

Doing Good, Investing Less? Substitution Effects between Digital Climate Engagement and Green Investment*

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May 21, 2026

Abstract

We study whether daily environmental actions substitute for or complement green investment. Using microdata from a digital platform that combines carbon-tracking features with mutual fund investing, we link users' carbon-reducing actions to their portfolio choices. Consistent with a model of individuals deriving decreasing marginal utility from their overall environmental impact, we find that green-point collection is negatively associated with green investing, and a promotion that increases the effectiveness of digital climate engagement crowds out green investment. Platform initiatives that raise environmental awareness instead spur green investment. Our findings reveal the nuanced impact of digital climate engagement on household financial decisions.

JEL Classification: D14, G11, G23, G41, G53, Q57.

Keywords: Green Investment, Green Action, Climate Finance, Sustainable Finance, Household Finance, Substitution Effect, Mental Accounting

*For many useful comments, we thank Vikas Agarwal, Simon Gervais, Christoph Merkle, David Robinson, Stefan Ruenzi, Kelly Shue, Paul Smeets, Oliver Spalt, Jean Tirole, and participants at 2026 2nd Warwick-CEPR Women in Environmental Economics workshop, 2026 2nd Annual Conference on Innovations in Sustainable Finance at Northwestern Kellogg, 2026 Ageing and Sustainable Finance Conference at ZEW and seminars at University of Mannheim and University of Warwick. Kya Qiye Han and Luca Moosmann provided excellent research assistance. We also thank Zhenhua Li at Ant Group Research Institute for the insightful talks about the data structure and the institutional details. All data are sampled, desensitized, and stored on the Ant Open Research Laboratory and remotely accessed for empirical analysis. All remaining errors are our own.

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1 Introduction

In response to growing environmental concerns over the past decades, green investing has emerged as an important channel through which individuals can contribute to environmental protection. Understanding green investment behavior is important because greater capital flows accelerate the energy transition (e.g., Battiston et al., 2021; Biais and Landier, 2022) and affect environmental outcomes through their allocation between green and brown firms (e.g., Berk and Van Binsbergen, 2025; Broccardo et al., 2022; Hartzmark and Shue, 2022).¹ Proponents of green investing view it as a transparent and scalable way to support environmental goals. Its impact is documented through standardized disclosures, third-party ESG ratings, and portfolio-level emissions metrics, which help investors with environmental preferences direct their investments and assess their impact.

A similar quantification of environmental impact has recently emerged for everyday behaviors. Climate-engagement and carbon-tracking platforms such as Alipay’s Ant Forest and GCash’s GForest enable users to measure the estimated emissions reductions from daily low-carbon actions, such as cycling or taking public transport instead of driving, reducing household energy use, or recycling. Beyond measurement, such platforms also amplify and socialize the impact of behavior by converting digital engagement into real-world environmental action. Since its launch in 2016, Ant Forest has engaged over 700 million users and funded the planting of 500 million trees (Hu et al., 2025).

The growing popularity of digital climate engagement can have important implications for green finance. Do users’ actions on climate-engagement platforms affect their green investment behavior? Do these platforms’ activities complement green investing by aligning environmental motives across domains, or do they substitute for it by allowing users to satisfy environmental preferences through measurable carbon-reducing actions and enhancing their impact?

Section 2 proposes a simple framework to formalize these questions. We consider the portfolio allocation and climate-engagement choices of individuals who derive utility from their total environmental impact—generated through carbon-reducing activities and financial investments—with diminishing marginal utility. The model delivers the following empirical predictions for individuals who allocate a positive share of their portfolio to green investments. First, it predicts a negative

¹Recent theoretical work shows that the environmental impact of socially responsible investing in equilibrium depends on the mix of value-aligned and impact-motivated investors (Landier and Lovo, 2025), the concentration of SRI across firms (Bisceglia et al., forthcoming), and the social-cost concerns of informed investors (Chen et al., 2026).

correlation between carbon-reducing activities and green investments. Intuitively, environmental preferences determine the desired level of environmental impact; individuals achieve this target through a combination of carbon-reducing activities and green investments, depending on the relative cost-effectiveness of these two channels, which varies across individuals (e.g., due to differences in the opportunity cost of engagement). Second, the model predicts that platform initiatives that amplify the impact of users’ carbon-reducing activities—thereby increasing their effectiveness as a means of environmental protection—crowd out green investing; conversely, initiatives that foster awareness and strengthen environmental preferences increase green investments. While the former (resp. latter) type of initiatives also reduces (resp. increases) the probability that an individual allocates a positive share to green investments, the relationship between digital climate engagement and participation in green finance is theoretically ambiguous.

We then test these predictions empirically using detailed individual-level data from Alipay, the first and largest third-party digital payment system in China.² We utilize two core components of the Alipay ecosystem. The first is Ant Forest, an environmental protection program in which users accumulate virtual trees through environmentally friendly actions such as walking or public transportation, with Alipay committing to plant corresponding real trees in desert-adjacent regions. The number of green points a user “produces” corresponds to the grams of CO₂ reduction attributed to the monitored behavior. Afterward, Alipay plants a real tree each time a user grows a virtual one by “collecting” sufficient green points, and users can earn badges and share them on social media (see Section 3 for more details). The second is Ant Fortune, launched in 2014, currently the largest online mutual fund investment platform in China, which provides access to a broad universe of mutual funds (Hong et al., 2025). By 2025, its equity fund assets under management reached 1.02 trillion RMB (USD 142 billion).

We study a randomized sample of 180,000 individuals who are active users of both Ant Forest and Ant Fortune over the period from January 2023 to December 2024.³ A key strength of our environmental protection data is that it captures real-world actions with tangible environmental impacts. Stated intentions often diverge from actual behavior due to hypothetical bias (List and

²Its active user base reached 1.43 billion in mid-2024. Beyond payments, the Alipay app integrates a wide range of daily services, including transportation, consumption, and financial services.

³Our sample is thus biased toward investors with relatively high awareness of climate risks. However, as emphasized in Krueger et al. (2020), understanding the behavior of environmentally active investors is particularly important, as their voluntary engagement with green investments can shape corporate climate policies and the integration of climate considerations into investment management.

Gallet, 2001), gaps between normative and revealed preferences (Beshears et al., 2008), and cognitive noise in translating subjective expectations into actions (Charles et al., 2024; Giglio et al., 2021; see Woodford, 2020 for a review). Studying revealed behavior rather than hypothetical choices is therefore essential for credible inference on individuals’ environmental preferences.

[INSERT Figure 1 AROUND HERE]

We match individual’s fund holdings with Morningstar to construct four green investment indicators, achieving a 100% matching rate throughout the sample period. Following the literature, we classify funds as green or non-green using three Morningstar-based indicators—the Sustainability Indicator, Globe Rating (Hartzmark & Sussman, 2019), and Low Carbon Designation (Ceccarelli et al., 2024)—as well as fund names (Van der Beck, forthcoming).⁴ As shown in Figure 1, green fund participation is widespread: 52% of users hold at least one sustainable or highly-rated Globe fund, 79% a Low Carbon Designation fund, and 61% a fund with a green-related name.⁵ The Low Carbon Designation yields the highest participation rate, consistent with Ant Forest’s focus on carbon reduction, while the prominence of the green-name classification reflects retail investors’ tendency to rely on simple heuristics. However, capital allocation shares—4.55%, 3.65%, 16.88%, and 7.31% across the four classifications—are substantially lower than participation rates, indicating that investors hold green funds but allocate only a modest fraction of their portfolios to them.

Our empirical results align with the model predictions. The cross-sectional regression analysis in Section 4 documents a robust negative association between green-point collection in Ant Forest and sustainable investment in Ant Fortune. This pattern holds across alternative green-fund classifications and is stronger on the *intensive margin*—in OLS regressions of the share of the portfolio allocated to green funds conditional on participation in green investing—than on the *extensive margin*—that is, in probit regressions for the probability of holding at least one green fund. Additional analyses using alternative measures of users’ Ant Forest activity, subcategories, and principal components confirm that the negative association is driven by environmentally meaningful activities

⁴In China, ESG funds are almost equivalent to environmental and green funds. The social and governance components rarely exist in Chinese domestic funds. Accordingly, we use the ESG rating (Globes) for green fund classification in this paper.

⁵This relatively high prevalence of green participation likely reflects the fact that our sample consists of users who are active in Ant Forest and so have a certain degree of environmental interest. This is similar to the survey-based papers in the recent literature (Krueger et al., 2020).

rather than by broader platform usage.

Section 5 provides causal evidence of the substitutability between digital climate engagement and green investments using the Solar Panel promotion, a large-scale Ant Forest event that substantially lowers the number of green points required to redeem badges (i.e., to trigger Ant Forest’s environmental actions). A difference-in-differences design shows no meaningful effect on the probability of holding green funds, but a negative and statistically significant effect on the share of green funds on the intensive margin. This finding is consistent with the model’s prediction that increasing the effectiveness of digital climate engagement crowds out green investing.

Section 6 turns to initiatives that do not change the impact of digital engagement but may strengthen environmental awareness. The first is the Earth Day event, a large-scale annual tree-planting campaign in which Ant Forest plants the trees previously redeemed by users. The second is the Beautiful China certificate, an official recognition awarded to users who accumulate enough green points to redeem trees. Because neither initiative changes the impact of users’ daily actions, any effect on green investments should operate through pro-environmental preferences. Consistent with this interpretation, we find that both initiatives are associated with higher green investments on the intensive margin. This finding extends the “green experience” mechanism in Hu et al. (2025) to financial markets: they show that greater appreciation of environmental improvement increases participation in Ant Forest; we find that increases in environmental awareness also spur green investments.⁶

Overall, our results reveal a nuanced impact of digital climate engagement on green finance. On the one hand, engagement platforms can crowd out green investments by enhancing the effectiveness of daily carbon-reducing activities as a way to express environmental preferences. On the other hand, they can raise environmental awareness, which strengthens pro-environmental preferences and thereby increases green investment. Building on these insights, Section 7 concludes with a discussion of the broader financial, strategic, and welfare implications of digital climate engagement initiatives.

⁶However, while Hu et al. (2025) emphasizes the gamification features of Ant Forest, we find that results for *Rob Green Points*—the main gamification component—are statistically insignificant. Interviews with frequent users indeed suggest that the primary motivation for using Ant Forest is environmental engagement rather than gaming.

Related Literature. Our paper is related to the growing literature on investor behavior in climate-related investment. Prior work shows that investors value sustainability in their investment decisions (Bollen, 2007; Ceccarelli et al., 2024; Hong & Kostovetsky, 2012), and that social preferences play an important role in investors’ allocation to socially responsible mutual funds (Hartzmark & Sussman, 2019; Riedl & Smeets, 2017), pension funds (Bauer et al., 2021), and venture capital investments (Barber et al., 2021). Subsequent work examines the motivations behind these preferences, including warm glow effects (Heeb, Kölbel, Paetzold, & Zeisberger, 2023) and value alignment versus impact seeking (Bonnefon et al., 2025). In addition, Dyck et al. (2019) show that both financial and social returns are important drivers of institutional investors’ impact on firms’ E&S performance. Cao et al. (2023) find that SRI institutions tend to focus more on the ESG performance and less on quantitative signals of value; however, Døskeland and Pedersen (2016) find that financial framing is more effective than moral framing in SRI fund investments. We contribute to this literature by showing that moral licensing and environmental awareness both shape green investment, but through distinct channels.

Another strand of the literature links personal experience and environmental exposure to investment behavior. Chang et al. (2018) show that health insurance sales increase with air pollution but are more likely to be canceled when air quality improves. Andersen et al. (2024) find that investors whose child is diagnosed with a respiratory disease tilt their portfolios away from brown and toward green stocks, though without adjusting ESG fund holdings. Andersen et al. (2023) find that wind-fall wealth increases the likelihood of holding responsible mutual funds and green energy stocks. Fisman et al. (2023) documents that retail investment in brown stocks declines after the installation of a local pollution monitor, particularly on days when air quality is flagged as harmful. Choi et al. (2020) show that retail investors—but not institutions—sell carbon-intensive stocks during hot weather, with return patterns unlikely to reflect fundamentals.⁷ We contribute to this literature by examining a distinct type of personal experience—direct environmental protection—and show that it is negatively associated with green investment, in contrast to the positive effects of pollution and climate exposure documented in prior work.

Our paper thus relates to recent studies documenting substitution effects in climate finance.

⁷Related work includes Cronqvist and Yu (2025) (Chernobyl exposure), Dessaint and Matray (2017) (hurricane risk), Alok et al. (2020) (climate disaster risk), and Huang et al. (2020), Li et al. (2021), and Dong et al. (2021) (air pollution).

Consistent with our findings, Anderson and Robinson (2022) find that clean-planet preferences are negatively associated with opting into ESG pension funds (but no relation with opting out of ESG pension funds) and positively associated with green daily-life behaviors, suggesting that green behaviors and investments act as substitutes. Our paper differs from theirs in two key respects. First, we examine mutual fund investments, which carry a lower risk profile and attract broader active retail participation—indeed, Anderson and Robinson (2022) attribute their mixed results⁸ to low financial market participation among green investors. Second, rather than relying on survey-based preference measures derived from a small number of questions, we capture green actions using real-world observations across a broad set of behaviors involving genuine commitment and effort. More generally, our evidence is consistent with Ceccarelli and Ramelli (2024), who find that green *taste* substitutes for *beliefs* in driving green investment expectations and preference. We complement their findings by showing that green *awareness* and *actions* similarly have opposite impacts on green investment decisions.

More broadly, our paper contributes to the growing literature on crowding-out and crowding-in effects in climate finance, with the distinction that we focus on individual-level rather than government actions, where the direct effort is from government agencies and under political influence. The existing evidence is mixed. Ceccarelli et al. (2025) find that many investors increased their non-pecuniary taste for green investments following the Trump victory of the 2024 election, anticipating a rollback of climate policy—suggesting that individual preferences substitute for government action. Similarly, Anderson and Robinson (2024) show that political polarization reduces belief-updating about global warming and dampens climate-friendly investment decisions. In contrast, Heeb, Kölbel, Ramelli, and Vasileva (2023) find that access to green investment products does not crowd out political donations or support for climate legislation. More generally, Flammer et al. (2025a, 2025b) document the effectiveness of blending private capital with public or philanthropic funding in sustainable finance. We contribute to this literature by examining the largest emerging market and focusing on household-level actions.

In the fintech context, our paper is related to Gargano and Rossi (2023), who study an Italian neobank and find that neither a carbon calculator nor a carbon offsetting service tied to reforestation affects users’ consumption. Their setting differs from ours in three respects. First, consumption—

⁸Anderson and Robinson (2022) also find a weak negative relation between clean-planet preference and energy stock investments, which is opposite to the findings on pension funds.

unlike green investment—is driven primarily by living needs rather than environmental concerns, which may explain their null result. Second, their offsetting tool requires only a modest fee,⁹ whereas carbon-reducing activities in our setting require sustained personal effort, which may explain why they find no change in consumption, whereas we document a significant negative relationship with green investment. Third, their carbon calculator only provides information, whereas the Earth Day campaign and Beautiful China certificates in our paper rely on media coverage and government endorsement, suggesting that information alone may be insufficient to shift behavior without additional motivational elements. Our paper also relates to recent studies using Ant Forest data—e.g., (Chen et al., 2024; Gao et al., 2023; Su et al., 2025)—where we provide a comprehensive and precise framework for identifying the key economic mechanisms through which environmental engagement transmits to individual financial decisions.

2 Theoretical Framework

This section develops a simple theoretical framework to analyze the relationship between daily carbon-reducing activities—potentially mediated by digital climate engagement platforms—and green investment behavior.

2.1 Set up

We consider a static model in which, over the relevant time horizon, an agent can undertake environmentally friendly actions both in financial markets—by investing in green funds—and in their daily life—by engaging in carbon-reducing activities.

Financial market. The agent allocates their investable wealth M_0 between green funds, which yield an expected return r_G , and non-green (hereafter, brown) funds, which yield an expected return r_B . Letting $\alpha \in [0, 1]$ denote the share of investable wealth allocated to green funds, terminal wealth is given by

$$M \equiv M_0(1 + r_B - \alpha\Delta),$$

⁹For €7 per month, users can subscribe to the “Carbon Offsetting” program, whereby the company pledges to offset up to 1,000,kg of emissions.

where

$$\Delta \equiv r_B - r_G > 0$$

represents the excess return of brown relative to green funds. Note that we can interpret r_B and r_G as risk-adjusted returns, so that M can be viewed as the certainty equivalent of terminal wealth.

Engagement activities. The agent can also engage in activities that reduce their carbon footprint by g grams. These activities entail non-monetary effort costs equal to $\theta\Psi(g)$, where $\theta > 0$ and $\Psi(\cdot)$ is an increasing and convex function, with $\Psi(0) = \Psi'(0) = 0$. In our application, $\Psi(g)$ captures the cost associated with *producing* and *collecting* g green points on the Ant Forest platform, while θ includes the opportunity cost of time, heterogeneous across individuals.

Environmental preferences. In addition to their private payoff, the agent derives utility from the environmental impact of their actions. Their pro-environmental preferences are captured by an increasing and concave function $\Gamma(I)$ of their overall environmental impact,

$$I \equiv \beta\alpha M_0 + \delta g,$$

which is given by the sum of (i) the impact of the amount αM_0 invested in green funds, measured by a parameter $\beta > 0$, and (ii) the impact of the reduction g in carbon emissions, measured by a parameter $\delta > 0$. In our application, the parameter δ also incorporates the platform’s activities: a higher δ captures the larger environmental impact per gram due to Ant Forest planting trees in proportion to users’ redeemed grams.¹⁰

The concavity of Γ captures the idea that agents aggregate their environmental contributions into a single *moral score* and derive diminishing marginal utility from this score.

While we focus on a consequentialist interpretation of environmental preferences—i.e., we interpret β and δ as the true environmental impact of green investments and emission reductions—the considered formulation of environmental preferences is also consistent with different interpretations, such as warm-glow motives and social-signalling concerns. Under such interpretations, β and δ are heterogeneous across individuals, as they reflect the psychological relevance of financial and

¹⁰We adopt a continuous formulation as an approximation of the underlying *badge redemption* system on Ant Forest, which allows us to abstract from discontinuities in the analysis.

real-world actions in generating moral satisfaction or image returns.

Objective. The agent chooses their portfolio allocation and their level of carbon-reducing activities by solving

$$\max_{\alpha \in [0,1], g \geq 0} M_0(1 + r_B - \alpha\Delta) - \theta\Psi(g) + \gamma\Gamma(\beta\alpha M_0 + \delta g), \quad (1)$$

where $\gamma \geq 0$ captures the strength of their environmental preferences.

