The Green Value of BigTech Credit*

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Abstract

We study an incentive-compatible mechanism—embedding financial incentives into non-financial actions—that fosters individual environmental engagement and facilitates the private sector's internalization of climate externalities. Using a novel dataset of 100,000 randomly selected users from Ant Forest, a widely used personal carbon tracking program within Alipay—China's leading BigTech platform, we demonstrate that tying eco-friendly behaviors to credit limit adjustments encourages users to engage in green actions. The platform benefits from reduced default risk even amid credit expansion, likely driven by a signaling mechanism in which costly green actions reveal environmental type. Climate-responsible individuals often exhibit conscientious and disciplined behavior across various domains, allowing lenders to infer creditworthiness from green actions. Our structural model estimates an annual green value of $413.20 million generated by linking credit access to green actions. This incentive-based approach yields larger welfare gains than traditional policy instruments such as mandates or subsidies, particularly when public green awareness is low. Our findings identify the screening role of green behaviors in household lending to align environmental *values* with financial *value* and highlight alternative data as a viable source for credit allocation.

JEL codes: G23; G51; Q54; Q55

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1 Introduction

In response to the escalating urgency of climate change, governments worldwide have introduced a variety of policies and initiatives aimed at accelerating the green transition. While the long-term advantages of these measures are widely recognized (e.g., Alex Edmans, 2023), their short-term costs—such as unemployment, inflation, and increased burdens on stakeholders—remain significant. At the same time, concerns over the effectiveness and sustainability of many initiatives, including corporate greenwashing and window-dressing, have sparked debates among academics and policymakers (e.g., Isabel Schnabel, 2022; The Economist, 2022; Lena Boneva, Gianluigi Ferrucci and Francesco Paolo Mongelli, 2022; Marco Del Negro, Julian Di Giovanni and Keshav Dogra, 2023; Gianpaolo Parise and Mirco Rubin, 2023; Ran Duchin, Janet Gao and Qiping Xu, Forthcoming). Central to these challenges is the design of incentive-compatible mechanisms that effectively promote environmentally sustainable behaviors among individuals and firms. Although governments can establish legislation and regulatory frameworks, the success of these efforts ultimately hinges upon both individual and collective actions. Without well-designed mechanisms to align private incentives (i.e., *value*) with broader environmental objectives (i.e., *values*), these policies remain susceptible to political volatility and fall short in ensuring long-term viability (e.g., Laura T. Starks, 2023).[1]

In this paper, we study a market-based, incentive-compatible framework that encourages environmentally responsible behavior by linking individual rewards with societal sustainability goals. More specifically, we investigate whether and how financial incentives can encourage households to adopt green behaviors, with a particular focus on the pivotal role of BigTech platforms in this process. We analyze data from Ant Forest—a feature within Alipay, one of China's leading BigTech super-apps—which enables users to track their carbon footprints through eco-friendly actions. A distinguishing feature of Ant Forest is its integration with Alipay's financial ecosystem, where various user behaviors, including carbon footprints, can contribute to their overall profile. The program offers those who consistently

[1]A notable example of this issue is the recent divergence in climate policy in the United States under the Biden and Trump administrations. The Biden administration emphasized bold climate initiatives, focusing on reducing greenhouse gas emissions and investing in renewable energy. Conversely, the preceding Trump administration actively dismantled key climate regulations and withdrew the United States from the Paris Agreement. This stark policy reversal underscores the fragility of environmental policies and raises critical concerns about their long-term sustainability and alignment with public incentives. Adopting an incentive-compatible approach to issues with significant positive externalities is crucial, as numerous theoretical studies have demonstrated that policies that are misaligned with incentives can be ineffective or even counterproductive (e.g., Daron Acemoglu and Joshua D. Angrist, 2001; Zoe B. Cullen and Bobak PakzadHurson, 2023).

engage in eco-friendly activities the potential for higher credit scores and increased credit limits. This interaction between non-financial and financial outcomes not only promotes sustainability but also enhances users' financial standing, making Ant Forest an ideal case to explore the financial incentives for green actions and quantify their significance in the real world.

Our empirical analysis combines granular user-level data on green actions, credit profiles, and default status from a panel of 100,000 randomly selected Ant Forest users, tracked over a 48-month period from January 2019 to December 2022. The dataset includes detailed breakdowns of various green behaviors across a broad spectrum of specific contexts. Our empirical analysis yields three main findings. First, we show that the platform adjusts users' credit limit based on their eco-friendly behaviors. The core principle of this design, however, is that green actions are intentionally made costly. Converting green behavior into a meaningful increase in credit limits is both gradual and effort-intensive, suggesting that the platform prioritizes sustained engagement over short-term compliance. Our estimates reveal that each additional kilogram of accumulated green energy—a standardized measure of eco-friendly behavior—is associated with a 0.17% increase in credit limit, or approximately 24.65 *yuan* ($\approx$ 3.52 US dollars).[2] Since generating one kilogram typically requires a week of consistent participation in activities such as walking, energy saving, or sustainable consumption, the modest return implies that only intrinsically motivated or forward-looking users are likely to persist. By contrast, credit allocation decisions do not respond to green actions that require minimal effort or are performed unintentionally. This suggests that only deliberate, effort-intensive behaviors provide meaningful insights into user attributes. Given the assumption that environmental responsibility is positively correlated with financial responsibility, the costliness of green actions is essential for preserving the credibility of the platform's screening mechanism. By deterring opportunistic or circumstance-driven participation, the system ensures that green behavior functions as a reliable signal of borrower quality. Over-incentivizing short-term behavior risks undermining this signal, introducing moral hazard, and reducing the informational value of green actions.

Second, we show that users exhibit a strong response to financial incentives linked to green actions. To do so, we investigate how individuals adjust their environmentally friendly behaviors when approaching borrowing constraints. One of our central estimates reveals that credit-constrained users—

[2] Throughout this paper, we use a fixed exchange rate of 1 USD = 7 *yuan*.

defined as those with credit utilization rates exceeding 80%—engage in 23.92% more green activities than unconstrained users, after controlling for income, demographic characteristics, other potential drivers of environmental behavior, and individual fixed effect. This pattern suggests that users act strategically, undertaking green actions not purely out of intrinsic motivation but also to enhance their financial standing. Put simply, users respond to financial incentives in both statistically and economically meaningful ways.

Third, we examine the benefits to the platform from adopting this redesigned credit system, focusing on its informational value. Our core finding is a robust negative relationship between users' green engagement and both the probability and magnitude of loan default—even though green activity is positively associated with higher credit limits. This inverse relationship is most pronounced among users with unused borrowing capacity and weakens for those already near their credit ceilings. In principle, providing incentives often entails a cost to the provider. However, we find that the BigTech platform does not incur financial losses from offering green-linked credit incentives. Instead, by incorporating green behaviors into credit assessments, the platform effectively enhances its screening capabilities. This mechanism is analogous to the use of soft information in traditional banking, where behavioral signals are employed to complement hard financial metrics in evaluating borrower risk (e.g., José M. Liberti and Mitchell A. Petersen, 2019). In addition, we exploit the introduction of China's Personal Information Protection Law (PIPL) in November 2021 as a quasi-natural experiment, which significantly restricted BigTech platforms' ability to access third-party data. This regulatory shift forced platforms to rely more heavily on user-generated behavioral data within their own ecosystems. We find that although green behaviors exhibited some predictive power for credit limits before PIPL, their predictive importance increased markedly afterward. This suggests that, in the absence of external data, internally observable green actions gained greater weight in credit-scoring algorithms.

To formally investigate the mechanisms behind our empirical findings and quantify welfare implications, we develop a partial equilibrium structural model featuring costly green actions and endogenous borrowing constraints. Users derive utility primarily from consumption but also possess intrinsic environmental preferences, captured through a green-in-utility formulation. They face subsistence volatility and lack access to formal credit markets, relying solely on saving and borrowing via the BigTech platform. Borrowing capacity is constrained and partially tied to accumulated green capital—a stock reflecting historical eco-friendly behavior. Green capital investment incurs convex adjustment costs, which is consistent with empirical patterns and strategically embedded in the platform's design. In our model, users are heterogeneous in unobserved types: green-types are environmentally and financially responsible, while brown-types are not. By imposing costs on green actions, the platform induces self-selection: green-types invest more in green capital, while brown-types are deterred, enabling a credible signaling mechanism for credit allocation. This mirrors the role of education as a screening device in classical signaling models (Michael Spence, 1973). In equilibrium, green behavior generates value through two channels: (1) directly, via intrinsic utility for green users; and (2) indirectly, by relaxing borrowing constraints through higher green capital. The latter channel is especially salient for financially constrained users, who gain the most from improved credit access. The model thus provides a unified explanation for our two key empirical findings. First, financially constrained users are more likely to engage in green actions, as the marginal benefit—via improved credit access—is greatest for them. Second, green actions are negatively associated with default behavior, particularly among users with low credit usage, where green engagement serves as an effective signal of financial responsibility.

We calibrate the model to evaluate the welfare consequences of data sharing between the platform's financial services and its public-good functions—specifically, the use of green behavior data in credit decisions. Our analysis shows that restricting access to this data diminishes both lending efficiency and environmental outcomes. A 10% reduction in the use of green activity data in credit limit calculations reduces the annual green value by approximately 53.23 million US dollars (or 372.63 million *yuan*). If the link between green behavior and credit limits is severed entirely—eliminating the financial incentive channel—the annual loss rises to an estimated 413.20 million US dollars (approximately 2.89 billion *yuan*). These losses are accompanied by higher default rates and lower platform profitability. These findings highlight the broader value of data-sharing within BigTech's integrated data ecosystem to deploy personalized, behavior-based incentives that simultaneously promote sustainable practices and enhance credit access.

The model also enables a comparative evaluation of policy instruments. Specifically, we benchmark our incentive-based mechanism against conventional tools such as environmental mandates and subsidies. While mandates can increase green participation, they often reduce perceived consumer welfare due to their coercive nature and limited flexibility. Subsidies are generally more attractive to individuals but entail significant fiscal costs and raise concerns about long-term sustainability. The divergence between perceived and actual welfare created by these instruments is characterized in the recent literature as a form of political failure (Timothy Besley and Torsten Persson, 2023): even policies that improve overall welfare may be politically untenable if individuals do not perceive direct benefits, as voters tend to evaluate policies based on private utility rather than social externalities. In this context, perceived welfare—defined as individual utility excluding externalities—serves as a more appropriate benchmark for assessing policy feasibility. Unlike mandates and subsidies, our market-based, incentive-compatible approach avoids these limitations by embedding data-driven nudges in the platform. Its effectiveness is especially salient in settings with low intrinsic green preferences, where traditional tools are either inefficient or distorted.

Literature Review This paper contributes to three main strands of literature, each offering a complementary perspective on the intersection of financial intermediation and green behavior. First, we contribute to the growing literature on environmental, social, and governance (ESG) practices by focusing on the alignment of environmental *values* with financial incentives. A central tension in ESG research is the tradeoff between *values* alignment (i.e., social goals) and *value* maximization (i.e., shareholder returns). Seminal works by Oliver Hart and Luigi Zingales (2017), Caroline Flammer (2021), and Laura Stark (2023) have explored how mechanisms can be designed to reconcile these objectives. In a recent study, Xiting Wu, Jiaxing You, Xiaoyun Yu and Clara Zhou (2024) show that environmental regulations are effective to engage private investment in projects with significant social value only when they design and deploy proper incentives. Our paper contributes to this debate by providing a market-driven mechanism that embeds carbon-reducing behaviors into credit allocation frameworks. Unlike approaches that rely solely on mandates or disclosure, our incentive-based design allows individual behaviors to generate financial signals that improve both environmental outcomes and credit access. In doing so, we speak to recent calls for mechanisms that reduce the distance between private and social returns (Besley and Persson, 2023).

Second, our paper extends the literature linking financial frictions to environmental behavior. Prior studies have shown that financial constraints hinder firms' investments in pollution control and green technologies (e.g., Qiping Xu and Taehyun Kim, 2021; Marcin Kacperczyk and Jose-Luis Peydro, 2022). More recent work by Antonio Accetturo, Giorgia Barboni, Michele Cascarano, Emilia Garcia-Appendini and Marco Tomasi (2024) emphasizes how credit supply affects firms' willingness to invest in sustainable practices. Our contribution shifts the focus from firms to households, demonstrating that individual green behaviors respond endogenously to borrowing constraints. Specifically, we show that embedding green actions into the credit scoring process can relax these constraints and incentivize participation in environmental efforts. This channel is particularly salient in digital financial ecosystems, where data-rich environments facilitate dynamic contract design.

Third, we contribute to the literature on soft information in financial intermediation. Classic studies such as Allen N. Berger, Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan and Jeremy C. Stein (2005), Rebel A. Cole, Lawrence G. Goldberg and Lawrence J. White (2004), and Liberti and Petersen (2019) have emphasized the value of qualitative borrower characteristics in loan evaluation, especially in contexts where hard financial data is limited. More recent work explores how BigTech platforms generate and utilize behavioral data to improve lending outcomes (e.g., Hanming Fang, Xiao Qin, Wenfeng Wu and Tong Yu, 2023; Yiping Huang, Xiang Li, Han Qiu, Dan Su and Changhua Yu, 2024; Guojun He, Yuhang Pan, Albert Park, Yasuyuki Sawada and Elaine S. Tan, 2023; Wenlong Bian, Lin William Cong and Yang Ji, 2024). Our study complements this literature by showing that green actions serve as a form of soft information that enhances credit assessment accuracy. We further demonstrate that the predictive power of green behaviors increases under data governance constraints, such as China's PIPL, which limits access to third-party data and forces greater reliance on internal behavioral signals. In this sense, our findings provide new insights into how financial intermediaries adapt to evolving privacy regulations by leveraging user-generated data.

Together, these three directions underscore a broader theme: the potential of financial innovation to align private incentives with societal goals. Our results highlight how BigTech ecosystems can deploy data-driven nudges to internalize climate externalities and unlock sustainable household-level behavior, offering a scalable policy tool in the absence of traditional regulatory levers.

Layout The remainder of the paper is structured as follows. Section 2 outlines the institutional background. Section 3 presents three core empirical findings based on the Ant Forest dataset, demonstrating how and why linking green actions to credit limits generates mutual benefits for both users and the platform. Section 4 introduces a quantitative model to evaluate the green value of our framework and analyze the welfare implications of the proposed incentive-compatible mechanism, benchmarked against traditional instruments such as mandates and subsidies. Section 5 concludes.

2 Institutional Background

Alipay, launched by Alibaba Group—the parent company of China's largest e-commerce platforms like Taobao and Tmall—was originally designed to build trust in online transactions but has since evolved into a comprehensive digital super-app. It now offers a broad array of services, including payments, wealth management, transportation, entertainment, and food delivery. This rich ecosystem enables Alipay to assess users' creditworthiness based on a variety of their financial and non-financial platform activities. It features its own credit scoring system—Zhima Credit Score—and offers dynamic virtual credit lines (i.e., Buy Now Pay Later), with limits adjusted in response to user behavior.

Within this broader platform, Alipay launched Ant Forest in August 2016. The program awards "green energy" points to users for environmentally friendly actions such as using public transportation, reducing waste, making electronic (instead of paper) payments, and recycling. Points are scientifically assigned based on the carbon emissions mitigated by these actions, with point values calibrated in collaboration with the China Beijing Environmental Exchange and the Nature Conservancy. For instance, users can earn 80 points by taking a bus and paying through Alipay (He et al., 2023). These points can then be redeemed for planting real trees or adopting protected areas in nature reserves, mostly located in ecologically sensitive regions of China.

By linking individual behaviors to tangible environmental outcomes—such as the number of trees planted or land conserved—Ant Forest enables users to directly observe the impact of their actions, thereby enhancing the program's appeal and reinforcing its environmental significance. Now as the world's largest personal carbon account program, Ant Forest has attracted over 600 million active users. In 2019, Ant Forest was awarded the Champions of the Earth—the United Nations' highest environmental honor—in recognition of its success in motivating consumers to reduce their carbon footprint and translating the environmentally conscious actions of over half a billion individuals into real trees planted across some of China's most arid regions.

The program incorporates two key features that drive user engagement. First, it integrates social interaction and gamification. Users generate green energy through eco-friendly actions, and if they fail to collect these points within a certain time frame, their points can be "stolen" by friends, creating a competitive dynamic. This social aspect encourages continuous participation, as users engage in four core activities: generating energy, collecting energy, stealing energy, and having their energy stolen.

Second, Ant Forest is seamlessly integrated with Alipay's broader financial ecosystem. Figure 1 provides a screenshot from a user's Aplipay's credit score interface, which displays various tips for boosting one's credit score within the BigTech platform. Ant Forest is prominently featured as a top recommendation. As illustrated in Figure 1, users who consistently engage in eco-friendly actions can receive benefits such as higher credit scores and increased credit limits. This connection between environmental behavior and financial outcomes creates a positive feedback loop, where contributions to sustainability enhance both environmental and personal financial goals. By embedding non-financial actions within a financial ecosystem, Ant Forest transforms eco-friendly behavior from a purely moral or social choice into a quantifiable, incentivized action. This unique combination of gamification, financial integration, and environmental impact enables Ant Forest to serve as both a personal carbon account and a soft-information infrastructure for digital lending. This paper focuses exclusively on the green value derived from linking credit scores to eco-friendly actions, while leaving other dimensions—such as gamification effects and environmental outcomes like trees planted or land conserved—for future research.

3 Empirics

3.1 Data

Our analysis relies on data accessed remotely through the Ant Open Research Laboratory. To ensure user privacy, all data was anonymized and analyzed within a secure sandbox environment, which prevents access to identifiable information and adheres to strict data protection protocols. Our final dataset comprises a monthly panel of 100,000 randomly selected Ant Forest users, covering the period from January 2019 to December 2022. This four-year window—the maximum permitted under Ant Group's data-sharing policy—provides a consistent and comprehensive panel for empirical analysis.

We chose 2019 as the starting point for several reasons. Although Ant Forest was launched in August 2016, the early years (2017-2018) involved significant adjustments in variables measurement, promotional strategies, and user demographics, which makes the data from this period less reliable for academic investigation. By focusing on 2019 and beyond, we avoid these complications arising from these initial transition years. Our sample selection was based on the following three criteria: (1) the users had to be registered with Alipay before, (2) they had to log into Alipay at least once during the sample period, and (3) they had to activate Ant Forest either before or during the sample period. Ant Group's data security team performed random sampling using a proprietary algorithm to ensure representativeness. Each user has a unique identifier, which enables us to match Ant Forest data with corresponding Alipay records to obtain information on the same user's credit limit, credit usage, and default status.

What sets our dataset apart is its unprecedented scale, granularity, and the seamless integration of behavioral and financial records within a single platform. Unlike survey-based or experimental studies, which often rely on self-reported or narrowly scoped data, our dataset captures real-world behaviors through a representative sample drawn from over half a billion users in a naturally occurring setting. This rich and unified structure enables us to examine the interaction between financial and non-financial outcomes with high external validity, offering fresh insights into how digital nudges and sustainability incentives shape credit access and risk assessment in emerging Fintech environments.

3.2 Variable Construction

The main regression variables in this study are categorized into four groups: user characteristics, green behaviors, credit information, and control variables. These categories are detailed below:

User Characteristics This category includes demographic information about the sampled users. Key variables include anonymized user IDs, age, gender, province and city codes, and the date of the user's first Ant Forest activation.

Green Behaviors Users' eco-friendly behaviors are classified into three main types: aggregate green behavior, structural green behavior, and biodiversity effort measures. In a nutshell, aggregate green behavior captures the total scope of a user's low-carbon activities, measuring their overall engagement in eco-friendly actions. Structural green behavior provides a breakdown of these actions across specific contexts, offering a deeper understanding of green behaviors in various scenarios. Biodiversity efforts measure users' contributions to conservation, including tree planting and reserve protection.

