The Green Value of BigTech Credit*

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Abstract

This study identifies an incentive-compatible mechanism to foster individual environmental engagement. Utilizing a dataset comprising 100,000 randomly selected users of Ant Forest—a prominent personal carbon accounting platform embedded within Alipay, China's leading BigTech super-app—we provide causal evidence that individuals strategically engage in eco-friendly behaviors to enhance their credit limits, particularly when approaching borrowing constraints. These behaviors not only illustrate the green nudging effect of BigTech but also generate value for the platform by leveraging individual green actions as soft information, thereby improving the efficiency of credit allocation. Using a structural model, we estimate an annual green value of 427.52 million US dollars generated by linking personal carbon accounting with BigTech credit. We also show that the incentive-based mechanism surpasses green mandates and subsidies in improving consumer welfare and overall societal welfare. Our findings highlight the role of an incentive-aligned approach, such as integrating personal carbon accounts into credit reporting frameworks, in addressing environmental challenges.

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—alongside the limited effectiveness and sustainability of many initiatives, including corporate greenwashing and window-dressing, have become focal points of 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 absence 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 mechanisms that align private incentives with broader environmental objectives, these policies remain susceptible to political volatility and fall short in ensuring long-term viability.[1]

This paper proposes an incentive-compatible solution to encourage personal environmental responsibility. 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. As illustrated in Figure 1, Users who consistently engage in eco-friendly activities can receive benefits such as higher credit scores and increased credit limits. This feedback loop between environmental actions and financial outcomes not

[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).

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 data comprises a panel of 100,000 randomly selected Ant Forest users over a 48-month period, from January 2019 to December 2022, with detailed breakdowns of various green actions across a wide range of specific contexts. To begin, we examine the correlation between individual credit limits and green energy production. Our findings reveal that small-scale engagement in green behaviors is positively and significantly associated with economically meaningful increases in credit limits. In our baseline estimate, an increase of 1 kilogram in green energy production corresponds to an approximate 0.17% increase in credit limits, or roughly 24.65 *yuan* (equivalent to 3.52 US dollars).[2] Furthermore, we investigate how individuals adjust their eco-friendly actions, particularly when nearing their credit limits. One of our estimations shows that credit-constrained individuals—defined as those with credit utilization rates exceeding 80%—engage in 23.92% more green activities than unconstrained users, after controlling for other potential determinants of green behavior. This strategic behavior suggests that data on green actions can simultaneously promote sustainability goals and influence financial outcomes on digital platforms.

To assess the causal impact of credit constraints on green actions, we employ a Difference-in-Differences (DiD) event study, leveraging an exogenous shock to credit line usage during the 2020 Singles Day shopping festival in China, which coincided with the suspension of Ant Group's IPO. This event triggered a temporary increase in consumer credit usage due to extensive promotional activities and government incentives aimed at stimulating spending during the COVID-19 pandemic. At the same time, it led to a reduction in credit limits, particularly for younger users, as a result of stricter regulatory measures. This quasi-natural experiment allows us to isolate changes in green behaviors driven by shifts in credit availability, while controlling for other confounding factors. Our results show that users who experienced an increase in credit usage between October and December 2020 engaged in 16.69% more green activities compared to those who did not, supporting the hypothesis that individuals strategically adopt eco-friendly behaviors to ease borrowing constraints.

Next, we evaluate the value of these green actions for the BigTech platform and find that they not only benefit users but also strengthen the platform's capacity to assess creditworthiness internally. This

[2] Throughout this paper, the exchange rate for the US dollar to Chinese *yuan* is set at 7.0.

function is akin to the use of soft information in traditional bank lending (e.g., José María Liberti and Mitchell A. Petersen, 2019). Our primary empirical strategy leverages an increase in data-sharing restrictions imposed by China's Personal Information Protection Law (PIPL), which limits BigTech firms' access to external, third-party data sources, thereby compelling them to rely more heavily on internally generated data. Our analysis shows that, prior to the implementation of PIPL, users' green behaviors had some predictive power with respect to their credit limits. Post PIPL, however, the predictive power of green behaviors in credit assessments increased substantially. Moreover, we document a negative association between green activities and both default rates and default amounts, despite their positive impact on credit limits. This negative relationship is most evident among unconstrained users, while the effects are negligible for those near the full utilization of their credit lines. These findings suggest that green behaviors are increasingly valuable for credit evaluations, highlighting how regulatory environments shape the use of data in financial decision-making.

To deepen our understanding of these findings, we develop a partial equilibrium structural model incorporating endogenous green capital accumulation and borrowing constraint. In this framework, platform users primarily value their own consumption but also possess intrinsic green preferences (i.e., green-in-utility). Their only means of smoothing consumption amid income volatility is through saving and borrowing from BigTech. However, their borrowing capacity is limited by credit constraints, which are partly determined by their accumulated green capital. Users can actively increase their green capital by engaging in eco-friendly behaviors, although these actions involve adjustment costs. In this way, green behaviors provide value to users in two ways: (1) directly through the utility derived from being environmentally conscious, and (2) indirectly by easing financial frictions, as higher green capital can expand credit limits. The latter benefit becomes more pronounced when the platform relies heavily on soft information to determine creditworthiness and when users have lower intrinsic green values. When calibrated, our model successfully replicates the empirical observation that borrowing-constrained users are more motivated to engage in green activities.