Note that the assumptions $\Delta > 0$ and $\Psi(g) \geq 0$ for all admissible α and g imply that an agent who does not care about the environmental impact of their actions would neither invest in green funds nor engage in carbon-reducing activities—that is, $\alpha^* = g^* = 0$ when $\gamma = 0$. These restrictions simplify the exposition but are not essential for the results. Moreover, in what follows, to ease exposition and focus on the empirically relevant scenario where agents do not hold a fully green portfolio (i.e., $\alpha < 1$ is optimal), we assume that the environmental preferences are not too strong: a sufficient condition is

$$\gamma\Gamma'(\beta M_0) < \frac{\Delta}{\beta}. \quad (\text{A1})$$

2.2 Optimal Choices

The solution of the agent's optimization problem (1) is as follows:

Proposition 1. *Define $g_0 > 0$ as the solution to*

$$\theta\Psi'(g) = \delta\gamma\Gamma'(\delta g). \quad (2)$$

The agent's optimal choices are as follows:

- *If $\gamma\Gamma'(\delta g_0) \leq \Delta/\beta$, $g = g_0$ and $\alpha = 0$;*
- *If $\gamma\Gamma'(\delta g_0) > \Delta/\beta$,*

$$g = g^* \equiv \Psi'^{-1}\left(\frac{\delta\Delta}{\theta\beta}\right) > g_0, \quad \text{and} \quad \alpha = \alpha^* \equiv \frac{1}{\beta M_0} \left[\Gamma'^{-1}\left(\frac{\Delta}{\gamma\beta}\right) - \delta g^* \right] \in (0, 1). \quad (3)$$

Because the agent can choose between an activity featuring increasing marginal costs—the carbon-reducing actions g —and one with constant marginal costs—the green portfolio allocation

α —in an interior solution (where $0 < \alpha^* < 1$) the optimal provision of carbon-reducing activities g^* is pinned down solely by the relative efficiency-to-cost ratio, $\frac{\delta/\theta}{\beta/\Delta}$. The reason is that the agent will only provide g up to the point where its marginal cost equals the constant marginal cost of achieving the same impact via α . The optimal overall impact level I^* is then determined by the efficiency-to-cost ratio of the constant-marginal-cost activity, α , and by the strength of environmental preferences, γ —i.e., $\gamma\Gamma'(I^*) = \Delta/\beta$.

Accordingly, overall impact I^* does not depend on the impact δ of carbon-reducing activities, which only affects the optimal mix green investments-carbon reducing activities to generate I^* . As a result, if δ increases, the agent optimally achieves the same desired overall impact I^* through less green investing and more carbon-reducing activities. Conversely, the increased demand for environmental impact of an agent with stronger pro-environmental preferences γ is entirely absorbed by the constant-marginal-cost activity, i.e., the green investments α^* , and translates into a lower terminal wealth.

The fact that g^* is pinned down solely by the relative efficiency-to-cost ratio of the two activities implies that a higher cost θ of carbon-reducing activities induces the agent to substitute away from carbon-reducing activities toward green investments, while a higher opportunity cost Δ of green investing has the opposite effects.¹¹ An increase in the impact β of green investments, while reducing g^* , has an ambiguous effect on the optimal share of green investments. This result reflects a standard trade-off between the substitution effect and the income effect. When β rises, the desired environmental impact I^* increases, and each unit of green investment α becomes more effective at producing I^* . On the one hand, this makes investment “cheaper” relative to its benefit, incentivizing the agent to substitute away from carbon-reducing activities g and increase α to capitalize on the higher marginal return (substitution effect). On the other hand, because α is now more potent, the agent can reach their desired level of impact with a smaller absolute green investment (income effect). If Γ is highly concave—meaning the agent experiences rapidly diminishing returns from environmental protection—the desire to maintain a specific “target” level of impact outweighs the incentive to expand: in such cases, the agent “cashes in” the productivity gain by reducing α .

The foregoing analysis has focused on the interior solution of Proposition 1—i.e., on the pop-

¹¹An increase in M_0 proportionally scales both the monetary cost and the environmental impact of green investments, implying that the total amount of carbon-reducing activities g^* and aggregate green investment α^*M_0 remain constant; hence, α^* decreases in M_0 .

ulation of agents choosing to invest a positive share of their portfolio in green funds. However, if an agent does not care enough about environmental protection (γ low) or if their cost θ of green effort is high, they do not invest at all in green funds and all their environmental impact takes place through carbon-reducing activities. Among these agents, more environmentally conscious ones and people with lower effort costs engage more in such activities. The effect of δ on g_0 instead depends on functional forms because while a higher δ increases the impact of green effort, it also allows an agent to achieve the desired level of environmental protection through lower efforts. However, a higher δ always dampens an agent's willingness to allocate a positive share of their portfolio to green funds because, as δ rises, they have stronger incentives to achieve the desired level of environmental impact through carbon-reducing activities only.

2.3 Empirical Predictions

The comparative statics results derived in the previous section yield important empirical predictions on (1) the correlation between green investments and carbon-reducing activities, and (2) the causal impact of platform policies that increase the impact δ of digital climate engagement (such as the Solar Panel Promotion: see Section 5) or strengthen people's pro-environmental preferences γ (such as Earth Day events or Beautiful China Certificates: see Section 6).

To simplify the exposition, we assume that $(M_0, \Delta, \beta, \delta)$ are homogeneous across individuals and focus on heterogeneity in effort costs θ and green preferences γ , so that each individual i is characterized by (θ_i, γ_i) .¹² Denoting by $\alpha^*(\theta_i, \gamma_i)$ and $g^*(\theta_i)$ the optimal choices of individual i characterized in Proposition 1, we have:

Corollary 1. *Consider a population of agents i with heterogeneous (θ_i, γ_i) who invest a positive share of their portfolios in green funds. The optimal share of green funds can be expressed as $\alpha^*(\theta_i, \gamma_i) = h(\gamma_i) + f(g^*(\theta_i))$, where $h'(\gamma) > 0$ and $f'(g) < 0$. Moreover, an increase in δ leaves $h(\gamma)$ unchanged and decreases $f(g^*)$.*

Corollary 1 implies that heterogeneity in effort costs generates a downward-sloping relationship

¹²Since M_0 is controlled for in our regressions, there is no unobserved heterogeneity along this dimension in our empirical analysis. Heterogeneity in Δ is likely second-order, as the excess return of brown funds is largely driven by financial market conditions (while differences in financial ability tend to affect both r_B and r_G , with no clear-cut implication for Δ). Finally, under a consequentialist preference specification, also the impact parameters β and δ are exogenous.

$\alpha(g)$ between the share of green funds and carbon-reducing activities among individuals with the same level of green preferences γ . The reason is that individuals with lower effort costs both engage more in carbon-reducing activities and invest less in green funds. Since the optimal g^* does not depend on γ , a higher level of γ simply shifts this negative relationship, $\alpha(g)$, upward in a parallel way: see Figure 2.

[INSERT Figure 2 AROUND HERE]

This result implies that, provided that θ and γ are not strongly negatively correlated, one should expect a negative correlation between green investments and carbon-reducing activities among individuals who invest a positive share of their portfolio in green funds.¹³

A second empirical prediction of Corollary 1 is that platform initiatives—such as Earth Day campaigns and Beautiful China Certificates—that increase environmental awareness and thereby strengthen green preferences γ are expected to increase green investment. The reason is that individuals with initial preference γ_i move to a higher $\alpha(g)$ schedule—corresponding to a higher level of γ —following the policy.

Moreover, our comparative statics results imply that, following platform activities that increase the impact δ of digital climate engagement, agents increase digital climate engagement and reduce their share of green investments. These activities therefore generate a crowding-out effect on green investments, as illustrated in Figure 3.

[INSERT Figure 3 AROUND HERE]

Summing up, the model delivers three empirical predictions for individuals who invest a positive share of their portfolio in green funds:

- H1** There is a negative correlation between the share of Ant Fortune’s portfolio invested in green funds and green points collected on Ant Forest;

¹³Holding the other parameters fixed, any unobserved heterogeneity that affects the optimal choices of α and g in opposite directions generates a downward-sloping $\alpha(g)$ relationship. Such negative correlation would therefore arise if the main source of heterogeneity is beliefs about the impact of digital climate engagement (δ) or—provided that the substitution effect dominates the income effect—green investments (β).

H2 Solar Panel Promotion reduces green investments;

H3 Earth Day Events and Beautiful China Certificates increase green investments.

Finally, the conditions for an interior solution in Proposition 1 can be used to derive empirical implications for the likelihood that individuals with different levels of digital climate engagement invest in green funds. Formally, let $P(g)$ denote the probability that an individual who optimally chooses a level g of carbon-reducing activities allocates a positive share of their portfolio to green funds, i.e., $P(g) \equiv \Pr[\alpha > 0 \mid g]$. The model, however, does not deliver a clear-cut prediction on the shape of the relationship $P(g)$. This is because the condition for $\alpha^* > 0$ is harder to satisfy the lower are γ and θ , so that a low value of g may reflect either individuals with weak environmental preferences who do not invest in green funds, or individuals with high effort costs who engage in environmental protection only through green investments. Hence, observing a higher level of digital climate engagement does not, in general, allow one to infer a higher or lower probability of investing in green funds.

Similarly, the effect of platform policies that increase δ or γ on $P(g)$ is generally ambiguous. An increase in δ (resp. a uniform increase in γ) unambiguously reduces (resp. increases) the probability of green investment at a given level of digital climate engagement. However, the equilibrium relationship between observed g and $\Pr[\alpha > 0 \mid g]$ need not shift monotonically, because changes in δ (resp. γ) also affect the optimal choice of g .

3 Data

The data used in this paper combine two sources. First, we obtain individual-level data from Alipay on users' participation in the tree-planting program Ant Forest and their mutual fund holdings through Ant Fortune. Second, we collect sustainable ratings and indicators from Morningstar.

Our main analysis focuses on a randomized sample of 180,000 active Ant Forest users over the period from January 2023 to December 2024. We additionally draw a randomized sample of 20,000 users who are only active in producing green points for robustness checks. All individuals in both samples also invest on Ant Fortune. See Section IA.1 for the details.¹⁴

¹⁴Ant Open Research imposes restrictions of a maximum sample size of 200,000 users and a maximum time span of two years.

3.1 Alipay: Individual-Level Environmental Actions and Mutual Fund Holdings

We obtain individual-level data from the Ant Open Research Platform at Ant Financial under Alipay.¹⁵ We merge three datasets to construct our individual-level cross-sectional sample: (i) basic demographic information, (ii) users’ Ant Forest activity and green points records, and (iii) users’ mutual fund holdings on Ant Fortune. [Figure IB.1](#) in the Internet Appendix illustrates the interfaces of Alipay, Ant Forest, and mutual fund investments.

Basic demographics. This dataset contains information on users who created a profile on Alipay. The main variables include the profile creation date, users’ age, gender, location of residence, stated risk tolerance, and total liquid wealth on Alipay.

Ant Forest activity and green points. This dataset contains detailed information on users’ *green point* activities on Ant Forest. Ant Forest is the largest digital initiative in China aimed at reducing carbon emissions and promoting reforestation. Since its launch, it has introduced multiple badge categories, including trees, biodiversity reserves, wildlife protection, and solar (photovoltaic) revegetation. By August 2023, in collaboration with nine charitable partners, Ant Forest had facilitated the planting of more than 475 million trees in 11 provinces and helped establish 31 biodiversity reserves in 13 provinces, protecting roughly 4,800 square kilometers of land.¹⁶

[INSERT [Figure 4](#) AROUND HERE]

[Figure 4](#) illustrates the sequence of actions through which users contribute to Ant Forest. In the first step, users *produce* “green points” by engaging in behaviors avoiding carbon emissions through various sub-apps embedded in Alipay. The five largest categories of green-point generation in our sample are walking, subway, (paperless) bill payment, train, and buses, which together account for approximately 88% of green-point production at the 95th percentile of users. [Table IB.1](#) in the Internet Appendix lists all 69 subcategories observed in our sample. Following Ant Research’s naming convention, we refer to these points as *Produce Grams*. Green points are generated automatically once users grant Alipay permission to track relevant behaviors.

¹⁵Most online platforms in China (including Alipay) require real-identity verification, implying that each individual can hold only one account. As a result, account-level data correspond one-to-one with individual-level data.

¹⁶Source: antgroup.com/en/esg/lowcarbon.

In the second step, users must manually *collect* the green points generated in the first step in order to contribute to Ant Forest. Following Ant Research’s terminology, we refer to the points as *Collect Grams*. This stage is highly labor intensive: unlike *Produce Grams*, *Collect Grams* is not automatic and requires daily logins and multiple clicks, with uncollected points expiring within 72 hours. More rules are discussed in Section IB.1 of the Internet Appendix. As a result, this step is both time- and attention-demanding and is meaningful only for users who actively choose to participate in Ant Forest. Variation in *Collect Grams* therefore closely reflects individuals’ willingness to engage in environmental protection through actions. Moreover, Ant Forest allows a user’s Alipay friends to collect available points first if they act earlier (*Rob Grams* in Ant Research’s terminology).

In the third step, users *redeem* accumulated green points for trees or other environmental protection badges (*Redeem Grams*). Upon redemption, users receive a badge that is visible to their social network on the Ant Forest interface (see Figure IB.2 in the Internet Appendix) and Alipay undertakes a concrete environmental protection action, such as planting a tree or protecting a biodiversity reserve. Badge redemption itself involves minimal additional effort beyond a single click. However, there is large heterogeneity in the number of green points needed to redeem different badge categories. Redeeming a tree requires a substantially larger number of green points than redeeming other badges, although these alternatives still require nontrivial point accumulation (see Table IB.2 in the Internet Appendix).

Our dataset includes the production, collection, and robbing of green points. To mitigate potential biases arising from extreme values, we winsorize all green-point-related variables at the 99th percentile (see Section IA.1 for the details). Moreover, the dataset includes information on the number of badges each user redeems in Ant Forest and the corresponding amount of green points consumed. We compute the total number of green points consumed for badge redemptions over the sample period. All badge redemption-related variables are winsorized at the 99th percentile to reduce the influence of extreme observations.

Finally, our dataset includes information on individual participation to the Solar Panel Promotion event (Section 5) and “Beautiful China” certificates (Section 6).

Mutual-fund trading and holding histories in Ant Fortune. This dataset contains information on holdings in mutual funds in Ant Fortune associated with each user. Ant Fortune is the largest mutual fund distribution platform in China and, by the end of 2025, it managed 1.81 trillion RMB (USD 252 billion) in non-money market fund assets and 1.02 trillion RMB (USD 142 billion) in equity fund assets.

We aggregate the information to the individual level and calculate variables on whether the individual has held at least one ESG mutual fund during our sample period and, conditional on holding at least one ESG fund, the proportion of money they put in ESG funds. In addition, we also calculate the average return, Sharpe ratio, and total amount of money that the individual puts into mutual funds on Ant Fortune.

3.2 Morningstar: Fund-Level Sustainable Ratings

We focus primarily on China open-end funds and additionally include closed-end funds, ETFs, and the “other” category in Morningstar. These funds are matched to those available in Ant Fortune using the CSDCC code. During our sample period (2023–2024), all funds listed in Ant Fortune are matched to a corresponding Morningstar fund, yielding a 100% matching rate.

To classify funds as green or non-green funds, we construct four alternative green classifications based on the following indicators: (1) the Sustainable Investment indicator, (2) the Morningstar Sustainability Rating (Globes), (3) the Low Carbon Designation indicator, and (4) whether the fund name contains green-related keywords. For the Low Carbon Designation and Sustainable Investment indicators, we follow Morningstar’s original binary classification, where a value of one indicates a green fund. For the Globes, funds with four or five Globes are classified as green funds, while all others are classified as non-green. For the fund-name-based classification, we identify a set of 41 green-related keywords using a hybrid approach that combines GPT detection with manual screening (see details in Section [IA.2](#)).

For the three green indicators obtained from Morningstar, we interpolate missing values. Details in Section [IA.3](#). Funds that do not have any Morningstar sustainability ratings are classified as non-sustainable funds. As a robustness check, Section [4.4](#) restricts the sample to funds with available Morningstar sustainability ratings.

3.3 Summary Statistics

[INSERT [Table 1](#) AROUND HERE]

[Table 1](#) reports summary statistics for the 180,000 active Ant Forest users in our sample. Panel A presents descriptive statistics for the dependent variables on green investments. The rate of green fund participation is high: 52% of users hold at least one fund classified as sustainable by Morningstar or rated Globes 4 or 5, 79% hold at least one Low Carbon Designation fund, and 61% hold at least one fund with a green name. On the intensive margin, conditional on holding at least one green fund, the median share of green funds in investors' portfolios ranges from 14% (Globes 4 or 5) to 44% (Low Carbon Designation).

Panel B reports summary statistics for green-point generation, measured as cumulative grams over the two-year sample period. *Collect* has a median of 24,448 grams, far exceeding *Rob* (median of 1,679 grams, about 6.9% of *Collect*). However, at the 95th percentile, *Rob* (155,385 grams) exceeds *Collect* (118,264 grams), suggesting that a small group of highly competitive users relies heavily on robbing. *Produce*—the total green points generated through daily activities—has a median of 97,825 grams, substantially exceeding *Collect*, indicating that users convert only a portion of their available green points into Ant Forest contributions. This gap reflects a key feature of the platform: collecting points and redeeming badges requires not only green points but also sustained effort and attention from users.

Produce Grams and its subcategories may actually be a noisy proxy for actual engagement, since production occurs through activities that may have a green impact but can also be undertaken for convenience reasons (e.g., taking the metro rather than one's own car to save money and time) or may have no green impact at all (e.g., using Alipay rather than an alternative payment system to pay bills). The additional repeated effort required to collect green points makes *Collect Grams* the most meaningful measure of individuals' willingness to protect the environment through daily actions. This is because *Redeem Grams* does not require additional effort, but only a sufficient number of previously collected grams, whereas *Rob Grams* is a noisier measure of environmental engagement, as it does not require effort to produce green points and may reflect behaviors driven by factors unrelated to environmental preferences (e.g., aversion to taking others' points or responsiveness to gamification incentives). Further discussion is provided in Section [IB.1](#) of the Internet Appendix.

Panel C reports statistics for badge redemption and the Solar Panel promotion variables. The *Solar Panel (Dummy)* variable is measured over two periods, one before the event and one during the event (360,000 observations). It shows that 58% of users participated in the promotion. The median user spent 298 green points on Solar Panel badges (slightly more than the cost of one Solar Panel badge), while the 95th-percentile user spent 19,072 points. *Beautiful China (N)* captures the number of “Beautiful China” commemorative badges a user redeemed; the median is zero and the 75th percentile is one, reflecting considerable variation in engagement with this badge category.

Panel D reports financial characteristics and demographics. Our sample is approximately gender-balanced (49% female) with a median age of 33. The median user registered on Alipay about 11 years ago—around 2014, coinciding with the rise of smartphones and digital payments in China—and holds approximately 84,458 RMB (about 11,900 USD) in mutual fund investments on Ant Fortune. The median Sharpe ratio is -0.11 , indicating that most investors in our sample experienced negative risk-adjusted returns during the sample period. The median self-reported risk level is 3 out of the range from -2 to 5, suggesting a moderate risk appetite.

4 Baseline Regression Analysis

In this section, we examine the association between the participation of individuals in Ant Forest and their sustainable investment behavior on Ant Fortune.

