated with lower required returns on SDG bonds, even if not causally.

7.2 Non-financial profile of sustainability finance

Our findings are in line with the previous findings that investors do not base their investment decisions on non-financial sustainability profiles. In line with Heeb et al. (2022) and Døskeland and Pedersen (2016), non-financial profiles do not affect pricing of sustainable finance even in the case of tangible differentiation. Even investors in ESG-relevant fields may only care about financial profiles (Barber et al., 2021). This study also shows investor-specific unobserved variables amplify the proximity heterogeneity in interval regression results in Table 5.

These findings demonstrate the necessity of internalizing socially positive externality in sustainable finance in institutional investment. This study demonstrates that proximate organizations demand higher returns from projects intended to benefit local sustainability. This suggests proximate organizations may demand projects with high financial credit rather than welcoming high local externality. This contrasts with retail investing that accounts for externality to beneficiaries (Bonnefon et al., 2025). In corporate investing, it might be more difficult for projects with positive externalities yet low profitability to materialize, even among public organizations as well as private ones, from the standpoint of profit maximization as pointed out by Flammer et al. (2025). Particularly, over the bond's 5-year maturity horizon, decarbonization may be preferred for profit maximization as it offers both financial and environmental validity, as opposed to other sustainable finance projects that are less profitable.

In light of the premium on GSSS bonds, the insignificant allocation composition effect suggests that the premium is not created by environmental quality but rather by a binary "green" label and other unobserved pre-issuance characteristics, as pointed out by Pástor et al. (2022). This stems from the absence of market mechanisms for investors to capture returns from sustainable investing unless sustainability is financially valued. Thus, greenium is generated primarily through binary green labels or external certifications such as CBI certification (Ando et al., 2024; Baker et al., 2022).

7.3 Conclusion

Sustainable finance may attract demand through the financial value of sustainability labels rather than non-financial sustainability profiles. We investigate whether such profiles change demand for projects with positive externalities yet low profitability (biodiversity and natural disaster resilience) among institutional investors proximate to issuers. We ran online surveys about bids for hypothetical municipal SDG bonds whose allocation to UoP randomly changes between decarbonization, biodiversity, disaster resilience, and social equity. The estimations find that changes in allocation to UoPs do not change bids for the bonds. By contrast, heterogeneity by proximity creates significant effects on bids. Proximate investors bid higher for greater allocation to disaster resilience compared to decarbonization. This suggests that proximate investors may not value local sustainability as much as financially valued projects like decarbonization.

Appendices

A Screening Processes

To ensure data quality and target institutional investors with relevant experience, we applied a two-stage screening process to the survey respondents.

A.1 First Filtering

The first stage filtered respondents to retain institutional investors who: (1) have been managing assets for 3 or more years, (2) are not self-employed, and (3) manage at least 10 million JPY in assets. These criteria ensure that respondents have sufficient professional experience and organizational backing for institutional investment decisions.

A.2 Second Filtering

The second stage applied attention checks and response quality filters. We dropped respondents who: (1) answered “yes” to the statement “Nikkei 225 will never go down” (implausible belief); (2) answered “no” to “Tokyo is capital of Japan” (attention check failure); (3) allocated 0% of their hypothetical capital to all 4 bonds (non-engagement); or (4) gave identical responses across all four bond evaluations (lack of differentiation). These filters removed 30,000 initial respondents down to 892 final respondents meeting all institutional investor criteria.

B Distance and Proximity Functions

Figure B.1 displays the geographical distribution of respondents across Japan. To measure proximity between investors and issuers, we use an exponential decay function $p = \exp(-\lambda d)$, where d is the great-circle distance (in km) between the investor's organization and the issuer prefecture, and λ is a decay parameter that governs how quickly proximity diminishes with distance.

The exponential form ensures that proximity is bounded between 0 and 1, with $p = 1$ when distance is zero and $p \to 0$ as distance increases. We calibrate λ such that proximity halves at a specified distance: for our baseline (mid) specification, $\lambda = \ln(2)/150 \approx 0.00462$, meaning proximity halves at 150km. Figure B.2 visualizes this decay function under three alternative specifications: slow decay (halves at 200km), mid decay (halves at 150km, baseline), and fast decay (halves at 100km). The robustness of our results to these alternative decay rates is examined in Appendix D.