Lastly, we use the model to assess the welfare implications of data sharing between BigTech's profit-driven services and public-good initiatives, such as linking green actions to credit limit decisions. Our results indicate that restricting this data sharing diminishes both platform efficiency and environmental outcomes. A 10% reduction in the use of green action data for credit limit decisions leads to an annual green value loss of 56.07 million US dollars, or approximately 392.52 million *yuan* per year. If our financial friction channel for green actions is completely removed, the total green value loss rises to an estimated 427.52 million US dollars per year (around 2.99 billion *yuan* per year). We observe comparable declines in BigTech lending profits alongside rises in equilibrium default rates. Our findings indicate that harnessing BigTech's market power and integrated ecosystem fosters a mutually beneficial environment, where detailed user data enables personalized incentives and credit limit adjustments based on green actions. This approach effectively motivates users to adopt more sustainable behaviors.

Importantly, our model allows us to compare the most commonly used tools for green transition—environmental mandates and subsidies—with our incentive-driven mechanism in shaping both consumer and aggregate welfare. Our analysis reveals that mandatory policies can negatively impact consumer welfare, while subsidies demand substantial government funding to sustain. In contrast, the incentive-based strategy avoids these pitfalls, outperforming mandated green actions and subsidies, especially in countries with low intrinsic awareness of environmental protection.

In summary, our findings highlight that financial incentives provided by BigTech platforms significantly boost households' motivations to adopt eco-friendly behaviors. By leveraging integrated data ecosystems, these platforms can play a pivotal role in promoting solutions that are both sustainable and economically viable. Specifically, our results offer three key policy implications. First, the business model proposed in this paper—linking credit limit increases to personal carbon accounts—provides a fresh perspective on environmental, social, and governance (ESG) policies. Unlike existing ESG policies, which are predominantly mandatory and often unsustainable, this approach utilizes the data generated by BigTech lending systems to incentivize green behaviors. By creating a sustainable, non-mandatory nudge for low-carbon actions, this model offers a market-driven, scalable solution to promote eco-friendly lifestyles, making it both appealing and easily adoptable by BigTech firms globally. Second, while environmental mandates and subsidies for green actions may yield short-term benefits, they face considerable challenges over time. Instead, our incentive-based mechanism stands out as a sustainable and scalable approach that aligns environmental goals with consumer welfare and economic growth. Finally, in regions or markets where BigTech platforms are still emerging, policymakers could consider integrating personal carbon accounts into existing credit reporting and scoring systems. This would enable traditional financial institutions to link carbon-friendly behaviors with improved creditworthiness, aligning financial incentives with environmental objectives, even without the presence of established BigTech ecosystems.

Literature Review This paper contributes to four distinct areas of literature. First, it advances the body of work on ESG issues. To begin with, our paper aligns with the debates on the effectiveness and challenges of ESG practices. Numerous studies highlight that ESG investments do not consistently yield excess returns (e.g., Huaigang Long, Mardy Chiah, Nusret Cakici, Adam Zaremba and Mehmet Huseyin Bilgin, 2024; Brad M. Barber, Adair Morse and Ayako Yasuda, 2021; Aneesh Raghunandan and Shiva Rajgopal, 2022). Furthermore, the adoption of ESG practices often increases corporate burdens, potentially widening the gap between firms' actual ESG performance and their stated or claimed commitments. The phenomenon of greenwashing, as emphasized by Duchin, Gao and Xu (Forthcoming), underscores the necessity of regulatory oversight, given that some firms misrepresent their environmental efforts. Similar concerns have been observed in mutual funds, with evidence of window-dressing behavior (Parise and Rubin, 2023). This paper addresses these challenges by proposing an incentive-driven approach that fosters a sustainable and long-term ESG implementation. In this context, we add to the emerging strand of ESG literature that highlights the effectiveness of incentives in motivating the green transition and curbing greenwashing. For instance, Caroline Flammer, Thomas Giroux and Geoffrey M. Heal (2025) finds that public capital's participation in risk sharing effectively crowds in private capital in high-risk, low-return biodiveristy projects. 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.

Furthermore, our research expands the literature by examining individual households' green actions, an area that remains underexplored compared to the predominant focus on financial markets and firms. For example, Lubos Pastor, Robert F. Stambaugh and Lucian A. Taylor (2022) and Lasse Heje Pedersen, Shaun Fitzgibbons and Lukasz Pomorski (2021) demonstrate how investor demand and expected cash flows drive positive returns for ESG-focused assets. Similarly, Stefano Giglio, Bryan Kelly and Johannes Stroebel (2021) explore the effects of climate risks on long-term discount rates, particularly in real estate, while Patrick Bolton and Marcin Kacperczyk (2021) analyze the impact of carbon-transition risks on global asset pricing. In corporate finance, studies have investigated firm-level responses to climate risks, such as the adverse effects of extreme weather events on financial performance (Zacharias Sautner, Laurence Van Lent, Grigory Vilkov and Ruishen Zhang, 2023) and the sector-specific demand shifts driven by temperature changes (Jawad M. Addoum, David T. Ng and Ariel Ortiz-Bobea, 2020). Furthermore, firms with strong governance structures are more likely to adopt sustainable practices (Sophie A. Shive and Margaret M. Forster, 2020), though many still struggle to meet climate-related commitments (Joseph E. Aldy, Patrick Bolton and Marcin Kacperczyk, 2023). While some recent studies have indirectly examined households' green consumption, direct evidence on individual carbon reduction behaviors remains scarce. For instance, Joel F Houston, Chen Lin, Hongyu Shan and Mo Shen (2022) matched negative ESG news coverage from the RepRisk database with U.S. household consumer data (2004–2019) and found that adverse ESG incidents significantly reduced consumer purchases, suggesting that ESG considerations influence consumption decisions. Diverging from this line of inquiry, our paper directly investigates household behaviors and demonstrates that financial incentives can effectively shape individual decisions to engage in sustainable actions.