4.1 Empirical Specifications

In the baseline, we conduct cross-sectional regression analyses on both the probability and proportion of green investments. A cross-sectional regression specification, rather than a monthly panel regression, is standard in the ESG investing literature (e.g., Bonnefon et al., 2025; Krueger et al., 2020; Riedl & Smeets, 2017) and aligns with the maintained assumption that individuals’ preferences for environmental protection remain stable over the short horizon covered by our sample.

More specifically, we measure environmentally oriented activity using various metrics of green points in Ant Forest and assess how these relate to both extensive and intensive margins of ESG investments. Following Riedl and Smeets (2017), we use the following specifications:

$$\Pr(\text{ESG}_i) = \Phi(\alpha + \beta \text{GreenPoints}_i + X_i' \Gamma + \alpha_c + \varepsilon_i), \quad (4)$$

$$\text{ESGShare}_i = \alpha + \beta \text{GreenPoints}_i + X_i' \Gamma + \alpha_c + \varepsilon_i, \quad (5)$$

where: Equation 4 considers the full sample and Equation 5 is limited to the subsample of investors holding at least one ESG fund. $\Pr(\text{ESG}_i)$ is the probability that investor i holds at least one ESG fund and ESG_i is a dummy variable that equals to one if the investor i holds at least one ESG fund; Φ is the cumulative distribution function (CDF) of the standard normal distribution; ESGShare_i denotes the proportion of the portfolio allocated to ESG funds for investor i , considering the maximum portfolio share allocated to green funds over the sample period; GreenPoints_i denotes user i 's Ant Forest green points; X_i includes the full set of portfolio- and individual-level controls; and α_c denotes city fixed effects that capture variation common for users in the same city.

Portfolio-related control variables include *Sharpe Ratio*, *Morningstar Rating* (averaged across all funds), and *Total Money* invested in all funds held by the individual on Alipay during our sample period from January 2023 to December 2024. Individual-level characteristics include *Registered Years* (the number of years since Alipay registration), *Female*, *Age*, and investment *Risk Level* (self-reported to Alipay at the start of investment).

Green funds are identified using four commonly used sustainability classifications: *Morningstar Sustainable Indicator* (columns (1)–(2)), *Globes 4 or 5* (columns (3)–(4)), *Low Carbon Designation* (LCD) (columns (5)–(6)), and *Green Name* (columns (7)–(8)). The key independent variables are *Collect* and *Rob*, which capture two ways of accumulating green points in Ant Forest to grow trees, protect animals, and support other environmental protection projects.

These specifications provide a comprehensive baseline characterization of how the environmental participation of individuals is related to their sustainability choices in mutual fund investments.

4.2 Collection of Green Points

[INSERT Table 2 AROUND HERE]

Table 2 presents results on the relationship between individuals' participation in Ant Forest—measured by *Collect Grams* and *Rob Grams*—and their sustainable mutual fund investments

on Ant Fortune. The odd-numbered columns report estimates for the *extensive margin*, presented as marginal effects from Probit regressions in Equation 4. The even-numbered columns report results for the *intensive margin* based on OLS regressions in Equation 5.¹⁷

The results reported in Table 2 provide consistent evidence of the negative correlation between environmental protection via digital engagement and via green investments predicted by our model (H1). Across all eight specifications, *Collect Grams* exhibits a consistently negative and statistically significant association with sustainable investment at both the extensive and intensive margins. In particular, we find that larger amounts of collected green points are associated with a lower proportion of mutual fund investments allocated to green funds. For example, column (2) reports OLS estimates based on the Morningstar Sustainable Investment indicator, showing that a one standard deviation increase in *Collect* is associated with a 87.08 basis point reduction in the share of mutual fund investments allocated to sustainable funds ($\frac{39820.07}{10^8} \times 21.87$). This effect corresponds to approximately 15.63% of the sample’s allocation to sustainable funds (4.55%) and is statistically significant at the 1% level. Our empirical results show that the same negative correlation pattern arises also at the extensive margin, though—in line with our theoretical formulation—its magnitude is much more modest.

Other specifications that classify green funds using alternative indicators yield consistent results. The marginal effect coefficients on *Collect* in the Probit models are close to that reported in column (1), ranging from −20.35 to −31.99. These estimates are statistically significant at the 5% level under green fund classifications based on Globes and at the 1% level under classifications using other indicators. Similarly, the coefficients on *Collect* in the OLS regressions are close to that reported in column (2), ranging from −21.71 to −35.89, and are uniformly statistically significant at the 1% level. Comparing coefficient magnitudes across green classifications, specifications that rely on fund names exhibit the largest effects in the Probit extensive-margin analysis. This pattern is likely driven by the lower level of sophistication among some individual investors, who may rely more heavily on salient and easily observable information such as fund names. In contrast, for the OLS intensive-margin analysis, specifications based on the Low Carbon Designation yield the largest coefficient magnitudes. This finding is consistent with Ant Forest being explicitly promoted as a low-carbon activity, making negative correlation strongest for green investment products that

¹⁷The reduction in observation numbers in each column is due to singletons with city fixed effects and clusters (Correia, 2015).

are most closely aligned with low-carbon indicators.

By contrast, the coefficients on *Rob Grams* are small and statistically insignificant across all eight specifications, with the only exception of column (3). These results indicate that robbing green points does not exhibit a systematic relationship with sustainable investing. A plausible explanation for this result is that, as discussed above, *Rob Grams* is a noisier measure of environmental engagement.

Next, we discuss the control variables. Table 2 shows that investors with higher *Sharpe Ratios* are more likely to invest in green funds and, conditional on doing so, allocate a larger portfolio share to them. For example, in columns (3)–(4), a 10% increase in the *Sharpe Ratio* is associated with a 9.47% higher likelihood of holding at least one green fund and a 2.01% higher allocation share.¹⁸ The average portfolio quality, measured by *Morningstar Rating*, is instead negatively associated with green fund participation but still positively associated with allocation shares. For instance, in column (1), a one-star increase in the average portfolio rating reduces the probability of holding any green fund by 44.32%, while in column (2), it increases the allocation share by 4.68% conditional on participation. Together, these results indicate that investors who enter ESG investments concentrate more heavily in higher-rated ESG funds. Finally, portfolio size (*Total Money*) is positively associated with green investment likelihood but negatively associated with allocation shares, consistent with Riedl and Smeets (2017) and suggesting a diversification mechanism. For example, a 10,000 RMB larger portfolio increases the likelihood of holding green funds by 13.68 percentage points, but it reduces the allocation share by 6.80 percentage points. All coefficients are statistically significant at the 1% level.

Finally, as for individual-level characteristics, we find that earlier Alipay users, female investors, and older individuals are less likely to invest in sustainable funds and, conditional on doing so, allocate a smaller share of their portfolios to these funds. The age difference is consistent with what Fisman et al., 2023 find for Indian investors but the gender gap is opposite to Fisman et al., 2023. For these characteristics, coefficients are generally of the same sign across specifications and are statistically significant at the 1% level. *Risk Level* exhibits a significant yet dual role: higher risk tolerance is associated with a greater likelihood of holding at least one green fund but a smaller

¹⁸Results vary across green fund classifications, consistent with the literature documenting both positive return–green relations driven by demand (Van der Beck (forthcoming)) and negative relations due to non-financial utility (Baker et al. (2024); Gantchev et al. (2024)).

proportion invested in green funds, with both effects significant at the 1% level, which is consistent with Riedl and Smeets (2017).

Our empirical results can be summarized as follows. First and foremost, we document a robust negative association between green-point collection in Ant Forest and sustainable investment in Ant Fortune, suggesting a substitution effect between environmental protection via actions and via investments, which we will causally identify in Section 5. While the economic magnitude on the extensive margin is tiny, it is sizable on the intensive margin compared to the entire sample’s allocation. These findings align with our theoretical framework, which predicts that individuals with strong environmental preferences optimally allocate environmental protection efforts across green investments and digital platform engagement, based on their heterogeneous opportunity costs, whereas digital platform engagement is not a strong predictor of the probability of undertaking green investments. Second, we find that portfolio characteristics and individual attributes significantly influence both the extensive and intensive margins of ESG investment. The two margins are aligned for individual characteristics. In contrast, the two margins exhibit opposite signs for portfolio characteristics, suggesting a portfolio-formation effect at work.

4.3 Production of Green Points

Another measure of environmental protection in Ant Forest is *Produce* green points. In this subsection we show that the negative correlation between environmental protection actions and green investments remains robust when *Produce* is used to measure Ant Forest participation.

[INSERT Table 3 AROUND HERE]

As shown in Table 3, the results based on *Produce Grams* are broadly consistent with those using *Collect Grams*. *Produce Grams* is also negatively associated with ESG investments on both the extensive and intensive margins, with all coefficients statistically significant at the 1% level. However, the economic magnitudes are smaller than those for *Collect Grams*: the effects of *Collect Grams* are larger by a factor of 4.60, 2.08, 3.69, and 4.34, respectively, for columns (1), (3), (5), and (7), on the extensive margin and 3.05, 2.62, 3.21, and 3.20, respectively, for columns (2), (4), (6), and (8), on the intensive margin. These results suggest that daily carbon-reducing activities are

negatively correlated with green investments, and that the additional effort required to *Collect* produced grams on Ant Forest—which magnifies the environmental impact of users’ pro-environmental actions—strengthens this negative association.

Table IC.2 in the Internet Appendix further analyzes the eleven largest subcategories of produced green points, which together account for over 96% of total production for the average user.¹⁹ The sole exception to the general negative pattern is *Offline Payment*—the largest category by usage—which exhibits significant positive coefficients across all eight specifications. However, *Offline Payment* may capture factors unrelated to environmental protection such as convenience and record-keeping. The majority of coefficients for the other subcategories—which are more closely related to environmental protection—are negative, especially on the intensive margin. These results suggest that the negative association between digital climate engagement and green investments is driven by environmentally meaningful activities, rather than by broader platform usage.

Moreover, we conduct two additional analyses using aggregated measures of produced green points. First, we aggregate the eleven subcategories into two broader groups based on their economic interpretation: *Green Travel* and *Digital Payment*.²⁰ As shown in Table IC.3, consistent with our previous findings, both *Green Travel* and *Digital Payment* exhibit negative coefficients on both margins; results are statistically significant at the 1% level on the intensive margin, while results on the extensive margin are mixed. Second, we apply principal component analysis (PCA) to the eleven subcategories and use the first principal component (*PC1*) as a summary measure. Table IC.4 shows that *Walking* dominates *PC1* (loading equal to 1.000), and that *PC1* explains 87.6% of the total variation. Consistent with the aggregated-category results, the regression estimates in Table IC.5 yield negative coefficients on both margins, which are statistically significant at the 1% level on the intensive margin.

¹⁹More than 80% of the remaining categories are rarely or never used even at the 99th percentile (Table IB.1), justifying our focus on the dominant subcategories.

²⁰The original five broad categories defined by Alipay (Table IB.1) suffer from cross-identification issues, with no clear mapping between subcategories and overarching groups. We therefore construct our own classification based on meanings, grouping the eleven largest subcategories into *Green Travel* (Shared Bicycle, Public Bus, Walking, and Subway) and *Digital Payment* (Bill Payment, E-invoice, Train Ticket, Ele.me (Food Delivery), E-Bill, Offline Payment, and Online Payment).

4.4 Robustness Checks

In unreported results (available upon request), we use *Redeem Grams* as an alternative measure of Ant Forest participation. The results again show a negative correlation between redemption activity and green investment on both intensive and extensive margins. A principal component analysis of badge subcategories further shows that the dominant component—primarily capturing individual tree planting—is negatively associated with green fund allocation, significant at the 1% level on the intensive margin.

In addition, we conduct two robustness checks based on alternative sample constructions. First, we remove outliers in green-point variables instead of winsorizing them, which leads to a nontrivial reduction in sample size: the full sample decreases from 179,997 to 136,845 users, and the subsample of green investors declines from 91,047 to 69,580. Second, we exclude funds without Morningstar sustainable indicators rather than assigning them a zero value in the green fund classifications. Specifically, 10.62%, 52.47%, and 21.88% of funds lack information on the Sustainable Investment indicator, Globes, and Low Carbon Designation, respectively. Across both checks, coefficients on green-point variables remain negative on both margins and statistically significant at the 1% level on the intensive margin. Results are available upon request.

Finally, we examine users who actively produce green points (see Section [IA.1](#)) but do not redeem any trees or reserve badges during the sample period, likely due to insufficient accumulation. The median number of collected green points is 668 for this group, compared to 24,448 for active Ant Forest users, corresponding to 1.42% and 24.99% of the respective median produced points. On the intensive margin, coefficients remain negative and statistically significant, while results on the extensive margin are mixed.

5 Identification of Substitution Effects

In this section, we identify the causal impact of environmental engagement on users’ green investments by exploiting a large-scale promotional event on the Ant Forest platform: the Solar Panel promotion, during which users can redeem badges at a substantially reduced number of green-points.

5.1 Solar Panel Promotion

In September 2024, Ant Forest launched the Solar Panel promotion event, a “photovoltaic + desert greening” initiative, inspired by real-world projects in Inner Mongolia, that combine solar energy generation with the planting of drought-resistant shrubs beneath photovoltaic panels. The promotion ran in two phases: Phase I from September 10 to October 10, 2024, at 999 green points per badge, and Phase II from October 14, 2024 to April 30, 2025, at just 289 green points per badge. For comparison, most Ant Forest badges require far more green points—tree-planting badges range from 16,930 to over 330,000 points, and even the cheapest biodiversity reserve badges requires an average of 978 points (see [Table IB.2](#)). The Phase II price of 289 points made the Solar Panel badge one of the cheapest available. The event has high relevance. 58% of users in our sample participated. The median green points redeemed for Solar Panel is 298 (slightly higher than one badge in Phase II) and the average is 3,980.97 (approximately 13.77 badges in Phase II). In comparison, in our sample, the median user redeemed one tree and the average user redeemed 1.8 tree during two years.²¹

This event provides a particularly compelling quasi-experiment for identifying the causal impact of environmental engagement on green investments. Crucially, the promotion was determined by Ant Forest’s operational decisions and was unrelated to individual users’ investment behavior, providing plausibly exogenous variation in the intensity of environmental engagement. The event generates both cross-sectional variation (participants versus non-participants) and temporal variation (pre-versus post-promotion), enabling a difference-in-differences design that isolates the causal effect.

In our theoretical framework, the promotion increases the effectiveness of digital climate engagement (δ), by allowing users to generate greater environmental impact from their collected points. The model predicts (H2) that this increase leads to a crowding-out effect on green investments, consistent with digital climate engagement acting as a substitute for environmental protection through green investments.

²¹The median user redeemed zero animals and the average user redeemed 1.57 animals over the two-year period. For reserves, the median user redeemed one and the average user redeemed 3.60 over the same period.

5.2 Difference-in-Differences Specifications

We estimate the difference in the green investments between the periods before and during the Solar Panel promotion event to identify the causal impact of Ant Forest on green investments. More specifically, we employ the following Difference-in-Differences (DiD) specification as an extension to the baseline specifications in Equation 4 and Equation 5 to study the impact of the Solar Panel promotion event:

$$\Pr(\text{Green}_{i,t}) = \Phi(\alpha + \beta_1 \text{SolarPanel}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{SolarPanel}_{i,t} + \beta_3 \text{Post}_{i,t} + X'_{i,t}\Gamma + \alpha_c + \varepsilon_i), \quad (6)$$

$$\text{GreenShare}_{i,t} = \alpha + \beta_1 \text{SolarPanel}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{SolarPanel}_{i,t} + \beta_3 \text{Post}_{i,t} + X'_{i,t}\Gamma + \alpha_c + \varepsilon_i, \quad (7)$$

where we construct an individual-level two-period panel, where one period corresponds to the pre-event window and the other to the post-event window. For the dependent variables, we compute the pre-event $\Pr(\text{Green}_{i,t})$ as the probability that the investor i holds at least one green fund during June to August 2024, which is chosen to avoid overlap with the Earth Day event. The post-event $\Pr(\text{Green}_{i,t})$ is the probability that the investor i holds at least one green fund during September 2024 to April 2025, when the Solar Panel promotion was active. The pre-event $\text{GreenShare}_{i,t}$ is measured by the maximum of the monetary value allocated to green funds during June to August 2024. The post-event $\text{GreenShare}_{i,t}$ is measured by the maximum of the monetary value allocated to green funds during September 2024 to April 2025.

We measure $\text{SolarPanel}_{i,t}$ using the following two variables. $\text{SolarPanel}(\text{Dummy})_{i,t}$ is an indicator that equals one if investor i participated in the Solar Panel promotion event and zero otherwise. $\text{SolarPanel}(\text{Grams})_{i,t}$ captures the number of green points investor i spent redeeming Solar Panel badges during the event, serving as a measure of treatment intensity. Post is a dummy variable that equals one for the period from September 2024 to April 2025 and zero for the period from June to August 2024. $X_{i,t}$ includes the full set of portfolio- and individual-level controls as in the baseline specifications, and α_c denotes city fixed effects.

The rationale for using accumulated amounts rather than monthly changes follows the logic of our baseline analysis: environmental behavior—whether through digital engagement or financial

investments—is more meaningfully studied over a longer horizon. An individual is unlikely to immediately adjust her mutual fund portfolio upon participating in the Solar Panel promotion, but may do so the next time she reviews her portfolio.

5.3 Causal Evidence of Substitution Effects

[INSERT Table 4 AROUND HERE]

Table 4 reports results from the baseline DiD specification using *Solar Panel (Dummy)* as the treatment variable. On the extensive margin, the interaction coefficients between *Solar Panel (Dummy)* and *Post* are insignificant both statistically and economically across all specifications, suggesting that the promotion event did not change the probability of holding green funds, which aligns with the theoretically ambiguous effect explained in Section 2.

On the intensive margin, however, the interaction coefficients are negative and statistically significant at the 5% level in columns (2) and (6), and at the 1% level in column (8), where green funds are classified using the Sustainable Investment indicator, Low Carbon Designation, and Green-name criteria, respectively. For example, in column (2), participation in the Solar Panel promotion event leads to a 0.64 percentage point reduction in the share of sustainable funds in investors’ portfolios during the event period relative to the pre-event period. Coefficients in other specifications are of similar magnitude. This finding confirms our theoretical prediction (H2) that the possibility to generate environmental impact at a lower cost through badge redemption crowds out green investments.

In addition, the standalone coefficients on *Solar Panel (Dummy)* are also negative and statistically significant at the 1% level on the intensive margin across all specifications, reinforcing the baseline negative correlation between digital climate engagement—measured here by the participation in the Solar Panel event—and the share of portfolio invested in green funds.

[INSERT Table 5 AROUND HERE]

Table 5 reports results using *Solar Panel (Grams)*—the number of green points spent on Solar Panel badges—as a continuous treatment intensity measure. On the extensive margin, the inter-

action coefficients between *Solar Panel (Grams)* and *Post* are again statistically and economically insignificant in all specifications (columns (1), (3), (5), and (7)). On the intensive margin, the interaction coefficients are negative and statistically significant at the 10% level in column (2) based on the Sustainable Investment indicator and at the 5% level in column (6) where green funds are classified by Low Carbon Designation. For instance, in column (6), we find that a one-standard-deviation increase in green points spent on Solar Panel badges is associated with a $24.23 \times \frac{11816.92}{10^8} \approx 0.29$ percentage point reduction in the share of Low Carbon funds during the event period relative to the pre-event period, reinforcing the causal interpretation of the substitution effect. The coefficient on *Solar Panel (Grams)* are negative and statistically significant at 1% in all intensive margin specifications.