In more detail, the aggregate green behavior measures include three key actions: production, collection, and stealing of green energy points, each quantified in grams of carbon reduction. Green energy production captures the carbon emissions avoided through users' environmentally friendly actions, while green energy collection represents users transferring previously accumulated energy points to their accounts. The stealing behavior refers to users acquiring unclaimed energy points from others within their Ant Forest network. For our main analysis, we quantify green energy production by aggregating the grams of carbon reduction resulting from all forms of environmentally friendly behavior, except those generated directly through digital payments. Since consumption-related payments are tightly linked to credit usage by design, this approach helps mitigate concerns about spurious correlation and isolates green behaviors unrelated to transactional activity. Alternatively, we adopt a more stringent definition by further excluding energy generated from walking and transportation-related activities. We also consider a broader definition that includes all forms of green energy production. Our robustness analysis confirms that the results remain invariant across these alternative measures of green actions.

Structural green behavior measures carbon reduction across different scenarios. The Ant Forest program features a total of 61 distinct green behaviors, including actions such as taking public transportation, driving electric vehicles, purchasing tickets online, using shared power banks, participating in the Clean Plate Campaign, and adopting eco-friendly appliances and packaging. Each behavior contributes to environmental sustainability by promoting low-carbon lifestyle choices. We categorize these behaviors based on the level of effort and time required to achieve measurable environmental impact, ranging from low-effort, quick actions to more sustained, high-effort commitments (Eco-high and Eco-low), as detailed in Tables A1 and A2 in the Online Appendix.[3] For example, walking and taking public transportation are categorized as Eco-high behaviors, while actions like electronic payments fall under Eco-low behaviors. Although our classification is ad hoc, the main findings remain robust under alternative groupings.

Finally, biodiversity engagement is assessed by three cumulative metrics: the number of trees planted, the number of reserves supported, and the area of reserves protected. These reflect users' involvement in environmental initiatives, such as reforestation and habitat preservation.

[3]When categorizing the green behaviors, we exclude those with a frequency of fewer than 3,000 user-months within our four-year sample.

Credit Information Credit information is represented by four variables: credit line limit, credit line usage, default amount, and default rate. The credit line limit indicates the maximum amount a user can borrow, while credit line usage shows the actual amount borrowed at the end of each month. The credit line usage rate, which is the ratio of actual usage to the credit limit, identifies users with higher financial constraints. We use two measures of defaults by following the industry practice: the first is the default rate, which is the percentage of the end-of-month overdue balance exceeding three days, relative to the total fixed limit of internet consumer credit. The second is the default amount, defined as the absolute value of the end-of-month overdue balance exceeding three days.

Control Variables Users' personal wealth can significantly influence their decisions to engage in eco-friendly behaviors. On one hand, individuals with lower income levels may adopt environmentally friendly practices out of necessity—choosing cost-effective options such as walking or using public transportation. On the other hand, those with higher levels of wealth may face fewer financial constraints and, as a result, may be more inclined to prioritize broader societal well-being, including sustainability and environmental impact.

To account for users' economic status, we include two control variables: monthly consumption and total financial assets at month-end. Monthly consumption captures user spending within the Alipay ecosystem, including both online and offline transactions. Total financial assets represent the balance of various Alipay-managed investments, such as funds, gold, and bonds. Given the long-tailed distribution of these variables, we apply a natural log transformation (adding 1 before transformation) to stabilize variance and improve the robustness of our analysis.

3.2.1 Summary Statistics

Panel A of Table 1 presents descriptive statistics for the main variables used in the regression sample. The raw dataset comprises monthly data from 100,000 users over a 48-month period, spanning January 2019 to December 2022. To be included in our regression subsample, individuals must have complete information on their credit limit history, resulting in a final sample size of 3,945,168 user-month observations. To be consistent with our following regression results, Table 1 shows the summary statistics after 1% winsorization at the right tail. The average age of users is 31.7 years, with a minimum age of 18 and a maximum of 69. Female users account for 47% of the sample, suggesting an approximately balanced sample in terms of gender distribution.

Users generate an average of 1,200 grams of green energy per month (equivalent to the amount of carbon absorbed by a tree over 24 days)[4], with a standard deviation of 1,501 grams, a median of 611 grams, and a maximum value of 6,965 grams. Users engage in green energy stealing at an average rate of 324 grams per month, with a standard deviation of 1,078 grams, while the average green energy collection is 516 grams, with a standard deviation of 1,120 grams.

In terms of structured green behaviors, besides the aggregate green energy variables, we tabulate two categories of green energy production based on their scenarios: Eco-high and Eco-low behaviors. As expected, Eco-high behaviors, which represent higher carbon reduction activities such as sustainable travel, average 1,096 grams of energy per month. Eco-low behaviors, associated with relatively lower individual impact, average 99 grams per month.

Biodiversity contributions are reflected in an average of 0.84 trees planted per user, with a maximum of 10 trees. Users also support an average of 1.23 reserves, covering an average area of 1.25 units, with both metrics reaching a maximum of 19. These statistics indicate that while the majority of users engage in green activities to some extent, a subset of highly active users drives the higher averages, demonstrating significant engagement in sustainable practices through multiple energy-gathering methods.

Credit-related variables provide insights into users' access to and utilization of credit. The average credit limit is 14,501 *yuan* ($\approx$ 2,072 dollars), with a standard deviation of 13,926 *yuan* ($\approx$ 1,989 dollars), ranging from 0 to a maximum of 55,000 *yuan* ($\approx$ 7,857 dollars). Credit line usage, which measures the proportion of credit limits utilized, averages 1,200 *yuan* ($\approx$ 171 dollars), with a standard deviation of 2,342 *yuan* ($\approx$ 335 dollars), ranging from 0 to a maximum of 14,697 *yuan* ($\approx$ 2,100 dollars). In contrast, the average default amount is 54 *yuan* ($\approx$ 7.7 dollars), with a standard deviation of 1,021 *yuan* ($\approx$ 146 dollars), ranging from 0 to a maximum of 55,000 *yuan* ($\approx$ 7,857 dollars). The average default rate is 0.98%, with a standard deviation of 9.8%, and ranges from 0% to a maximum of 100%. These statistics reflect substantial heterogeneity in credit usage and default behavior, with some users utilizing their credit lines to a significant extent.

The final set of variables in Panel A includes additional financial wealth and consumption metrics.

[4]The calculation of equivalent days is based on the fact that one tree can absorb 18.3 kilograms of carbon dioxide per year.

The natural logarithm of monthly consumption has a mean of 6.4 (equivalent to 601.8 *yuan* ($\approx$ 86 dollars)), with a standard deviation of 2.6, ranging from 0 to 10.7 (equivalent to 44,355.8 *yuan* ($\approx$ 6,350 dollars)). This variable captures users' expenditures within the Alipay ecosystem, including both online and offline transactions. The financial assets variable, also measured as a natural logarithm, has a mean of 3.9 (equivalent to 49.4 *yuan* ($\approx$ 7 dollars)), with a standard deviation of 3.7, ranging from 0 to a maximum of 11.8 (equivalent to 133,252.3 *yuan* ($\approx$ 19,036 dollars)). This measure captures users' accumulated wealth and investments in funds, gold, bonds, and other financial products available on Alipay. The broad variation in financial asset holdings highlights significant disparities in users' wealth and engagement with digital financial services, potentially reflecting differences in financial goals, risk preferences, and levels of economic participation.

3.3 The Incentive-Compatible Design

We begin by explaining the design mechanism underlying our approach. The key feature is that green actions are deliberately made costly, enabling them to serve as a screening device that reveals users' underlying traits and improves credit allocation. This design explains why the mechanism generates gains for both users and the platform. As we will see later, unlike typical incentive schemes that impose costs on the provider, the platform in this case does not incur such losses.

3.3.1 Baseline Regression

We first validate empirically the relationship between individual credit limits and green energy production as illustrated in Figure 1. Columns (1) through (4) of Panel A of Table 2 reports results from OLS regressions using our benchmark measure of green energy production. Odd-numbered columns exclude control variables, while even-numbered columns include controls. The results consistently show a positive and statistically significant relationship: higher levels of green energy production are associated with higher credit limits across all model specifications. With the inclusion of individual fixed effects, Column (2) indicates that a one-kilogram increase in green energy by the *same* user is associated with a 0.17% rise in their credit limits—equivalent to roughly 24.65 *yuan* (approximately 3.52 USD). While modest in size, this effect is robust. Moreover, Columns (3) and (4) demonstrate that the results hold even when we control for monthly city-level COVID-19 case counts, mitigating concerns that the association is merely a byproduct of pandemic-related behavioral shifts.

In Column (5), we consider cross-user variation by excluding individual fixed effects while continuing to control for time and city-by-year effects. This specification yields a substantially larger coefficient on green energy production—0.0371 compared to 0.0017 in Column (2), which isolates within-user variation through the inclusion of individual fixed effects. The approximately 20-fold increase in the coefficient magnitude suggests that the baseline specification absorbs a substantial portion of the cross-sectional variation in credit limits through individual fixed effects, which capture unobserved, time-invariant user characteristics—such as intrinsic financial responsibility or behavioral types. This contrast implies that most of the predictive power of green behaviors on credit limits comes from persistent differences between individuals, rather than from time-varying changes within the same user. In other words, green behavior is more a reflection of a user's underlying type, not just temporary actions. As such, green behaviors act as informative cross-sectional screening signals: they help the platform reveal latent user quality—especially for newer users whose financial histories may be limited.

3.3.2 The Screening Role of Costly Green Actions

We now quantify the implicit cost of converting green behaviors into higher credit limits, estimating the effort and time required to engage in platform-endorsed environmentally friendly activities—such as walking instead of driving, reducing household energy consumption, or making sustainable purchases. Table A3 in the Online Appendix presents a list of green actions and their corresponding energy points, as specified in Ant Forest's official documents. According to the table, to accumulate one kilogram of green energy—which yields a 0.17% boost in credit limit or an additional 24.65 *yuan* (Column (2) of Table 2 Panel A), one would need to walk 600 steps daily for approximately 100 days, or take the subway for roughly 20 days. For money-related activities, roughly six second-hand book trades or six online ticket purchases would achieve the same amount of green energy. These calculations illustrate how different behaviors contribute at varying intensities to green energy accumulation. The large number of repeated actions or monetary transactions required highlights the relatively low *direct* financial return associated with each unit of green energy, and this low return is unlikely to attract users driven purely by short-term financial gain. Instead, it implies that only individuals with either strong intrinsic environmental preferences or forward-looking financial strategies are likely to persist in such behaviors.

Corroborating the above evidence, the platform appears to differentiate between types of green energy generation when making credit adjustment decisions. Notably, individuals can accumulate substantial amounts of green energy points with minimal effort or cost by simply harvesting unclaimed points from friends, provided that they maintain a large social network within Ant Forest. In Panel B of Table 2, we consider two alternative methods of accumulating grams of carbon reduction: "stealing" points from friends and collecting points produced by themselves. Columns (1) and (2) of Panel B indicate that points obtained through these "easy green" behaviors—activities that reflect social interaction more than personal environmental effort—do not result in a significant increase in credit limits. This suggests that the BigTech platform adjusts credit access based on the informational value of effort-intensive, costly green behaviors in signaling creditworthiness, rather than on platform-based social interactions that lack meaningful effort or time commitment.

Individuals may also accumulate green energy points incidentally—for instance, due to economic constraints—by walking or using public transportation for work, without a deliberate intention to behave in an environmentally responsible way. To isolate those with an intrinsic preference for sustainability, a more intuitive approach is to identify users who actively and consistently convert their accumulated energy points into tangible environmental actions, such as planting trees or protecting ecological reserves. Such behaviors serve as credible signals of genuine environmental commitment, distinguishing them from incidental or circumstance-driven green activities.

Columns (3) through (5) of Panel B show that the number of trees planted, the number of reserves protected, and the total area of protected reserves are all positively and statistically significantly associated with credit limits. Economically, these results imply that planting one more tree or protecting one more reserve is associated with a 1.33% (i.e., 192.86 *yuan* or 27.55 dollars) and 0.37% (i.e., 53.65 *yuan* or 7.66 dollars) increase in credit limits, respectively. Across all models, the high R-squared values (around 0.927) indicate that the variables, along with controls and fixed effects, explain a substantial proportion of the variation in credit limits. Collectively, these findings suggest that the platform adjusts credit access based on perceived creditworthiness inferred from genuine climate-responsible behaviors, rather than from socially driven or passive environmental actions.

Put differently, the design of the mechanism appears to be intentional: by making green actions relatively costly in terms of time and engagement, the platform discourages opportunistic participation and enhances the credibility of observed green behavior. In effect, these costs serve a strategic screening purpose—ensuring that green activity reflects genuine commitment rather than tactical exploitation or incidental environmental actions. As explained later in Section 3.3.3, this mechanism closely mirrors the logic of signaling & screening models in labor and credit markets, where costly actions (e.g., educational attainment or collateral provision) are used to separate high-quality individuals from others under asymmetric information (e.g., Spence, 1973). Similarly, in this context, sustained green engagement—despite low immediate financial payoff—functions as a credible signal of user type, allowing the platform to more accurately assess creditworthiness using soft behavioral data.

3.3.3 The Underlying Rationale

In the economics of education, signaling theory (e.g., Spence, 1973; Andrew Weiss, 1983; John G. Riley, 1979; Kenneth J. Arrow, 1973) demonstrates how costly actions—such as acquiring education—can reveal hidden traits like ability, provided those costs vary across types. High-ability individuals are more willing to incur these costs, making education a credible signal to prospective employers even when it does not directly enhance productivity.

We draw a parallel in our context, where green actions serve a similar signaling role. This signaling mechanism provides a theoretical rationale for how green actions can indicate creditworthiness. As shown formally in the Online Appendix, the key assumption behind is that although users differ in unobservable characteristics such as environmental consciousness and financial prudence, these two characteristics are positively correlated. High-type users—who are both environmentally and financially responsible—face lower psychological or opportunity costs of engaging in green actions, and thus are more likely to invest in costly green behaviors. While the platform cannot observe user types directly, it can observe green engagement ω, which it uses to assign credit limits. In this setup, high-type users choose higher ω to credibly signal their type, while low-type users refrain from mimicking due to the convex cost structure (e.g., $\Psi(\omega) = \frac{\phi}{2}\omega^2$) that makes signaling prohibitively expensive. We will return to this prediction in Section 3.5, where we provide empirical evidence on how green behaviors relate to default risk.

Evidence Supporting the Core Assumption As for whether users with strong intrinsic green preferences are also more likely to exhibit financial responsibility, we provide support from both existing literature and our own data. First, this assumption is consistent with prior empirical and theoretical work. Annette Vissing-Jørgensen (2021) offers direct evidence that consumer purchasing behavior reveals credit risk. By analyzing transaction-level data, the study shows that the composition of consumption—such as the balance between discretionary and essential spending—can predict loan default, suggesting that daily financial choices reflect deeper traits like patience, self-control, and discipline. In this context, environmentally conscious consumption may similarly signal financial prudence. Complementing this empirical evidence, Martin L. Weitzman (1994) and Martin L. Weitzman (2001) develop theoretical models linking environmental preferences to intertemporal decision-making. These studies argue that individuals with stronger environmental concerns tend to adopt lower discount rates, placing more weight on long-term outcomes. Such forward-looking preferences are also associated with financially responsible behaviors, such as greater saving and lower credit delinquency. Together, these studies highlight a shared behavioral mechanism—time preference—that helps explain the positive correlation between environmental engagement and financial discipline. This connection provides a theoretical foundation for the screening role of green actions in our framework.

Second, we provide empirical evidence from our dataset to support this assumption. We classify users into high and low intrinsic green types based on the median of cumulative green energy points (42,075 grams) accumulated over the sample period. To proxy patience and forward-looking behavior, we construct two measures. The first is the *Tree-to-Reserve Ratio*, calculated as the number of trees planted divided by the number of reserves protected by each user. Since planting a tree requires significantly more green energy points and a longer accumulation period than adopting a reserve, a higher ratio indicates greater patience. The average Tree-to-Reserve Ratio is 0.71 for the high-green group, compared to just 0.13 for the low-green group.

The second measure is the *(Collect − Steal)/Produce Ratio*, defined as the monthly average of the difference between green energy collected and green energy stolen, scaled by the total green energy produced. A higher value reflects more consistent and self-driven green engagement rather than opportunistic or socially motivated behavior. The high-green group has an average ratio of 0.016, while the low-green group shows a negative average of 0.11. These patterns confirm that users with stronger green preferences also display behaviors consistent with greater patience and intrinsic motivation—traits commonly linked to financial responsibility. This further supports our assumption that green behaviors can credibly signal unobserved financial discipline and validate their use in screening mechanisms.

Finally, this framework has important welfare implications. Because signaling relies on users' ability to bear the cost of green engagement, access to financial services becomes conditional on both preferences and means. As shown in the following quantitative exercise, our analysis focuses on *perceived welfare*—defined as individual utility excluding externalities—as a more relevant metric for evaluating the feasibility and political acceptability of green credit schemes. In this context, green behaviors function not only as behavioral nudges but also as instruments of strategic self-selection that shape economic opportunity within data-driven credit systems.

3.3.4 The 2021 Personal Information Protection Law

While our previous findings reveal a positive correlation between credit limits and green actions on the Ant Forest platform—suggesting that such behaviors may carry informative value for credit evaluation—this relationship may be affected by unobserved confounding factors. For instance, users without Ant Forest accounts may disproportionately belong to demographic groups with lower education or income levels, which could independently shape their credit limits. To further isolate the soft information value effect of green actions, we leverage the enactment of the Personal Information Protection Law (PIPL) in China in November 2021. The PIPL imposes strict restrictions on the use of alternative data sources for credit lending, significantly limiting BigTech companies' ability to access and utilize external data without explicit user consent. This regulatory change compelled BigTech firms to rely more heavily on platform-specific data—such as users' engagement in green energy production—when making credit-lending decisions.

To analyze the impact of this regulatory shift, we restrict our sample to a balanced three-month window surrounding the implementation of the PIPL. We employ a difference-in-differences framework, introducing an interaction term between the PIPL policy and green energy production in our baseline regression model. The results in Table 3 provide insights into how reliance on users' green behaviors for credit decisions evolved pre- and post-PIPL. Columns (1) and (2) examine green energy production as a predictor of credit limits, both independently and in interaction with the PIPL policy. The coefficient estimate on green energy production is positive and significant at the 1% level, suggesting that green energy production has already contributed to increases in credit limits before the PIPL came into effect. The positive and highly significant interaction term implies that green energy production became even more relevant as a predictor of credit limits after the implementation of restrictions on alternative data. Post-PIPL, a one-kilogram increase in green actions corresponds to an additional 0.55% (without controls) or 0.56% (with controls) increase in credit limits.

These findings suggest that BigTech firms have increasingly relied on internal behavioral data, such as green energy production, to assess creditworthiness when they can no longer easily access external data sources. This regulation-driven shift underscores the strategic value of data-sharing across business segments within the BigTech ecosystem and highlights the role of internal, non-financial data—such as environmentally conscious behaviors—in shaping credit evaluations. Put differently, by tightening controls on external data sourcing and reinforcing user consent protocols, the PIPL has incentivized BigTech firms to mine platform-native behavioral data, including green actions, as alternative indicators of creditworthiness. The incorporation of green behaviors into credit evaluation parallels the use of soft information in the banking literature. As highlighted in several studies (e.g., Berger et al., 2005; Cole, Goldberg and White, 2004), banks—particularly smaller institutions—are known to leverage soft information to alleviate credit constraints for small enterprises.