Second, our paper contributes to the expanding literature on BigTech platform to reveal its green nudging effect. Earlier studies have primarily examined BigTech credit provided to consumers, online merchants, small businesses, and entrepreneurs, highlighting its role in enhancing financial inclusion and supporting business growth (e.g., Harald Hau, Yi Huang, Chen Lin, Sheng Shan, Zhu Sheng and Lei Wei, Forthcoming; Manasa Gopal and Philipp Schnabl, 2022). For example, Wenlong Bian, Lin William Cong and Yang Ji (2024) investigate super-app digital wallets in consumer finance, finding that a new type of BigTech credit, Buy-Now-Pay-Later (BNPL) acts as "digital cash," extending credit access to underserved populations without increasing default risks, contingent on the super-app's cross-sales capabilities and incentive structure. Similarly, Yiping Huang, Xiang Li, Han Qiu, Dan Su and Changhua Yu (2024) explore the role of BigTech in monetary policy transmission, noting key differences in how digital lending platforms respond to policy shifts compared to traditional banks. One pioneering research on BigTech's green nudging effect is Guojun He, Yuhang Pan, Albert Park, Yasuyuki Sawada and Elaine S. Tan (2023), which utilize the food delivery function on the BigTech App and shows changing the default option to "No single-use cutlery" would significantly increase household's green behaviors. Our paper extends this literature by examining the environmental impacts of BigTech credit on individual consumers and households. This perspective highlights the potential of BigTech credit to serve as a tool for sustainable finance by influencing environmental behaviors.

Third, our study contributes to research on the relationship between financial constraints and green behaviors. For instance, Qiping Xu and Taehyun Kim (2021) show that credit-constrained firms are less likely to invest in pollution abatement, underscoring the importance of financial flexibility for firms facing environmental regulations. Marcin Kacperczyk and Jose-Luis Peydro (2022) examine the influence of carbon emissions on bank lending practices, focusing on banks committed to carbon reduction targets through initiatives such as the "Science Based Targets Initiative." Their findings reveal that high-emission firms with environmentally committed banking relationships receive reduced credit inflows but show limited improvement in climate performance. This highlights the complexities of aligning financial incentives with environmental objectives and the challenges faced by financial institutions in supporting genuine emission reductions. In contrast, our paper explores the reverse relationship by leveraging the unique setup of Ant Forest to investigate how relaxing borrowing constraints incentivizes individual households to engage in eco-friendly behaviors.

Finally, our paper contributes to the understanding of soft information utilization in banking literature (Liberti and Petersen, 2019). For instance, Allen N. Berger, Nathan H. Miller, Mitchell A. Petersen, Raghuram G. Rajan and Jeremy C. Stein (2005) note that large banks often favor lending to larger firms or those with more formal financial histories, and typically engage with clients in a more impersonal manner over larger distances. In contrast, small banks are known to maintain longer and more exclusive relationships with borrowers, enhancing their use of soft information and easing credit constraints for small enterprises. Rebel A. Cole, Lawrence G. Goldberg and Lawrence J. White (2004) explore differences in lending practices between large and small banks, observing that large banks commonly rely on standardized, data-driven criteria, while smaller banks prioritize qualitative assessments and the personal attributes of borrowers. On the other hand, Chun Chang, Guanmin Liao, Xiaoyun Yu and Zheng Ni (2014) find that soft information, evolved through banks' relationship lending, still matters for large firms, despite the fact that hard information for such firms is abundant. These studies reveal a more intricate relationship between bank size, information type, and firm size than previously understood. Our results further extend these insights by demonstrating that BigTech lending also incorporates soft information, such as individual green activities, potentially enriching the data spectrum available to banks in the evolving Fintech landscape.

Layout The remainder of this paper is organized as follows. Section 2 provides an overview of the relevant institutional background. Section 3 presents our various empirical analysis of the financial friction channel in green activities, using the Ant Forest dataset. In Section 4, we develop a quantitative model to assess the green value of our framework and discuss the welfare implications of our proposed incentive-compatible mechanism, comparing it to conventional approaches such as mandated green activity requirements and subsidies. Finally, Section 5 concludes with policy discussions.

2 Institutional Background

2.1 Alipay and Ant Forest

The global push for environmental sustainability has led to significant shifts in both individual and corporate behaviors, particularly in efforts to reduce carbon emissions and combat climate change. Household activities, which account for about two-thirds of global carbon emissions(Anne Olhoff and John M. Christensen, 2020), have been a focal point for various initiatives aimed at promoting sustainable practices. Recognizing that encouraging eco-friendly behaviors at the household level is critical for addressing global warming and biodiversity loss, both governments and private organizations have rolled out programs to incentivize such actions. Among the most effective tools are personal carbon accounts, such as South Korea's "Green Credit Card"(Moon-Yong Kim, 2022) and the United Kingdom's Personal Carbon Allowance, which help individuals monitor and reduce their carbon footprints (Francesco Fuso Nerini, Tina Fawcett, Yael Parag and Paul Ekins, 2021).

Launched by Alipay in August 2016, Ant Forest has become the world's largest personal carbon account program. Originally created by China's largest e-commerce company to enhance trust in online transactions, Alipay has since evolved into a comprehensive super-app. It now offers a wide range of services, including wealth management, transportation, entertainment, hotel bookings, and food delivery. This expansive ecosystem allows Alipay to assess users' creditworthiness through their digital activities, while also featuring its own credit scoring system (the Zhima Credit Score) and offering virtual credit cards (i.e., Buy Now Pay Later) with dynamic limits based on users' platform behavior.

Ant Forest, with over 600 million active users, highlights the potential of technology to drive large-scale public engagement in sustainable practices. The program awards "green energy" points to users for environmentally friendly actions such as using public transportation, reducing waste, making online payments, and recycling. Points are 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 concrete environmental outcomes—such as the number of trees planted or land conserved—Ant Forest enables users to directly observe the impact of their actions, which enhances the program's appeal and underscores its environmental benefits. For further analysis, Tables A1 and A2 in the appendix provide a classification of actions with high and low environmental value, respectively.