6 Environmental Awareness, Certification, and Green Investments

The results of Section 5 suggest that environmental engagement platforms can crowd out green investments because, by magnifying the impact of daily carbon-reducing activities, they may induce individuals to achieve their desired level of environmental protection through digital climate engagement rather than through green investments. However, these platforms may also promote environmental awareness, thereby strengthening pro-environmental preferences, which, all else equal, stimulates green investments.

To empirically validate this second channel of platform impact on green investments, we consider Ant Forest’s Earth Day events and Beautiful China Certificates. Unlike the Solar Panel Promotion, these initiatives do not enhance the actual impact of digital climate engagement: during the Earth Day events, the platform plants only the trees previously redeemed by users, while the Beautiful China Certificates simply provide official certification of users’ environmental impact. However, they may raise awareness of environmental protection and strengthen pro-environmental preferences. In our theoretical framework, such initiatives, by increasing the strength of environmental protection preferences, γ , are expected to increase green investments (H3).

6.1 Earth Day Events

Ant Forest holds large-scale tree planting events to the level of several millions of trees on the Earth Day each year.²² These events generate substantial media coverage and public attention of the environmental protection effort Ant Forest has made.

Empirical specifications. To estimate the effect of the Earth Day events on green investments, we employ the following Event Study specification, which extend the baseline specifications in Equation 4 and Equation 5 to capture the changes in the elasticity between green points and green investments before and after the Earth Day Event in Ant Forest:

$$\Pr(\text{Green}_{i,t}) = \Phi(\alpha + \beta_1 \text{GreenPoints}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{GreenPoints}_{i,t} + \beta_3 \text{Post}_{i,t} + X'_{i,t}\Gamma + \alpha_c + \varepsilon_i), \quad (8)$$

$$\text{GreenShare}_{i,t} = \alpha + \beta_1 \text{GreenPoints}_{i,t} \times \text{Post}_{i,t} + \beta_2 \text{GreenPoints}_{i,t} + \beta_3 \text{Post}_{i,t} + X'_{i,t}\Gamma + \alpha_c + \varepsilon_i, \quad (9)$$

where $\Pr(\text{Green}_{i,t})$ is the probability that investor i holds at least one green fund, and $\text{GreenShare}_{i,t}$ denotes the proportion of the mutual fund portfolio of investor i , measured by the maximum of the monetary value during the corresponding post/before period, that is allocated to green funds. $\text{GreenPoints}_{i,t}$ denotes user i 's Ant Forest green points actions, $X_{i,t}$ includes the full set of portfolio- and individual-level controls as in the baseline specifications, and α_c denotes city fixed effects. $\text{Post}_{i,t}$ equals one for periods after Earth Day through August of each year, and zero for periods from January through Earth Day. Similar to the specifications in Equation 6 and Equation 7, all variables are calculated as the *accumulation* over period t , except for controls. Specifically, we construct an individual-level two-period panel, splitting the sample period each year into a pre-event window and a post-event window around Earth Day. For each year, the pre-event period spans January to March and the post-event period spans April to August.²³

²²<https://www.techinasia.com/news/alipay-ant-forest-marks-600m-trees-milestone-on-earth-day>.

²³The choice of cutoff month is determined by when Ant Forest planted the millions of real trees in each year's campaign. We do not have data for the full year of 2025 due to the six-month data protection policy at Ant Research. August is chosen for the purpose of no overlap with the Solar Panel Promotion Event in 2024 and consistent in both years.

[INSERT [Table 6](#) AROUND HERE]

Results for 2023 event. [Table 6](#) presents the results for the 2023 Earth Day event. Panel A reports estimates using *Collect Grams* as the key independent variable. We find strong effects on the intensive margin but no effect on the extensive margin. On the intensive margin, the interaction coefficients are positive and statistically significant at the 1% level in all specifications (columns (2), (4), (6), and (8)). Take the largest effect in column (6) as an example where where green funds are classified using the Low Carbon Designation, for the same amount of green points, individuals invest 81.96% more after the Earth Day Event than before the event. In light of our model, this result indicates that the Earth Day event raises environmental awareness, which increases individuals' willingness to protect the environment through their financial decisions and thus reduces the negative elasticity between green points and green investments. Nevertheless, the coefficients on *Collect Grams* are negative and larger in magnitude than the positive interaction terms in all specifications, so the net effect of digital climate engagement on green investments remains negative. For instance, in column (2) where the dependent variable is based on the Morningstar Sustainable Investment indicator, the interaction coefficient is 64.12 and the coefficient on *Collect Grams* is -105.55, resulting in a net effect of -41.43.

On the extensive margin, the coefficients on the interaction between *Collect Grams* and *Post* are statistically insignificant and close to zero across all specifications (columns (1), (3), (5), and (7)). These results remain consistent with Earth Day strengthening pro-environmental preferences: The event may raise such preferences among individuals who are still unwilling to invest in green funds, thereby increasing their engagement with the platform; this implies that accumulated green points become a weaker predictor of green investments. In addition, the interaction between *Rob Grams* and *Post* is statistically insignificant in all eight specifications, suggesting that the attenuating role of an increase in environmental awareness on the substitution effect does not operate through robbing green points.

Panel B reports results using *Produce Grams*. The results are consistent with Panel A and the effects are stronger: on the intensive margin, both the interaction and standalone coefficients are statistically significant at the 1% level across all four specifications (columns (2), (4), (6), and (8)).

In terms of magnitude, the interaction coefficients for *Produce Grams* are 1.07 to 1.78 times as large as those for *Collect Grams*. This contrasts with our baseline regressions in [Table 2](#) and [Table 3](#), where the *Produce Grams* coefficients are roughly 0.22 to 0.48 times the *Collect Grams* coefficients. The amplified effect for *Produce Grams* suggests that the recognition generated by the Earth Day event influences behavior more strongly through everyday environmentally friendly activities—such as using public transit or making digital payments—than through the conscious act of collecting green points for tree planting. Finally, the net effect (the sum of the interaction and standalone coefficients) remains negative, consistent with the negative correlation pattern documented throughout. On the extensive margin, however, we do not find any significant effects.

[INSERT [Table 7](#) AROUND HERE]

Results for 2024 event. [Table 7](#) presents the results for the 2024 Earth Day event, which are weaker in both magnitude and statistical significance than those for 2023. In Panel A, the interaction coefficients between *Collect Grams* and *Post* on the intensive margin are again positive and statistically significant at the 1% level in column (6) where green funds are classified using the Low Carbon Designation, indicating 54.20% more green investment after the Earth Day Event compared to before the event for the same amount of green points collected. Coefficients are statistically significant at the 10% level in column (2) and (8) where green funds are classified using overall sustainable indicator and fund name and insignificant in column (4) where green funds are classified using Globes. Other patterns, including the coefficients on *Collect Grams* alone, the sum of the two coefficients, the coefficients on the interaction between *Rob Grams* and *Post* and results on the extensive margin, are all consistent with the findings in 2023. Moreover, similar as in the analysis in 2023, Panel B reports results using *Produce Grams* for the 2024 event where we also find evidence consistent with the results using *Collect Grams* but stronger in magnitude and statistical significance.

Overall, we find weaker effects of the 2024 Earth Day event relative to 2023, which is consistent with the possibility that the larger scale of the 2023 event generated greater environmental awareness. According to news reports, over 34 million users participated in the 2023 event, compared with only over 15 million in 2024. In our sample of 180,000 users, participation was 64,610 in 2023

and 31,946 in 2024. The stronger moderating effect in 2023 likely reflects the greater social visibility of a larger event such as via social media sharing, news coverage, and peer exposure, amplifying the warm glow channel.

6.2 Beautiful China Certificates

Ant Forest allows users to claim certificates known as “Beautiful China,” which are formally recognized by the Chinese government. Such official recognition of individuals’ contributions to environmental protection can stimulate environmental awareness and thereby strengthen green preferences. Importantly, obtaining the certificate does not require additional effort, but merely a single click to apply. All users who accumulate sufficient green points to redeem one tree within a calendar year are eligible to apply for a certificate. More trees correspond to more Beautiful China certificates. In addition, the certificate itself does not generate any additional environmental impact and serves only as a form of certification for the user.

In the empirical specification, we control for the number of Beautiful China certificates claimed by each user and compare users who have obtained the certificate and those who have not.

[INSERT [Table 8](#) AROUND HERE]

[Table 8](#) presents the results. Panel A interacts *Collect Grams* with the *Beautiful China*. On the intensive margin, the interaction coefficients are positive and statistically significant at the 10% level in columns (2), (6), and (8), and at the 5% level in column (4) when the dependent variable is based on Globes. The magnitudes of these coefficients are similar in all specifications, ranging from 2.63 to 2.96. On the extensive margin, the coefficients on the interaction are statistically insignificant. These results align with those on the effects of the Earth Day events, suggesting that also “Beautiful China” certificates may act as a stimulus to green investments by fostering environmental preferences among Ant Forest users.

Panel B reports robustness results using *Produce Grams*. The results are qualitatively similar to those in Panel A. In particular, the interaction coefficients with *Beautiful China* remain positive and statistically significant on the intensive margin—at the 1% level in all specifications—while results on the extensive margin are positive but statistically insignificant.

Finally, in both Panels A and B, the coefficients of *Beautiful China* are negative and statistically significant at the 1% or 5% level in most specifications, although they are small in magnitude. This is consistent with a social-image channel: for individuals who value certification of their environmental efforts, recognition through the certificates increases the utility from digital climate engagement and thereby crowds out green investments.

7 Concluding Remarks

Using detailed microdata from Alipay, we document a robust substitution effect between daily carbon-reducing actions and green investment. We further show that digital climate-engagement platforms play an important but nuanced role in shaping household financial choices: they enhance the effectiveness of daily pro-environmental actions, which crowds out green investment, while also raising environmental awareness, which can encourage it. These findings are consistent with a model of individual decision-making in which agents derive decreasing marginal utility from their overall environmental impact, generated by daily actions—whose effectiveness is amplified by climate-engagement platforms—and green investment. Our model and findings have important financial, strategic, and welfare implications.

The implications of the growing popularity of digital climate-engagement platforms for green finance depend on whether the crowding-out or the environmental-awareness channel dominates. In the former case, the reduced demand for green assets could increase their expected returns, which limits the crowding out but at the cost of raising the cost of capital for environmentally sustainable firms. As a result, crowding out of green investment may discourage firms from adopting greener practices, ultimately slowing the transition to a more sustainable economy. By contrast, if the environmental-awareness channel prevails, the opposite dynamic emerges; greater awareness can also increase demand for sustainable products, improving green firms’ profitability and expected returns, and thereby further stimulate green investment.

On the strategic side, our results highlight the scope for payment and financial institutions to enter the market for digital climate engagement, following Alipay’s lead. The crowding out of green investment has limited implications for the ecosystem’s profitability insofar as users’ total invested wealth remains unchanged and there are no significant differences in management or intermedia-

tion fees between green and brown funds. By contrast, the operating costs of digital engagement platforms can be offset by revenues from user-data monetization and in-app advertising. Moreover, such platforms allow firms to monetize users who are less profitable in financial services and, from a competitive perspective, may attract users who would otherwise invest in green funds through rival fintech companies that do not offer a digital climate-engagement app. The intensified competition in the broader market for environmental protection may help advance the transition to a greener economy through several channels.

As digital climate-engagement initiatives continue to expand, understanding their broader implications for financial markets and environmental outcomes remains an important area for future research.

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Appendix A: Figures and Tables

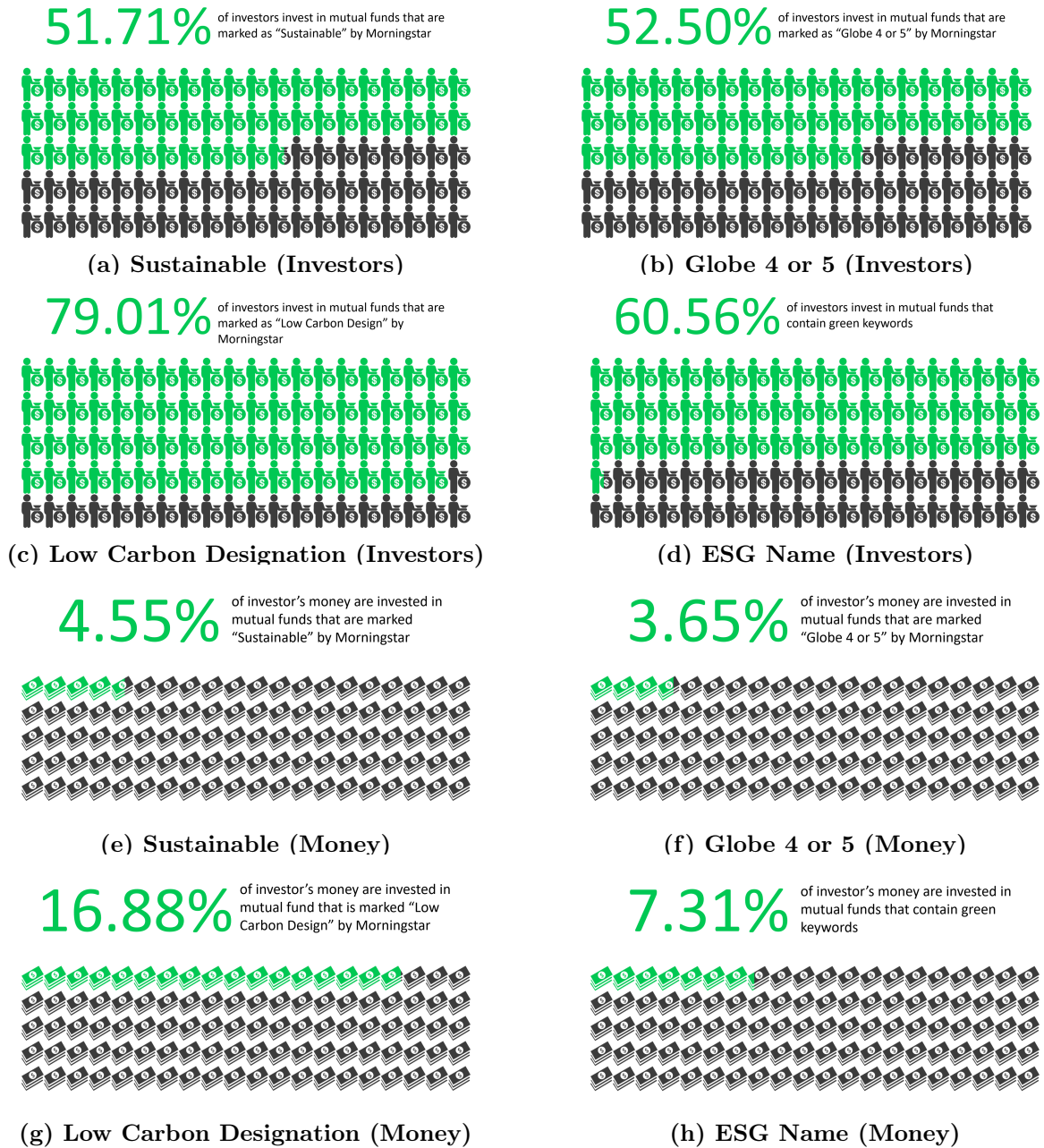


Figure 1: Aggregate Share of ESG Investments

Note: This figure plots ESG investments across four classifications (Sustainable, Globes 4 or 5, Low Carbon Design, and ESG fund name). Upper panels report the share of investors who hold at least one ESG-labeled fund. Lower pannels report the share of money invested in ESG-labeled funds in the entire sample. Green icons represent ESG investments, while gray icons represent non-ESG investments.

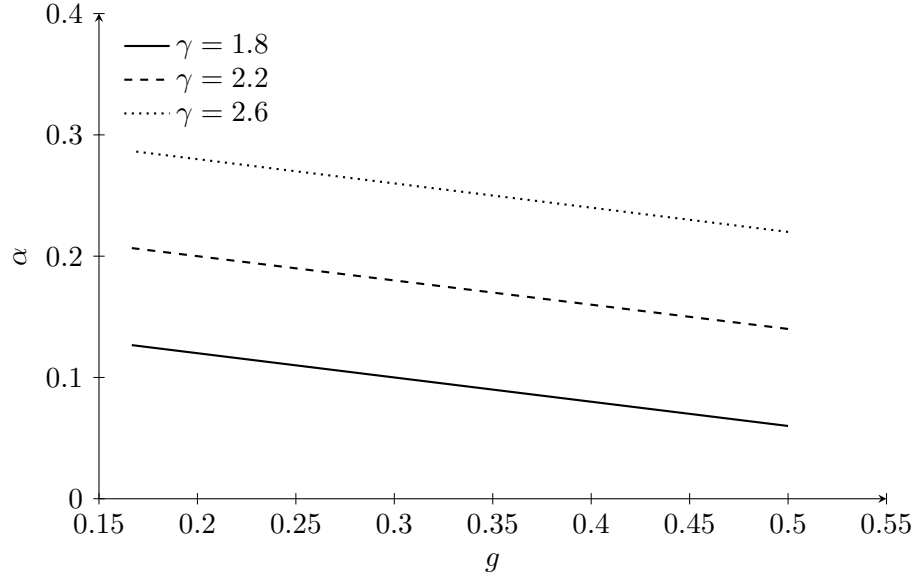


Figure 2: Relation between green-fund investments α and carbon-reducing activities g in the population of individuals with $\alpha^* > 0$.

Model specification: $\Gamma(I) = \ln(1 + I)$ and $\Psi(g) = g^2/2$, with parameter values $M_0 = 5$, $\Delta = \beta = \delta = 1$, $\theta \in [2, 6]$. For this specification, $h(\gamma) = \frac{\gamma-1}{5}$ and $f(g) = -\frac{g}{5}$.

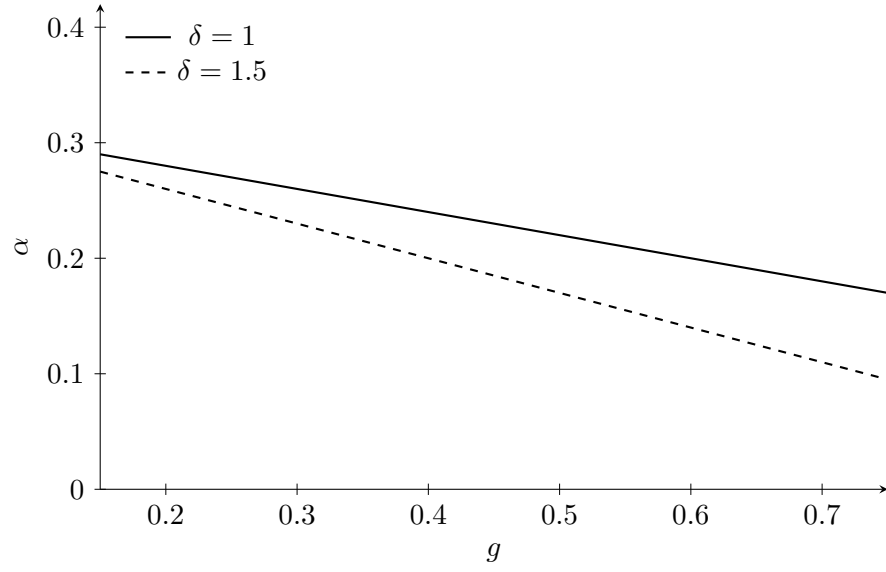


Figure 3: Effects of an increase in δ on the relation between green-fund investments α and carbon-reducing activities g in the population of individuals with $\alpha^* > 0$.