Lastly, we explore the heterogeneous soft information value embedded in Eco-high versus Eco-low behaviors. As discussed previously, compared to Eco-low behaviors, which tend to be low-effort, quick actions, Eco-high actions typically involve more sustained, high-effort commitments, thereby offering deeper insight into user characteristics. Columns (3) and (4) present the results for Eco-high behaviors, showing a pattern consistent with total green energy production. Prior to the implementation of the PIPL, Eco-high behaviors had some predictive power for credit limits. The positive and significant interaction term indicates that these behaviors become a stronger and more positive predictor of future credit limits following the policy, suggesting their increased relevance in credit evaluations when access to alternative data is restricted. A one-kilogram increase in Eco-high green actions corresponds to an additional 0.53% (without controls) or 0.54% (with controls) increase in credit limits.

Columns (5) and (6) show the corresponding results for Eco-low behaviors. The coefficient on Eco-low behaviors is statistically insignificant, indicating that prior to the implementation of the PIPL, these low-effort environmentally conscious behaviors did not meaningfully contribute to increases in credit limits, as BigTech platforms had access to alternative data sources for assessing a user's creditability. The interaction term is positive and highly significant, implying that even low-effort behavioral data became useful for credit evaluation when BigTech platforms were restricted from accessing alternative data sources. In comparing the economic magnitude, the standardized coefficient of the interaction term for Eco-high behaviors is 0.0040, while that for Eco-low behaviors is 0.0025, showing that Eco-high behaviors are more instrumental in raising credit limits.[5]

The robustness of these results highlights the significant impact of the PIPL on BigTech credit-lending practices by increasing their reliance on green behavior metrics as a substitute for restricted external data sources. This regulatory shift amplifies the financial value of data-sharing and demonstrates that green actions carry substantial soft information value for BigTech. Importantly, this implication suggests that even without environmental concerns, BigTech firms could benefit from promoting environmentally friendly behaviors due to their potential utility in credit evaluations as one source of soft information.

3.3.5 Other Robustness Checks

Omitted Variables To further address potential omitted variable bias, we follow the approach proposed by Emily Oster (2019), gradually introducing controls to assess the stability of our estimates. This sequential inclusion of covariates reveals that the change in the model's explanatory power is negligible, with the R^2 hovering between 0.926 and 0.927 after accounting for additional controls. The minimal change suggests that most of the variation in credit limits is already captured by the baseline specification. Consequently, the influence of omitted variables is likely limited, reinforcing the interpretation that green behavior contains meaningful informational value for determining creditworthiness.

Alternative Specifications Recent studies have raised concerns about using log-transformed linear regressions for count data (e.g., Jonathan B. Cohn, Zack Liu and Malcolm I. Wardlaw, 2022; Jiafeng Chen and Jonathan Roth, 2024). To address this, we employ Poisson regressions and inverse hyperbolic sine (IHS) transformations to verify the robustness of our findings.[6] Table A4 in the Online Appendix shows

[5] The standardized coefficient is calculated as $\beta_{\text{std}} = \beta \cdot \frac{\sigma_X}{\sigma_Y}$, where β is the estimated raw coefficient, and σ_X and σ_Y are the standard deviations of the independent variable X and dependent variable Y, respectively.

[6] The IHS transformation, defined as $IHS(x) = \ln(x + \sqrt{x^2 + 1})$, offers several advantages: (i) it behaves similarly to a logarithmic transformation, (ii) it retains zero-valued observations, and (iii) it accommodates negative values. This method

that, across all specifications, green energy production exhibits consistently positive and statistically significant coefficients, indicating a robust association between higher green energy production and increased credit limits. In particular, Columns (3) and (4), which apply IHS transformations, produce coefficients that are comparable in magnitude to those from the OLS estimates in Columns (1) and (2) of Table 2 Panel A. Given that most users have non-zero credit limits, concerns raised by Cohn, Liu and Wardlaw (2022) and Chen and Roth (2024) about the OLS method for count data appear to have limited impact on our results.

In Table A4, we also consider two alternative approaches to measure green energy production. In Column (5), we aggregate the grams of carbon reduction generated from all forms of environmentally friendly behavior, including those linked to payment activities. In Column (6), we instead adopt a more stringent definition by excluding not only payment-related energy contributions but also those arising from behaviors such as walking and using public transportation. The results remain consistent with those obtained using our benchmark measure: green energy production continues to be positively and significantly associated with credit limits.

Feature Importance Analysis In Figure A1 in the Online Appendix, we further perform a random forest regression to evaluate the relative importance of green energy production in determining credit limits. Random forest regression is a supervised learning algorithm and bagging technique that employs an ensemble method for regression tasks in machine learning. The algorithm builds multiple decision trees that operate independently, with no interaction between them during the construction process. This approach allows us to isolate the orthogonal contribution of green energy production to credit limits, separating it from other potentially correlated factors such as consumption, financial assets, age, and gender. The x-axis represents the feature importance of various factors influencing credit limits, highlighting their relative contribution. The results shown in the figure indicate that green energy production is a significant factor in determining credit limits, ranking just below financial assets and consumption in importance.

In summary, these findings highlight the value of green behaviors as data inputs for BigTech platforms, influencing assessments of creditworthiness and credit limit decisions. These implications are

was introduced by John B. Burbidge, Lonnie Magee and A. Leslie Robb (1988) and James G. MacKinnon and Lonnie Magee (1990).

consistent with the findings in the Section 3.5.

3.4 Does It Work For Individuals?

3.4.1 Baseline Regression

This section examines whether users respond to financial incentives embedded in the platform's green engagement mechanism. We hypothesize that many eco-friendly actions are not purely intrinsic but strategically undertaken to relax borrowing constraints, as users expect green participation to enhance their creditworthiness and expand credit access.

To empirically test this financial friction hypothesis, we employ three complementary approaches. First, we use the lagged natural logarithm of the credit usage rate as the independent variable. Users with high credit usage rates are more likely to face tighter borrowing constraints due to limited available credit relative to their limits. If financial frictions play a role, we would expect these users to engage more actively in green behaviors as a strategy to increase their credit limits. The model specification for this analysis is as follows:

$$\ln(GreenEnergyProduction)_{i,t} = \alpha CreditUsage_{i,t-1} + \Gamma Control_{i,t} + \eta_i + \omega_t + v_{c,y} + \epsilon_{i,t} \tag{1}$$

where i, c, y, and t represent the individual user, the city where the user is located, the year, and the month, respectively. The dependent variable, $\ln(GreenEnergyProduction)$, denotes the natural logarithm of green energy production in kilograms. The key independent variable is the relative ratio of credit usage to credit limit. Lagged terms are employed to mitigate concerns about contemporaneous shocks. The term $Control$ includes control variables that potentially influence green actions in month t, such as the natural logarithms of total financial assets and consumption. As a result, any wealth-related effects —whether richer or poorer users are more likely to engage in green behavior—are accounted for by these controls. Fixed effects for individual users (η_i), months (ω_t), and city-year combinations ($v_{c,y}$) are included to account for unobserved heterogeneity across these dimensions. Throughout the paper, all the standard errors are clustered at the individual user level.

Second, we replace the natural logarithm of the credit usage rate with a dummy variable to identify users facing high credit constraints. This borrowing-constrained dummy *Constraint* is set to 1 if a user's credit line usage rate is 80% or higher, indicating a heavy reliance on available credit, and 0 otherwise. This dummy variable enables us to isolate the behaviors of high-constraint users and examine whether their green activities differ systematically from those with lower credit usage. More specifically, our model specification is shown as below:

$$\ln(GreenEnergyProduction)_{i,t} = \alpha Constraint_{i,t-1} + \Gamma Control_{i,t} + \eta_i + \omega_t + v_{c,y} + \epsilon_{i,t} \quad (2)$$

where $Constraint_{i,t-1}$ is borrowing-constrained dummy variable that indicates user i's financial slack in the previous month $t-1$. The remaining variables are as defined previously. A positive and significant coefficient suggests that users with less financial flexibility are more likely to engage in green behaviors.

Lastly, we estimate a binned indicator regression, dividing the sample into five groups based on credit line usage rates: users with credit usage below 20%, between 20% and 40%, between 40% and 60%, between 60% and 80%, and above 80%. This segmentation allows us to investigate whether higher credit usage rates are associated with increased green behaviors in a nonlinear way. By categorizing users in this manner, we can explore how varying levels of credit dependency influence green production. The regression model is specified as follows:

$$\begin{aligned} \ln(GreenEngergyProduction)_{i,t} &= \alpha_1 Constraint^{20-40}_{i,t-1} + \alpha_2 Constraint^{40-60}_{i,t-1} + \alpha_3 Constraint^{60-80}_{i,t-1} \\ &+ \alpha_4 Constraint^{over80}_{i,t-1} + \Gamma Control_{i,t} + \eta_i + \omega_t + v_{c,y} + \epsilon_{i,t} \quad (3) \end{aligned}$$

Here, $Constraint^{20-40}_{i,t-1}$, $Constraint^{40-60}_{i,t-1}$, $Constraint^{60-80}_{i,t-1}$, and $Constraint^{over80}_{i,t-1}$ are dummy variables indicating the credit usage rate of user i in the previous month $(t-1)$. The remaining variables are as defined previously. The coefficients α_1 to α_4 capture the impact of different credit usage levels on green production, relative to the baseline group of users with credit usage below 20%. A positive and significant coefficient for higher usage groups would suggest that users with greater credit dependency engage more in green behaviors, potentially to mitigate borrowing constraints.

These three empirical strategies aim to provide robust evidence that financial frictions influence users' green behaviors on the platform. If users with high credit usage exhibit greater engagement in green actions, it would support the view that these behaviors are, at least partially, motivated by the desire to improve credit limit. This framework allows us to differentiate between general correlations and specific behavioral responses to financial constraints, reinforcing the financial friction hypothesis.

The results, summarized in Table 4, examine the relationship between borrowing constraints, credit usage, and green behaviors. Columns (1) and (2) show that the credit usage rate is positively and significantly associated with green energy production. The coefficients suggest that a 1% increase in credit usage corresponds to an approximate 0.13% to 0.25% increase in green energy production. The difference between these two columns lies in the inclusion of control variables in Column (2), which suggests that while wealth differences do influence green behavior, they do not preclude the additional role of financial frictions in shaping users' green actions. This relationship remains robust across specifications, as indicated by consistently high R-squared values (around 0.55–0.58).

Using model specification (2), the estimated borrowing-constrained dummy variable in Columns (3) and (4) is positively associated with green production, indicating that constrained users engage in 50.47% or 23.92% higher levels of green actions compared to unconstrained users. These findings suggest that constrained individuals are incentivized to pursue more green activities.

Finally, Column (5) analyzes varying levels of credit usage using the binned indicator regression specification (model 3). The coefficient estimates for these ranges are all positive and significant, and more importantly, increase monotonically. The dummy variable for the highest credit usage bin (80%–100%) is associated with a coefficient of 0.3202, indicating that users in this group generate 32.02% higher levels of green actions compared to the baseline group with credit usage below 20%.

To further validate the monotonic pattern, we formally test for coefficient differences across groups. The pairwise comparisons reveal that the difference between the 20–40% and 40–60% groups is statistically significant with a p-value of 0.045, the increase from 60–80% to 80–100% is also significant with a p-value of 0.000, and jointly, we reject the null hypothesis that all group coefficients are equal with a p-value of 0.000. These results imply that the relationship between green behavior and credit usage is not only upward-sloping but also discontinuously stronger among more constrained users, consistent with a threshold-based behavioral adjustment mechanism. In other words, green behavior appears to serve a strategic function under financial pressure, reinforcing the interpretation that the green-credit linkage acts as a form of incentive-compatible screening.[7]

Table A5 in the Online Appendix further expands our analysis by comparing "Eco-High" and "Eco-

[7] Based on unreported analyses, the regression results in Table 4 remain robust when estimated on subsamples defined by various demographic indicators.

Low" behaviors. The results show that although both types of behaviors are positively and significantly correlated with credit usage, their effects differ in magnitude. For instance, Columns (1) and (4) report coefficients of 0.1264 for Eco-High and 0.0539 for Eco-Low behaviors. The coefficient estimates for the borrowing-constrained dummy are 0.2318 for Eco-High and 0.0887 for Eco-Low behaviors, which again are both significant at the 1% level. We observe a similar pattern using the binned indicator regression framework: while there is a monotonically increasing pattern of green incentives in relation to the degree of financial constraints, Eco-High behaviors show a stronger response to financial constraints, indicating that these behaviors are more sensitive to credit limits.

In conclusion, our results in this section highlight the significant role of credit usage and financial constraints in driving green behaviors. Financially constrained individuals are more likely to engage in environmentally conscious activities, potentially to enhance their creditworthiness. In other words, linking credit scores to green actions creates incentives for certain users to engage in environmentally friendly behaviors.

3.4.2 Additional Results

In the Online Appendix, we present complementary evidence on how users respond to the credit-linked green incentive structure on the platform. In Section B.1.1, we explore the demographic and financial characteristics of users grouped by their credit usage rates, which are shown in Panel B of Table 1. The results show that individuals with higher credit utilization tend to be younger, more likely male, and face tighter financial constraints—characterized by lower financial assets and smaller credit limits—compared to those with lower usage. However, green production does not increase monotonically with credit usage, suggesting that user characteristics alone cannot fully explain green behavior. Instead, other mechanisms—such as constrained users engaging more in green actions when these behaviors offer potential credit-related benefits—likely play a role.

In Section B.1.2, to establish a causal relationship between credit constraints and green behavior, we conduct a Difference-in-Differences (DiD) event study leveraging a quasi-natural experiment surrounding the 2020 Singles Day shopping festival in China. This period was marked by two simultaneous shocks: a surge in consumer credit demand driven by aggressive promotional campaigns and pandemic-related stimulus measures, and a tightening of credit supply triggered by the suspension of Ant Group's

IPO and the introduction of stricter regulatory controls, particularly for younger users. These dual dynamics—rising credit usage and declining credit limits—provide a unique opportunity to isolate changes in green activity attributable to shifts in credit availability. Our results show that users who experienced an increase in credit utilization between October and December 2020 subsequently undertook 23.74% more green activities than their counterparts, reinforcing the interpretation that green behaviors are responsive to financial incentives.[8] [9]

Finally, we explore whether the credit-linked green incentive scheme generates lasting behavioral changes. To assess persistence, we define a positive change in green behavior as an individual whose green production was below the sample median in the initial period and subsequently rises above the median. For these users, we track how long their green production remains above this threshold. On average, the improvement persists for 5.6 months, indicating that the incentive mechanism has a meaningful long-run impact on user behavior rather than inducing only temporary changes.

Alternatively, we analyze platform engagement through average number of Ant Forest page visits following the 2020 Singles Day shopping festival. In Figure A2, we observe a gradual and persistent decline rather than an immediate drop, with engagement levels remaining elevated through early 2021. The exponential decay rate is approximately 0.0165, corresponding to a half-life of about 60.5 months, which means the average number of page visits declines slowly over time and cuts in half roughly every 5 years. This empirical pattern supports the argument that the platform's incentive mechanism induces persistent behavioral engagement.

Lastly, in Table A6, we present results from a staggered DiD regression examining the impact of entering the Ant Forest program on the number of homepage visits per month. We find compelling evidence that participation in Ant Forest significantly increases user engagement on the BigTech platform. Specifically, entering Ant Forest is associated with an average increase of approximately 16 additional homepage visits per month. This effect is statistically significant at the 1% level, indicating a robust relationship between green participation and platform usage. All these results indicate that the platform's

[8] This finding is not inconsistent with the fact that green energy accumulation typically takes time. The key mechanism here is that when users face sudden borrowing constraints, they gain stronger short-term incentives to engage in green behaviors —such as walking or using public transit—to unlock additional credit. Even if point accumulation is gradual, the perceived value of initiating these actions increases under financial stress.

[9] One may wonder whether the spike in credit usage around incentive-driven events leads to prolonged overconsumption. To assess the duration of elevated spending, we identify users whose credit utilization rates exceeded 80% during the 2020 Singles Day shopping festival and track how long they remained above this threshold. On average, utilization rates return to normal within two months, indicating that the surge in credit-fueled consumption is mostly short-lived and self-correcting.

credit-linked green actions not only induce immediate responses but also promote sustained behavioral and engagement improvements.

3.5 Does It Work for the BigTech?

In this section, we evaluate the impact of implementing a green-action-linked credit policy on the BigTech platform. Our primary focus lies in the potential screening value of green actions—that is, their role as informative signals that enable lenders to better identify low-risk borrowers and improve credit allocation.

This aligns with the core mechanism of our model as outlined in Section 4, where green behaviors—observable but costly actions—indicate greater financial responsibility and lower default risk.[10]

3.5.1 Baseline Regression

As a starting point, we assess whether linking credit limit increases to green behaviors introduces any credit risk. As described previously, we assess defaults using two metrics: the default rate and the actual amount of credit defaulted. If higher credit limits granted for eco-friendly actions do not increase—and may even reduce—default rates, this would indicate that integrating green behaviors into credit evaluations enhances allocation efficiency without undermining financial stability.

The first two columns in Panel A of Table 5 reveal a significant and negative relationship between green production and default rates. Specifically, Column (2) indicates that each additional kilogram of green production is associated with a 0.2096% reduction in the default rate. In the last two columns of Panel A, we replicate the empirical analysis using the default amounts as the dependent variable. Column (4) shows that each additional kilogram of green energy production is linked to a 17.17 *yuan* drop in overdue balance. Across all specifications, the control variables for personal financial wealth and

[10] The benefits of such a green-credit-integration policy may extend beyond credit risk screening. Notably, recent studies suggest broader strategic gains for BigTech platforms. For example, Zhenyu Gao, Yan Luo, Shu Tian and Hao Yang (2024) document that when digital platforms offer and promote green investment products such as green funds, they benefit not only from direct product uptake but also from strengthened user engagement and trust, ultimately enhancing the platform's financial ecosystem. Jiayin Hu, Shang-Jin Wei, Jianwei Xing and Eric Zou (2025) show that green actions facilitated through gamified digital platforms can foster long-term habit formation. Their findings suggest that once users adopt environmentally friendly behaviors—encouraged through small nudges or incentives—they are more likely to sustain these behaviors over time, leading to persistent engagement with the platform. Such habit persistence provides additional value to BigTech beyond immediate credit or environmental goals, including increased user stickiness, cross-product synergies, and enhanced brand reputation. Taken together, these results suggest that a green-credit-integration policy offers a multi-dimensional payoff for BigTech. To be consistent with the theoretical foundation we establish in the structural model, we emphasize the role of financial frictions in this analysis.

consumption exhibit significant and negative relationships with both default rates and default amounts. This is consistent with the expectation that greater financial resources and consumption are linked to lower default risks. Overall, our findings in Panel A suggest that individuals' green behaviors exhibit significant predictive power for default risk, indicating that environmentally responsible actions may serve as reliable and informative indicators of creditworthiness.[11]

In Panel B, we explore how the relationship between green activities and default rates varies across users with different levels of financial constraints. In Columns (1) and (2), we split the sample based on users' credit constraint levels. Users with a credit line usage rate exceeding 80% are categorized as highly constrained, indicating elevated reliance on available credit facilities. This approach allows us to compare the impact of green activities on default rates between highly constrained users and those with lower levels of credit usage.[12] In Columns (3) through (7), we segment the sample into credit line usage quintiles: users with credit usage below 20%, between 20% and 40%, between 40% and 60%, between 60% and 80%, and above 80%. This segmentation helps assess whether higher credit usage correlates with increased green behaviors.