Ant Forest 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. By linking green behaviors to financial incentives, the program offers users who consistently engage in eco-friendly actions the potential for higher credit scores and increased credit limits.[3] 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 environmental actions within its financial framework, Alipay sets Ant Forest apart from other personal carbon account programs.

[3]According to Order No.4 [2021] of the People's Bank of China (Measures for the Administration of Credit Reporting Services), only a limited number of officially licensed credit reporting providers are eligible to offer credit reporting services for financial products. As a result, although the Zhima credit score reflects users' overall creditworthiness, a higher score does not automatically translate into an increase in credit limits. With this caveat in mind, we conduct the initial correlation analysis between individual credit limits and green energy production in Section 3.2.

2.2 November 2020: Shopping Festival Met Regulatory Shocks[4]

The Double 11 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. Initially a one-day event, it has grown significantly in scale and duration, surpassing both Black Friday and Cyber Monday in sales volume. 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.

The 2020 Double 11 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 Double 11 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.[5]

Our data further corroborates this analysis, as shown in the time series of average credit line usage rates in Figure 2. 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 pro-

[4]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/

[5]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.

vides a valuable opportunity to investigate how these factors may influence individuals' engagement in green behaviors.

3 Empirics

3.1 Data and Variables

3.1.1 Data Source

Our study was conducted remotely using data from the Ant Open Research Laboratory (https://www.deor.org.cn/labstore/laboratory), which operates within the Ant Group environment. To safeguard user privacy, all data was anonymized and analyzed within the laboratory's sandbox, ensuring that individual observations remained concealed and data security protocols were strictly followed. The dataset includes a monthly panel of 100,000 randomly selected Ant Forest users, spanning from January 2019 to December 2022. This four-year period, which represents the maximum sample size allowed under the Ant Group's data-sharing policies, ensures the data's completeness and consistency, enabling a robust 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, promotional strategies, and user demographics, making the data from this period less reliable for analysis. By focusing on 2019 and beyond, we avoid complications arising from these initial transition years.

The sample selection was based on three criteria: (1) users had to be registered with Alipay before the launch of Ant Forest, (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.

3.1.2 Variable Construction

The main regression variables in this study are categorized into three groups: user characteristics, green behaviors, and credit information. 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, all quantified in grams of carbon reduction. Green energy production measures the carbon emissions avoided through users' actions, while green energy collection represents users transferring their accumulated energy to their accounts. The stealing aspect refers to users taking energy points from others if left uncollected.

Structural green behavior measures carbon reduction across different scenarios, such as using public transport, electric vehicles, or digital services like online ticketing. Other actions include the use of shared power banks, participation in the Clean Plate Campaign, and adoption of eco-friendly appliances and packaging. There are a total of 61 different green behaviors on the Ant Forest platform. These behaviors are further classified into high and low environmental impact categories (Eco-high and Eco-low), as detailed in Tables A1 and A2.[6] For example, walking and public transport 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.

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

Credit Credit information is represented by two variables: the credit line limit and credit line usage. 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.

Control Variable 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.

3.1.3 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. For the gender variable, "0" indicates male and "1" indicates female, with a mean value of 0.47, suggesting an approximately balanced sample in terms of gender distribution.

We considered three different scopes for measuring green energy production: Scope 1 includes all forms of green energy production, Scope 2 excludes energy generated through digital payments, and Scope 3 applies an even stricter criterion, further excluding energy produced through walking, public transport, and subway. Our preferred and baseline measure is Scope 2, as payments are closely related to credit line usage. To avoid any potential spurious correlations, we focus on green energy production that does not result from digital payments. Using the Scope 2 measure, 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)[7], 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 further define two categories of green energy production based on their scenarios: Eco-high and Eco-low behaviors. 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). These figures indicate considerable heterogeneity in users' credit usage patterns, with some users making extensive use of their credit lines.

The final set of variables in Panel A includes additional financial and behavioral metrics. 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 encompasses users' accumulated wealth and investments in funds, gold, bonds, and other financial products available on Alipay. The

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

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.

3.2 Initial Evidence

We begin our empirical analysis by examining the correlation between individual credit limits and green energy production. The model specification for this analysis is as follows:

$$\ln\left(CreditLimit_{i,t}\right) = \alpha GreenProduce_{i,t-1} + \Gamma Control_{i,t} + \eta_i + \omega_t + v_{c,y} + \epsilon_{i,t} \tag{1}$$

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 is the natural logarithm of the credit limit. The key independent variable, *GreenProduce*, denotes the green energy production in kilograms in our baseline regressions. Lagged terms are employed to mitigate concerns about contemporaneous shocks. The term *Control* includes control variables that potentially influence credit limits in month t, such as the natural logarithms of total financial assets and consumption. 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.

Panel A of Table 2 presents the regression results on the relationship between green behaviors and credit limits, using three different definitions of green energy production. Columns (1) and (2) use the overall green energy production (Scope 1), while Columns (3) and (4) exclude the green energy generated through digital payments (Scope 2) as consumption-related payments are closely linked to credit limits by default. Columns (5) and (6) further exclude the green energy produced through walking, public transport, and subway (Scope 3), applying a more stringent criterion. Odd-numbered columns omit control variables, while even-numbered columns include them. According to Panel A of Table 2, we find a positive association between higher green energy production and increased credit limits, and this relationship is robust across all different model specifications. According to our preferred model specification in Column (4), an increase of 1 kilogram in green energy production corresponds to a roughly 0.17% increase in credit limits (i.e., 24.65 *yuan* or 3.52 dollars), an effect that is both statistically and economically significant.