Model specification: $\Gamma(x) = \ln(1 + x)$ and $\Psi(g) = g^2/2$, with parameter values $M_0 = 5$, $\Delta = \beta = \delta = 1$, $\theta \in [2, 6]$, and $\gamma = 2.6$.

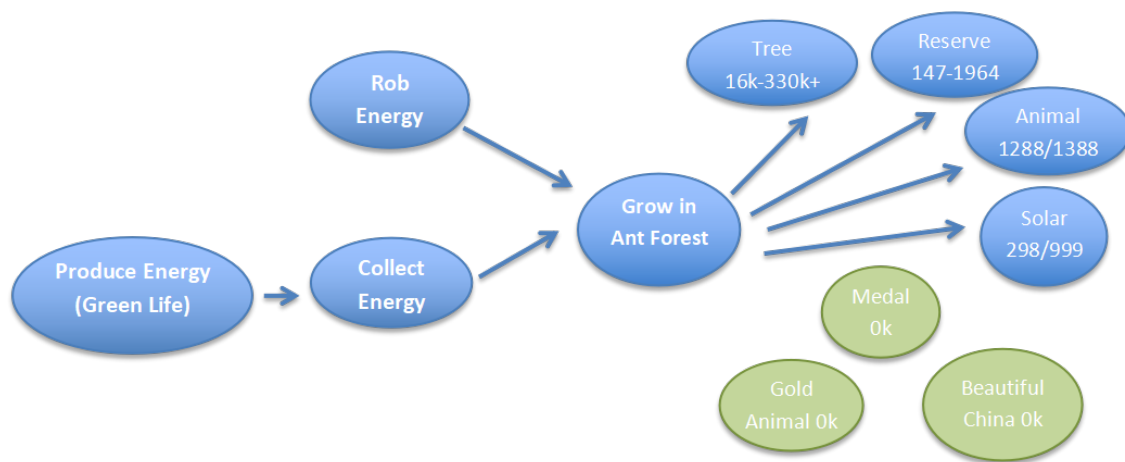


Figure 4: Structure of Ant Forest

Note: This figure shows the relationship between different actions (i.e., produce, collect, rob, and redeem green points) when using Ant Forest.

Table 1: Summary Statistics for Key Variables – Active Users

This table reports summary statistics for variables used in the regression analysis. The sample consists of 180,000 active Ant Forest users from January 2023 to December 2024. Detailed variable definitions and sample construction procedures are provided in [subsection IA.1](#). Green point variables are winsorized at the 99th percentile (i.e., results presented in this table are based on the same variable values used in the regressions).

Variables	Num	Mean	S.d.	Min	5th	25th	50th	75th	95th	Max
Panel A: Dependent Variables										
Sustainable (Dummy)	180,000	0.52	0.50	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Globes 4 or 5 (Dummy)	180,000	0.52	0.50	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Low Carbon (Dummy)	180,000	0.79	0.41	0.00	0.00	1.00	1.00	1.00	1.00	1.00
Green Name (Dummy)	180,000	0.61	0.49	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Regression Sample										
Sustainable (Proportion)	93,072	0.25	0.27	0.00	0.00	0.06	0.15	0.35	0.99	1.00
Globes 4 or 5 (Proportion)	94,498	0.24	0.26	0.00	0.00	0.05	0.14	0.32	0.95	1.00
Low Carbon (Proportion)	142,214	0.48	0.33	0.00	0.01	0.20	0.44	0.75	1.00	1.00
Green Name (Proportion)	109,002	0.31	0.28	0.00	0.01	0.09	0.22	0.44	1.00	1.00
Full Sample										
Sustainable (Proportion)	180,000	0.13	0.23	0.00	0.00	0.00	0.00	0.16	0.70	1.00
Globes 4 or 5 (Proportion)	180,000	0.12	0.22	0.00	0.00	0.00	0.00	0.16	0.65	1.00
Low Carbon (Proportion)	180,000	0.38	0.35	0.00	0.01	0.01	0.31	0.64	1.00	1.00
Green Name (Proportion)	180,000	0.19	0.27	0.00	0.00	0.00	0.06	0.28	0.88	1.00
Panel B: Green Points Generation in Alipay										
Collect Grams	180,000	37,263.19	39,820.07	0.00	671.00	6,684	24,448	54,703	118,263.50	196,029.11
Rob Grams	180,000	28,099.90	63,592.34	0.00	0.00	120.00	1,678.50	22,065.25	155,385.15	382,493.30
Produce Grams	180,000	133,162.75	116,411.51	1,848	23,672	56,850	97,824.50	168,955.75	368,127.20	873,864.64
Panel C: Badge Redemptions in Ant Forest										
Solar Panel (Dummy)	360,000	0.58	0.50	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Solar Panel (Grams)	360,000	3,980.97	11,816.92	0.00	0.00	0.00	298.00	2,384	19,072	84,036
Beautiful China (N)	180,000	0.77	1.25	0.00	0.00	0.00	0.00	1.00	3.00	6.00
Badge-Green-Point Ratio	180,000	0.47	0.70	0.00	0.02	0.05	0.10	0.77	1.85	6.80
Panel D: Financial Characteristics & Demographics										
Sharpe Ratio	180,000	-0.12	0.21	-2.95	-0.45	-0.21	-0.11	-0.00	0.19	1.26
Morningstar Rating	180,000	3.87	0.74	0.00	2.77	3.33	3.88	4.50	5.00	5.00
Total Money	180,000	177,694.34	323,483.12	5,068.15	12,557.89	36,330.64	84,457.61	196,970.27	632,264.19	27,978,066.06
Registered Years	180,000	11.54	3.24	2.00	6.84	9.26	11.17	13.59	17.60	20.10
Female	180,000	0.49	0.50	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Age	180,000	35.50	9.31	20.00	24.00	29.00	33.00	40.00	54.00	82.00
Risk Level	180,000	2.55	1.58	-2.00	-1.00	2.00	3.00	4.00	4.00	5.00

Table 2: Collecting Green Points and Green Investments

This table reports regression results from Probit and OLS models examining the relationship between collecting green points in Ant Forest and sustainable investment in Ant Fortune. The dependent variables are a dummy variable that equals to one if the individual invests in at least one green fund (odd columns) and the proportion of money an individual invested in green funds for the subsample of individuals who hold at least one green fund (even columns). More specifically, green funds are identified using Morningstar Sustainable Indicator (columns (1), (2)), Globes 4 or 5 (columns (3), (4)), Low Carbon Designation (columns (5), (6)), and Green name (columns (7), (8)), respectively. The independent variable of interest is *Collect Grams* (unit: grams of green points) which is the total number of green points a user collected in Ant Forest during the sample period from January 2023 to December 2024. For demonstration purposes, *Collect Grams* and *Rob Grams* are divided by 10^8 , *Total Money* by 10^6 , and other control variables by 100. Detailed sample and variable construction in [subsection IA.1](#). All columns include city fixed effects, and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		Green name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Environmental protection</i>								
Collect Grams	-28.77*** (9.23)	-21.87*** (2.60)	-20.35** (9.40)	-21.71*** (2.51)	-28.38*** (10.84)	-35.89*** (2.54)	-31.99*** (9.41)	-27.94*** (2.53)
Rob Grams	2.76 (5.66)	0.84 (1.54)	-11.89** (5.76)	-2.43 (1.51)	-1.12 (6.70)	-0.18 (1.54)	1.79 (5.79)	1.06 (1.50)
<i>Portfolio characteristics</i>								
Sharpe Ratio	5.99*** (1.48)	-6.17*** (0.64)	94.65*** (1.59)	20.10*** (0.63)	95.10*** (1.65)	16.33*** (0.55)	4.45*** (1.47)	-12.59*** (0.61)
Morningstar Rating	-44.32*** (0.42)	4.68*** (0.15)	-52.31*** (0.43)	1.01*** (0.14)	-66.57*** (0.50)	-6.06*** (0.13)	-53.08*** (0.43)	1.83*** (0.14)
Total Money	13.68*** (1.02)	-6.80*** (0.64)	38.01*** (1.18)	-5.43*** (0.51)	10.10*** (1.31)	-8.75*** (0.66)	14.50*** (1.07)	-7.42*** (0.62)
<i>Individual characteristics</i>								
Registered Years	-1.73*** (0.10)	-0.40*** (0.03)	-1.57*** (0.10)	-0.29*** (0.03)	0.32*** (0.12)	-0.37*** (0.03)	-1.34*** (0.10)	-0.48*** (0.03)
Female	-14.39*** (0.62)	-5.82*** (0.18)	-18.23*** (0.63)	-6.29*** (0.17)	-24.94*** (0.74)	-8.70*** (0.17)	-14.61*** (0.64)	-6.40*** (0.17)
Age	-0.35*** (0.04)	-0.12*** (0.01)	-0.40*** (0.04)	0.02* (0.01)	-0.90*** (0.04)	-0.21*** (0.01)	-0.64*** (0.04)	-0.18*** (0.01)
Risk Level	4.16*** (0.20)	-0.87*** (0.06)	4.49*** (0.20)	-0.54*** (0.06)	6.07*** (0.23)	-0.43*** (0.06)	4.97*** (0.20)	-0.84*** (0.06)
Pseudo R^2 /Adj R^2	0.058	0.053	0.096	0.046	0.147	0.065	0.080	0.049
City FE	✓	✓	✓	✓	✓	✓	✓	✓
N. Obs.	179,997	91,047	179,999	91,891	179,985	140,129	179,997	106,846

Table 3: Producing Green Points and Green Investments

This table reports regression results from Probit and OLS models examining the relationship between producing green points via Alipay and sustainable investment in Ant Fortune. The dependent variables are the same as in Table 2. The independent variable of interest is *Produce Grams* (unit: grams of green points) which is the total number of green points a user produced using Alipay during the sample period from January 2023 to December 2024. For demonstration purposes, *Produce Grams* is divided by 10^8 , *Total Money* by 10^6 , and other control variables by 100. Detailed sample and variable construction in subsection IA.1. All columns include city fixed effects, and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		Green name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Environmental protection</i>								
Produce Grams	-6.25** (2.66)	-7.16*** (0.75)	-9.79*** (2.71)	-8.28*** (0.72)	-7.69** (3.13)	-11.17*** (0.73)	-7.37*** (2.71)	-8.73*** (0.72)
<i>Portfolio characteristics</i>								
Sharpe Ratio	6.00*** (1.48)	-6.20*** (0.64)	94.69*** (1.59)	20.09*** (0.63)	95.13*** (1.65)	16.30*** (0.55)	4.48*** (1.47)	-12.62*** (0.61)
Morningstar Rating	-44.33*** (0.42)	4.68*** (0.15)	-52.30*** (0.43)	1.01*** (0.14)	-66.56*** (0.50)	-6.07*** (0.13)	-53.08*** (0.43)	1.82*** (0.14)
Total Money	13.67*** (1.02)	-6.80*** (0.64)	37.99*** (1.18)	-5.43*** (0.51)	10.08*** (1.31)	-8.75*** (0.66)	14.48*** (1.07)	-7.42*** (0.62)
<i>Individual characteristics</i>								
Registered Years	-1.70*** (0.10)	-0.39*** (0.03)	-1.58*** (0.10)	-0.28*** (0.03)	0.36*** (0.12)	-0.35*** (0.03)	-1.30*** (0.10)	-0.46*** (0.03)
Female	-14.20*** (0.62)	-5.83*** (0.18)	-18.39*** (0.63)	-6.32*** (0.17)	-24.76*** (0.74)	-8.70*** (0.17)	-14.41*** (0.64)	-6.40*** (0.17)
Age	-0.40*** (0.03)	-0.13*** (0.01)	-0.41*** (0.04)	0.01 (0.01)	-0.95*** (0.04)	-0.22*** (0.01)	-0.69*** (0.04)	-0.19*** (0.01)
Risk Level	4.14*** (0.20)	-0.88*** (0.06)	4.48*** (0.20)	-0.54*** (0.06)	6.05*** (0.23)	-0.43*** (0.06)	4.96*** (0.20)	-0.84*** (0.06)
Pseudo R^2 /Adj R^2	0.058	0.053	0.096	0.046	0.147	0.065	0.080	0.049
City FE	✓	✓	✓	✓	✓	✓	✓	✓
N. Obs.	179,997	91,047	179,999	91,891	179,985	140,129	179,997	106,846

Table 4: Effect of Solar Panel Promotion Event on Green Investments (Baseline DID)

This table reports regression results from Probit and OLS models examining the impact of the Solar Panel promotion event in Ant Forest on sustainable investment in Ant Fortune using a difference-in-differences framework. Specifications in Equation 6 and Equation 7. The dependent variables are the same as in Table 2. *Solar Panel* is a dummy variable that equals to one if the individual redeemed a Solar Panel badge (divided by 100 for demonstration purpose). *Post* is a dummy variable that equals one for the period from September 2024 to April 2025 (i.e., during the Solar Panel promotion event) and zero for the period from June 2024 to August 2024 (non-overlap with Earth Day event). Other control variables are the same as in Table 2. Sample construction in subsection IA.1. All columns include city fixed effects and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		Green name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Panel (Dummy) $\times$ Post	0.01 (0.87)	-0.64** (0.25)	0.01 (0.86)	-0.24 (0.25)	0.01 (0.87)	-0.60** (0.25)	0.02 (0.86)	-0.71*** (0.25)
Solar Panel (Dummy)	0.02 (0.62)	-1.74*** (0.17)	0.01 (0.62)	-2.09*** (0.18)	0.02 (0.61)	-2.85*** (0.17)	0.03 (0.61)	-1.85*** (0.17)
Post	0.03*** (0.01)	0.05*** (0.00)	0.09*** (0.01)	0.06*** (0.00)	0.06*** (0.01)	0.11*** (0.00)	0.18*** (0.01)	0.06*** (0.00)
<i>Portfolio characteristics</i>								
Sharpe Ratio	0.14 (1.08)	-0.92 (0.57)	0.22 (1.06)	15.94*** (0.54)	0.46 (1.02)	26.81*** (0.48)	0.19 (1.04)	-3.47*** (0.55)
Morningstar Rating	-0.67*** (0.21)	-2.67*** (0.15)	-0.39* (0.21)	-1.81*** (0.12)	-0.70*** (0.20)	-9.95*** (0.10)	-0.56*** (0.20)	-5.88*** (0.13)
Total Money	0.28*** (0.01)	-0.07*** (0.01)	0.53*** (0.01)	-0.06*** (0.01)	0.37*** (0.01)	-0.10*** (0.01)	0.43*** (0.01)	-0.08*** (0.01)
<i>Individual characteristics</i>								
Registered Years	-0.21*** (0.07)	-0.10*** (0.02)	-0.32*** (0.07)	-0.15*** (0.02)	0.50*** (0.07)	-0.20*** (0.02)	0.06 (0.07)	-0.13*** (0.02)
Female	-0.11 (0.44)	-3.23*** (0.13)	-0.18 (0.44)	-4.42*** (0.13)	-0.33 (0.44)	-6.69*** (0.13)	-0.09 (0.43)	-3.68*** (0.13)
Age	0.45*** (0.02)	-0.09*** (0.01)	0.42*** (0.02)	0.01 (0.01)	0.01 (0.02)	-0.10*** (0.01)	0.31*** (0.02)	-0.11*** (0.01)
Risk Level	0.48*** (0.14)	-0.63*** (0.04)	0.50*** (0.14)	-0.46*** (0.04)	1.10*** (0.14)	-0.30*** (0.04)	0.62*** (0.14)	-0.59*** (0.04)
Pseudo R^2 /Adj R^2	0.006	0.045	0.013	0.051	0.009	0.120	0.013	0.065
Controls	✓	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓	✓
N. Obs.	359,994	120,872	359,998	137,291	359,998	229,685	359,996	143,246

Table 5: Solar Panel Promotion Event and Green Investments (Baseline DID, Grams)

This table reports regression results from Probit and OLS models examining the impact of the Solar Panel promotion event in Ant Forest on sustainable investment in Ant Fortune using a difference-in-differences framework. Specifications in Equation 6 and Equation 7. The dependent variables are the same as in Table 2. *Solar Panel (Grams)* is the number of green points (unit: grams) that the individual redeemed for Solar Panel badges in the promotion event (divided by 10^8 for demonstration purpose). *Post* is a dummy variable that equals one for the period from September 2024 to April 2025 (i.e., during the Solar Panel promotion event) and zero for the period from June 2024 to August 2024 (non-overlap with Earth Day event). Other control variables are the same as in Table 2. Sample construction in subsection IA.1. All columns include city fixed effects and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		Green name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Panel (Grams) $\times$ Post	0.00 (36.33)	-15.74* (9.56)	0.00 (36.06)	0.02 (9.83)	0.00 (36.60)	-24.23** (10.17)	0.00 (35.87)	-14.69 (9.56)
Solar Panel (Grams)	0.00 (25.88)	-25.32*** (6.43)	0.00 (25.84)	-47.60*** (6.67)	0.00 (25.63)	-48.79*** (6.99)	0.00 (25.40)	-30.92*** (6.40)
Post	0.03*** (0.00)	0.05*** (0.00)	0.09*** (0.00)	0.06*** (0.00)	0.06*** (0.00)	0.10*** (0.00)	0.18*** (0.00)	0.06*** (0.00)
<i>Portfolio characteristics</i>								
Sharpe Ratio	0.14 (1.08)	-0.88 (0.57)	0.22 (1.06)	16.03*** (0.54)	0.46 (1.02)	26.95*** (0.48)	0.19 (1.04)	-3.41*** (0.55)
Morningstar Rating	-0.67*** (0.21)	-2.69*** (0.15)	-0.39* (0.21)	-1.82*** (0.12)	-0.70*** (0.20)	-9.97*** (0.10)	-0.56*** (0.20)	-5.90*** (0.13)
Total Money	0.28*** (0.01)	-0.07*** (0.01)	0.53*** (0.01)	-0.06*** (0.01)	0.37*** (0.01)	-0.10*** (0.01)	0.43*** (0.01)	-0.08*** (0.01)
<i>Individual characteristics</i>								
Registered Years	-0.21*** (0.07)	-0.11*** (0.02)	-0.32*** (0.07)	-0.17*** (0.02)	0.50*** (0.07)	-0.22*** (0.02)	0.06 (0.07)	-0.15*** (0.02)
Female	-0.11 (0.44)	-3.30*** (0.13)	-0.18 (0.44)	-4.51*** (0.13)	-0.33 (0.44)	-6.81*** (0.13)	-0.09 (0.43)	-3.76*** (0.13)
Age	0.45*** (0.02)	-0.08*** (0.01)	0.42*** (0.02)	0.01* (0.01)	0.01 (0.02)	-0.09*** (0.01)	0.31*** (0.02)	-0.10*** (0.01)
Risk Level	0.47*** (0.14)	-0.64*** (0.04)	0.50*** (0.14)	-0.47*** (0.04)	1.10*** (0.14)	-0.31*** (0.04)	0.62*** (0.14)	-0.60*** (0.04)
Pseudo R^2 /Adj R^2	0.006	0.043	0.013	0.050	0.009	0.118	0.013	0.064
Controls	✓	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓	✓
N. Obs.	359,994	120,872	359,998	137,291	359,998	229,685	359,996	143,246