From the results in Panel B of Table 5, we draw two key insights. First, the significant and negative relationship between green energy production and default rates is most evident among unconstrained users, suggesting that environmentally responsible behavior is more predictive of financial reliability in this group. Second, among constrained users, green activities do not significantly predict default rates.

These patterns are consistent with the theoretical model presented in the Online Appendix. For individuals with low credit utilization, green action costs make it difficult for low-type users to mimic high-type behavior, thereby allowing the platform to distinguish responsible borrowers from others and justify differentiated credit allocation. By contrast, for users already close to their credit ceilings, low-type users can more easily imitate high-type engagement, reducing the marginal signaling value of green behaviors. In this case, the platform is more likely to treat users uniformly, leading to pooling outcomes.

Overall, these findings highlight the strategic value of green behaviors for BigTech platforms. First, green actions serve as informative signals that enhance credit risk assessment. Second, they allow plat-

[11]Unreported regression results suggest that user default behavior significantly reduces credit limits. Specifically, each additional *yuan* of default amount is associated with an average 0.11% decrease in credit limits, even after controlling for individual characteristics and fixed effects. This finding underscores the platform's active penalization of risky borrower behavior and complements our main analysis on the reward side through green behavior.

[12]Our results remain invariant if we match unconstrained users with constrained ones.

forms to expand credit access without raising default risk. In this way, integrating sustainability signals into credit evaluation improves both user outcomes and platform efficiency, which delivers financial benefits to users without imposing losses on the platform.

3.5.2 Additional Results

In the Online Appendix, we present supplementary empirical evidence supporting the platform-level benefits of incorporating green behaviors into credit evaluation systems. First, in Section B.2.1, we show that users who activate Ant Forest accounts experience significantly larger increases in credit limits compared to those who do not, suggesting that environmentally linked engagement contributes positively to credit assessment.

Second, we explore the heterogeneity by user tenure in Table A7, splitting the sample at the median of Alipay registration date or Ant Forest participation date. Our key findings are twofold. To begin with, we show that green behavior signals matter more for new users. The first two columns of Table A7 reveal that for long-time users, the estimated effect of green production on credit limits is small and statistically insignificant. However, for new users, the effect is both economically and statistically meaningful: each additional unit of green energy produced is associated with a 0.26% increase in credit limit (significant at the 1% level). TThis asymmetry suggests that platforms like Alipay place greater emphasis on behavioral signals—in this case, environmentally conscious actions—when evaluating users with limited historical financial data. That is, green behavior plays a stronger screening role for new users, consistent with the idea that such behavior serves as a proxy for unobservable traits like responsibility or conscientiousness. Furthermore, in the last four columns, we flip the analysis, examining how financial constraints affect green behaviors and find that financial constraint incentive is stronger for new users. Across all users, higher credit usage rates and a high-constraint dummy are positively associated with increased green energy production. Importantly, the coefficients are substantially larger for new users: the elasticity of green behavior with respect to credit usage is 0.148 for new users versus 0.103 for long-time users. The effect of binding credit constraints is also stronger among new users (0.268) compared to old users (0.179). These results imply that new users are more responsive to financial incentives when engaging in green actions. One plausible interpretation is that newer participants in Ant Forest may be more attentive to immediate, extrinsic benefits—such as credit access—compared to long-time users who might already be habituated or less reactive to marginal credit gains.

Taken together, these findings reinforce the value of green engagement as a rich source of soft information for BigTech lenders, particularly when external data is limited or unavailable and during the on-boarding phase of a user's platform lifecycle. The platform benefits not only through improved risk screening but also by extending credit access in a sustainable and inclusive manner.

4 Quantitative Analysis

To interpret our empirical findings and formally evaluate the policy implications, we develop a partial-equilibrium dynamic model featuring endogenous green behavior and borrowing constraints. This model serves two key purposes. First, it allows us to quantify the "green value" of linking credit access to eco-friendly actions. Second, the model enables a welfare comparison between this incentive-compatible mechanism and more traditional approaches, such as environmental mandates and subsidies.

4.1 Model Setup

The model features an infinite-horizon, discrete-time economy with a constant risk-free rate r. Users are heterogeneous in two dimensions: (perceived) green costs and financial responsibility. For tractability, we assume these traits are perfectly correlated, i.e., users with low perceived green costs are also financially responsible (green type), while those with high green costs are financially irresponsible (brown type). The share of green-type users in the population is denoted by α. All users on the Ant Forest platform maximize the following expected present value of future utility $\mathcal{V}_0$:

$$\mathcal{V}_0 = \mathbb{E}\left[\sum_{t=0}^{\infty} \frac{u\left(c_t, \omega_t; \underline{c}_t\right)}{(1+r)^t}\right] \tag{4}$$

where c_t denotes consumption, ω_t measures the green activities, and $\underline{c}$ is the subsistence level of consumption at time t. For simplicity, we omit time subscripts going forward and use a prime symbol $'$ to denote next-period variables, and $i \in \{G, B\}$ indexes user types and captures the source of heterogeneity in the model.

The utility function $u(c, \omega; \underline{c})$ is given by the following functional form:

$$u(c,\omega;\underline{c}) = \left[\gamma\,(c-\underline{c})^{\frac{\xi-1}{\xi}} + (1-\gamma)\,\omega^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi}{\xi-1}} \tag{5}$$

The equation above represents a nonhomothetic Stone-Geary preference, where $0 < \gamma < 1$ and $\xi > 0$. $\underline{c}$ follows a stochastic process, with its natural logarithm, $\ln \underline{c}$, evolving according to an AR(1) process shown below:

$$\ln \underline{c}' = \rho \ln \underline{c} + \sigma\varepsilon \tag{6}$$

where $\rho \in (0,1)$ is the autoregressive coefficient, $\sigma > 0$ is the volatility of subsistence consumption shocks, and $\varepsilon \sim \mathcal{N}(0,1)$ is a standard normal random variable. When σ increases, users face greater uncertainty in their consumption requirements. A larger value of ρ suggests that these shocks have more lasting or prolonged effects over time.

The utility function specified in Equation (5) is inspired by the structural transformation literature (e.g., Berthold Herrendorf, Richard Rogerson and Akos Valentinyi, 2013; Piyabha Kongsamut, Sergio Rebelo and Danyang Xie, 2001), which examines how household preferences influence sectoral labor reallocation dynamics. Several important features characterize this utility function. First, the function incorporates environmental consciousness through green activities ω, which directly contribute to user utility (i.e., green-in-utility). The parameter γ represents the share parameter, while $\frac{\xi-1}{\xi}$ determines whether consumption and green activities are substitutes (if $\xi > 1$) or complements (if $0 < \xi < 1$).[13] Second, the parameter $\underline{c}$ represents a minimum consumption threshold that users must maintain, i.e., $c \geq \underline{c}$. This threshold varies over time due to random shocks, which acts similarly as liquidity shocks and thus makes access to credit valuable for users facing liquidity constraints. Third, the positive value of $\underline{c}$ implies that the income elasticity of consumption is lower than that of green activities. This aligns with empirical observations that environmental consciousness tends to increase with wealth.

We model the user's income as a constant stream of $\bar{y}$ per period, as either income shocks or unexpected consumption shocks are necessary to make borrowing constraints relevant in our framework. Users can manage their consumption through the BigTech platform by either borrowing or saving (b'). When users save (i.e., $b' < 0$), they earn the risk-free interest rate r. For borrowing (i.e., $b' > 0$), the

[13]The parameter γ, representing intrinsic green awareness, plays a crucial role in our subsequent welfare analysis, as it influences the effectiveness of different policy instruments across countries with varying levels of environmental consciousness.

cost structure is two-tiered: borrowing within the credit limit $\bar{b}$ incurs a standard interest rate r^{BNPL} (i.e., the interest rate users need to pay when using the Alipay's virtual credit card "Buy Now Pay Later"), while exceeding this limit triggers an additional penalty cost of $\left(b' - \bar{b}\right)^{\eta^i}$, where $\eta^i > 0$ represents the severity of the penalty. This penalty parameter η can be justified by real-world circumstances: users might need to resort to more expensive alternative funding sources for unexpected expenses, or they might face negative consequences from damaged credit scores when exceeding their limits. This modeling approach, following the dynamic credit constraint literature (e.g., Niklas Amberg, Tor Jacobson, Vincenzo Quadrini and Anna Rogantini Picco, 2023), allows us to capture financial distress without explicitly modeling complex default scenarios. To capture behavioral heterogeneity across user types, we assume that green users face steeper penalties, i.e., $\eta^G > \eta^B$. This assumption reflects the idea that green users are more financially responsible and more averse to breaching credit limits—either due to better access to formal credit or a stronger preference for maintaining financial health. In contrast, brown users are modeled as less financially disciplined, facing lower perceived or actual penalties when exceeding borrowing limits. This brown-green heterogeneity plays a key role in shaping both default behavior and green engagement within the model.

The user's credit limit $\bar{b}$ is linked to their accumulated green capital stock κ, reflecting both the BigTech platform's actual lending practices and our empirical findings presented in Section 3.3. The borrowing constraint takes the following form:

$$\bar{b} = \lambda \bar{y} \kappa^{\theta} \tag{7}$$

Here $\bar{y}$ serves merely as a normalization factor. The parameter λ determines the baseline credit constraint, while θ quantifies how much green behavior influences the credit limit. Through this formulation, users can expand their borrowing capacity by increasing their green capital stock κ. In our model, λ represents the platform's universal lending standard applied to all users regardless of their environmental behavior. Meanwhile, θ is shaped by both the extent of data-sharing within the BigTech ecosystem and regulatory restrictions on using external data for credit assessment. While this approach shares some similarities with the financial development literature (e.g., Francisco J. Buera and Yongseok Shin, 2013), our primary focus is on evaluating the benefits of connecting green behavior to credit access. The credit limit plays a crucial role as it provides the only tool for consumption smoothing and managing unexpected expenses. As a result, in our model, green actions become valuable through two channels: they directly enhance utility through the "green-in-utility" feature and indirectly benefit users by expanding their borrowing capacity and reducing financial constraints.

Green capital κ has a depreciation rate of $0 < \delta < 1$, and is accumulated through investment ω, which represents the costly green actions undertaken by users. In line with Fumio Hayashi (1982) and related studies, we assume that there are quadratic adjustment costs associated with converting final goods into green capital:

$$\Psi^i\left(\kappa, \frac{\omega}{\kappa}\right) = \frac{1}{2\phi^i}\left(\frac{\omega}{\kappa}\right)^2 \kappa \tag{8}$$

where ϕ^i governs the inflexibility of green capital accumulation for user type $i \in \{G, B\}$. A higher ϕ^i implies lower adjustment costs and greater flexibility in undertaking green investment. We assume that $\phi^G > \phi^B$, meaning that green users face lower adjustment costs and are more efficient in translating costly green actions into accumulated green capital. This captures the idea that green users are either more informed, more intrinsically motivated, or more practiced in adopting sustainable behaviors, whereas brown users face higher frictions—psychological, informational, or logistical—that make green investment more rigid and costly. This heterogeneity plays a central role in shaping the differential responses to incentives across user types in our model. To better reflect real-world constraints, we assume that green capital investment is irreversible, i.e., $\omega \geq 0$. Although the modeling of green actions as costly may seem counterintuitive at first glance, this feature is grounded in the signaling-based microfoundation developed in Section 3.3.3.

In this way, the user's budget constraint on the Ant Forest platform is:

$$c + \omega + \Psi^i\left(\kappa, \frac{\omega}{\kappa}\right) + b = \bar{y} + \mathbb{1}_{b'<0}\frac{b'}{1+r} + \mathbb{1}_{0<b'<\bar{b}}\frac{b'}{1+r^{BNPL}} + \mathbb{1}_{b'>\bar{b}}\frac{\left(b'-\bar{b}\right)^{\eta^i} + \bar{b}}{1+r^{BNPL}} \tag{9}$$

where $c > \underline{c}$ is consumption, ω is investment in green capital, b is the existing debt or saving, and b' is the new borrowing or saving.

To sum up, the user's optimization problem with value function $\mathcal{V}$ can then be expressed below:

$$\mathcal{V}\left(\underline{c}, \kappa, b\right) = \max_{c,\omega,b'}\left\{u\left(c, \omega; \underline{c}\right) + \frac{1}{1+r}\mathbb{E}\left[\mathcal{V}\left(\underline{c}', \kappa', b'\right)\right]\right\} \tag{10}$$

subject to the constraints:

$$
\begin{aligned}
c+\omega+\Psi^{i}\left(\kappa,\frac{\omega}{\kappa}\right)+b &= \bar{y}+\mathbb{1}_{b'<0}\frac{b'}{1+r}+\mathbb{1}_{0<b'<\bar{b}}\frac{b'}{1+r^{BNPL}}+\mathbb{1}_{b'>\bar{b}}\frac{\left(b'-\bar{b}\right)^{\eta^{i}}+\bar{b}}{1+r^{BNPL}}, \\
\kappa' &= \omega+(1-\delta)\,\kappa, \\
\kappa',\omega &\geq 0, \\
c &\geq \underline{c}.
\end{aligned}
$$

As in Mikhail Golosov, John Hassler, Per Krusell and Aleh Tsyvinski (2014), we assume that green actions generate a positive externality represented by $D(\omega)$, where D is an increasing function of green investment ω. In this way, there is room for policy intervention. This formulation provides a rationale for government intervention, as individual choices do not fully internalize the social benefits of green behavior. While the specific functional form of D does not affect our analysis—since we focus on perceived individual welfare, which excludes externalities—the inclusion of $D(\omega)$ serves to justify the normative foundation for policy intervention within the model.

4.2 Parametrization

The model is calibrated on an annual frequency. To minimize computational complexity, we externally calibrate a subset of parameters while structurally estimating the remaining ones. Since the model lacks analytical solutions, we employ the simulated method of moments (SMM) approach (e.g., Daniel McFadden, 1989; Boris Nikolov and Toni M. Whited, 2014) for the structural parameter estimation.

Panel A of Table 6 summarizes the externally calibrated parameters. The risk-free interest rate is set at 1.5%, which is based on the average deposit interest rate in China from 2019 to 2022. The borrowing interest rate through Ant Group Financial is set at 18%, derived from its daily rate of 0.05%. For the subsistence consumption dynamics, given the challenges in directly observing these fluctuations and our assumption of fixed periodic income, we align these dynamics with those of income.[14] Following Tak Wing Chan, John Ermisch and Rob Gruijters (2019), we set the persistence parameter to 0.37 and

[14] We also tested an alternative specification where we normalized the long-run average income to 1.0, maintained the same persistence in subsistence consumption as income, and estimated the volatility of subsistence consumption internally. This approach yielded similar results.

the shock volatility to 1.11. These values capture the autoregressive nature and variability of household income or subsistence consumption patterns in China, where households typically experience lower income persistence and higher volatility compared to their counterparts in advanced economies such as Germany and the United States.

We use the Simulated Method of Moments (SMM) to jointly estimate eleven key structural parameters: long-run average income ($\bar{y}$), the share parameter (γ), the elasticity of intertemporal substitution (ξ), the capital depreciation rate δ, the degree of financial frictions (λ), the soft-information lending sensitivity (θ), the fraction of intrinsic green users α, the green capital adjustment cost parameter (ϕ^i, where $i \in \{G, B\}$), and the repayment penalty (η^i, where $i \in \{G, B\}$). Panel B of Table 6 reports the model's fit by comparing empirical moments with their simulated counterparts. The standard deviation of consumption is 0.35 in the data, compared to 0.43 in the model. The average consumption-to-income ratio is 0.60 empirically and 0.55 in the model; both values in the data are drawn from Marcos Chamon, Kai Liu and Eswar Prasad (2013). The median log ratio of consumption to green energy production is 0.56 in the data and 0.64 in the model. The median credit usage rate stands at 2.9% in the data and 3.3% in the model. Regarding the relationship between green activity and credit access, the median ratio of green capital investment to credit limit is 0.05 in the data and 0.09 in the model, consistent with the idea that users leverage green behavior to improve credit outcomes. For default rates, the empirical average is 0.99%, while the model produces 1.05%. Within subsamples, the default rate for the 0–20% credit usage group is 1.35% in the data and 1.48% in the model, and for the 80–100% group, the corresponding rates are 0.06% and 0.10%. The correlation between credit limit and green capital investment—capturing the predictive power of soft behavioral signals—is 0.11 in the data and 0.13 in the model. This relationship is especially strong for users with low credit usage (0–20%), where the correlation is 0.25 in both the data and the model. Among users with high credit usage (80–100%), the correlation drops to 0.04 empirically and 0.09 in the model. Finally, we consider the correlation between credit usage rate and green activity, which helps identify the share parameter γ that reflects intrinsic environmental concern. For the full sample, this correlation is 0.20 in the data and 0.25 in the model. Among users with low credit usage (0–20%), the correlation is 0.18 in the data and 0.15 in the model, whereas for the high-usage group (80–100%), it is 0.04 empirically and 0.07 in the model.

Using these data moments, we estimate the internally calibrated parameters reported in Panel B of

Table 6. Specifically, the long-run average income is estimated at 1.35 with a standard error of 0.11. The share parameter γ is 0.70, with a standard error of 0.05.[15] The elasticity of substitution parameter ξ is estimated at 2.11 (s.e. = 0.30), suggesting that consumption and green actions act as substitutes. The green capital depreciation rate δ is estimated at 0.20 with a standard error of 0.06. The degree of financial frictions λ is estimated at 0.46 (s.e. = 0.08), indicating moderate but non-negligible borrowing constraints. The soft-information lending sensitivity θ is 0.66 with a standard error of 0.10. The adjustment cost parameter ϕ differs by type: for green-type users, it is estimated at 2.30 (s.e. = 0.31), while for brown-type users, it is 1.05 (s.e. = 0.12). This implies that brown users face steeper adjustment costs, reflecting greater frictions in modifying their green capital stock. Lastly, the estimated repayment penalty parameter η is 1.78 (s.e. = 0.24) for green-type users and 1.19 (s.e. = 0.17) for brown-type users. The higher value for green users suggests that they face stronger penalties for delayed repayments, consistent with more disciplined financial behavior and a greater aversion to delinquency.

4.3 Quantitative Performance

Figure 2 assesses the quantitative performance of the calibrated model by comparing model-generated outcomes (shown as orange and purple diamonds) with untargeted empirical data (represented by blue and green circles) across varying credit usage rates. The horizontal axis categorizes credit usage rates into intervals ranging from 0–20% to 80–100%. Graph (a) examines how green behaviors respond to credit usage rates across different credit usage groups. The empirical estimates are from Column (5) of Table 4. This graph highlights the role of financial incentives in driving green activities, as evidenced in both the data and the model. Graph (b) analyzes how green energy production affects default rate sensitivity across credit usage groups. The empirical estimates here are drawn from Columns (3)–(7) in Panel B of Table 5. This graph demonstrates the influence of green activities on reducing default rates, as captured by both the data and the model.

According to Figure 2, our model closely matches the empirical data across most credit usage ranges, indicating that the calibrated parameters effectively capture the varying incentives and consequences of green energy production across different credit line usage groups. In Graph A, the group with the low-

[15]The green-in-utility term in our model captures all non-financial motivations for green behavior, including intrinsic environmental preferences and platform-specific features such as gamification. Our focus is on distinguishing green actions driven by financial constraints from those motivated by other factors.

est credit usage rates (0–20%) serves as the benchmark, which explains the zero coefficient for financial incentives related to green actions in this category. As credit usage rates increase, both the model and the data exhibit a clear upward trend in scaled green energy production. In addition, the estimated absolute values from the model and empirical data are largely consistent, though the model slightly underestimates the coefficients for moderate credit usage ranges (20–40% and 40–60%) and slightly overestimates them for users with higher credit usage rates (60–80%). These discrepancies may arise because the model focuses exclusively on the financial friction mechanism, whereas real-world users may have additional motivations for engaging in green behaviors. Another possible explanation is that, in reality, the borrowing constraint parameter λ may vary across credit usage groups, whereas the model assumes a constant λ for all groups. At the highest credit usage range (80–100%), the model slightly exceeds the empirical data. This suggests that users near the upper limit of their credit lines are the most active in producing green energy. The underlying mechanism is that individuals with greater borrowing capacity have stronger incentives to engage in green activities. This alignment at high credit usage rates further supports the model's accuracy in predicting green investment behavior for financially engaged users. The model's slightly stronger incentives compared to the data may be due to additional platform-imposed credit limits (e.g., a maximum credit limit of 55,000 *yuan* or 7,857 US dollars), which are not explicitly accounted for in the model.