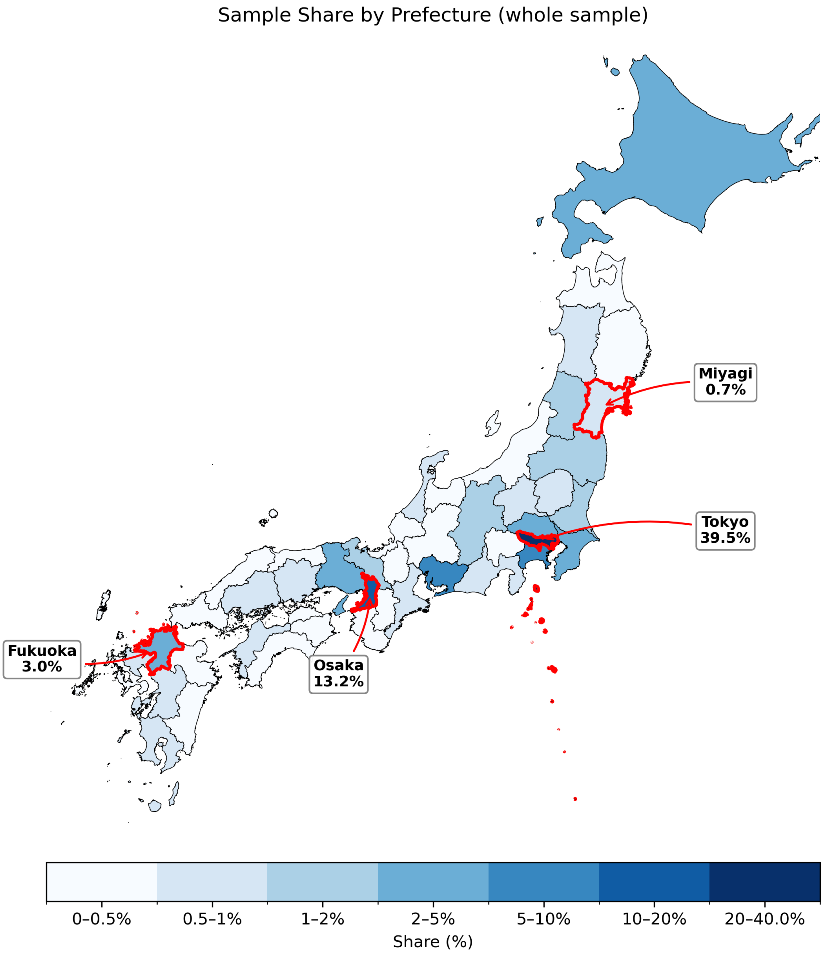


Figure B.1: Geographical distribution of respondents

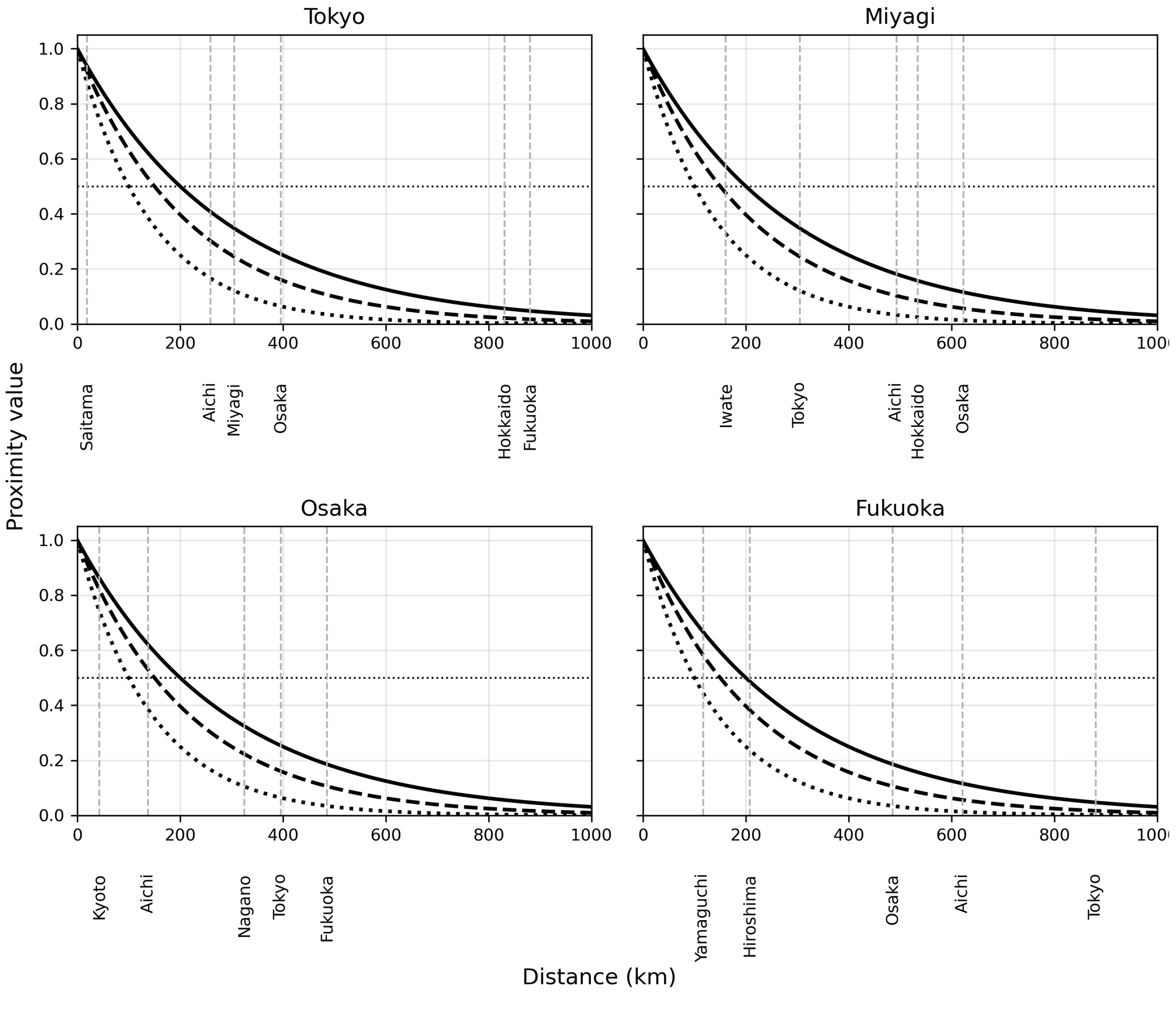


Figure B.2: Proximity decay function (exponential)

Notes: Each λ chosen for proximity to halve at 200km (slow), 150km (mid), 100km (fast). Main results use mid specification.

C Robustness Check Without Investors in Large Cities

To address the concern that proximity effects might be driven by investors located in issuer prefectures (who mechanically have $p = 1$), we re-estimate the FE specification excluding all investors whose organizations are headquartered in Miyagi, Tokyo, Osaka, or Fukuoka prefectures. This sample retains 389 respondents, representing investors who cannot achieve maximum proximity to any issuer.

Table C.1 presents the results using the same format as Table 6. The proximity heterogeneity patterns are broadly consistent with the full sample.

Table C.1: Fixed Effects Panel: Continuous vs Categorical Specification (FAR Sample)