Table 6: 2023 Earth Day Tree-Planting Event (Elasticity Event Study)

This table reports regression results from Probit and OLS models examining how the relationship between green-point activity in Ant Forest and sustainable investment in Ant Fortune is affected by the 2023 Earth Day tree-planting event. Specifications in Equation 8 and Equation 9. The dependent variables are the same as in Table 2. In Panel A, the independent variables of interest are *Collect Grams* and its interaction with the dummy variable *Post*. In Panel B, the independent variables of interest are *Produce Grams* and its interaction with *Post*. *Post* is a dummy variable that equals one for the period from April 2023 to August 2023 (i.e., after the Earth Day event) and zero for the period from January 2023 to March 2023. For demonstration purposes, *Collect Grams*, *Rob Grams*, and *Produce Grams* are divided by 10^8 . Sample construction in subsection IA.1. All columns include city fixed effects and other control variables as in Table 2, and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		Green name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Collect Grams								
Collect Grams $\times$ Post	0.00 (73.58)	45.26** (18.87)	0.00 (76.31)	39.94** (19.04)	0.00 (75.39)	81.96*** (19.08)	0.00 (73.61)	53.40*** (18.33)
Collect Grams	0.00 (63.67)	-104.61*** (16.19)	0.00 (65.97)	-69.38*** (16.04)	0.00 (65.06)	-144.97*** (16.50)	0.00 (63.66)	-127.94*** (15.67)
Rob Grams $\times$ Post	0.00 (44.38)	-4.99 (10.91)	-0.00 (46.11)	-1.07 (11.28)	0.00 (45.75)	-13.87 (11.27)	0.00 (44.50)	-1.41 (10.62)
Rob Grams	0.00 (36.93)	0.05 (8.98)	-0.00 (38.28)	-11.91 (9.03)	0.00 (37.96)	6.30 (9.34)	0.00 (37.01)	-2.06 (8.68)
Post	0.01** (0.01)	0.01*** (0.00)	-0.01 (0.01)	-0.01*** (0.00)	0.02*** (0.01)	0.01*** (0.00)	0.00 (0.01)	0.01*** (0.00)
Pseudo R^2 /Adj R^2	0.007	0.051	0.014	0.042	0.014	0.076	0.009	0.057
N. Obs.	359,994	158,385	360,000	109,502	359,998	228,233	359,994	191,944
Panel B: Produce Grams								
Produce Grams $\times$ Post	0.00 (68.70)	80.50*** (18.14)	0.00 (71.35)	51.02*** (18.16)	0.00 (70.34)	87.97*** (18.14)	0.00 (68.69)	90.68*** (17.58)
Produce Grams	0.00 (60.91)	-153.15*** (16.04)	0.00 (63.21)	-99.33*** (15.82)	0.00 (62.20)	-149.07*** (16.08)	0.00 (60.86)	-171.03*** (15.49)
Post	0.01 (0.01)	0.01*** (0.00)	-0.01 (0.01)	-0.01** (0.00)	0.02** (0.01)	0.00 (0.00)	0.00 (0.01)	0.01*** (0.00)
Pseudo R^2 /Adj R^2	0.007	0.051	0.014	0.042	0.014	0.076	0.009	0.057
N. Obs.	359,994	158,385	360,000	109,502	359,998	228,233	359,994	191,944
Controls	✓	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 7: 2024 Earth Day Tree-Planting Event (Elasticity Event Study)

This table reports regression results from Probit and OLS models examining how the relationship between green-point activity in Ant Forest and sustainable investment in Ant Fortune is affected by the 2024 Earth Day tree-planting event. Specifications in [Equation 8](#) and [Equation 9](#). The dependent variables are the same as in [Table 2](#). In Panel A, the independent variables of interest are *Collect Grams* and its interaction with the dummy variable *Post*. In Panel B, the independent variables of interest are *Produce Grams* and its interaction with *Post*. *Post* is a dummy variable that equals one for the period from April 2024 to August 2024 (i.e., after the Earth Day event but before the Solar Panel Promotion) and zero for the period from January 2024 to March 2024. For demonstration purposes, *Collect Grams*, *Rob Grams*, and *Produce Grams* are divided by 10^8 . Sample construction in [subsection IA.1](#). All columns include city fixed effects and other control variables as in [Table 2](#), and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		Green name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Collect Grams								
Collect Grams $\times$ Post	−0.00 (74.44)	34.28* (19.04)	−0.00 (75.64)	−4.82 (20.41)	−0.00 (75.18)	54.20*** (20.03)	−0.00 (73.40)	35.03* (18.76)
Collect Grams	−0.00 (62.86)	−108.05*** (15.98)	−0.00 (64.40)	−58.04*** (17.05)	−0.00 (63.53)	−146.80*** (16.80)	−0.00 (62.03)	−113.71*** (15.72)
Rob Grams $\times$ Post	0.00 (47.87)	−13.11 (11.73)	−0.00 (48.81)	−2.19 (13.06)	−0.00 (48.37)	−11.36 (12.73)	0.00 (47.19)	−12.14 (11.51)
Rob Grams	0.00 (39.58)	5.94 (9.62)	−0.00 (40.73)	−0.63 (10.63)	−0.00 (40.02)	3.33 (10.43)	0.00 (39.04)	0.56 (9.45)
Post	−0.02*** (0.01)	0.01*** (0.00)	0.05*** (0.01)	0.04*** (0.00)	0.01* (0.01)	0.05*** (0.00)	−0.04*** (0.01)	0.01*** (0.00)
Pseudo R^2 /Adj R^2	0.006	0.042	0.010	0.041	0.010	0.111	0.009	0.068
N. Obs.	359,994	125,702	359,994	116,446	359,998	225,564	359,994	151,619
Panel B: Produce Grams								
Produce Grams $\times$ Post	0.00 (68.10)	43.64** (17.93)	0.00 (69.29)	12.38 (19.09)	0.00 (68.77)	69.14*** (18.57)	0.00 (67.11)	46.92*** (17.44)
Produce Grams	0.00 (59.69)	−142.81*** (15.63)	0.00 (61.14)	−81.96*** (16.65)	0.00 (60.31)	−155.41*** (16.20)	0.00 (58.86)	−155.51*** (15.18)
Post	−0.02*** (0.01)	0.01*** (0.00)	0.05*** (0.01)	0.04*** (0.00)	0.01 (0.01)	0.05*** (0.00)	−0.04*** (0.01)	0.01*** (0.00)
Pseudo R^2 /Adj R^2	0.006	0.043	0.010	0.042	0.010	0.110	0.009	0.069
N. Obs.	359,994	125,702	359,994	116,446	359,998	225,564	359,994	151,619
Controls	✓	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 8: Role of Certification: Beautiful China

This table reports regression results from Probit and OLS models examining the relationship between collecting (Panel A) and producing (Panel B) green points in Ant Forest and sustainable investment in Ant Fortune, interacted with the number of “Beautiful China” certificates earned (*Beautiful China*). The dependent variables are the same as in Table 2. For demonstration purposes, *Collect Grams*, *Rob Grams*, and *Produce Grams* are divided by 10^8 , Total Money by 10^6 , and other control variables by 100. Detailed sample and variable construction in subsection IA.1. All columns include city fixed effects and other control variables as in Table 2, and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		ESG name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Collect Green Points								
Collect Grams × Beautiful China	−3.19 (5.48)	2.66* (1.50)	−2.62 (5.59)	2.96** (1.44)	0.75 (6.41)	2.63* (1.51)	−3.86 (5.59)	2.64* (1.46)
Collect Grams	−22.98* (12.51)	−24.60*** (3.52)	−12.51 (12.75)	−24.49*** (3.41)	−28.96* (14.78)	−36.32*** (3.44)	−24.93* (12.79)	−30.21*** (3.44)
Rob Grams × Beautiful China	1.08 (2.99)	−0.26 (0.81)	3.12 (3.05)	0.78 (0.78)	0.96 (3.55)	−0.80 (0.81)	1.04 (3.07)	−0.53 (0.79)
Rob Grams	1.36 (10.15)	1.41 (2.79)	−18.30* (10.32)	−5.30** (2.67)	−4.33 (12.04)	4.06 (2.76)	1.00 (10.40)	2.92 (2.72)
Beautiful China	0.0002 (0.00)	−0.0020 (0.00)	−0.0028 (0.00)	−0.0025** (0.00)	−0.0008 (0.01)	−0.0042*** (0.00)	0.0002 (0.00)	−0.0025** (0.00)
Pseudo R^2 /Adj R^2	0.058	0.053	0.096	0.046	0.147	0.065	0.080	0.049
Panel B: Produce Green Points								
Produce Grams × Beautiful China	0.31 (1.39)	1.58*** (0.39)	0.04 (1.42)	1.74*** (0.39)	0.90 (1.64)	1.48*** (0.38)	0.07 (1.42)	1.58*** (0.38)
Produce Grams	−5.45 (4.27)	−10.46*** (1.21)	−6.70 (4.34)	−11.80*** (1.15)	−8.70* (5.06)	−12.20*** (1.17)	−5.58 (4.36)	−11.56*** (1.17)
Beautiful China	−0.0027 (0.00)	−0.0030** (0.00)	−0.0047 (0.00)	−0.0035*** (0.00)	−0.0031 (0.01)	−0.0059*** (0.00)	−0.0029 (0.00)	−0.0037*** (0.00)
Pseudo R^2 /Adj R^2	0.058	0.053	0.096	0.046	0.147	0.065	0.080	0.049
Controls	✓	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓	✓
N. Obs.	179,997	91,047	179,999	91,891	179,985	140,129	179,997	106,846

Appendix B: Proofs of the Results of Section 2

Proof of Proposition 1. Taking the FOC of problem (1) with respect to g and α for an interior solution, respectively, gives

$$-M_0\Delta + \gamma\Gamma'(\cdot)\beta M_0 = 0 \Rightarrow \gamma\Gamma'(\cdot) = \frac{\Delta}{\beta}, \quad (10)$$

and

$$-\theta\Psi'(\cdot) + \gamma\Gamma'(\cdot)\delta = 0 \Rightarrow \gamma\Gamma'(\cdot) = \theta\Psi'(\cdot). \quad (11)$$

Dividing (11) for (10) and simplifying yields g^* in (3); substituting it into (10) yields α^* in an interior solution.

This (unique) solution provides the global maximum if the Hessian matrix of problem (1), given by

$$H = \begin{pmatrix} \gamma\Gamma''(\cdot)\beta^2 M_0^2 & \gamma\Gamma''(\cdot)\beta\delta M_0 \\ \gamma\Gamma''(\cdot)\beta\delta M_0 & -\theta\Psi''(\cdot) + \gamma\Gamma''(\cdot)\delta^2 \end{pmatrix},$$

is negative definite. This is the case if and only if

$$\gamma\Gamma''(\cdot)\beta^2 M_0^2 < 0,$$

and

$$\det(H) = -\gamma\Gamma''(\cdot)\beta^2 M_0^2 \theta\Psi''(\cdot) > 0.$$

Both conditions hold under our assumptions $\Psi''(\cdot) > 0 > \Gamma''(\cdot)$.

From simple inspections of g^* and α^* , noting that $\Psi'^{-1}(\cdot)$ (resp. $\Gamma'^{-1}(\cdot)$) is an increasing (resp. decreasing) function, it follows that g^* is increasing in Δ and δ , and decreasing in θ and β ; whereas α^* is increasing in γ and θ , and decreasing in M_0 , Δ , and δ . The effect of β on α^* depends on functional forms.²⁴

Finally, since $g^* > 0$ always holds and the objective is globally concave in α , the above solution

²⁴Indeed, using the implicit function theorem and simplifying we find

$$\frac{\partial\alpha^*}{\partial\beta} > 0 \iff \frac{\Delta}{\beta} \left(\frac{\delta^2}{\theta\Psi''(g^*)} - \frac{1}{\gamma\Gamma''(Y)} \right) > Y - \delta g^*,$$

where $Y \equiv \Gamma'^{-1}(\Delta/(\gamma\beta))$.

is feasible iff $\alpha^* \in (0, 1)$. Assumption (A1) rules out that $\alpha = 1$. A corner solution $\alpha = 0$ emerges if and only if

$$\gamma \Gamma'(\delta g) \leq \frac{\Delta}{\beta},$$

where (11) then writes as (2). It can be immediately seen that (2) admits a unique solution $g_0 > 0$, which is increasing in γ and decreasing in θ ; the effect of δ on g^* depends on functional forms. $\square$

Proof of Corollary 1. Consider a population of agents i with heterogeneous (θ_i, γ_i) whose optimal choices are given in (3). Denoting these choices by individual i as $\alpha^*(\theta_i, \gamma_i)$ and $g^*(\theta_i)$ (since g^* does not depend on γ), one has that $\alpha^*(\theta_i, \gamma_i) = h(\gamma_i) + f(g^*(\theta_i))$, where $h(\gamma) \equiv \frac{1}{\beta M_0} \Gamma'^{-1}(\frac{\Delta}{\gamma \beta})$ is such that $h'(\gamma) = -\frac{\Delta}{\beta^2 M_0 \gamma^2 \Gamma''(\cdot)} > 0$, and $f(g) \equiv -\frac{\delta}{\beta M_0} g$ is such that $f'(g) = -\frac{\delta}{\beta M_0} < 0$. Moreover, $h(\gamma)$ is independent of δ , whereas $\frac{\partial f(g^*)}{\partial \delta} = -\frac{g^*}{\beta M_0} - \frac{\delta \Delta}{\beta^2 M_0 \theta \Psi''(g^*)} < 0$. $\square$

Table A.1: Variable Definitions

Variable	Definition
<i>Panel A: Dependent Variables (Sustainable Investment)</i>	
<i>Note: For each category, we construct both a binary dummy (1 if the user holds at least one such fund) and a continuous variable (proportion of total fund assets invested in such funds).</i>	
Globes 4 or 5	Funds with a Morningstar Sustainability Rating (“Globes”) of 4 or 5.
Sustainable	Funds flagged by the Morningstar “Sustainable Investment” indicator.
Low Carbon	Funds flagged by the Morningstar “Low Carbon Designation” indicator.
Green Name	Funds whose names contain at least one of the Green-related keywords (e.g., “carbon neutrality,” “clean energy”) identified via GPT-4 and manual verification.
<i>Panel B: Green Points (Independent Variables)</i>	
Collect Grams	The total amount of green points (in grams) a user actively collected from their own low-carbon activities during the sample period.
Rob Grams	The total amount of green points (in grams) a user collected (“robbed”) from friends’ uncollected points within the Alipay social network.
Produce Grams	The total amount of green points (in grams) generated by a user’s low-carbon behaviors (e.g., walking, subway, digital payment), regardless of whether they were collected.
Subcategories	The specific sources of green points, including <i>Bill Payment</i> , <i>E-invoice</i> , <i>Train Ticket</i> , <i>Ele.me</i> (food delivery), <i>E-Bill</i> , <i>Offline Payment</i> , <i>Online Payment</i> , <i>Shared Bicycle</i> , <i>Public Bus</i> , <i>Walking</i> , and <i>Subway</i> . Measured in grams.
Green Travel	Aggregated green points from travel subcategories: such as <i>Walking</i> , <i>Shared Bicycle</i> , <i>Public Bus</i> , and <i>Subway</i> .
Digital Payment	Aggregated green points from payment subcategories: <i>Online Payment</i> , <i>Offline Payment</i> , <i>E-invoice</i> , etc.
PC1 (Produce)	The first principal component extracted from the 11 production subcategories listed above.
<i>Panel C: Badge Redemptions & Interactions (Independent Variables)</i>	
Solar Panel (Dummy)	A dummy variable that equals one if the user redeemed at least one Solar Panel badge during the Solar Panel promotion event (September 2024–April 2025) and zero otherwise.
Solar Panel (Grams)	The number of green points (grams) the user spent redeeming Solar Panel badges during the Solar Panel promotion event, serving as a measure of treatment intensity.
Beautiful China	The count of “Wild China” certificates earned (does not require green point consumption).
Badge-Green-Point Ratio	The total count of badges a user redeemed divided by the total number of green points (grams) consumed during the sample period.
Earth Day 2023	A dummy variable that equals one if the user has a 2023 Earth Day certificate and zero otherwise.
Earth Day 2024	A dummy variable that equals one if the user has a 2024 Earth Day certificate and zero otherwise.
Post	A dummy variable used in the difference-in-differences specifications. For the Earth Day analysis, equals one for months after the Earth Day event and zero before April–December 2023 vs. January–March 2023 for the 2023 event; May–December 2024 vs. January–April 2024 for the 2024 event. For the Solar Panel promotion analysis: equals one for September 2024–April 2025 (during the promotion) and zero for June–August 2024 (chosen to avoid overlap with the Earth Day event).
<i>Panel D: Financial Controls & Demographics</i>	
Total Money	The total amount of money (RMB) the user holds in mutual funds in Ant Fortune.
Sharpe Ratio	The Sharpe ratio of the user’s mutual fund portfolio, calculated using monthly returns.
Morningstar Rating	The asset-weighted average Morningstar Rating (star rating) of the funds held by the user.
Risk Level	The user’s self-reported risk tolerance level to Alipay (Scale: 1-5).
Registered Years	The number of years since the user registered their Alipay profile.
Age	The user’s age in years.
Female	A dummy variable equaling one if the user is female and zero otherwise.

Internet Appendices

Internet Appendix A: Data Construction	Online Appendix-1
Internet Appendix B: More Institutional Details	Online Appendix-4
Internet Appendix C: Additional Tables	Online Appendix-11

Internet Appendix A: Data Construction

IA.1 Ant Forest Sample and Variable Construction

Alipay anonymizes all user information to protect privacy. For most projects conducted through Ant's Open Research Platform, data access is subject to restrictions on both sample size and time coverage, with a maximum of 200,000 users and a maximum sample period of two years. In accordance with these constraints, we draw a randomized sample of 200,000 users, consisting of 180,000 users who are active in both generating green points and participating in Ant Forest, and 20,000 users who are active only in generating green points. Our main analysis focuses on the 180,000 active Ant Forest users. The sample period spans January 2023 to December 2024, which falls after the lockdown and control phases of the COVID-19 pandemic in China.