Graph B further illustrates that the model closely mirrors empirical patterns in how green energy production affects default rates across credit usage groups. Specifically, both the model and the data show that higher green energy production is associated with lower default rates among users with low credit usage (0–20%), while the relationship weakens or disappears for users with high credit usage. This pattern is consistent with the model's underlying signaling mechanism. For users with low credit usage, the platform is able to distinguish between high- and low-type individuals based on their green investment behavior—resulting in a separating equilibrium where green actions credibly signal user type and thus predict default risk. In contrast, for high-usage users, borrowing constraints bind tightly and the marginal informativeness of green behavior diminishes. This leads to a pooling equilibrium, where green actions no longer provide a reliable signal of user type, and their predictive power for default outcomes fades. In this way, the model not only replicates the observed heterogeneity in the green-default relationship but also provides a microfoundation for interpreting when and why green actions serve as effective screening devices for creditworthiness.

Overall, the calibrated model closely matches the empirical patterns across credit usage groups, underscoring how credit limits and financial constraints shape green investment behavior without raising default risk.

4.4 Quantifying the Green Value of BigTech Credit

In this section, we perform counterfactual analyses using our calibrated model to quantify the green value of BigTech credit by varying the strength of the link between green behavior and credit outcomes, captured by the parameter θ. This parameter reflects the degree of integration between users' environmentally friendly actions and their credit limit determinations within the BigTech ecosystem. Reductions in θ represent weaker internal linkages across business functions, which in turn reduce the platform's ability to translate green behavior into credit benefits. Our counterfactual simulations explore two dimensions of impact. On the societal side, we measure green losses as the percentage decline in equilibrium green capital stock when θ is lowered. On the platform side, we decompose losses into (1) the value loss from diminished predictive power of behavioral signals, captured by an increase in equilibrium default probability, and (2) the decline in lending profits. Both metrics are calculated as percentage deviations from the steady-state outcomes in the baseline case.

Figure 3 reports model-implied losses under varying degrees of weakening the link between green actions and credit limits, captured by reductions in the parameter θ from its baseline value of 0.66. For example, a 10% reduction corresponds to $\theta = 0.59$. We compute the new steady-state for each θ level and compare the outcomes against the baseline to evaluate three loss categories: BigTech Credit Value Loss, BigTech Soft Information Value Loss, and Green Value Loss.

Three key insights emerge. First, profits from BigTech lending decline substantially as the credit-green linkage weakens. The BigTech Credit Value Loss increases from 3.28% at a 10% reduction to 22.07% at full severance. This decline is driven by (i) reduced borrowing as users receive lower credit limits and (ii) lower bond prices stemming from higher default risk. These results highlight the central role of user behavioral data in credit risk assessment and lending profitability. Second, the BigTech Soft Information Value Loss, proxied by increases in default probability, rises more gradually—from 1.49% to 15.36%—but accounts for a growing share of total lending losses. For instance, at 10% linkage reduction, soft information explains 45.4% of the overall profit decline (i.e., 1.49% out of 3.28%); this share rises to 69.5% under complete unlinking. Thus, green behaviors offer not only environmental but also financial value by helping reduce credit risk. Third, weakening the green-credit connection leads to a sharp reduction in equilibrium green capital stock. Green Value Loss grows from 3.94% at a 10% reduction to 30.58% under full disconnection. During our sample period, average cumulative green capital per user is estimated at 68,181 grams. A 10% weakening reduces annual green energy production by 671.58 grams—roughly equal to the carbon absorbed by one tree over 13 days.

Given Ant Forest's scale (over 600 million users), these reductions translate into sizable societal costs. At current EU carbon prices of $132.12/ton,[16] the annual cost of a 10% reduction is $53.23 million (approximately 372.63 million *yuan*), while a full break raises this to $413.20 million (approximately 2.89 billion *yuan*). On average, the green value per user is modest—$0.69/year—because only a minority are severely credit constrained. However, for the 3.5% of users with credit usage above 80%, the average green value rises to $19.60/year (approximately 137.24 *yuan*), equivalent to 4.3% of their wealth.

These results underscore that weakening the green-credit linkage undermines both lending performance and green outcomes. Unlike lending losses, which platforms could potentially recoup by relaxing credit standards (e.g., raising λ), green value losses are not easily restored by alternative means. This distinction will be further explored in the next section.

4.5 Welfare Analysis and Policy Implications

4.5.1 Social Welfare vs. Perceived Welfare

In this section, we analyze the welfare implications of various policy tools by comparing our proposed data-sharing policy with alternatives such as mandatory green action thresholds and subsidies for green activities. We focus on two welfare indicators: consumer perceived welfare, which represents the lifetime utility $\mathcal{V}$ of a typical platform user, and total perceived welfare, which is the sum of consumer perceived welfare and the profits generated by the BigTech platform. This welfare analysis strengthens the case that a green-actions-integrated credit framework offers greater advantages than alternative policy tools.

We focus on perceived welfare—defined as individual utility excluding externalities—rather than actual social welfare. In our model, a benevolent government ensures that any policy intervention raises

[16] Sourced from the World Bank's Carbon Pricing Dashboard, February 2025.

actual welfare. However, following the argument in Besley and Persson (2023), even welfare-improving policies may not be politically sustainable if individuals do not perceive these gains. Because voters typically base their decisions on personal utility rather than accounting for broader externalities, governments that raise actual welfare may still face electoral backlash. Therefore, perceived welfare provides a more relevant metric for assessing the feasibility and political acceptability of green credit policies.

Our analysis of the green-credit-integration policy mirrors the approach used in the prior section. To evaluate the effectiveness of the mandatory green action tool, we impose a requirement that green capital investment in each period must exceed a specified threshold, denoted by $\bar{\omega}$. This threshold is calibrated to the average green energy production level of the bottom 10% of inactive users in our model simulation. For the subsidy policy, we introduce a negative tax on the adjustment costs associated with green capital investments. The baseline subsidy is set at 10%,[17] financed through a lump-sum tax on BigTech profits. To isolate the effects of each policy tool, we set the parameters of the other tools to zero during testing.

To explore the cross-country implications of our findings, we use the Climate Perceptions Index from the Social Progress website, which incorporates insights from over 100,000 active Facebook users across 107 countries. The index captures three key dimensions: awareness of climate change, risk perception, and commitment to taking action. It offers valuable insights into the societal implications of climate change and serves as a guide for political leaders in identifying areas to strengthen public support for climate initiatives. To ensure consistent comparisons, we normalize the values by setting China's score to 1.0 and display them as green markers in Figure 4. The plot is arranged in a monotonically decreasing order of climate perception degree along the x-axis.[18] In our model, these variations are reflected in the parameter γ, which represents users' intrinsic green value. In our framework, higher climate perception corresponds to a lower γ value.[19] This approach enables us to compare the relative effectiveness of different policy tools across countries with varying levels of climate perception.

[17]While the choice of 10% is ad hoc, our main conclusions remain robust to alternative values.
[18]Due to the lack of Facebook data from mainland China, the average score from Hong Kong and Taiwan is used as a proxy.
[19]For instance, Portugal's rescaled climate perception index is 1.31, resulting in a γ value of 0.67/1.31 = 0.51.

4.5.2 Comparing Perceived Welfare

Graphs A and B in Figure 4 present the results of our consumer welfare and total welfare analyses, respectively. We compare the welfare changes associated with each policy tool as the climate perception level γ varies across countries. Generally speaking, these policy tools have distinct impacts on consumer welfare, as well as different effectiveness across countries. Our main conclusions are threefold. First, mandatory green action levels are not effective under any circumstances. As shown by the solid blue line in Figure 4, these mandates are ineffective in countries with high climate perception, where the mandatory levels do not constrain behavior. In contrast, in countries with low climate perceptions, mandated green actions are effective in raising the equilibrium green capital stock, but they negatively impact both consumer and total welfare. This result comes from the fact that while higher mandated green activity may offer environmental benefits, it places a heavy burden on consumers, as households must incur significant costs to comply with these actions. This increased burden effectively reduces consumers' average income levels. Additionally, it also harms BigTech's profits, as consumers have less disposable income to save or borrow, given the reduced expected income due to the mandatory green action policy.

Second, as shown in the orange dashed lines in Figure 4, the subsidy policy is more effective in enhancing consumer welfare in countries with high climate perception, but not so much in raising total welfare. By reducing the costs of green actions, the subsidy makes these behaviors more affordable, thus improving consumer welfare. However, this policy alone does not provide any additional motivation for consumers to engage in green activities. As a result, the policy is more effective in countries where many people are already inclined to take green actions, such as European countries (e.g., France, Germany, and Switzerland). In contrast, in countries with lower climate perception, where green actions offer lower perceived benefits, the subsidy's effectiveness is less pronounced. Additionally, we find that the total welfare impact of this subsidy policy is negligible. In our model, the subsidy is financed through lump-sum taxes on BigTech, making the policy a zero-sum game for consumers and BigTech as a whole. These findings suggest that while both mandatory green action levels and subsidies for green activities may increase green behavior in the short term, they face significant long-term challenges. The mandatory policy creates negative welfare impacts for consumers in countries with low intrinsic green values, while subsidies require substantial accompanied financing, either from the corporate taxes or government deficits.

Third, as shown by the purple dotted lines in Figure 4, our proposed Green Credit Signaling Framework significantly enhances both consumer and total welfare, especially in countries with low climate awareness. This effectiveness stems from the framework's incentive-compatible and selective structure, which targets households most constrained by credit. In oil-producing and developing economies such as China, Malaysia, and Indonesia, the framework is particularly impactful—motivating environmentally passive users to engage in green activities by linking such actions to tangible financial benefits. At the same time, it increases BigTech profits by raising users' borrowing limits, thereby expanding lending margins. These dual benefits highlight the long-run sustainability of the approach. Unlike traditional mandates or subsidies, the framework we identify offers a scalable and market-aligned solution that aligns private incentives with public environmental objectives. In settings like China, where digital platforms such as Alipay and Tencent play central economic roles, regulators may find value in adopting an integrated model that links commercial engagement with contributions to environmental public goods.

Our last finding is particularly relevant to ongoing debates about the role of BigTech firms and the extent to which data sharing across their business segments should be regulated. While concerns over consumer privacy and the broader influence of dominant firms remain central to these discussions,[20] our analysis here seeks to highlight the potential welfare trade-offs associated with stricter data-sharing policies. Policymakers should strike a balance between protecting privacy and preserving the economic and environmental benefits that integrated data services can offer.

5 Conclusion

This paper investigates the green value of BigTech lending by analyzing data from 100,000 randomly selected users of Ant Forest, a carbon accounting platform embedded within Alipay—a central component of China's BigTech ecosystem. Using 48 months of user-level panel data, we show that individuals engage in eco-friendly behaviors to enhance their credit limits, particularly when approaching borrowing constraints. These costly green actions serve a dual function: they improve users' perceived financial standing and simultaneously provide soft information that enables the platform to better assess cred-

[20]For related discussions, see, for example, https://www.nytimes.com/2023/03/28/business/alibaba-china-e-commerce.html, https://www.economist.com/leaders/2024/10/03/dismantling-google-is-a-terrible-idea, and https://www.economist.com/briefing/2018/01/20/the-techlash-against-amazon-facebook-and-google-and-what-they-can-do.

itworthiness. This screening mechanism parallels classical signaling models, wherein only financially responsible users are willing to bear the cost of sustained green engagement. We further develop a structural model to quantify the welfare implications of this incentive-compatible mechanism, emphasizing perceived welfare—utility excluding externalities—as the relevant benchmark for policy evaluation. Our findings suggest that green behaviors, when embedded in lending decisions, can align private incentives with environmental goals without sacrificing user welfare or platform efficiency.

Our results show that while it is well understood that credit can serve as an incentive tool for promoting green investment, particularly among firms, our findings reveal a novel insight: green actions can also serve as a *screening mechanism* in household lending. This role of green behavior as soft information—correlated with financial responsibility—has been overlooked in both the policy and academic literature. The integration of personal carbon accounts into BigTech credit systems provides a scalable, market-based approach to promoting sustainability. Unlike traditional ESG policies, which often rely on mandates or subsidies, this data-driven mechanism aligns private and environmental incentives without imposing direct fiscal costs. For policymakers, especially in regions without mature BigTech or banking ecosystems, our findings suggest that personal carbon account data could be incorporated into existing credit reporting or digital finance frameworks to enhance both sustainability and financial inclusion. By highlighting the screening function of green actions, our study offers new directions for leveraging behavioral data in the transition to low-carbon economies.

One limitation of our proposed financial reward approach is that it appears less effective for high-income individuals. Since our approach is incentive-compatible, it cannot effectively motivate wealthy individuals through financial benefits. As noted in the survey by Luis Mundaca and Christine Wamsler (2025), other possible interventions aimed at high-income earners also have limited success in motivating climate action. Specifically, neither injunctive social norms nor guilt and pride priming are effective in engaging high earners in climate behaviors. We suggest that future research investigate the role of household inequality to provide valuable policy insights into the challenges and opportunities of involving affluent individuals in urgent climate action.

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Figures and Tables

Figure 1: **Green Energy Production and Credit Score within the Alipay Ecosystem**

Notes: This image is a screenshot from a user's BigTech app interface, displaying various tips for improving one's credit score within the BigTech ecosystem. Notably, Ant Forest is prominently featured as a top recommendation, carrying similar weight in credit score improvement as submitting a housing fund certificate.

Figure 2: **Quantitative Performance: Model vs. Data**

Notes: This figure demonstrates the quantitative performance of the calibrated model by comparing model-generated outcomes (represented by orange and purple diamonds) with empirical data (represented by blue and green circles) across different credit line usage rates. In both graphs, the horizontal axis categorizes credit line usage rates into five groups, ranging from 0–20% to 80–100%. In Graph (a), the vertical axis shows the sensitivity of green actions to credit usage rate, while in Graph (b), the y-axis represents the sensitivity of default rates to green energy production.

(a) financial incentives (b) default rate consequences

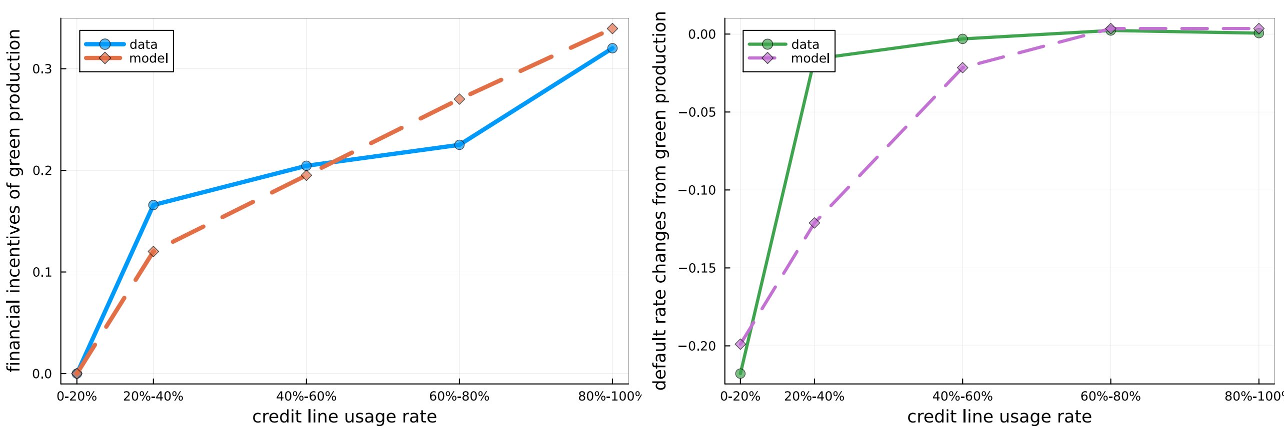

Figure 3: **Counterfactual Exercises**

Notes: This figure summarizes the counterfactual analyses using our calibrated model to examine the welfare implications of changes in green-linked credit policies. In our model, data-sharing restrictions are represented as a percentage reduction in θ from its baseline value of 0.66, which was estimated in our baseline analysis. Our focus is on two key aspects: societal green losses and BigTech losses. Green losses refer to the decline in the equilibrium green capital stock under different levels of data-sharing restrictions. BigTech losses are further broken down into two components: the soft information value loss, which is computed as the increases in equilibrium default rate, and the net profit loss from lending services. These losses are calculated as the difference between the steady-state outcomes under the new regulatory environment and those observed in our baseline analysis.

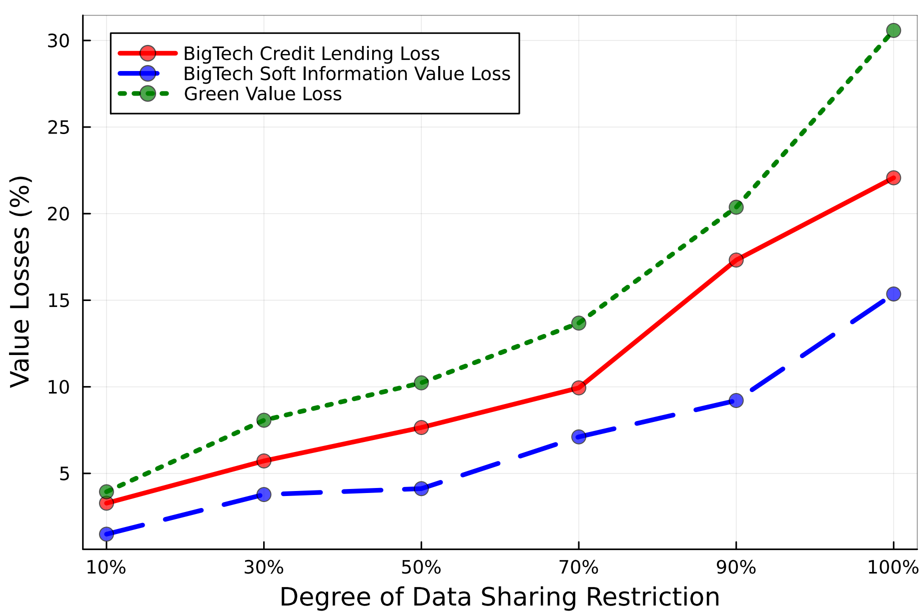

Figure 4: **Welfare Analysis**

Notes: This figure examines the welfare implications of various policy tools by comparing our proposed data-sharing policy with alternatives, such as mandatory green action levels and subsidies for green activities. The consumer perceived welfare target is the lifetime utility of the representative platform user. Meanwhile, the total perceived welfare is the sum of consumer perceived welfare and platform profits. The impact of our proposed green-linked credit policy on welfare is shown as the purple dashed line in the figure. For the mandatory green activity policy, represented by the blue solid line, we impose a requirement that each period's green capital investment must exceed a specified threshold, $\bar{\omega}$, calibrated to the average green energy production level of the bottom 10% of inactive users in our dataset. For the subsidy policy, represented by the orange dashed line, we introduce a negative tax on the adjustment costs related to green capital investments. The baseline subsidy is set to 10%, which is from the taxes imposed on BigTech profits. The underlying climate perceptions index is a comprehensive metric designed to assess public views on climate change, and the data for the index is sourced from Social Progress. To facilitate comparison, we have rescaled the values by normalizing China's score to 1.0. For detailed descriptions, please refer to Figure A7 in the Online Appendix.