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 also employ Poisson regressions and inverse hyperbolic sine (IHS) transformations to verify the robustness of our findings.[8] According to Panel B of Table 2, our results are robust under various econometric models, including ordinary least squares (OLS), Poisson regressions, and IHS transformations. 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. Columns (3) and (4) present results from Poisson regressions, yielding slightly lower coefficients (0.002 to 0.003), which remain significant at the 1% level. Columns (5) and (6), using IHS transformations, produce results consistent with the OLS estimates. 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.

Panel C of Table 2 extends the analysis to alternative measures of green behaviors, including green energy stealing, green energy collection, the number of trees planted, and both the number and area of reserves protected. Unlike the positive and statistically significant relationship between green energy production and credit limits, neither green energy stealing or collection exhibit significant relationship with credit limit (Columns (1) and (2)), emphasizing the informativeness of green behaviors rather than the social actions on the Alipay. While in Columns (3) to (5), the number of trees planted, and both the number and area of reserves protected exhibit positive and statistically significant relationships with credit limits, providing robust evidence of a strong correlation between diverse environmentally conscious behaviors and perceived creditworthiness. 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. Collectively, these findings suggest that small-scale (actual not social) engagement in green behaviors can lead to meaningful differences in credit limit.

Across all models, the high R-squared values (around 0.925) indicate that the variables, along with

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

controls and fixed effects, explain a substantial proportion of the variation in credit limits. In addition, in Figure A4 in the 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 further explored in the following Section 3.4.

Financial Inclusion Role of Green Behaviors In Table A3 in the appendix, we explore the heterogeneous effects of green actions on credit limits across different cities. Our key finding emphasizes the financial inclusion potential of linking credit limits to green behavior, with the connection between green actions and credit limits being notably stronger in smaller cities. Specifically, in the first two columns of Table A3, we classify cities into tier-1 and non-tier-1 categories. Tier-1 cities refer to the four largest cities in China—Beijing, Shanghai, Guangzhou, and Shenzhen. As shown in Columns (1) and (2), we observe a positive relationship between increased green energy production and higher credit limits, but this effect is only significant for users residing in non-tier-1 cities. To put this into perspective, for users living in non-tier-1 cities, a 1-kilogram increase in green energy production corresponds to a roughly 0.16% increase in their credit limits, equivalent to an additional 23.20 *yuan* (or approximately 3.31 US dollars). In contrast, no significant association is found among users in tier-1 cities.

The analysis continues in Columns (3) and (4), where we extend the classification to include users in both tier-1 and tier-2 cities versus those in other cities. Tier-2 cities, as defined here, include municipalities directly under central government control and provincial capitals. The results remain largely consistent with the previous analysis, although with some minor variations in magnitude. Among users living in non-tier-1 and non-tier-2 cities, an increase of 1 kilogram in green energy production results in a roughly 0.24% increase in credit limits, which is equivalent to an additional 34.80 *yuan* (or about 4.97 US dollars). Again, we do not observe any significant association among users in tier-1 and tier-2 cities.

These findings underscore the important role that linking credit limits to green actions plays in promoting financial inclusion, especially in areas where individuals have limited access to traditional financial services. Many studies have documented that users in rural or smaller cities often face challenges in accessing credit or increasing their borrowing limits through conventional means (e.g., Robin Burgess and Rohini Pande, 2005; Franklin Allen, Asli Demirguc-Kunt, Leora Klapper and Maria Soledad Martinez Peria, 2016). The incentive structure described in our paper offers a novel mechanism to provide financial services to these underserved populations, enabling them to improve their financial standing through environmentally sustainable actions. By linking credit to green behaviors, BigTech platforms can not only encourage eco-friendly actions but also help to integrate economically marginalized groups into the financial system, offering them a path to better access credit and other financial products.

3.3 Financial Friction and Individual Green Behaviors

3.3.1 Baseline Regression

Our initial findings reveal a positive correlation between users' credit limits and their engagement in green behaviors. However, this observed relationship may stem from various underlying factors. In this section, we aim to strengthen the evidence supporting our hypothesis that this correlation is driven by financial frictions. Specifically, we propose that a significant portion of users' green behaviors are motivated by their desire to alleviate borrowing constraints. By engaging in green activities, users may enhance their within-platform scores or creditworthiness, potentially leading to increased credit limits.

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.

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:

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

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.

Third, we divide 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. 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:

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

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 3, examine the relationship between borrowing constraints, credit usage, and green behaviors. Using total green energy production excluding payments (i.e., Scope 2) as the dependent variable, Columns (1) and (2) show that the credit usage rate is positively and significantly associated with green production, with coefficients of 0.2451 and 0.1326, respectively. The difference between these two columns lies in the inclusion of control variables in Column (2). These coefficients suggest that a 1% increase in credit usage corresponds to an approximate 0.13% to 0.25% increase in green production. This relationship remains robust across specifications, as indicated by consistently high R-squared values (around 0.55–0.58).

Additionally, using model specification (2), the estimated borrowing-constrained dummy variable in Columns (3) and (4) is positively associated with green production, with coefficients of 0.5047 and 0.2392, respectively. It means that for constrained users, they generate 50.47% or 23.92% higher level of green actions. These findings indicate that constrained individuals are incentivized to pursue more green activities.

Finally, using model specification (3), Column (5) further analyzes varying credit usage levels, dividing credit usage into distinct ranges. The coefficients for these ranges are all positive and significant at the 1% level. More importantly, the estimated coefficients are monotonically increasing, with the highest level (80%-100%) associated with a coefficient of 0.3202. It indicates that relative to the baseline group of users with credit usage below 20%, users with credit usage rate between 80% and 100% generate 32.02% higher level of green actions. This pattern suggests that as users approach their credit limits, their green energy production increases substantially, highlighting a potential behavioral response to financial constraints.