	Continuous					**Categorical**			
	Miy	Tok	Osa	Fuk		Miy	Tok	Osa	Fuk
UoP2 (Biodiversity)									
β_k	2.785	-3.212	2.534	-2.816	β_M	0.577	-1.322	0.227	-1.851*
	(2.663)	(3.131)	(2.893)	(2.124)		(1.339)	(1.349)	(1.263)	(1.016)
					β_H	1.836	-1.169	1.129	-0.468
						(1.518)	(1.990)	(2.038)	(1.373)
δ_k	-5.736	14.420	-0.750	-0.937	δ_M	-2.697	4.695	-1.031	4.949
	(6.072)	(12.380)	(7.820)	(10.727)		(2.463)	(6.985)	(2.452)	(3.739)
					δ_H	-1.535	5.466	1.502	-8.635
						(3.000)	(6.845)	(5.790)	(7.596)
UoP3 (Disaster Resilience)									
β_k	-3.833	-4.519	-1.079	-0.187	β_M	-2.166†	-0.913	-1.001	0.858
	(3.219)	(3.594)	(2.922)	(2.719)		(1.356)	(1.306)	(1.218)	(0.960)
					β_H	0.103	-2.978	0.281	-1.296
						(2.172)	(2.731)	(1.959)	(2.078)
δ_k	9.009	18.458	-0.594	8.785	δ_M	5.557**	9.619	1.760	-1.758
	(6.443)	(14.710)	(6.919)	(8.046)		(2.654)	(6.692)	(2.315)	(4.248)
					δ_H	-0.679	5.328	-1.639	9.214**
						(3.843)	(9.854)	(4.160)	(4.249)
UoP4 (Social Equity)									
β_k	-2.005	0.981	-5.196**	-2.864	β_M	0.429	-0.067	-0.153	-1.341
	(3.482)	(2.516)	(2.360)	(2.403)		(1.405)	(1.194)	(1.065)	(1.113)
					β_H	-1.487	0.011	-2.792*	-1.397
						(2.625)	(1.432)	(1.474)	(1.561)
δ_k	5.656	-13.606*	15.943***	8.371	δ_M	0.425	-2.957	3.687†	6.493†
	(6.863)	(8.175)	(6.134)	(9.876)		(2.787)	(4.747)	(2.452)	(4.302)
					δ_H	2.665	-6.647*	8.118**	-1.424
						(3.992)	(3.966)	(3.760)	(5.560)
N	1556					1556			
Respondents	389					389			
Individual FE	Yes					Yes			

Notes: FAR sample excludes investors located in issuer prefectures (Miyagi, Tokyo, Osaka, Fukuoka). Spread in bps; UoP scaled 0–1. Estimates are issuer-specific: $\beta_k + \phi_{kj}$ (baseline) and $\delta_k + \omega_{kj}$ (proximity) per Eq. 3. **Continuous:** β_k = linear UoP effect; δ_k = proximity heterogeneity. **Categorical:** β_M, β_H = Medium/High vs Low (0.125); δ_M, δ_H = proximity heterogeneity. Proximity p = mid exponential (halves at 150km). ***, **, *, †: $p < 0.01, 0.05, 0.10, 0.15$. Clustered SEs.

D Proximity Decay Robustness Check

Our baseline specification uses an exponential proximity function $p = \exp(-\lambda d)$ with $\lambda = 0.00462$, implying that proximity halves at 150km. To test the sensitivity of our results to this parametric choice, we re-estimate the FE specification using alternative decay rates:

- **Slow decay** ($\lambda = 0.00347$): proximity halves at 200km, implying that investors remain "close" to issuers even at moderate distances.
- **Fast decay** ($\lambda = 0.00693$): proximity halves at 100km, implying that proximity effects attenuate

quickly with distance.

Tables D.1 and D.2 present the results. The key findings are robust to these alternative decay specifications. UoP3 (disaster resilience) continues to show significant positive proximity heterogeneity ($\delta_k > 0$) for Miyagi, Tokyo, and Fukuoka across both slow and fast decay. UoP4 (social equity) maintains its negative proximity heterogeneity for Tokyo ($\delta_k < 0$, $\delta_H < 0$) and positive for Osaka. The consistency of these patterns across decay specifications suggests that our proximity findings are not artifacts of the specific functional form assumption.