(a) consumer welfare (b) total welfare

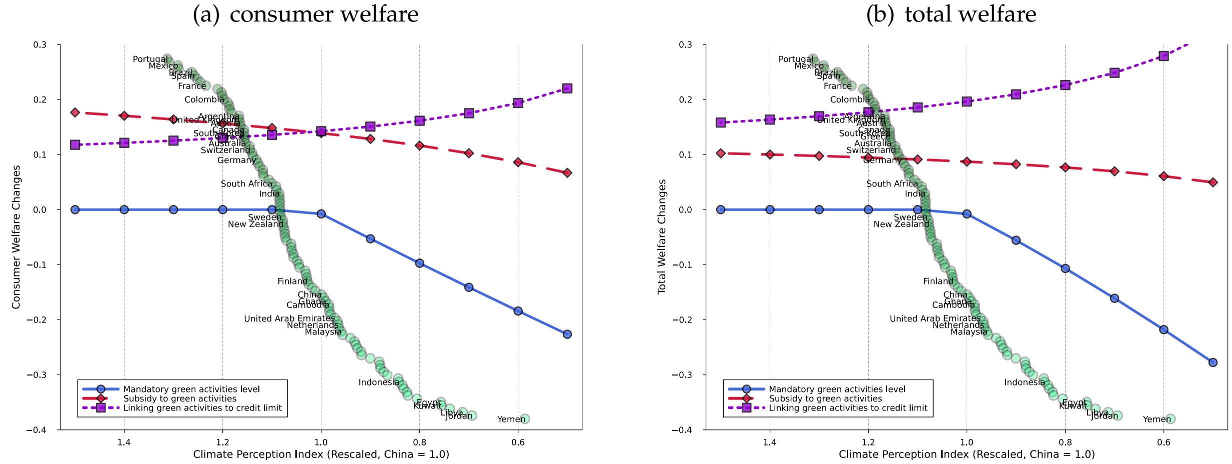

Table 1: **Descriptive Statistics**

Notes: Panel A provides the summary statistics for our full sample. The raw dataset comprises monthly data from 100,000 users over a 48-month period, spanning January 2019 to December 2022. To be included in our regression sample, individuals must have complete information on their credit limit history, resulting in a final sample size of 3,945,168 user-month observations. In Panel B, we provide the summary statistics for subsamples with different credit usage rates. The credit usage rate is defined as the percentage obtained by dividing the amount of credit utilized by the total credit limit. Users are classified into categories ranging from those with zero credit usage to individuals fully utilizing their credit limits.

Panel A: Full Sample

Category	Variable	Sample Size	Mean	Std Dev	Min	Median	Max
User characteristics	age	3,945,168	31.7	9.6	18	30	69
	gender	3,945,168	0.47	0.50	0	0	1
Green Behaviors	green energy production	3,945,168	1,200	1,501	0	611	6,965
	green energy stealing	3,945,168	324	1,078	0	0	6,982
	green energy collection	3,945,168	516	1,120	0	0	5,847
	Eco-high behaviors	3,945,168	1,096	1,440	0	511	6,708
	Eco-low behaviors	3,945,168	99	203	0	0	1,048
Biodiversity protection efforts	accumulated # of trees planted	3,945,168	0.84	1.87	0	0	10
	accumulated # of reserves protected	3,945,168	1.23	3.03	0	0	19
	accumulated area of reserve protected	3,945,168	1.25	3.05	0	0	19
Credit	credit line limit	3,945,168	14,501	13,926	0	9,600	55,000
	credit line usage	3,945,168	1,200	2,342	0	301	14,697
	default amount	3,945,168	54	1,021	0	0	55,000
	default rate	3,899,640	0.98%	9.8%	0	0	100%
Other Variables	ln(consumption)	3,945,168	6.4	2.6	0	7.0	10.7
	ln(total financial assets)	3,945,168	3.9	3.7	0	3.0	11.8

Panel B: Subsample with Different Credit Usage Rates

Credit usage rate μ	$\mu = 0$	$0 < \mu \leq 20\%$	$20\% < \mu \leq 40\%$	$40\% < \mu \leq 60\%$	$60\% < \mu \leq 80\%$	$80\% < \mu < 100\%$	$\mu = 100\%$
Average Age	33.4	31.8	29.1	28.5	28.4	29.2	27.6
Average Gender: 0 (Male), 1 (Female)	0.47	0.49	0.46	0.44	0.42	0.37	0.37
Average ln(Total Financial Assets)	3.11	4.34	3.93	3.76	3.62	3.32	3.21
Average ln(Consumption Amount)	4.58	6.89	7.70	7.77	7.77	7.59	7.58
Average Credit Limit	9,904	18,910	12,686	8,829	6,322	4,194	2,506
Average ln(Green Production)	3.91	5.62	5.85	5.83	5.76	5.58	5.66
# of Observations	1,062,534	2,065,305	339,823	139,060	74,262	62,332	74,821
Percentages	26.9%	52.4%	8.6%	3.5%	1.9%	1.6%	1.9%

Table 2: **Screening Role of Green Behaviors for Determining Credit Limit**

Notes: Panel A reports OLS estimates of the relationship between log credit limits and green energy production. Columns (1) and (3) exclude control variables such as financial assets and consumption. Columns (3) and (4) additionally account for potential COVID-related effects by controlling for city-level monthly case counts. All regressions include fixed effects at the individual (except for the last column), time, and city-by-year levels. Standard errors are clustered at the individual level. Panel B examines alternative green behavior indicators, including green energy stealing, energy collection, number of trees planted, number of nature reserves protected, and total reserve area. All regressions include standard control variables as well as fixed effects for individuals, time, and city-by-year. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Green Energy Production and Credit Access

	Dependent Variable: ln(Credit Limit)				
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
green energy production	0.0043***	0.0017**	0.0046***	0.0019***	0.0371***
	(6.00)	(2.41)	(6.38)	(2.72)	(13.69)
ln(# of Covid cases+1)			-0.0010	-0.0005	
			(-1.62)	(-0.89)	
ln(financial assets)		0.0010***		0.0010***	0.0633***
		(2.95)		(2.88)	(53.83)
ln(consumption)		0.0111***		0.0113***	0.1521***
		(33.58)		(33.86)	(101.82)
Observations	3,862,977	3,862,977	3,862,977	3,862,977	3,862,977
R-squared	0.927	0.927	0.926	0.926	0.116
Individual FE	YES	YES	YES	YES	NO
Time FE	YES	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES	YES

Panel B: What Kind of Green Actions Matter?

	Dependent Variable: ln(Credit Limit)				
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS
green energy stealing	–0.0002				
	(–0.18)				
green energy collection		0.0003			
		(0.26)			
# Trees planted			0.0133***		
			(8.71)		
# Reserves protected				0.0037***	
				(5.47)	
Reserve area					0.0037***
					(5.47)
Observations	3,862,977	3,862,977	3,862,977	3,862,977	3,862,977
R-squared	0.927	0.927	0.927	0.927	0.927
Controls	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES	YES

Table 3: **Evidence from the PIPL Policy**

Notes: We focus on the timeframe on the three months before and after the enactment of the personal information protection law (PIPL) from August 2021 to Jan 2022. Columns (1) and (2) investigate green energy production (in kilogram) as a predictor of credit limits, in interaction with the PIPL policy. Columns (3) and (4) replace the original green energy production variable with the green energy produced by the Eco-high behaviors, while Columns (5) and (6) show the corresponding results for Eco-low behaviors. In each case, odd-numbered columns exclude control variables, whereas even-numbered columns include them. All specifications include user, month, and city-year fixed effects, with standard errors clustered at the user level. All continuous variables are winsorized at the 1% level. *** p<0.01, ** p<0.05, * p<0.1.

	ln(Credit Limit)					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
green energy production	0.0035***	0.0027**				
	(3.00)	(2.32)				
PIPL $\times$ green energy production	0.0055***	0.0056***				
	(7.27)	(7.38)				
Eco-high behavior			0.0031***	0.0022*		
			(2.60)	(1.87)		
PIPL $\times$ Eco-high behavior			0.0053***	0.0054***		
			(6.75)	(6.85)		
Eco-low behavior					-0.0011	-0.0009
					(-0.20)	(-0.17)
PIPL $\times$ Eco-low behavior					0.0253***	0.0255***
					(4.25)	(4.29)
ln (total financial assets)		0.0001		0.0001		0.0002
		(0.33)		(0.33)		(0.36)
ln (consumption amount)		0.0125***		0.0125***		0.0126***
		(26.74)		(26.76)		(26.80)
Observations	493,146	493,146	493,146	493,146	493,146	493,146
R-squared	0.966	0.966	0.966	0.966	0.966	0.966
Control	NO	YES	NO	YES	NO	YES
Individual FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES	YES	YES

Table 4: **Users' Gains: Borrowing Constraint and Green Behaviors**

Notes: This table examines the relationship between financial constraints and green energy production using three different measures of financial constraints. Columns (1) and (2) use the lagged natural logarithm of the credit usage rate as the independent variable. Columns (3) and (4) replace the natural logarithm of the credit usage rate with a dummy variable to identify users facing high credit constraints. Column (5) divides the sample into five groups based on credit line usage rates. Columns (1) and (3) exclude controls, while the remaining columns include ln(Total Financial Assets) and ln(Consumption). All specifications include user, month, and city-year fixed effects, with standard errors clustered at the user level. All continuous variables are winsorized at the 1% level. *** p<0.01, ** p<0.05, * p<0.1.

	ln(Green Energy Production)				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
ln(credit usage rate)	0.2451***	0.1326***			
	(104.00)	(65.65)			
borrowing constrained dummy			0.5047***	0.2392***	
			(41.41)	(21.73)	
20%-40% credit usage					0.1659***
					(31.40)
40%-60% credit usage					0.2045***
					(25.91)
60%-80% credit usage					0.2251***
					(21.34)
80%-100% credit usage					0.3202***
					(27.16)
ln (total financial assets)		0.0444***		0.0447***	0.0446***
		(40.08)		(40.25)	(40.14)
ln (consumption amount)		0.2546***		0.2748***	0.2700***
		(175.68)		(179.75)	(179.26)
Observations	3,818,137	3,818,137	3,818,137	3,818,137	3,818,137
R-squared	0.557	0.577	0.551	0.576	0.576
Control	NO	YES	NO	YES	YES
Individual FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES	YES

Table 5: **BigTech's Benefits: Evidence from Default**

Notes: This table explores the relationship between green actions and default. Panel A presents regression results using the default rate (Columns (1) and (2)) and default amount (Columns (3) and (4)) as dependent variables. The default rate is defined as the percentage of the end-of-month overdue balance on Huabei exceeding three days, relative to the total fixed limit of internet consumer credit. The default amount is the absolute value of the end-of-month overdue balance on Huabei exceeding three days. Panel B conducts a cross-sectional analysis of the sensitivity of default rates across different credit usage rate groups. The first classification approach, shown in Columns (1)-(2), involves creating a dummy variable to identify users with high credit constraints. This "borrowing-constrained" dummy is set to 1 if a user's credit usage rate is 80% or higher, indicating substantial reliance on available credit, and 0 otherwise. This allows us to isolate the behaviors of highly constrained users and examine whether their green actions differ from those with lower credit usage. The second approach, shown in Columns (3)-(7), divides the sample into five groups based on credit line usage: below 20%, between 20% and 40%, between 40% and 60%, between 60% and 80%, and above 80%. This segmentation helps assess whether credit usage rate influence the association between green behaviors and default risk. All specifications include user, month, and city-year fixed effects, with standard errors clustered at the user level. All continuous variables are winsorized at the 1% level. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Baseline

	Default Rate		Default Amount	
	(1)	(2)	(3)	(4)
green energy production	-0.4348***	-0.2096***	-32.20***	-17.17***
	(-33.09)	(-20.01)	(-17.81)	(-11.75)
ln(total financial assets)		-0.1012***		-8.86***
		(-25.72)		(-12.63)
ln(consumption amount)		-0.9513***		-62.26***
		(-54.48)		(-27.02)
Observations	3,818,137	3,818,137	3,862,977	3,862,977
R-squared	0.240	0.267	0.229	0.239
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES

Panel B: Default Rates and Financial Frictions

	Unconstrained	Constrained	0-20%	20%-40%	40%-60%	60%-80%	80%-100%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
green energy production	-0.2088***	0.0006	-0.2178***	-0.0160***	-0.0031	0.0023	0.0006
	(-19.88)	(0.09)	(-19.11)	(-3.07)	(-0.42)	(0.31)	(0.09)
ln(total financial assets)	-0.1026***	-0.0083***	-0.1109***	-0.0139***	-0.0119***	-0.0079*	-0.0083***
	(-25.71)	(-3.34)	(-25.16)	(-6.70)	(-3.58)	(-1.82)	(-3.34)
ln(consumption amount)	-0.9185***	-0.0775***	-0.8769***	-0.0821***	-0.0603**	-0.0794***	-0.0775***
	(-52.98)	(-4.77)	(-51.13)	(-6.20)	(-2.33)	(-2.77)	(-4.77)
Observations	3,679,037	139,100	3,124,373	339,967	139,685	75,012	139,100
R-squared	0.287	0.013	0.336	0.129	0.119	0.310	0.013
Individual FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES	YES	YES	YES

Table 6: **Parameterization**

Notes: Our model operates on an annual frequency. We employ a two-step calibration strategy: first, we externally calibrate some parameters to reduce computational burden, and then structurally estimate the remaining parameters. Given the model's lack of closed-form solutions, we utilize the simulated method of moments (SMM) for structural estimation. Panel A lists the externally calibrated parameters, while Panel B shows both the SMM-estimated parameters and their corresponding targeted moments from the data.

Panel A: External Calibration

Parameter	Description	Value	Source/Reference
r	risk-free interest rate	0.015	2019-2022 China average deposit interest rate
r^{BNPL}	interest rate for consumption loans	0.18	Ant Group Financial
ρ	subsistence consumption persistence	0.37	Chan, Ermisch and Gruijters (2019)
σ	subsistence consumption volatility	1.11	

Panel B: Internal Estimation

Parameter	Description	Value	Standard errors
$\bar{y}$	long-run average income	1.35	0.11
γ	share parameter	0.70	0.05
ξ	elasticity of substitution	2.11	0.30
δ	green capital depreciation rate	0.20	0.06
λ	degree of financial frictions	0.46	0.08
θ	degree of soft-info usage	0.66	0.10
α	fraction of intrinsic green users	0.23	0.06
ϕ^G	green investment inflexibility: green type	2.30	0.31
ϕ^B	green investment inflexibility: brown type	1.05	0.12
η^G	repayment delay punishment: green type	1.78	0.24
η^B	repayment delay punishment: brown type	1.19	0.17

Moments	Model Counterpart	Data	Model
consumption volatility	$\sigma(c)$	0.35	0.43
average consumption-to-income ratio	$\frac{c}{y}$	0.60	0.55
median consumption-to-green-energy-production-ratio	$\ln(\frac{c}{\omega})$	0.56	0.64
median credit usage rate	$\frac{b}{\lambda\bar{y}\kappa^\theta}$	2.9%	3.3%
median green capital investment to credit limit	$\frac{\omega}{\lambda\bar{y}\kappa^\theta}$	0.05	0.09
mean of repayment delay probability: whole sample	$\frac{\int \mathbb{1}_{b'>\bar{b}}}{\int \mathbb{1}_{b'>\bar{b}}+\int \mathbb{1}_{0<b'<\bar{b}}}$	0.99%	1.05%
mean of repayment delay probability: 0-20% usage group	$\frac{\int \mathbb{1}_{b'>\bar{b}}}{\int \mathbb{1}_{b'>\bar{b}}+\int \mathbb{1}_{0<b'<\bar{b}}}$	1.35%	1.48%
mean of repayment delay probability: 80%-100% usage group	$\frac{\int \mathbb{1}_{b'>\bar{b}}}{\int \mathbb{1}_{b'>\bar{b}}+\int \mathbb{1}_{0<b'<\bar{b}}}$	0.06%	0.10%
corr. (credit limit, green energy production): whole sample	corr($\lambda\kappa^\theta$,ω)	0.11	0.13
corr. (credit limit, green energy production): 0-20% usage group	corr($\lambda\kappa^\theta$,ω)	0.25	0.25
corr. (credit limit, green energy production): 80%-100% usage group	corr($\lambda\kappa^\theta$,ω)	0.04	0.09
corr. (credit usage, green energy production): whole sample	corr($\frac{b}{\lambda\kappa^\theta}$,$\omega$)	0.20	0.25
corr. (credit usage, green energy production): 0-20% usage group	corr($\frac{b}{\lambda\kappa^\theta}$,$\omega$)	0.18	0.15
corr. (credit usage, green energy production): 80%-100% usage group	corr($\frac{b}{\lambda\kappa^\theta}$,$\omega$)	0.04	0.07

Internet Appendix

A Formal Proof of Screening via Costly Green Actions

We present a simple signaling game to illustrate how costly green actions can serve as a screening mechanism for users with unobservable types. Each user has a private type $\tau \in \{\tau^H, \tau^L\}$, where $\tau^H > \tau^L > 0$, capturing traits such as environmental and financial responsibility. These traits are not directly observable by the platform, which must instead rely on behavioral signals.

The game unfolds as follows. Nature assigns each user a type τ, drawn with probabilities α for τ^H and $1-\alpha$ for τ^L. After observing their own type, each user chooses a level of green investment $\omega \in \mathbb{R}_+$, which is publicly observable. Based on the observed ω, the platform assigns a credit limit $\bar{b}(\omega)$. The user then receives utility from the resulting credit access minus the cost of green investment.

User utility is given by

$$U^\tau(\omega) = v(\bar{b}(\omega)) - \Psi^\tau(\omega),$$

where $v(\cdot)$ is strictly increasing and concave in credit, and $\Psi^\tau(\omega)$ is the cost of green engagement. We assume a linear, type-dependent cost function of the form

$$\Psi^\tau(\omega) = \frac{\phi}{\tau} \cdot \omega,$$

where $\phi > 0$ is a common scaling factor and τ reflects the user's efficiency in undertaking green actions. Thus, high-type users face lower marginal costs.

The platform maps green behavior into credit access via the function $\bar{b}(\omega) = \lambda \bar{y} \omega^\theta$, where $\lambda > 0$, $\bar{y}$ is long-run average income, and $\theta > 0$ governs the responsiveness of credit to green actions. Substituting into the utility expression and assuming $v(\bar{b}) = \sqrt{\bar{b}}$, we have:

$$U^\tau(\omega) = \sqrt{\lambda \bar{y}} \cdot \omega^{\theta/2} - \frac{\phi}{\tau} \cdot \omega.$$

We analyze two regimes that align with our empirical findings. For users with low credit usage—those not facing urgent liquidity needs—the platform can effectively distinguish types. In this case, a separating equilibrium arises, supported by the following incentive compatibility constraints:

$$\sqrt{\lambda\bar{y}}(\omega^H)^{\theta/2} - \frac{\phi}{\tau^H}\omega^H \geq \sqrt{\lambda\bar{y}}(\omega^L)^{\theta/2} - \frac{\phi}{\tau^H}\omega^L, \tag{A1}$$

$$\sqrt{\lambda\bar{y}}(\omega^L)^{\theta/2} - \frac{\phi}{\tau^L}\omega^L \geq \sqrt{\lambda\bar{y}}(\omega^H)^{\theta/2} - \frac{\phi}{\tau^L}\omega^H. \tag{A2}$$

Let $A = \sqrt{\lambda\bar{y}}$. Then these simplify to:

$$A(\omega^H)^{\theta/2} - \frac{\phi}{\tau^H}\omega^H \geq A(\omega^L)^{\theta/2} - \frac{\phi}{\tau^H}\omega^L, \tag{A3}$$

$$A(\omega^L)^{\theta/2} - \frac{\phi}{\tau^L}\omega^L \geq A(\omega^H)^{\theta/2} - \frac{\phi}{\tau^L}\omega^H. \tag{A4}$$

Given $\tau^H > \tau^L$, high types face lower marginal signaling costs, making a higher ω^H optimal if $\theta \in (0,1]$ and ϕ are not too small. The platform then uses green engagement to screen types, justifying the observed negative relationship between green actions and default risk in low-usage users.