Table A4 in the appendix further expands our analysis by comparing "Eco-High" and "Eco-Low" behaviors. The results show that both types of behaviors are positively and significantly correlated with credit usage. For instance, Columns (1) and (4) report coefficients of 0.1264 for Eco-High and 0.0539 for Eco-Low behaviors, both significant at the 1% level. The borrowing-constrained dummy also shows positive associations with both types of behaviors, as indicated in Columns (2) and (5). More specifically, the estimated coefficients are 0.2318 for Eco-High and 0.0887 for Eco-Low behaviors, which again are both significant at the 1% level. Furthermore, Columns (3) and (6) reveal a similar, monotonically increasing pattern of green incentives in relation to the degree of financial constraints, regardless of whether the behaviors are classified as Eco-High or Eco-Low. Notably, Eco-High behaviors show a stronger response to financial constraints, indicating that these behaviors are more sensitive to credit limits.

In conclusion, our results 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. These findings underscore the importance of understanding how financial pressures shape behaviors and suggest that green actions may increasingly serve as indicators of creditworthiness in the financial sector.

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.[9]

[9] 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.

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 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.

Moreover, the regression results in Tables 3 remain robust when applied to subsamples based on different demographic indicators. For example, Graph (a) in Figure 3 illustrates the relationship between credit usage rates and green energy production for male and female users. The gray solid line represents the estimated results for the entire sample (as shown in Tables 3), while the red dashed line and green dotted line correspond to the female and male subsamples, respectively. The figure shows that the coefficient for credit usage rate increases steadily across usage brackets (0-20%, 20-40%, etc.), in line with the findings in Table 3. More importantly, the trend is similar for both male and female groups, although males exhibit slightly higher coefficients, indicating stronger financial incentives for green production. Despite these small differences, the overall pattern remains consistent: as credit usage rises, so does the coefficient for green behavior. This alignment across genders demonstrates that both male and female users respond similarly to credit constraints in their engagement with green behaviors. Graph (b) of Figure 3 replicates this analysis for younger and older users, with those under 30 classified as "young". As shown in the graph, our primary findings hold across these age groups. The consistency of these results further supports the robustness of our findings, suggesting that the positive relationship between financial constraints and environmentally friendly actions, such as green energy production, is not dependent on gender or age. Instead, it reflects a broader behavioral response to credit limitations across the population.

3.3.2 Identification with Difference-in-Difference Approach

To establish a causal relationship, we adopt a DiD event study approach. This identification strategy leverages the 2020 Double 11 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 Double 11 festival, combined with the regulatory shock of Alipay's IPO suspension, serve 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 Double 11 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:

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

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 increased by at least 50% in October–December 2020 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 Double 11 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 Double 11 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 Double 11 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 4, which plots the coefficients over time to illustrate the impact of the 2020 Double 11 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 or negative, suggesting no significant differences in green production between the treated and control groups before the event. The only exception is a significantly negative coefficient for the month immediately preceding September 2020. However, starting in October 2020, the coefficients show a clear positive trend, reaching a peak in February 2021. The estimated coefficient for February 2021 is 0.1669, indicating that users with increased credit usage during the Double 11 event engaged in 16.69% 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 A3 in the appendix 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 February 2021, the estimated coefficient peaks at 0.2154, which means that individuals with increased credit usage performed 21.54% more Eco-high actions. In contrast, we observe a decreasing trend for Eco-low behaviors, suggesting that individuals with increased credit usage performed less Eco-low actions compared to control users, with a coefficient peaked at four months after the shock (i.e., -0.0845).

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 Double 11 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.

3.4 Green Actions as Soft Information for BigTech

3.4.1 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 4 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* ($\approx$ 286 dollars), 5,200 *yuan* ($\approx$ 743 dollars), 10,600 *yuan* ($\approx$ 1,514 dollars), and 55,000 *yuan* ($\approx$ 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* ($\approx$ 1,161 dollars) to 8,984 *yuan* ($\approx$ 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* ($\approx$ 2,168 dollars) to 17,280 *yuan* ($\approx$ 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 4 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).

3.4.2 Evidence from Personal Information Protection Law

While our previous findings indicate a positive correlation between credit limits and green actions on the Ant Forest platform, this relationship may be influenced 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 affect their credit limits. To isolate the soft information value effect of green actions, we leverage the enactment of the Personal Information Protection Law 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 introduce an interaction term between the PIPL policy and green energy production in our baseline regression model, focusing on the three-month periods before and after the PIPL's implementation. The results, presented in Table 5, provide insights into how reliance on users' green behaviors for credit decisions evolved pre- and post-PIPL. As in previous analyses, odd-numbered columns exclude control variables, while even-numbered columns include them. Columns (1) and (2) examine green energy production as a predictor of credit limits, both independently and in interaction with the PIPL policy. Before the implementation of the PIPL, the coefficient on green energy production is significant, suggesting that in the absence of restrictions on alternative data, green energy production have already contributed to increases in credit limits. While after the PIPL came into effect, the positive and highly significant interaction term implies that green energy production became more relevant as a predictor of credit limits. Post-PIPL, a 1000-gram 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 in response to the regulatory constraints. This shift underscores how the PIPL has amplified the role of environmentally conscious behaviors in credit evaluations. 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.