Table D.1: Fixed Effects Panel: Slow Decay (λ=0.0035, half-life 200km)

	Continuous					**Categorical**			
	Miy	Tok	Osa	Fuk		Miy	Tok	Osa	Fuk
UoP2 (Biodiversity)									
β_k	3.509*	-3.618	0.420	-0.626	β_M	0.586	-0.727	0.122	-0.057
	(1.998)	(2.615)	(2.058)	(1.467)		(0.964)	(1.080)	(0.891)	(0.662)
					β_H	2.520**	-2.047	0.276	-0.454
						(1.166)	(1.806)	(1.386)	(0.940)
δ_k	-2.917	11.147	2.474	-2.837	δ_M	-1.080	3.732	0.225	1.239
	(3.114)	(8.043)	(4.040)	(4.943)		(1.326)	(3.685)	(1.634)	(2.026)
					δ_H	-1.789	4.113	1.890	-3.549
						(1.750)	(5.467)	(2.612)	(3.369)
UoP3 (Disaster Resilience)									
β_k	-2.218	-3.192	-0.328	-1.515	β_M	-1.084	-0.969	-0.146	-0.646
	(2.438)	(2.551)	(2.017)	(1.678)		(0.984)	(0.974)	(0.835)	(0.596)
					β_H	0.038	-1.430	-0.243	-0.546
						(1.798)	(1.867)	(1.294)	(1.159)
δ_k	7.451**	16.861**	-0.757	8.116*	δ_M	3.680**	5.155†	-0.034	2.465
	(3.466)	(7.841)	(4.020)	(4.362)		(1.482)	(3.356)	(1.609)	(2.178)
					δ_H	1.284	6.193	-0.162	3.578
						(2.197)	(5.421)	(2.489)	(2.594)
UoP4 (Social Equity)									
β_k	-1.831	2.390	-1.910	-1.097	β_M	0.935	-0.180	-0.073	-0.545
	(2.419)	(2.012)	(1.751)	(1.611)		(1.051)	(0.969)	(0.813)	(0.688)
					β_H	-2.102	1.638	-1.283	-0.111
						(1.747)	(1.182)	(1.073)	(1.011)
δ_k	3.379	-14.149**	6.877**	5.719	δ_M	-0.876	-1.435	1.436	2.302
	(3.654)	(5.831)	(3.485)	(5.364)		(1.472)	(3.072)	(1.588)	(2.352)
					δ_H	3.277	-8.949***	4.006*	-0.430
						(2.341)	(3.391)	(2.191)	(3.684)
N	3568					3568			
Respondents	892					892			
Individual FE	Yes					Yes			

Notes: Slow decay: $p = \exp(-0.0035 \cdot d)$, proximity halves at 200km. Spread in bps; UoP scaled 0–1. Estimates are issuer-specific: $\beta_k + \phi_{kj}$ (baseline) and $\delta_k + \omega_{kj}$ (proximity) per Eq. 3. **Continuous:** β_k = linear UoP effect; δ_k = proximity heterogeneity. **Categorical:** β_M, β_H = Medium/High vs Low (0.125); δ_M, δ_H = proximity heterogeneity. ***, **, *, †: $p < 0.01, 0.05, 0.10, 0.15$. Clustered SEs.

Table D.2: Fixed Effects Panel: Fast Decay (λ=0.0069, half-life 100km)

	Continuous					**Categorical**			
	Miy	Tok	Osa	Fuk		Miy	Tok	Osa	Fuk
UoP2 (Biodiversity)									
β_k	2.868*	-2.341	0.985	-0.700	β_M	0.218	-0.190	0.156	0.065
	(1.632)	(1.789)	(1.554)	(1.215)		(0.795)	(0.730)	(0.697)	(0.590)
					β_H	2.254**	-1.597	0.838	-0.688
						(0.967)	(1.193)	(1.069)	(0.798)
δ_k	-2.316	17.207†	1.479	-3.208	δ_M	-0.652	4.741	0.038	0.953
	(2.678)	(11.283)	(3.448)	(4.932)		(1.142)	(5.859)	(1.445)	(2.195)
					δ_H	-1.660	7.002	0.684	-3.295
						(1.501)	(6.870)	(2.083)	(3.295)
UoP3 (Disaster Resilience)									
β_k	-1.102	-0.193	-0.584	-0.616	β_M	-0.399	-0.212	-0.134	-0.401
	(2.014)	(1.562)	(1.442)	(1.461)		(0.793)	(0.621)	(0.642)	(0.515)
					β_H	0.017	-0.158	-0.265	-0.109
						(1.499)	(1.069)	(0.907)	(1.030)
δ_k	6.652**	14.698†	-0.511	6.396†	δ_M	2.993**	6.014	-0.063	1.920
	(3.016)	(9.161)	(3.500)	(4.265)		(1.264)	(4.471)	(1.402)	(2.217)
					δ_H	1.460	4.325	-0.271	2.640
						(1.894)	(5.425)	(2.160)	(2.516)
UoP4 (Social Equity)									
β_k	-1.203	-0.061	-0.654	-0.521	β_M	0.920	-0.447	0.213	-0.286
	(1.896)	(1.492)	(1.369)	(1.330)		(0.839)	(0.663)	(0.615)	(0.573)
					β_H	-1.579	0.127	-0.439	-0.126
						(1.367)	(0.942)	(0.822)	(0.880)
δ_k	2.755	-14.057**	5.752*	6.258	δ_M	-1.007	-0.942	1.136	1.865
	(3.151)	(7.007)	(3.066)	(5.494)		(1.246)	(3.768)	(1.384)	(2.510)
					δ_H	2.770	-8.864**	2.988†	0.134
						(1.953)	(3.919)	(1.932)	(3.902)
N	3568					3568			
Respondents	892					892			
Individual FE	Yes					Yes			