By contrast, for users with high credit utilization, green behavior is less informative because all types are strongly incentivized to engage in green actions to relax binding borrowing constraints. In this regime, the cost differential between types is insufficient to deter mimicking, and a pooling equilibrium arises. The platform cannot effectively distinguish between high and low types, leading to a breakdown in the screening mechanism.

This distinction mirrors our empirical results: green actions negatively predict default risk primarily among users with low credit usage, consistent with a separating equilibrium. Among high-usage users, where green engagement is driven largely by financial desperation, green behavior loses its screening power—consistent with a pooling equilibrium.

Thus, this simple signaling model provides a theoretical foundation for our empirical finding that the screening role of green actions is strongest when financial pressure is moderate and weakest when credit constraints are severe. The model also rationalizes the platform's use of strict adjustment costs, which sustain the separating equilibrium in the low-usage group by making it prohibitively costly for low-type users to mimic high-type behavior.

B Extended Empirical Analysis

B.1 Additional results for User's Gains

B.1.1 Demographics and credit usage rate

Panel B of Table 1 summarizes the demographic and financial characteristics of users grouped by their credit usage rates. Users are classified into categories ranging from those with zero credit usage to individuals fully utilizing their credit limits. According to this table, users with higher credit utilization, particularly those nearing full usage, tend to be younger and more likely to be male. For example, the average age decreases from 33.4 years in the zero-usage group to 27.6 years in the full-usage group. Similarly, the proportion of females steadily declines, reaching just 37% among users who fully utilize their credit lines. This demographic trend suggests that younger male users with high credit usage may have more optimistic expectations about their future earning potential, influencing their greater reliance on credit.

Financial characteristics further distinguish users across credit usage groups. Those in the zero-to-low usage categories tend to have significantly higher financial assets and credit limits. For instance, the average ln(Total Financial Assets) is 4.34 for the 0-20% usage group but drops to 3.21 for the full-usage group. Similarly, the average credit limit for low-usage users is 18,910 *yuan* ($\approx$ 2,701 dollars), compared to just 2,506 *yuan* ($\approx$ 358 dollars) for full-usage users. These differences indicate that users with high credit dependency are more likely to face financial constraints, such as limited savings and smaller credit lines, which may drive their reliance on credit to meet consumption demands. Additionally, high-credit-usage users exhibit elevated levels of consumption, with an average ln(Consumption Amount) of 7.58, suggesting a pattern of overconsumption likely supported by credit rather than savings or income.[1]

These patterns suggest that high credit usage rates are influenced by demographic factors, such as youth and gender, as well as financial constraints, such as lower assets, smaller credit limits, and higher consumption needs. These factors, *rather than a specific motivation for green production*, underlie the reliance on credit among certain users. Indeed, the data in Panel B of Table 1 indicate no clear increase in green behaviors with higher credit usage. Green production peaks at 5.85 for users with moderate credit

[1]It is worth noting that this credit-boosted overconsumption is only temporary, as the credit limit is negatively associated with users' debt level and adjusted dynamically, both the consumption levels and credit usage rates of these users quickly return to normal within two months on average.

utilization (20%-40%) and declines among those with higher credit dependency. This suggests that incentives for green behaviors are not necessarily stronger among heavy credit users. Instead, the lower green production observed in high-credit-usage groups may reflect their limited resources or reduced focus on sustainability efforts, unless such behaviors provide indirect benefits, such as relaxing borrowing constraints.

B.1.2 Identification with Difference-in-Difference Approach

Institutional Background The Singles Day shopping festival, held annually on November 11, is one of the largest e-commerce events in China. Initiated in 2009 by Alibaba's Tmall and Taobao, this one-day event has grown significantly in scale and duration, surpassing both Black Friday and Cyber Monday in sales volume. As shown in Figure A3, by 2020, the festival's gross merchandise volume (GMV) exceeded $56.3 billion US dollars, highlighting its importance as a key economic event in China and a major indicator of consumer sentiment.[2]

The 2020 Singles Day shopping festival was particularly notable due to its timing, which coincided with the suspension of Ant Group's IPO and broader economic policies introduced in response to the COVID-19 pandemic. Ant Group, the parent company of Alipay, had been set to launch the largest IPO in history on November 4, 2020. However, on November 3, the Shanghai Stock Exchange suspended the offering, citing "major issues regarding changes in the Fintech regulatory environment" that could prevent the company from meeting listing conditions. In response, Alipay reduced credit limits, particularly for younger users. Meanwhile, to counter deflationary pressures, the Chinese government introduced fiscal and monetary stimulus measures. As part of these efforts, the Singles Day shopping festival was extended, with promotions running from late October through mid-November. This extension likely encouraged increased consumer spending and borrowing, as consumers had more time to plan their purchases. E-commerce platforms further facilitated this by offering deferred payment options and installment plans, aligning with government initiatives to boost demand during economic uncertainty.[3]

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[2] This section draws on information from the following news articles and reports: https://news.cgtn.com/news/2020-11-11/-56-billion-sales-boom-displays-China-s-sustainable-consumption-power--Vk25C5mN8I/index.html https://www.sse.com.cn/disclosure/listedinfo/bulletin/star/c/688688_20201104_1.pdf https://www.reuters.com/world/china/chinas-ant-cuts-credit-limits-some-young-huabei-users-2020-12-23/ https://daxueconsulting.com/double-11-2020-results/

[3] Using transaction data from a major e-commerce platform, Jing Ding, Lei Jiang, Lucy Msall and Matthew J Notowidigdo (2024) study China's digital coupon program launched in 2020 to boost consumer spending in specific sectors like restaurants and supermarkets.

Our data further corroborates this analysis, as shown in the time series of average credit line usage rates in Figure A4. The series reveals a sharp spike in credit utilization around November 2020, indicating that the month was marked by a significant increase in credit usage. This pattern suggests that November 2020, influenced by the suspension of Ant Group's IPO, changes in credit limits, and consumption stimulus policies, served as an exogenous shock to credit line usage. This period offers a unique natural experiment for analyzing how external shocks—combined with promotional credit incentives and abrupt regulatory changes—impact consumer borrowing and spending behavior. Additionally, it provides a valuable opportunity to investigate how these factors may influence individuals' engagement in green behaviors.

DiD Results To establish a causal relationship, we adopt a DiD event study approach. This identification strategy leverages the 2020 Singles Day shopping festival as an exogenous shock to examine the effects of increased credit usage on green production behaviors on the Ant Forest platform. The 2020 Singles Day shopping festival, combined with the regulatory shock of Alipay's IPO suspension, serves as a plausible exogenous shock due to its unique context. First, the festival took place during the COVID-19 pandemic, which disrupted regular economic activities and prompted government policies to stimulate consumer spending. In response, e-commerce platforms extended sales periods and implemented aggressive promotional strategies, resulting in a sharp and unanticipated surge in consumer demand and credit usage that was external to users' typical spending patterns. Second, the sudden suspension of Alipay's IPO on November 3, 2020, put significant pressure on the platform to restructure and scale back its consumer credit business. This led to unexpected credit limit reductions, particularly for younger users who heavily relied on credit to finance their consumption. Together, these factors make the 2020 Singles Day shopping festival an ideal setting to analyze changes in credit usage and their subsequent impact on green energy production.

More specifically, our estimation framework is specified as follows:

$$\begin{aligned}\ln(GreenEnergyProduction)_{i,t} &= \sum_{k=-4}^{-1} \alpha_k D_k \times Constraint_i + \sum_{k=1}^{5} \alpha_k D_k \times Constraint_i \\ &+ \Gamma Control_{i,t} + \eta_i + \omega_t + v_{c,y} + \epsilon_{i,t} \end{aligned} \tag{A5}$$

where $GreenProduce_{i,t}$ represents the green energy production by user i at month t; $Constraint_i$ is a dummy variable that equals 1 if the user's credit usage rate in October–December 2020 was higher than 50% and increased by at least 100% compared to July–September 2020, and 0 otherwise. D_k is a set of time dummies indicating the relative month k before or after September 2020, with $D_k = 1$ if an observation corresponds to the k-th month relative to the event and 0 otherwise. $Control_{i,t}$ includes additional control variables that may influence green production. Fixed effects η_i, ω_t, and $v_{c,y}$ control for individual, month, and city-year factors, respectively, while $\epsilon_{i,t}$ is the error term. September 2020 serves as the benchmark month, as the Singles Day shopping festival spans from October to December, making it more than a one-day event.

This specification utilizes an event study framework within a DiD setup. By interacting D_k with the treatment indicator $Constraint_i$, we estimate the impact of increased credit usage on green production before and after the shopping event. The coefficients α_k capture the differential effect of the treatment (i.e., a significant increase in credit usage) on green production at each time point relative to the shock, allowing us to observe behavioral changes leading up to and following the event. The pre-treatment terms ($k = -5$ to $k = -1$) serve as a parallel trends test, ensuring that treated and control groups exhibited similar trends in green production prior to the shock, validating the DiD approach.

Our identification strategy assumes that in the absence of the Singles Day shopping event, green production levels for treated (increased credit usage) and control (reduced or unchanged credit usage) users would have followed parallel paths. By focusing on users with significant increases in credit usage during the Double 11 festival, we isolate the effects of enhanced credit usage on green behaviors while controlling for potential confounding factors.

The results from the DiD regression are presented in Figure A5, which plots the coefficients over time to illustrate the impact of the 2020 Singles Day shopping festival on green production. The solid blue line represents the estimated coefficients, while the shaded areas denote the 95% confidence intervals. Prior to September 2020, the coefficients are close to zero, suggesting no significant differences in green production between the treated and control groups before the event. However, starting in October 2020, the coefficients show a clear positive trend, reaching a peak in January 2021. The estimated coefficient for January 2021 is 0.2374, indicating that users with increased credit usage during the shopping event engaged in 23.74% more green actions compared to those who did not. As previously noted, our green energy calculations exclude contributions from both online and offline payments, addressing potential concerns that the additional green actions may simply result from factors related to shopping behavior.

Graphs (a) and (b) in Figure A6 provide further analysis of Eco-high and Eco-low behaviors, respectively. As in the main analysis, the solid lines represent the estimated coefficients, and the shaded areas indicate the corresponding 95% confidence intervals. For Eco-high behaviors, the result mirrors that for total green production, showing a significant and positive increase post-shock. In December 2020, the estimated coefficient peaks at 0.2440, which means that individuals with increased credit usage performed 24.40% more Eco-high actions. In contrast, we observe a relatively flat trend for Eco-low behaviors, with a coefficient significant three months after the shock and peaked at February 2021 with a value of 0.1211. These results are consistent with our earlier findings that Eco-high behaviors play a more significant role in increasing credit limits, explaining the shift in focus among treated users.

These findings show that the 2020 Singles Day shopping event had a lasting positive effect on green production behaviors, especially among users with increased credit usage. The rising coefficients after the shock suggest that tightened credit constraints motivated users to participate more in green activities. The statistical significance of these results, as indicated by the confidence intervals, further supports the robustness of these findings. Overall, the results highlight the potential of credit availability and promotional events to encourage environmentally friendly behaviors, through our proposed story that financial incentives can effectively promote sustainability initiatives.

B.2 Additional Results for the Platform's Benefits

B.2.1 Direct Comparison

We now examine the potential soft-information value of users' green actions for BigTech firms. To begin, we present summary statistics that illustrate how opening Ant Forest account alone contributes to the determination of credit limits.

Table A8 presents credit limit data for two groups of users: those who initially lacked Ant Forest accounts but opened one during the sample period, and those who already had accounts at the start of the period. For users who initially lacked Ant Forest accounts, Column (1) provides summary statistics for January 2019, the beginning of our analysis, while Column (2) presents data for the last month prior to account activation. The table reveals only a modest increase in credit limits during this period. Specifically, the average credit limit rose from 8,099 *yuan* ($\approx$ 1,157 dollars) to 8,124 *yuan* ($\approx$ 1,161 dollars), reflecting a marginal increase of 0.3%. Similar trends are observed across quartiles: the first quartile, the median, the third quartile and the maximum remain unchanged at 2,000 *yuan* (≈ 286 dollars), 5,200 *yuan* (≈ 743 dollars), 10,600 *yuan* (≈ 1,514 dollars), and 55,000 *yuan* (≈ 7,857 dollars) respectively. These findings suggest that credit limits for users without Ant Forest accounts show minimal improvement over time. In contrast, once these users activated their Ant Forest accounts, the average credit limit increased from 8,130 *yuan* (≈ 1,161 dollars) to 8,984 *yuan* (≈ 1,283 dollars), which is a 10.5% rise. Columns (5) and (6) shift the focus to users who had Ant Forest accounts at the start of the sample period. These users experienced a substantial increase in their average credit limit, from 15,177 *yuan* (≈ 2,168 dollars) to 17,280 *yuan* (≈ 2,469 dollars), marking a substantial increase of 13.9%. These results further support the findings in Table 2, which show a positive correlation between green energy production and credit limits. The raw evidence presented in Table A8 thus suggests that green actions play a meaningful role in determining users' credit limits, thus possibly offering value to the platform. This result aligns with the existing literature on the financial friction-reducing effects of soft information and alternative data (Julapa Jagtiani and Catharine Lemieux, 2019).

C Additional Figures and Tables

Figure A1: **Random Forest Regression Results on Credit Limit**

Notes: The y-axis represents the feature importance of various factors influencing credit limits, highlighting their relative contribution. This approach allows us to isolate the orthogonal contribution of green energy production to credit limits, separating it from other potentially correlated factors such as consumption, financial assets, age and gender.

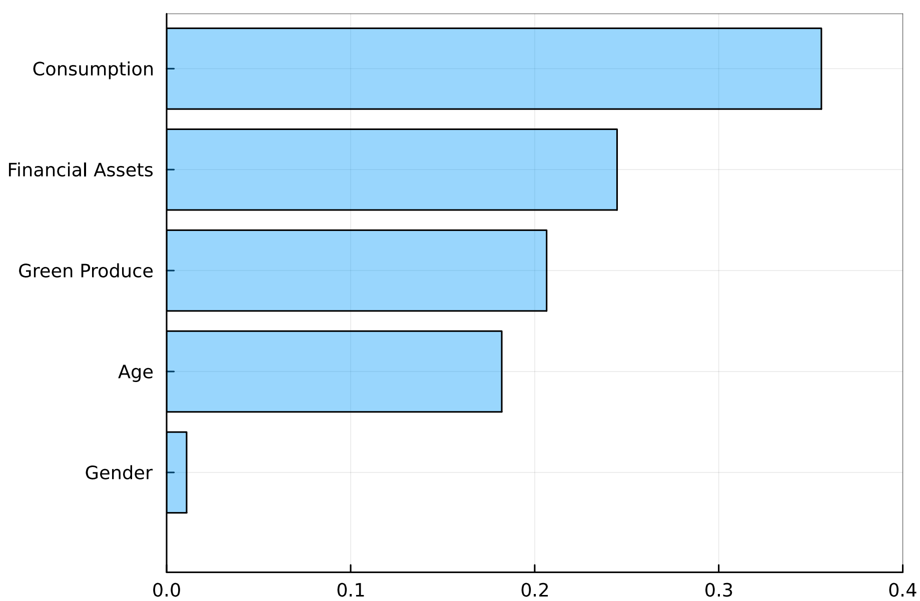


Figure A2: **Trends in Page Visits Around Singles Day Shopping Festival**

Notes: This figure plots the average number of page visits over time, focusing on user engagement before and after the 2020 Singles Day shopping festival. The x-axis displays the time dimension (in months), beginning from September. The y-axis shows the average number of visits.

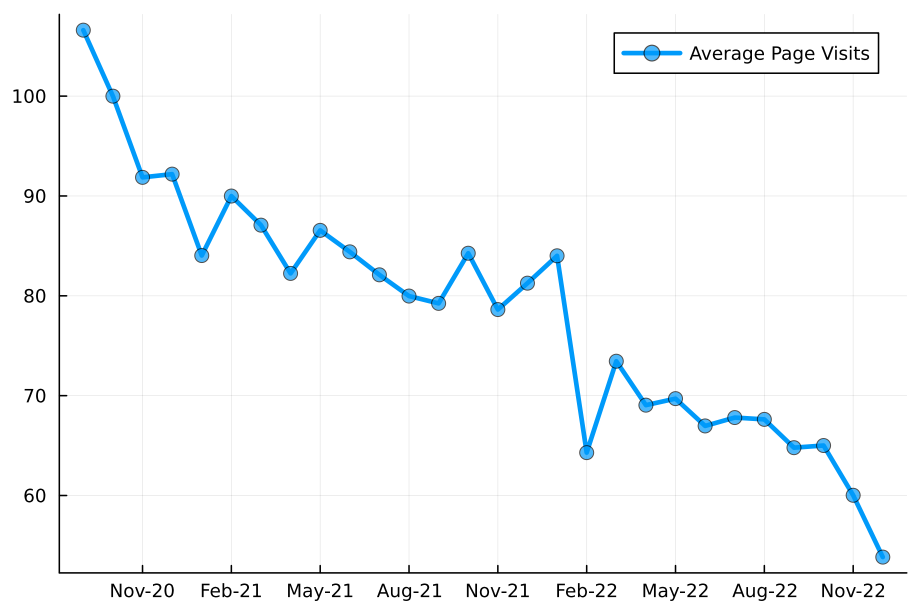


Figure A3: **Time-series Overview of the Gross Merchandise Value (GMV) generated during the Singles Day Shopping Festival**

Notes: This figure illustrates the annual gross merchandise value (GMV) across major online shopping platforms during China's Singles Day shopping festival from 2009 to 2021. The data is sourced from Syntun (http://www.syntun.com.cn/datanews/hotspot.html).