We further explore the heterogeneous soft information value of Eco-high and Eco-low behaviors. Columns (3) and (4) present the results for Eco-high behaviors, showing a pattern consistent with total green energy production. Before the PIPL, Eco-high behaviors had some predictive power for credit limits. After the policy, Eco-high behaviors become a more significant and more positive predictor of future credit limits. According to the estimated values of coefficients, a 1000-gram increase in Eco-high green actions corresponds to an additional 0.53% (without controls) or 0.54% (with controls) increase in credit limits, which is significant at the 1% level. Columns (5) and (6) show the corresponding results for Eco-low behaviors. Before the implementation of the PIPL, the coefficient on Eco-low behaviors is insignificant, suggesting that in the absence of restrictions on alternative data, Eco-low behaviors do not contribute significantly to increases in credit limits, as BigTech has alternative ways to assess a user's creditability. However, after the PIPL came into effect, the interaction term becomes positive and highly significant, implying that Eco-low behaviors became more relevant as a predictor of credit limits. The standardized coefficient [10] 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.

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 may incentivize individuals to engage in green behaviors as a strategy to improve their creditworthiness, demonstrating that green actions hold 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

[10]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.

credit evaluations as one source of soft information.

3.4.3 Evidence from Default

To delve deeper into the soft information value of green activities, we replicate the previous regressions, but shift the focus from credit limits to defaults. This analysis aims to examine whether the increase in credit limits associated with green behaviors could unintentionally lead to higher default risks. If the default risk remains unchanged or even decreases alongside increases in credit limits, it would suggest that using green actions to determine credit limits actually improves allocation efficiency for the BigTech platform.

Specifically, we use two measures of defaults: 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. The key regression results are summarized in Panel A of Table 6. Column (1) of Panel A shows a significant and negative relationship between green production and default rates, indicating that for each additional kilogram of green production, the default rate decreases by 0.4348. After controlling for additional factors in Column (2), this relationship remains significant but weaker, with a reduction of 0.2096 in the default rate per kilogram of green production. Column (3) includes the variable for green stealing, which exhibits a modest but statistically significant negative correlation with default rates, where an increase of 1 kilogram in green stealing is associated with a 0.0744 decrease in the default rate. This result aligns with our previous findings in Table 2, where the social aspect of green actions did not play a major role in credit limit determinations. Finally, Column (4) reveals that green collection is linked to a 0.1735 reduction in the default rate per kilogram, highlighting its similar role in predicting financial responsibility. Across all specifications, financial and consumption variables, such as ln(Total Financial Assets) and ln(Consumption Amount), also exhibit significant negative relationships with default rates, which is consistent with the expectation that greater financial resources and consumption are linked to lower default risks. In the final four columns, we replicate the empirical analysis using default amounts as the dependent variable. Overall, our key findings remain consistent, and the relative magnitudes across different model specifications and variable choices show similar patterns. Together, these results highlight the differentiated impact of various green behaviors on default probabilities, with green production exhibiting the most substantial predictive power.

Additionally, we replicate the analysis from Section 3.3 to explore how the relationship between green activities and default rates varies across users with different levels of financial constraints. Specifically, we apply two methods to classify users into distinct groups. The first approach 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 line usage rate is 80% or higher, indicating significant reliance on available credit, and 0 otherwise. This allows us to isolate the behaviors of highly constrained users and investigate whether their green activities differ from those of users with lower credit usage. The second approach segments 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 helps assess whether higher credit usage correlates with increased green behaviors. The key regression results are summarized in Panel B of Table 6. From these two sets of regressions, we draw two key insights. First, the significant negative effects are most pronounced in the unconstrained group, suggesting that borrowers with greater financial flexibility are better able to translate their green behaviors into responsible financial actions, thereby reducing default risks. Second, for the constrained group, the effects of green activities on default rates and amounts are largely insignificant, indicating that the increased credit limit of these users simply prevent an increase in their default rates. These findings have broader implications. On one hand, they demonstrate that green values can provide valuable data for BigTech platforms to assess creditworthiness. On the other hand, these green indicators allow platforms to expand lending without raising default risks, highlighting the dual benefits of promoting sustainability while ensuring financial stability. This synergy underscores the potential of combining green values with FinTech innovation in credit markets.

4 Quantitative Analysis

4.1 Model Setup

To rationalize our previous empirical findings and conduct related welfare analysis, we propose a partial-equilibrium dynamic model with endogenous green actions and borrowing constraints. Specifically, we analyze an infinite-horizon, discrete-time economy with a constant risk-free rate r. In this economy, a representative user on the Ant Forest platform maximizes the following expected present value of future utility $\mathcal{V}_0$:

$$\mathcal{V}_0 = \mathbb{E}\left[\sum_{t=0}^{\infty} \frac{u\left(c_t, \omega_t\right)}{\left(1+r\right)^t}\right] \tag{5}$$

where c_t denotes consumption and ω_t measures the green activities at time t. For simplicity, we omit time subscripts going forward and use a prime symbol $'$ to denote next-period variables.

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

$$u\left(c, \omega\right) = \left[\gamma\left(c - \underline{c}\right)^{\frac{\xi-1}{\xi}} + \left(1-\gamma\right)\omega^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi}{\xi-1}} \tag{6}$$

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

$$\ln \underline{c}' = \rho \ln \underline{c} + \sigma \varepsilon \tag{7}$$

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 (6) 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 $0 < \xi < 1$).[11] Second, the parameter $\underline{c}$ represents a minimum consumption threshold that users must maintain, i.e.,

[11]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.

$c \geq \underline{c}$. 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 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 $\left(b' - \bar{b}\right)^{\eta}$, where $\eta > 0$ 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.