One potential concern is that our measures may capture variation in Alipay usage rather than differences in environmental preferences. To mitigate this concern, we restrict our sample to active Ant Forest users as described above. For example, walking is the most prevalent activity through which users generate green points, but it requires explicit authorization for Alipay to track step counts. An individual may walk extensively yet fail to enable this function. By focusing on users who are active in generating green points, we ensure that low green point accumulation reflects limited interest in Ant Forest contribution rather than lack of app usage. Specifically, following suggestions from Ant Open Research, we define active green-point users as those who generate green points on at least 15 days per month for more than 50% of the months in the sample period. Active Ant Forest users are defined as those who successfully redeemed at least one tree or reserve badge during the sample period.

A related concern is whether our measures capture individuals' preferences for green investments or merely their propensity to invest via Alipay. To address this issue, we further restrict the sample to individuals who hold at least RMB 5,000 in the asset management sub-app Ant Fortune for more than 50% of the months in the sample period. Although we cannot fully rule out the possibility that some individuals invest in green funds outside Alipay, focusing on active mutual fund holders within the platform allows us to infer individual green investment behavior under the assumption of consistency across platforms—that is, individuals who invest heavily in green funds elsewhere are also likely to hold more green funds through Alipay.

The primary analysis is conducted using a user-level cross-sectional dataset. To harmonize information across data sources, all time-series variables are aggregated to the user level. Behavioral measures—such as `rob grams`, `collect grams`, and “small-category” variables—are summed over the observation window to capture total activity. Financial and fund-holding variables, including asset values and Morningstar indicators, are aggregated using the maximum observed value for each user. Portfolio-level summaries, such as the Sharpe ratio and the overall Morningstar rating, are incorporated as deduplicated user-level snapshots.

We apply a multi-stage data-cleaning procedure to mitigate the influence of extreme values and improve data quality across both behavioral and wealth variables. *Wealth* is winsorized at the 1st and 99th percentiles and subsequently scaled by dividing by 1,000,000. For behavioral measures, we first winsorize the “small-category” variables at the 1st and 99th percentiles. We then aggregate these variables by summation to construct composite behavioral measures. Finally, the aggregated behavioral variables are rescaled (e.g., by 10^8) to facilitate coefficient readability.

IA.2 Fund Name Keyword List

To determine keywords related to ESG, we perform a two-step procedure for reliability, cost savings, and scalability. In the first step, we use the GPT 4o API to judge whether the name of the fund indicates an ESG fund for a sample of around 20,000 funds in our sample. The prompt we use is the following one: *Based on the content of LocalNameCN, determine whether it is an ESG fund; Output in JSON format as: result: ‘Yes/No’, reason: ‘Because ...’.* This step of AI labeling gives us 517 funds whose names are considered ESG by GPT. In the second step, we manually read the fund names and reasons provided by GPT.

This two-step procedure has several advantages over directly using GPT to make a judgment. First, manual detection in the second step improves the reliability of the keyword list. While GPT makes good judgment in most cases, we disagree with GPT for 23 funds (4.45%). This ensures that our final measure of ESG fund name relies purely on domain knowledge (i.e., the keyword list) even if we use GPT to narrow down the scale of human work. Second, using the GPT API is expensive for large samples, and a combination of GPT and other methods is a good way to lower the cost (for example, Chen et al., 2025). Third, the keyword list can be easily applied to a new set of fund names without additional cost.

The 41 ESG keywords we identified are the following: new energy, ESG, ESG strategy, photovoltaic industry, green, carbon neutrality, health, climate change, climate, low-carbon technology, new energy vehicles, environmental governance, low-carbon economy, environmentally friendly new energy, environmental protection, environmental protection industry, green power, clean energy, energy innovation, photovoltaics, low-carbon, Yangtze River protection, protection, new materials, green energy, social responsibility, ecology, low-carbon investment, energy saving and environmental protection, energy saving, responsible investment, modern energy, green bonds, environmental themes, sustainable, sustainable development, eco-environmental protection, low-carbon lifestyle, green credit, green inclusive finance, and ecological priority.

IA.3 Interpolation of ESG Fund Indicators

We collect fund-level data from Morningstar between January 2020 and December 2024 and perform an interpolation of missing values for the variables from Morningstar in the following way. We first use the values before the current observation to replace the missing values. If the current observation is still missing, we then use the values afterwards to do the replacement. If the observation remains a missing value after the interpolation, we set it as zero. That is, we assume funds without sustainable ratings/indicators in Morningstar are non-sustainable funds.

Internet Appendix B: More Institutional Details

IB.1 More Institutional Details and Analysis

Rules for gaining and using green points in the Ant Forest

- Rule 1: Green points are generated 24 hours after eco-friendly activities. One needs to collect them within 72 hours and the green points expire if not collected. This is why we focus on collected instead of produced green points.
- Rule 2: Users can collect not only their own green points, but also their Alipay friends' uncollected green points (called "rob" by Ant and in our paper). Users can choose to give back 5g (or not) after collecting one friend's green points.
- Rule 3: Users can voluntarily give their green points to their Alipay friends (called 'donating/watering a friend's tree' by Ant). One user can water one friend's tree three times per day as the maximum. There are four choices for the number of green points to be donated: 10, 18, 33, 66.
- Rule 4: Users can see their Alipay friends' green points and badges, which can serve as a desirable social signaling effect. Unfortunately, the network data are massive and Ant did not store it.
- Rule 5: The calculation of green points is based on carbon reduction and carbon sink equivalence, and 1 green energy gram corresponds to 1g of carbon reduction.
- Rule 6: All trees planted in Ant Forest by users using their accumulated grams will be planted in reality.

Unlike *Collect Grams*, which require active user effort, *Produce Grams* arise passively once users allow Alipay to track their activities for walking and simply when using Alipay in most other cases. but it captures several factors more than the intention to participate in Ant Forest: first, the user's life circumstances—for example, lower-income users may take public transportation more frequently; second, using Alipay instead of cash, bank cards or competing digital payment platforms. Individuals produce green points regardless of whether they actively participate in Ant Forest,

although some behaviors—most notably walking—can be deliberately increased to produce more points. Anecdotal evidence suggests that Ant Forest enthusiasts substantially increase their walking for this purpose. By contrast, it is unlikely that users alter routine bill payments or transportation modes solely to accumulate green points, though they may switch from alternative payment methods (e.g. cash, WeChat Pay, or bank cards) to Alipay when making necessary transactions.

More specifically, the interpretation of several categories is inherently ambiguous. For example, using shared bikes or taking the subway may reflect either cost-saving or environmental preferences, and walking can be motivated by health considerations as much as by environmental concerns. Digital payments are classified as environmentally friendly because they reduce paper usage, yet their adoption is often due to its convenience, and there is even speculation that such features may serve consumption-boosting objectives (Lau and Shan, 2024).

Robbing involves clicking on “bubbles” on friends’ Ant Forest pages to take their unused points, while collecting refers to harvesting one’s own points. Notice that while Alipay uses the word rob for the transfer of green points among friends, it is not necessarily a bad behavior because if these green points are uncollected within 72 hours, they expire. Robbing a friend’s uncollected green points and using them to plant a tree still constitutes a contribution to environmental protection.

IB.2 Badge Redemption Ratio

In this subsection, we test the impact of cost of labor on the tradeoff between contributing to environmental protection via effort and via investment. One prediction of the moral account theory is that the substitution effect depends on the relative cost of labor to investment. Consider two people: A values his/her labor as more costly, say 1 unit of labor is worth 2 yuan, while B values 1 unit of his/her labor as worth only 1 yuan. Assume that the environmental impact of different activities in Ant Forest is the same across individuals. For the same reduction in digital effort, A substitutes twice as much into financial investment as B. That is, the substitution effect is larger for A than for B.

To empirically test this prediction, we take the advantage of one distinctive feature of Ant Forest that the number of green points required to redeem different badges varies as shown in [Table IB.2](#).¹

¹Having different number of green points for various badges is a typical practice for tech companies to have user stickiness. It would be boring for the users to aim for the same number of green points repeatedly.

We construct the *Badge–Green-Point Ratio*, defined as the number of badges a user redeems divided by the total number of green points redeemed during the sample period, as a proxy for labor cost. A higher *Badge–Green-Point Ratio* is associated with less labor effort for the same number of badges, i.e., the user prefers to redeem less labor intensive (cheaper) badges, which means a higher labor cost. Our theory predicts a larger substitution effect for users with higher *Badge–Green-Point Ratio*.

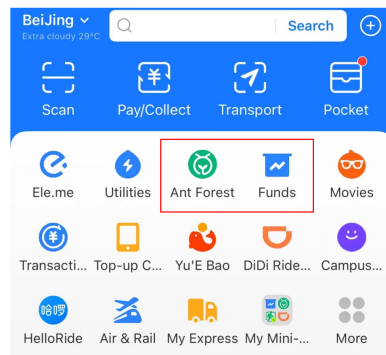
[INSERT Table IC.6 AROUND HERE]

Table IC.6 reports results. Panel A interacts *Collect Grams* with the *Badge–Green-Point Ratio*. On the intensive margin, the coefficients on the interaction term between *Badge–Green-Point Ratio* and *Collect Grams* are negative and statistically significant at the 1% or the 5% level, implying a larger substitution effect for individuals having higher *Badge–Green-Point Ratio*. For example, in column (2), holding *Collect Grams* constant, a one-standard-deviation increase in the *Badge–Green-Point Ratio* leads to an 11.52% (0.70×16.46) increase in the substitution effect and corresponds to 68% of the substitution effect itself ($\frac{0.70 \times 16.46}{17.05}$). On the extensive margin, the coefficients on the interaction term are positive but statistically insignificant. The coefficients on *Collect Grams* remain negative and statistically significant at the 1% or the 5% level across all specifications. Panel B interacts *Produce Grams* with the *Badge–Green-Point Ratio* and delivers similarly robust results.

Taken together, we find that the substitution effect between environmental protection through digital effort and through mutual fund investments is stronger among individuals with higher labor costs.

References for Internet Appendix

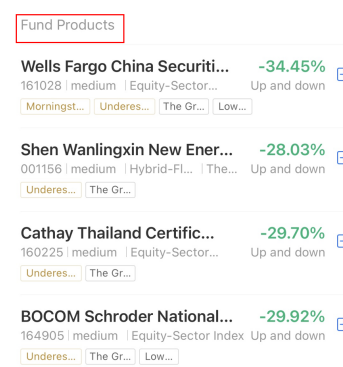
- Chen, S., Peng, L., & Zhou, D. (2025). Wisdom or whims? decoding the language of retail trading with social media and ai.
- Lau, J., & Shan, F. (2024). *Fake step counts and point farms: How 'addicted' gamers are cheating a chinese app designed to help the climate*. <https://www.bbc.com/future/article/20241120-chinas-ant-forest-users-cheat-in-game-that-helps-the-climate>



(a) Main Screen



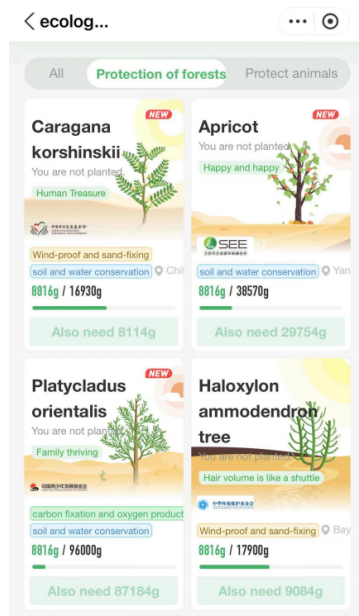
(b) Ant Forest



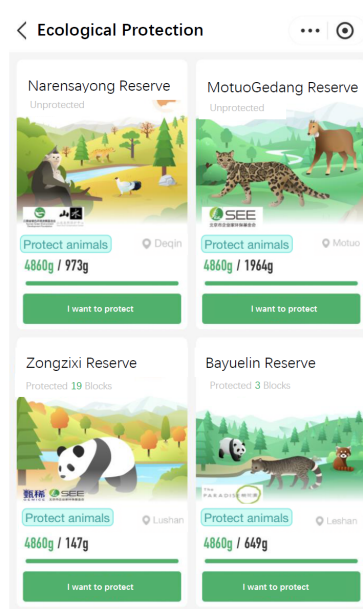
(c) Fund Products

Figure IB.1: Alipay Screens

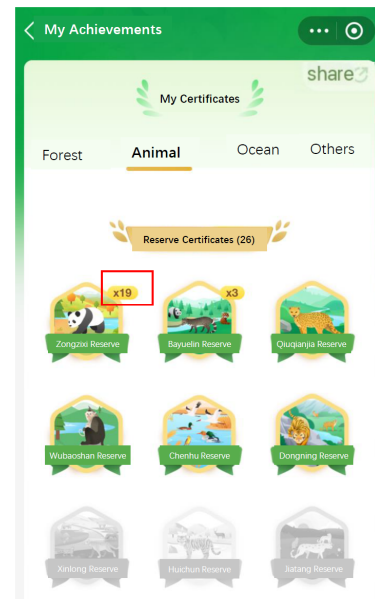
Note: This figure presents the screens of Alipay. Panel (a) shows the main screen of the Alipay app. Users can navigate to various functional interfaces by clicking on the corresponding icons. Panel (b) shows the screen of Ant Forest, where users can earn green points through daily low-carbon activities and use these points to participate in environmental protection projects. Panel (c) shows the fund selection screen in Alipay, where users can choose and invest in funds of interest.



(a) Tree



(b) Biodiversity Reserve



(c) Badge Collection

Figure IB.2: Environmental Protection Projects in Ant Forest

Note: Panel (a) shows the selection interface for tree projects in Ant Forest. Take the first small panel for example, 8816g represents the number of green points the user has and 16930g are the green points required to redeem for one caragana korshinskii. Panel (b) shows the selection interface for biodiversity protection projects. Take the first small panel for example, 4860g represents the number of green points the user has and 973g are the green points required to redeem for one square meter of protected land in Narensayong Reserve. Panel (c) shows the user's reserve badge collection. In this example, the user holds 19 certificates for Zongzixi Reserve.

Table IB.1: Production of Green Points Category Summary Table

This table shows the full list of 69 subcategories of producing green points that appear in our main sample. The specific small categories are presented in the first column, the five big categories classified by Alipay are presented in the second column, the 99th percentile of usages of each category in the third column, and the maximum number of usages of each category in the fourth column. Carbon emissions are transferred in a uniform unit called *Green Points* using a method co-developed by Alipay and the China Beijing Environmental Exchange (CBEEEX).

Small Category	Big category by Ant	99th p. N.	Max N.
Health Code	-	5	727
Green Appliances	Energy Conservation	0	7
Green Car Insurance	Energy Conservation	0	44
Green Communication	Energy Conservation	0	2
Green Decoration	Energy Conservation	0	2
Low Carbon Route	Energy Conservation	0	33
Near-expiry Food	Energy Conservation	0	26
Parking Payment	Energy Conservation	11	856
Power Bank	Energy Conservation	15	317
Empty Plate Campaign	Energy Conservation	73	731
E-bike Ride	Green Travel	0	336
Green Flight	Green Travel	0	1
New Energy Car Rental	Green Travel	0	4
New Energy Vehicle	Green Travel	0	686
Pure Electric Car Ride	Green Travel	0	398
Shared Rental	Green Travel	0	9
Public Charging Pile	Green Travel	11	105
Shared Bicycle	Green Travel	351	3232
Public Bus	Green Travel	582	2922
Walking	Green Travel	731	731
Subway	Green Travel	864	3584
Book Borrowing	Paper and Plastic Reduction	0	92
Credit Stay	Paper and Plastic Reduction	0	16
Direct Drinking Water	Paper and Plastic Reduction	0	2139
Green Design Product	Paper and Plastic Reduction	0	3
Green Logistics Product	Paper and Plastic Reduction	0	1
Green Manufactured Goods	Paper and Plastic Reduction	0	15
Green Packaging	Paper and Plastic Reduction	0	37
Green Packaging Pro	Paper and Plastic Reduction	0	2
Green Parcel	Paper and Plastic Reduction	0	6
Green Venue	Paper and Plastic Reduction	0	91
LSBG Smart Form Filling	Paper and Plastic Reduction	0	365
No Return & Exchange	Paper and Plastic Reduction	0	15
Self Pickup	Paper and Plastic Reduction	0	3
Bring Your Own Cup	Paper and Plastic Reduction	1	338
E-signature	Paper and Plastic Reduction	1	710

Small Category	Big category by Ant	99th p. N.	Max N.
International Tax Refund	Paper and Plastic Reduction	1	61
QR Code Ticketing	Paper and Plastic Reduction	2	52
E-insurance policy	Paper and Plastic Reduction	2	16
E-boarding Pass	Paper and Plastic Reduction	3	107
Online Loan	Paper and Plastic Reduction	4	3649
Online Delivery	Paper and Plastic Reduction	15	2005
E-receipt	Paper and Plastic Reduction	35	930
QR Code Ordering	Paper and Plastic Reduction	60	3623
Plastic Reduction	Paper and Plastic Reduction	70	582
Paperless Reading	Paper and Plastic Reduction	89	10610
E-invoice	Paper and Plastic Reduction	93	1582
Ele.me	Paper and Plastic Reduction	129	1440
E-Bill	Paper and Plastic Reduction	186	284
Offline Payment	Paper and Plastic Reduction	2212	7320
Online Payment	Paper and Plastic Reduction	2272	7091
Green Check-in	Recycling & Reuse	0	27
Eco Recycling	Recycling & Reuse	0	11
goofish.com(Xianyu)	Recycling & Reuse	4	67
Alipay Labs	Reduced Travel	0	6
Collaborative Office	Reduced Travel	0	862
LSBG Video Conference	Reduced Travel	0	426
LSBG Live Streaming	Reduced Travel	0	77
LSBG Phone Conference	Reduced Travel	0	108
Vehicle Stoppage	Reduced Travel	6	105
DingTalk	Reduced Travel	13	352
Hospital Registration	Reduced Travel	17	1158
Online Ticket Purchase	Reduced Travel	20	235
Credit Card Repayment	Reduced Travel	24	25
Green E-Government	Reduced Travel	35	1176
ETC Toll Payment	Reduced Travel	79	1753
Bill Payment	Reduced Travel	93	240
Train Ticket	Reduced Travel	116	243
Online Window Shopping	Reduced Travel	194	854

Table IB.2: Green Points Badge Summary Table

This table reports the green points (GP) required for the different badges within Ant Forest. The table is organized into three panels: Biodiversity Reserves, Animals, and Trees. The columns present the specific badge name and its corresponding green point cost.