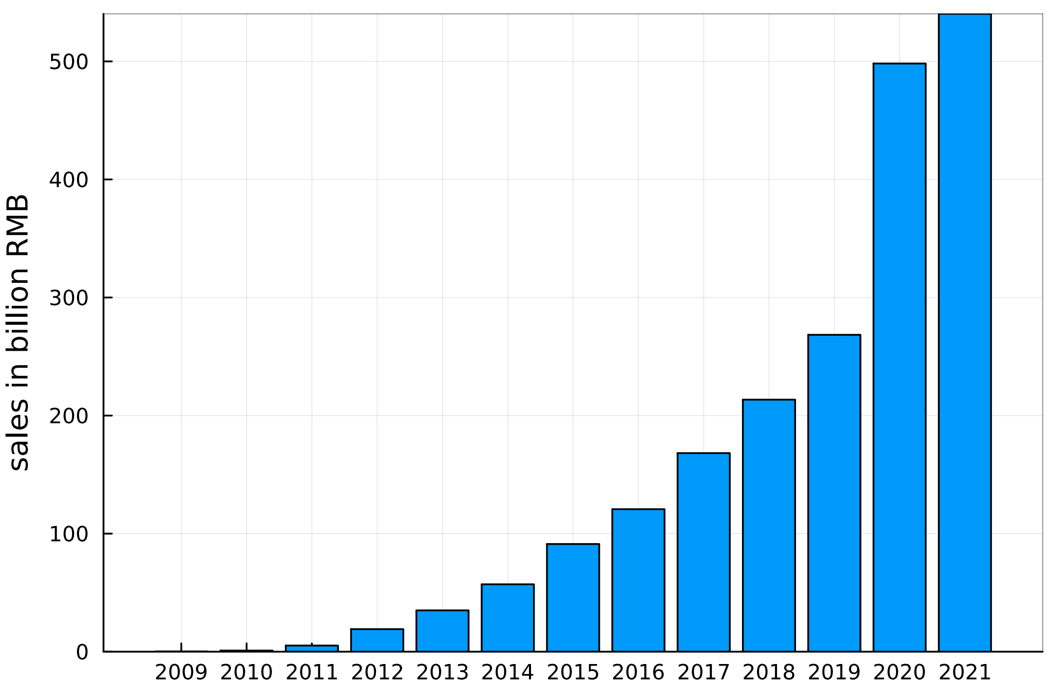


Figure A4: **Time-Series of Average Credit Line Usage Rate**

Notes: This figure displays the time series of the average credit usage rate for Ant Forest users over the course of our data sample. The credit usage rate is calculated as the percentage obtained by dividing the amount of credit used by the total credit limit.

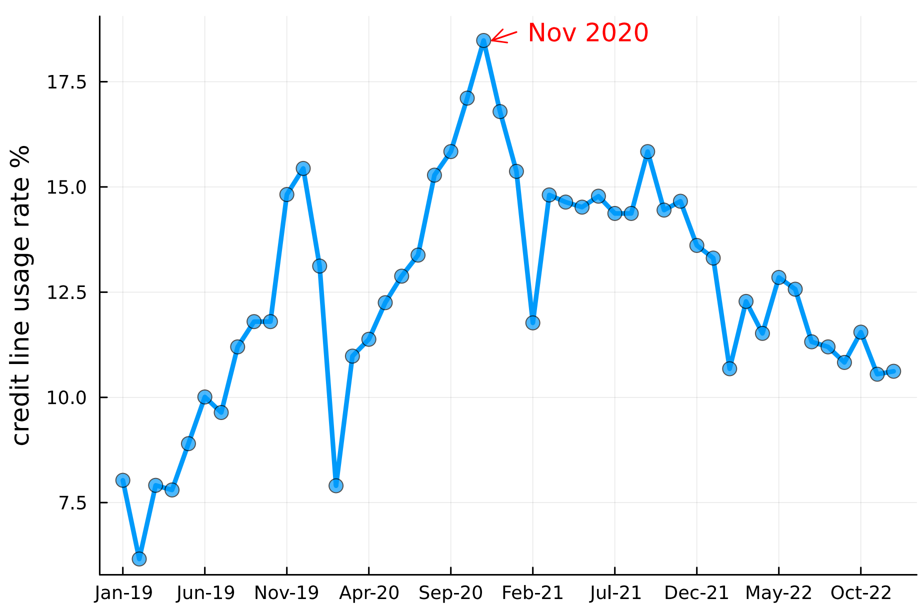


Figure A5: **Dynamic Effects of Increased Credit Usage on Green Actions**

Notes: This figure presents the results of a Difference-in-Difference event study. The identification strategy leverages the 2020 Singles Day shopping festival as an exogenous shock to examine the effects of increased credit usage on green production behaviors on the Ant Forest platform. Our estimation framework is specified as follows:

$$\ln(GreenEnergyProduction)_{i,t} = \sum_{k=-4}^{-1} \alpha_k D_k \times Constraint_i + \sum_{k=1}^{5} \alpha_k D_k \times Constraint_i + \Gamma Control_{i,t} + \eta_i + \omega_t + v_{c,y} + \epsilon_{i,t}$$

where $GreenProduce_{i,t}$ represents the green energy production by user i at month t; $Constraint_i$ is a dummy variable that equals 1 if the user's credit usage rate in October–December 2020 is higher than 50% and increased by at least 100% compared to July–September 2020, and 0 otherwise. D_k is a set of time dummies indicating the relative month k before or after September 2020, with $D_k = 1$ if an observation corresponds to the k-th month relative to the event and 0 otherwise. $Control_{i,t}$ includes additional control variables that may influence green production. Fixed effects η_i, ω_t, and $v_{c,y}$ control for individual, month, and city-year factors, respectively, while $\epsilon_{i,t}$ is the error term. September 2020 serves as the benchmark month, as the Singles Day shopping festival spans from October to December, making it more than a one-day event. The solid line represents the estimated coefficients, while the shaded areas indicate 95% confidence intervals.

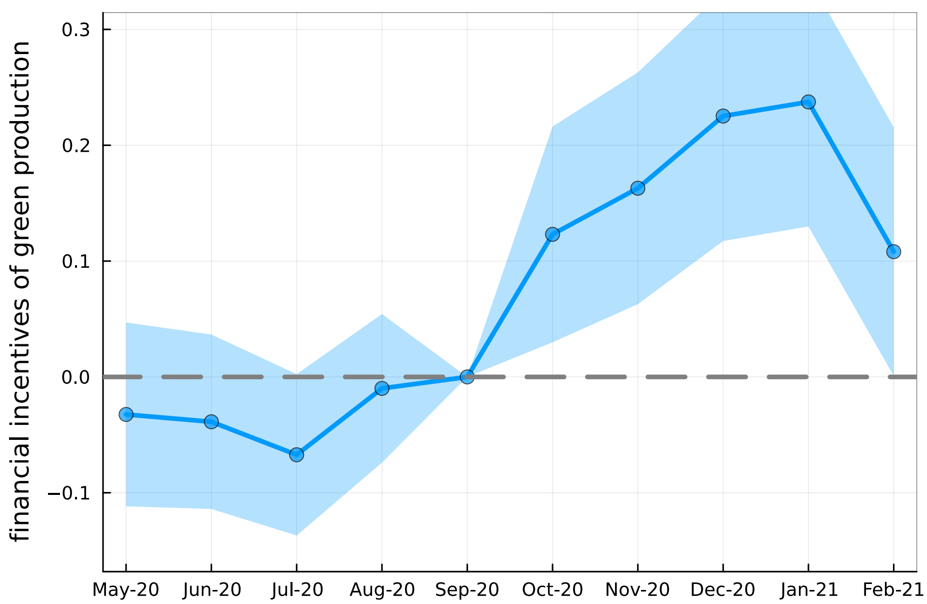
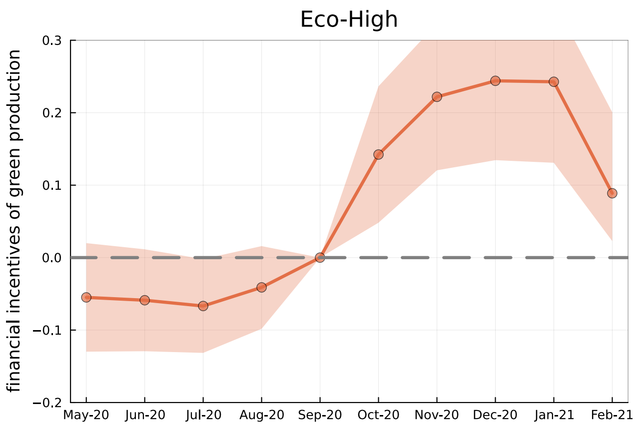


Figure A6: **Dynamic Effects of Increased Credit Usage on Green Actions**

Notes: This DiD specification utilizes data spanning from April 2020 to February 2021, treating September 2020 as the benchmark month. The regression model specification takes the same format as in Figure A5. Graphs (a) and (b) analyze Eco-high and Eco-low behaviors, respectively. The solid line represents the estimated coefficients, while the shaded areas indicate 95% confidence intervals.

(a) Eco-High Behaviors



(b) Eco-Low Behaviors

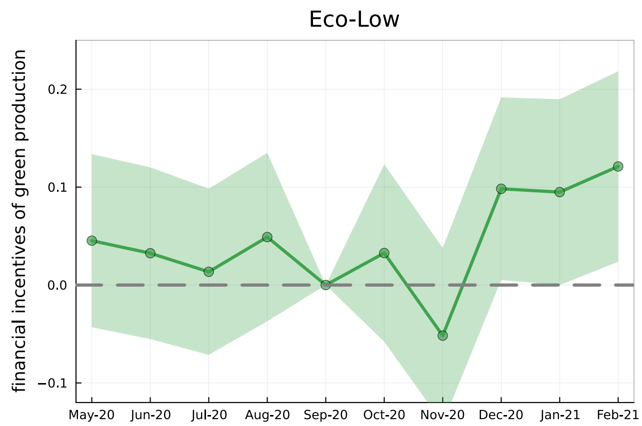


Figure A7: **Climate Perceptions Index**

Notes: The Climate Perceptions Index is a comprehensive metric designed to assess public views on climate change. Data for the index is sourced from Social Progress and reflects insights from over 100,000 active Facebook users across 107 countries. It examines three key areas: awareness of climate change, perception of its risks, and commitment to taking action. The index provides valuable insights into the societal impact of climate change and aims to guide political leaders in identifying areas where they can enhance public support for climate action in their nations. Due to the lack of data from mainland China, we use the average score from Hong Kong and Taiwan as a proxy. To facilitate comparison, we have rescaled the values by normalizing China's score to 1.0.

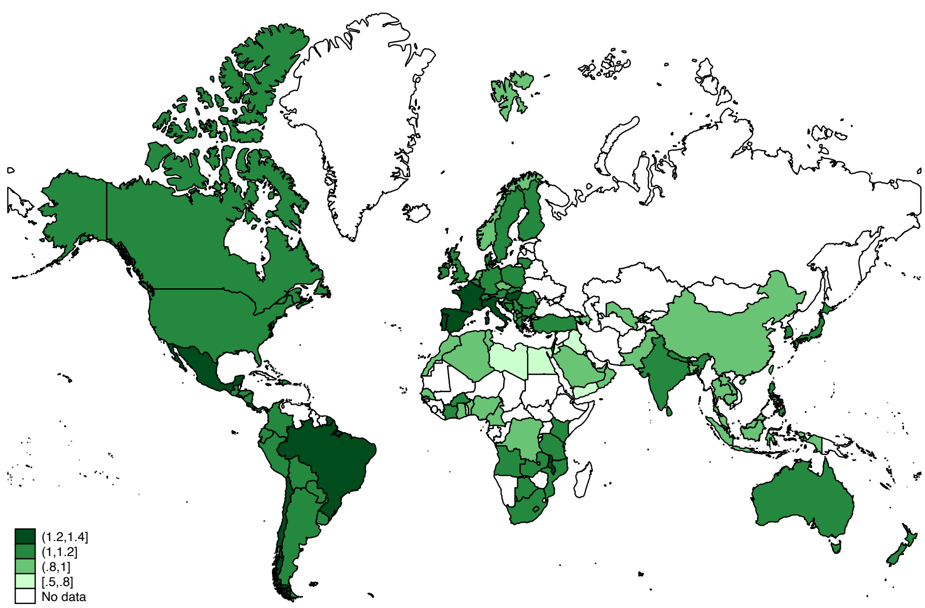


Table A1: **List of Eco-High Behaviors**

Notes: This table presents high environmental impact activities available on the Ant Forest platform, listing them in both English and Chinese. In our classification, we only include green behaviors that occurred in at least 3,000 user-months during our four-year sample period.

UTF8gbsn

中文 (Chinese)	英文 (English)
行走	Walking
公交	Public Transport
地铁	Subway
共享单车	Shared Bicycle
环保减塑	Environmental Protection and Plastic Reduction
绿色包裹	Green Delivery Packages
自带杯	Bring Your Own Cup
咸鱼	Dried Fish (second-hand item trading)
直饮水	Drinkable Water without Plastics
二手交易	Recycling Second-hand
车辆停驶	Vehicle Non-use

Table A2: **List of Eco-Low Behaviors**

Notes: This table presents low environmental impact activities available on the Ant Forest platform, listing them in both English and Chinese. In our classification, we only include green behaviors that occurred in at least 3,000 user-months during our four-year sample period.

UTF8gbsn

中文 (Chinese)	英文 (English)
生活缴费	Utility Bill Payment
电子账单	Electronic Bill
火车票	Train Ticket
健康码	Health Code
绿色政务	Green Governance
信用卡还款	Credit Card Repayment
发票	Electric Invoice
网络购票	Online Ticket Purchase
饿了么	Ele.me (a food delivery service)
扫码点餐	Scan to Order
网上寄件	Online Parcel Shipping
充电宝	Portable Charger
电子小票	Electronic Receipt
ETC	Electronic Toll Collection
线上贷款	Online Loan
钉钉	DingTalk (a communication and collaboration tool)
挂号	Registration (for medical services)
停车缴费	Parking Payment

Table A3: **Green Actions and Their Associated Energy Points**

Notes: The table follows the structure of Ant Forest's official documents. The calculation of green energy relies on scientific algorithms for carbon emission reduction and sequestration, developed by organizations such as the Beijing Environmental Exchange and The Nature Conservancy.

Green Behavior	Green Energy Points	Monthly Cap
Eco-High Behaviors		
Walk 600 steps	10	8,880
Public transport	80	12,000
Subway	52	7,800
Ride a shared bicycle for 10 mins	18	4,752
Plastic reduction	12	360
Green delivery packages	16	2,400
Bring your own cup	30	180,000
Second-hand home appliance trading	9,763	48,815
Second-hand book trading	195	975
Drinkable water without plastics	4	480
Vehicle non-use	819	3,276
Eco-Low Behaviors		
Utility bill payment	262	2,620
Electronic bill	8	32
Train ticket	136	1,360
Health code	5	150
Green governance	104	5,200
Credit card repayment	21	21
Electric invoice	5	750
Online ticket purchase	180	1,800
Food delivery without cutlery	16	2,400
Scan to order	7	1,050
Online parcel shipping	4	600
Portable charger	13	390
Electronic receipt	4	1,200
Electronic toll collection	23	6,900
Online loan	35	35
Online meeting by DingTalk	20	600
Registration (for medical services)	277	1,385
Parking payment	18	1,620

Table A4: **Screening Role of Green Behaviors: Alternative Regression Settings**

Notes: This table presents robustness checks using Poisson regressions and IHS transformations. And this table examines alternative measures of green behaviors as predictors of users' credit limits. Scope-2 includes all forms of green activity, while Scope-3 applies the strictest definition by excluding behaviors such as walking and public transport. Specific green behavior indicators include green energy stealing, energy collection, number of trees planted, number of nature reserves protected, and total reserve area. All regressions include standard control variables as well as fixed effects for individuals, time, and city-by-year. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	Dependent Variable: Credit Limit					
	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	Poisson	IHS	IHS	OLS	OLS
green energy production	0.003***	0.002***	0.0042***	0.0016**		
	(7.50)	(5.00)	(5.64)	(2.20)		
green energy production (scope 2)					0.0023***	
					(3.32)	
green energy production (scope 3)						0.0119***
						(3.40)
Observations	3,830,641	3,830,641	3,862,977	3,862,977	3,862,977	3,862,977
R-squared	-	-	0.925	0.925	0.927	0.927
Controls	NO	YES	NO	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES	YES	YES

Table A5: **Borrowing Constraint and Green Behaviors: Eco-High vs. Econ-Low**

Notes: Here we extend the analysis in Table 4 to "Eco-High" and "Eco-Low" behaviors as alternative dependent variables.

	ln(Eco-High)			ln(Eco-Low)		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
ln(credit usage rate)	0.1264***			0.0539***		
	(55.17)			(40.23)		
borrowing constrained dummy		0.2318***			0.0887***	
		(18.74)			(11.82)	
20%-40% credit usage			0.1577***			0.0843***
			(26.26)			(19.25)
40%-60% credit usage			0.1853***			0.1135***
			(20.67)			(17.36)
60%-80% credit usage			0.2067***			0.1313***
			(17.41)			(15.44)
80%-100% credit usage			0.3069***			0.1328***
			(23.15)			(16.74)
ln (total financial assets)	0.0474***	0.0477***	0.0476***	0.0096***	0.0098***	0.0097***
	(36.91)	(37.08)	(36.99)	(13.46)	(13.65)	(13.54)
ln (consumption amount)	0.2135***	0.2327***	0.2284***	0.1535***	0.1618***	0.1593***
	(141.91)	(145.71)	(145.48)	(158.46)	(164.24)	(162.40)
Observations	3,818,137	3,818,137	3,818,137	3,818,137	3,818,137	3,818,137
R-squared	0.578	0.576	0.576	0.489	0.489	0.489
Control	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES	YES	YES

Table A6: **Impact of Entering Ant Forest on Homepage Visit Frequency**

Notes: This table presents results from a staggered Difference-in-Differences (DiD) regression examining the impact of entering the Ant Forest program on the number of homepage visits per month. The dependent variable is the monthly count of homepage visits. The key explanatory variable is an indicator for whether the user has entered Ant Forest. Standard controls include demographic and behavioral variables. All regressions include individual fixed effects, time fixed effects, and city-by-year fixed effects. Standard errors are clustered at the individual level and reported in parentheses.

	Monthly Homepage Visit
Enter Ant Forest	15.849***
	(6.730)
Observations	64,827
R-squared	0.677
Individual FE	Yes
Time FE	Yes
City*Year FE	Yes
Controls	Yes

Table A7: **Heterogeneous Effects by User Tenure on Platform and Ant Forest**

Notes: This table explores heterogeneity by user tenure, splitting the sample at the median of Alipay registration date or Ant Forest participation date. Standard errors are clustered at the individual level. *, **, *** denote significance at the 10%, 5%, and 1% levels respectively.

	Credit Limit as Outcome		**Green Behavior as Outcome**			
	Long-time Users	New Users	Long-time Users		New Users	
green energy production	0.0011	0.0026***				
	(1.00)	(2.87)				
ln(credit usage rate)			0.1031***		0.1480***	
			(41.49)		(47.40)	
borrowing constrained dummy				0.1793***		0.2677***
				(13.36)		(16.05)
Observations	1,971,227	1,891,750	1,994,991	1,994,991	1,822,112	1,822,112
R-squared	0.910	0.934	0.538	0.537	0.548	0.546
Controls	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
City×Year FE	YES	YES	YES	YES	YES	YES

Table A8: **Green Behavior's Soft Information Value for BigTech: Direct Comparison**

Notes: This table presents changes in credit limits for two groups of users: those who did not have Ant Forest accounts at the beginning of the sample period but opened one during the period, and those who already had accounts at the start. Columns (1) and (2) display summary statistics for credit limit changes before users opened their Ant Forest accounts, while Columns (3) and (4) show summary statistics for credit limit changes after the accounts were opened. In Columns (5) and (6), we focus on users who already had Ant Forest accounts at the beginning of the sample period.

	No Account at Beginning		**After Opening Account**		**Have Account at Beginning**	
	Jan 2019	Before Opening Account	Opening Account	Dec 2022	Jan 2019	Dec 2022
	(1)	(2)	(3)	(4)	(5)	(6)
# of Obs.	11,607	11,607	11,607	11,607	70,562	70,562
Mean	8,099	8,124	8,130	8,984	15,177	17,280
Std	9,042	9,126	9,137	11,209	13,576	16,454
Min	0	0	0	0	0	0
Q1	2,000	2,000	2,000	1,000	4,400	3,050
Median	5,200	5,200	5,200	5,000	11,900	12,000
Q3	10,600	10,600	10,650	12,000	23,300	27,400
Max	55,000	55,000	55,000	55,000	55,000	55,000