Notes: Fast decay: $p = \exp(-0.0069 \cdot d)$, proximity halves at 100km. Spread in bps; UoP scaled 0–1. Estimates are issuer-specific: $\beta_k + \phi_{kj}$ (baseline) and $\delta_k + \omega_{kj}$ (proximity) per Eq. 3. **Continuous:** β_k = linear UoP effect; δ_k = proximity heterogeneity. **Categorical:** β_M, β_H = Medium/High vs Low (0.125); δ_M, δ_H = proximity heterogeneity. ***, **, *, †: $p < 0.01, 0.05, 0.10, 0.15$. Clustered SEs.

E UoP Allocation Patterns

Table E.1 presents the complete distribution of Use of Proceeds (UoP) allocation patterns used in the survey experiment. Each respondent was shown bonds with one of these 10 unique allocation patterns, where the four UoP categories (Decarbonization, Biodiversity, Disaster Resilience, and Social Equity) sum to 100%. The patterns were designed such that each category takes one of three discrete levels: 12.5% (Low), 37.5% (Medium), or 62.5% (High). Since UoP1 (Decarbonization) is calculated as the residual (UoP1 = 100 − UoP2 − UoP3 − UoP4), the 10 patterns represent all feasible combinations where each component remains within the valid range.

Table E.1: Distribution of Use of Proceeds (UoP) Allocation Patterns by Issuer

	Miyagi				Tokyo				Osaka				Fukuoka				
Pattern	U1	U2	U3	U4	U1	U2	U3	U4	U1	U2	U3	U4	U1	U2	U3	U4	N
1	1	1	1	5	1	1	1	5	1	1	1	5	1	1	1	5	89
2	1	1	3	3	1	1	3	3	1	1	3	3	1	1	3	3	89
3	1	1	5	1	1	1	5	1	1	1	5	1	1	1	5	1	89
4	1	3	1	3	1	3	1	3	1	3	1	3	1	3	1	3	89
5	1	3	3	1	1	3	3	1	1	3	3	1	1	3	3	1	89
6	1	5	1	1	1	5	1	1	1	5	1	1	1	5	1	1	89
7	3	1	1	3	3	1	1	3	3	1	1	3	3	1	1	3	90
8	3	1	3	1	3	1	3	1	3	1	3	1	3	1	3	1	90
9	3	3	1	1	3	3	1	1	3	3	1	1	3	3	1	1	89
10	5	1	1	1	5	1	1	1	5	1	1	1	5	1	1	1	89
Total																	892

Notes: U1 = Decarbonization, U2 = Biodiversity, U3 = Disaster Resilience, U4 = Social Equity. Allocation levels: 1 = 1.25bn JPY (12.5%), 3 = 3.75bn JPY (37.5%), 5 = 6.25bn JPY (62.5%), with total fixed at 10bn JPY. Each respondent was randomly assigned one pattern that applied to all four issuer bonds. N = number of respondents per pattern.

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