Biodiversity Reserve		Animal		Tree	
Badge Name	GP	Badge Name	GP	Badge Name	GP
Caozixi Reserve	147	Snow Leopard	1,288	Caragana (Peashrub)	16,930
Suojia Yagu Reserve	540	Giant Panda	1,388	Haloxylon	17,900
Bayuelin Reserve	649	Yunnan Snub-nosed Monkey	1,388	Sea Buckthorn	18,880
Qiuqianjia Reserve	790	Siberian Tiger	1,388	Desert Willow	19,680
Daguping Reserve	869			Huabang shrub	21,310
Wubaoshan Reserve	936			Yangchai shrub	21,310
Nanren Sayong Reserve	973			Forsythia	22,390
Chenhu Reserve	1,181			Tamarisk	22,400
Hunchun Reserve	1,320			Yellow Willow	22,632
Dongning Reserve	1,388			David's Peach	37,980
Motuo Gedang Reserve	1,964			Siberian Apricot	38,570
				Elm	85,760
				Oriental Arborvitae	96,000
				Chinese Pine	114,000
				Chinese Pine (Old)	114,800
				Birch	128,980
				Yellowhorn	128,980
				Maple	144,700
				Mongolian Scotch Pine	146,210
				Armand Pine	185,000
				Spruce	198,000
				Euphrates Poplar	215,680
				Cliff Cypress	220,800
				Fir	330,759

Internet Appendix C: Additional Tables

Table IC.1: Summary Statistics for Green Behaviors (Internet Appendix Variables)

This table reports summary statistics for green behavior variables used in the appendix regression analysis. In Panels A and B, all variables are in grams of green points, except for PC1 which is a principal component score. In Panel C, it reports summary statistics for the dummies on Earth Day participation.

Variables	Num	Mean	S.d.	Min	5th	25th	50th	75th	95th	Max
Panel A: Eleven Subcategories of Produced Green Points (Grams)										
Walking	180,000	50,980.24	32,305.07	0.00	3,590.90	28,858.75	46,110.00	67,541.00	112,372.10	164,071.23
Bill Payment	180,000	3,692.54	5,194.69	0.00	0.00	0.00	1,048.00	6,026.00	14,410.00	24,366.00
Public Bus	180,000	2,690.20	6,955.74	0.00	0.00	0.00	320.00	1,760.00	13,840.00	46,560.00
Offline Payment	180,000	2,442.63	2,297.74	0.00	150.00	700.00	1,750.00	3,465.00	7,225.00	11,060.00
Online Payment	180,000	2,256.72	2,451.13	0.00	0.00	50.00	1,585.00	3,390.00	7,295.00	11,360.00
Subway	180,000	2,988.18	7,247.21	0.00	0.00	0.00	416.00	2,132.00	16,016.00	44,928.00
Train Ticket	180,000	1,867.12	2,919.38	0.00	0.00	0.00	680.00	2,448.00	8,024.00	15,776.00
E-Bill	180,000	533.84	339.10	0.00	80.00	264.00	480.00	752.00	1,184.00	1,488.00
Shared Bicycle	180,000	246.08	889.30	0.00	0.00	0.00	0.00	90.00	1,120.00	6,805.01
E-invoice	180,000	25.66	68.64	0.00	0.00	0.00	0.00	20.00	135.00	465.00
Ele.me	180,000	76.45	288.18	0.00	0.00	0.00	0.00	16.00	432.00	2,064.00
Panel B: Aggregated Categories and Principal Component (Grams)										
Green Travel	180,000	56,658.63	34,884.00	0.00	8,956.85	31,983.00	50,817.00	75,062.25	124,038.50	255,559.23
Digital Payment	180,000	10,894.96	7,707.36	0.00	1,475.95	5,108.00	9,242.00	14,988.25	26,074.05	63,382.00
PC1 (Produce)	180,000	51,145.80	32,319.97	4.11	3,763.45	28,998.56	46,267.03	67,744.16	112,536.20	165,598.62
Panel C: Earth Day Badge										
Earth Day 2023 (Dummy)	360,000	0.36	0.48	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Earth Day 2024 (Dummy)	360,000	0.18	0.38	0.00	0.00	0.00	0.00	0.00	1.00	1.00

Table IC.2: Eleven Subcategories of Produced Green Points and ESG Investments

This table reports regression results from Probit and OLS models examining the relationship between producing green points across 11 sub-categories in Alipay and sustainable investment in Ant Fortune. The dependent variables are the same as in Table 2. The independent variables of interest are the 11 categories of produced green points (*Bill Payment to Subway*, unit: grams of green points). The number after the variable name denotes the number of times used by the 95th percentile user in our sample, ranking from the largest one to the smallest one. For demonstration purposes, the 11 subcategory variables are divided by 10^5 . The same control variables as in Table 2 are included in all columns. Detailed sample and variable construction in subsection IA.1. All columns include city fixed effects, and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		ESG name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Offline Payment (1459)	0.14 (0.15)	0.14*** (0.04)	0.20 (0.15)	0.16*** (0.04)	0.07 (0.18)	0.18*** (0.04)	0.03 (0.15)	0.11** (0.04)
Online Payment (1445)	-0.07 (0.14)	-0.15*** (0.04)	-0.09 (0.15)	-0.21*** (0.04)	-0.14 (0.17)	-0.26*** (0.04)	-0.12 (0.15)	-0.26*** (0.04)
Walking (731)	-0.01 (0.01)	-0.02*** (0.00)	-0.01 (0.01)	-0.02*** (0.00)	-0.02 (0.01)	-0.03*** (0.00)	-0.01 (0.01)	-0.02*** (0.00)
Subway (308)	0.00 (0.05)	-0.05*** (0.01)	0.07 (0.05)	-0.01 (0.01)	0.07 (0.06)	0.01 (0.01)	0.03 (0.05)	-0.05*** (0.01)
Public Bus (173)	-0.02 (0.05)	-0.06*** (0.01)	0.03 (0.05)	-0.04*** (0.01)	-0.01 (0.05)	-0.05*** (0.01)	-0.03 (0.05)	-0.07*** (0.01)
E-Bill (148)	-1.48 (0.95)	-1.03*** (0.28)	-1.74* (0.97)	-1.62*** (0.26)	-2.53** (1.12)	-1.25*** (0.27)	-2.30** (0.97)	-0.46* (0.27)
Train Ticket (59)	-0.06 (0.11)	-0.10*** (0.03)	-0.03 (0.11)	-0.13*** (0.03)	0.11 (0.13)	-0.11*** (0.03)	-0.00 (0.11)	-0.10*** (0.03)
Bill Payment (55)	-0.11* (0.07)	-0.05** (0.02)	-0.13* (0.07)	-0.04** (0.02)	-0.07 (0.08)	-0.04** (0.02)	-0.10 (0.07)	-0.04** (0.02)
Shared Bicycle (55)	0.08 (0.35)	-0.38*** (0.10)	0.21 (0.36)	-0.31*** (0.09)	0.31 (0.44)	-0.33*** (0.09)	0.08 (0.36)	-0.34*** (0.09)
E-invoice (27)	-0.75 (4.61)	-6.78*** (1.26)	-0.71 (4.70)	-7.53*** (1.19)	0.80 (5.51)	-7.76*** (1.26)	1.11 (4.71)	-7.64*** (1.23)
Ele.me (27)	-0.75 (1.13)	-0.38 (0.31)	0.78 (1.15)	0.22 (0.29)	0.49 (1.33)	-0.79*** (0.30)	-0.85 (1.15)	-0.84*** (0.30)
Pseudo R^2 /Adj R^2	0.058	0.054	0.096	0.047	0.146	0.066	0.079	0.051
Controls	✓	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓	✓
N. Obs.	179,997	91,047	179,999	91,891	179,985	140,129	179,997	106,846

Table IC.3: Produced Green Points (Two Main Categories) and ESG Investments

This table reports regression results from Probit and OLS models examining the relationship between producing green points via Alipay, grouped by the two big categories *Green Travel* and *Digital Payment*, and sustainable investment in Ant Fortune. The dependent variables are the same as in Table 2. The independent variables of interest are *Green Travel* and *Digital Payment* (unit: grams of green points) which are the aggregated variables of the 11 subcategories in Table IC.2. For demonstration purposes, *Green Travel* and *Digital Payment* are divided by 10^6 , Total Money by 10^6 , and other control variables by 100. Detailed sample and variable construction in subsection IA.1. All columns include city fixed effects, and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		ESG name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Green Travel Grams	-0.07 (0.09)	-0.24*** (0.03)	-0.01 (0.09)	-0.21*** (0.03)	-0.09 (0.11)	-0.30*** (0.03)	-0.06 (0.09)	-0.27*** (0.03)
Digital Payment Grams	-0.79* (0.43)	-0.80*** (0.12)	-0.62 (0.44)	-0.88*** (0.12)	-0.42 (0.51)	-0.94*** (0.12)	-0.93** (0.44)	-0.95*** (0.12)
<i>Portfolio characteristics</i>								
Sharpe Ratio	6.05*** (1.48)	-6.14*** (0.63)	94.74*** (1.59)	20.13*** (0.63)	95.19*** (1.65)	16.35*** (0.55)	4.53*** (1.47)	-12.56*** (0.61)
Morningstar Rating	-44.31*** (0.42)	4.68*** (0.15)	-52.22*** (0.43)	1.02*** (0.14)	-66.51*** (0.50)	-6.05*** (0.13)	-53.05*** (0.43)	1.83*** (0.14)
Total Money	13.85*** (1.02)	-6.74*** (0.63)	38.07*** (1.18)	-5.37*** (0.50)	10.14*** (1.31)	-8.68*** (0.65)	14.72*** (1.07)	-7.35*** (0.61)
<i>Individual characteristics</i>								
Registered Years	-1.62*** (0.10)	-0.37*** (0.03)	-1.55*** (0.10)	-0.26*** (0.03)	0.37*** (0.12)	-0.33*** (0.03)	-1.21*** (0.10)	-0.44*** (0.03)
Female	-14.27*** (0.63)	-6.11*** (0.18)	-17.88*** (0.64)	-6.52*** (0.18)	-24.60*** (0.75)	-8.96*** (0.18)	-14.40*** (0.65)	-6.69*** (0.18)
Age	-0.40*** (0.04)	-0.12*** (0.01)	-0.43*** (0.04)	0.01 (0.01)	-0.97*** (0.04)	-0.22*** (0.01)	-0.70*** (0.04)	-0.18*** (0.01)
Risk Level	4.16*** (0.20)	-0.87*** (0.06)	4.47*** (0.20)	-0.54*** (0.06)	6.05*** (0.23)	-0.42*** (0.06)	4.97*** (0.20)	-0.83*** (0.06)
Pseudo R^2 /Adj R^2	0.058	0.053	0.096	0.046	0.147	0.065	0.079	0.050
City FE	✓	✓	✓	✓	✓	✓	✓	✓
N. Obs.	179,997	91,047	179,999	91,891	179,985	140,129	179,997	106,846

Table IC.4: Principal Component Analyses of Eleven Subcategories to Produce Green Points

This table reports the results of principal component analyses (PCA) where we decompose the 11 subcategories to produce green points into six orthogonal principal components (i.e., PC1, PC2 to PC6). The upper panel reports the loadings, indicating the extent to which each green point variable contributes to a PC. The bottom panel reports the proportion of variance explained by each PC. Detailed sample and variable construction in [subsection IA.1](#). Standard errors in parentheses are obtained via bootstrap of 1000 times.

Variables	PC1	PC2	PC3	PC4	PC5	PC6
Walking	1.000 (0.000)	−0.018 (0.002)	−0.003 (0.001)	−0.019 (0.000)	−0.006 (0.000)	−0.003 (0.001)
Bill Payment	0.018 (0.000)	−0.009 (0.003)	−0.023 (0.006)	0.996 (0.000)	−0.028 (0.002)	−0.067 (0.002)
Offline Payment	0.017 (0.000)	0.021 (0.001)	−0.006 (0.001)	0.058 (0.001)	0.203 (0.005)	0.336 (0.013)
Public Bus	0.014 (0.001)	0.630 (0.012)	0.776 (0.010)	0.860 (0.014)	−0.021 (0.001)	−0.009 (0.001)
Subway	0.011 (0.000)	0.770 (0.010)	−0.628 (0.012)	0.485 (0.024)	−0.094 (0.002)	−0.059 (0.002)
Train Ticket	0.004 (0.000)	0.070 (0.001)	−0.034 (0.002)	0.040 (0.002)	0.950 (0.002)	−0.281 (0.007)
Shared Bicycle	0.003 (0.000)	0.017 (0.000)	−0.005 (0.001)	0.004 (0.000)	0.033 (0.003)	0.046 (0.002)
E-Bill	0.001 (0.000)	0.001 (0.000)	0.000 (0.000)	0.010 (0.000)	0.012 (0.000)	0.030 (0.000)
Online Payment	0.001 (0.000)	0.070 (0.001)	−0.044 (0.002)	0.053 (0.002)	0.212 (0.007)	0.892 (0.005)
E-invoice	0.000 (0.000)	0.000 (0.001)	−0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.004 (0.000)
Ele.me	0.000 (0.000)	0.003 (0.000)	−0.002 (0.000)	0.005 (0.000)	0.007 (0.000)	0.035 (0.001)
Explained	87.6% (0.001)	5.2% (0.000)	3.3% (0.000)	2.2% (0.000)	0.7% (0.000)	0.5% (0.000)

Table IC.5: First Principal Component of Eleven Subcategories to Produce Green Points and ESG Investments

This table reports regression results from Probit and OLS models examining the relationship between the top principal component (PC1) in [Table IC.4](#) and sustainable investment in Ant Fortune. The dependent variables are the same as in [Table 2](#). The independent variable of interest is the top principal component (PC1) that explains the largest share of variance in the original variables on producing green points. For demonstration purposes, PC1 is divided by 10^8 , Total Money by 10^6 , and other control variables by 100. Detailed sample and variable construction in [subsection IA.1](#). All columns include city fixed effects, and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		ESG name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Environmental protection</i>								
PC1 (Produce)	-10.27 (9.90)	-24.81*** (2.88)	-9.97 (10.08)	-23.98*** (2.78)	-15.78 (11.76)	-34.47*** (2.75)	-10.87 (10.13)	-27.96*** (2.77)
<i>Portfolio characteristics</i>								
Sharpe Ratio	6.07*** (1.48)	-6.16*** (0.64)	94.76*** (1.59)	20.10*** (0.63)	95.22*** (1.65)	16.33*** (0.55)	4.57*** (1.47)	-12.58*** (0.61)
Morningstar Rating	-44.30*** (0.42)	4.68*** (0.15)	-52.23*** (0.43)	1.03*** (0.14)	-66.51*** (0.50)	-6.05*** (0.13)	-53.04*** (0.43)	1.83*** (0.14)
Total Money	13.62*** (1.02)	-6.82*** (0.64)	37.87*** (1.17)	-5.45*** (0.51)	9.98*** (1.31)	-8.77*** (0.66)	14.43*** (1.07)	-7.44*** (0.62)
<i>Individual characteristics</i>								
Registered Years	-1.74*** (0.10)	-0.41*** (0.03)	-1.65*** (0.10)	-0.30*** (0.03)	0.27** (0.12)	-0.38*** (0.03)	-1.36*** (0.10)	-0.49*** (0.03)
Female	-14.17*** (0.64)	-6.04*** (0.18)	-18.05*** (0.65)	-6.48*** (0.18)	-24.90*** (0.76)	-8.95*** (0.18)	-14.31*** (0.65)	-6.62*** (0.18)
Age	-0.40*** (0.04)	-0.12*** (0.01)	-0.42*** (0.04)	0.02 (0.01)	-0.95*** (0.04)	-0.21*** (0.01)	-0.69*** (0.04)	-0.18*** (0.01)
Risk Level	4.13*** (0.19)	-0.88*** (0.06)	4.45*** (0.20)	-0.55*** (0.06)	6.04*** (0.23)	-0.44*** (0.06)	4.94*** (0.20)	-0.84*** (0.06)
Pseudo R^2 /Adj R^2	0.058	0.053	0.096	0.045	0.147	0.064	0.080	0.049
City FE	✓	✓	✓	✓	✓	✓	✓	✓
N. Obs.	179,997	91,047	179,999	91,891	179,985	140,129	179,997	106,846

Table IC.6: Cost of Labor: Badge Redemption Ratios

This table reports regression results from Probit and OLS models examining the relationship between collecting (Panel A) or producing (Panel B) green points in Ant Forest and sustainable investment in Ant Fortune, interacted with *Badge-Green-Point Ratio*. *Badge-Green-Point Ratio* equals the number of badges a user redeemed divided by total number of green points consumed during the sample period. The dependent variables are the same as in Table 2. For demonstration purposes, *Collect Grams*, *Rob Grams*, and *Produce Grams* are divided by 10^8 , and *Badge-Green-Point Ratio* multiplied by 1000. Detailed sample and variable construction in subsection IA.1. All columns include city fixed effects and other control variables as in Table 2, and robust standard errors clustered at the city level are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Dep. Var.	Sustainable		Globes 4 or 5		Low Carbon		ESG name	
	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)	Probit (D)	OLS (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Collect Green Points								
Collect Grams $\times$ Badge-Green-Point Ratio	5.01 (18.97)	-16.46*** (5.42)	13.14 (19.47)	-13.11** (5.92)	0.41 (22.31)	-12.26** (5.53)	6.01 (19.44)	-11.45** (5.41)
Collect Grams	-29.84*** (10.43)	-17.05*** (2.93)	-21.15** (10.63)	-17.17*** (2.87)	-29.83** (12.23)	-32.07*** (2.88)	-34.12*** (10.63)	-24.55*** (2.84)
Rob Grams $\times$ Badge-Green-Point Ratio	17.50 (29.64)	11.92 (8.50)	-8.23 (29.61)	1.71 (8.93)	-8.17 (34.09)	13.60 (8.84)	13.43 (30.54)	12.89 (8.36)
Rob Grams	1.73 (6.25)	-0.65 (1.72)	-10.36 (6.35)	-2.95* (1.71)	-0.71 (7.37)	-1.56 (1.72)	0.98 (6.40)	-0.30 (1.67)
Badge-Green-Point Ratio	-0.0007 (0.01)	0.0044*** (0.00)	0.0026 (0.01)	0.0049*** (0.00)	-0.0028 (0.01)	0.0039** (0.00)	-0.0025 (0.01)	0.0032** (0.00)
Adj R^2 /Pseudo R^2	0.058	0.053	0.096	0.046	0.147	0.065	0.080	0.049
Panel B: Produce Green Points								
Produce Grams $\times$ Badge-Green-Point Ratio	3.89 (7.47)	-8.10*** (2.17)	6.09 (7.62)	-5.97*** (2.23)	-1.37 (8.81)	-7.41*** (2.18)	3.57 (7.66)	-6.34*** (2.13)
Produce Grams	-6.39** (2.98)	-5.56*** (0.84)	-9.67*** (3.03)	-6.87*** (0.81)	-7.76** (3.50)	-9.54*** (0.82)	-7.75** (3.04)	-7.43*** (0.81)
Badge-Green-Point Ratio	-0.0006 (0.01)	0.0083*** (0.00)	0.0010 (0.01)	0.0073*** (0.00)	-0.0005 (0.01)	0.0086*** (0.00)	-0.0019 (0.01)	0.0068*** (0.00)
Pseudo R^2 /Adj R^2	0.058	0.053	0.096	0.046	0.147	0.065	0.080	0.049
Controls	✓	✓	✓	✓	✓	✓	✓	✓
City FE	✓	✓	✓	✓	✓	✓	✓	✓
N. Obs.	179,997	91,047	179,999	91,891	179,985	140,129	179,997	106,846