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 3.2. The borrowing constraint takes the following form:

$$b \leq \bar{b} = \lambda \bar{y} \kappa^{\theta} \tag{8}$$

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:

$$\Psi\left(\kappa, \frac{\omega}{\kappa}\right) = \frac{\phi}{2}\left(\frac{\omega}{\kappa}\right)^2 \kappa \tag{9}$$

where ϕ governs the inflexibility of green capital accumulation. To better align with reality, we assume that green capital investment has a feature of irreversibility, i.e., $\omega \geq 0$. In this way, the user's budget constraint on the Ant Forest platform is:

$$c + \omega + \Psi\left(\kappa, \frac{\omega}{\kappa}\right) + b = \bar{y} + \mathbb{1}_{b'<0}\frac{b'}{1+r} + \mathbb{1}_{0<b'<\bar{b}}\frac{b'}{1+r^{BNPL}} + \mathbb{1}_{b'>\bar{b}}\frac{\left(b'-\bar{b}\right)^{\eta}+\bar{b}}{1+r^{BNPL}} \tag{10}$$

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:

$$\mathcal{V}\left(\underline{c}, \kappa, b\right) = \max_{c,\omega,b'}\left\{u\left(c,\omega\right) + \frac{1}{1+r}\mathbb{E}\left[\mathcal{V}\left(\underline{c}', \kappa', b'\right)\right]\right\} \tag{11}$$

subject to the constraints:

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

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 7 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.[12] Following Tak Wing Chan, John Ermisch and Rob Gruijters (2019), we set the persistence parameter to 0.37 and 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 employ the SMM approach to jointly estimate the remaining eight key parameters: long-run average income ($\bar{y}$), share parameter (γ), degree of elasticity (ξ), degree of green capital investment inflexibility (ϕ), degree of financial frictions (λ), soft-information lending parameter (θ), and repayment delay punishment (η). Panel B of Table 7 evaluates the model's performance by comparing empirical and model-generated moments. First, consumption volatility is 0.35 in the data versus 0.42 in the model.

[12] 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.

Second, the average consumption-to-income ratio shows 0.60 in the data compared to 0.53 in the model. Third, the median log consumption-to-green-energy production ratio (using Scope 2 green energy production) is 0.56 in the data versus 0.66 in the model. Fourth, the median credit usage rate is 2.9% empirically and 3.4% in the model. Fifth, the median ratio of green capital investment to credit limit is 0.05 in the data compared to 0.08 in the model, validating our representation of how users leverage green behaviors for credit access. Sixth, the average default rate shows 0.99% in the data versus 1.08% in the model. Seventh, the correlation between credit limit and green capital investment, reflecting the role of soft-information in credit determination, is 0.11 empirically and 0.15 in the model. Finally, the correlation between credit usage rate and green actions, which helps identify the share parameter γ (measuring intrinsic environmental concern in China), is 0.20 in the data compared to 0.22 in the model.

Using these data moments, we report the estimated values for our internally calibrated parameters in Panel B of Table 7. More specifically, the long-run average income in our model is 1.31 with a standard error of 0.12. The estimated share parameter γ is 0.71, with a standard error of 0.07.[13] The elasticity of substitution parameter ξ is estimated at 2.09 with a standard error of 0.33, indicating that consumption and green actions function as substitutes. The value of ϕ, which captures the adjustment costs associated with green capital investment, is estimated at 1.30, with a standard error of 0.12. This relatively high value indicates substantial friction in modifying green capital stock, suggesting users face considerable challenges in scaling up or down their environmental activities. The estimated value of λ, representing the degree of financial frictions, is 0.43, with a standard error of 0.05. This moderate value indicates meaningful but not severe borrowing constraints for users. Additionally, the estimated degree of soft-information used for lending θ is 0.65, with a standard deviation of 0.08. Lastly, the estimated degree of repayment delay punishment(ν) is 1.52, with a standard error of 0.24. This relatively high value of ν suggests that users face significant penalties for delayed repayments, effectively deterring their delinquent behavior.

[13]The green-in-utility component in our model serves as a catch-all term for all green incentives that are not related to financial frictions. This encompasses both intrinsic environmental values and other motivations, such as the gamification benefits users derive from the Ant Forest platform. Our analysis focuses on distinguishing between two main drivers of green behavior: those motivated by financial frictions and those driven by all other factors combined.

4.3 Quantitative Performance

Figure 5 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 3. 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 6. This graph demonstrates the influence of green activities on reducing default rates, as captured by both the data and the model.

According to Figure 5, 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 lowest 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 aligns with empirical data in capturing the real-world impact of green energy production on default rates across different credit usage groups. A key pattern observed in both the model and the data is that increased green energy production reduces default rates for users with low credit usage (0–20%), but has minimal or negligible effects for those with higher credit usage. This result is consistent with the model's mechanism, where the total debt limit decreases as credit usage increases, thereby constraining borrowing capacity and lowering the likelihood of default among users with lower credit usage rates.

Overall, the calibrated model demonstrates strong predictive performance across various credit usage segments, which emphasizes the role of credit limits and financial constraints in encouraging green investments without exacerbating default risks. These findings have several key implications. First, they suggest that access to financial resources and credit line utilization are crucial drivers of green behavior on the Ant Forest platform. Second, the strong alignment between the model and empirical data across different usage segments highlights the economic significance of financial frictions and borrowing constraints in shaping environmentally conscious actions. Finally, offering financial incentives tied to increased credit limits can serve as an effective mechanism for encouraging sustainable behavior without raising default rates. In this regard, BigTech platforms hold significant potential to drive environmental sustainability initiatives forward.

4.4 Quantifying the Green Value of BigTech Credit

In this section, we conduct counterfactual analyses using our calibrated model to quantify the green value of BigTech credit by examining changes in data-sharing policies (i.e., θ parameter in our structural model). Data-sharing restrictions are modeled as percentage reductions in θ from its baseline value of 0.65, as estimated in our baseline analysis. The parameter θ captures the extent of business integration across BigTech services, specifically the linkage between green activities and household credit limits. Consequently, reductions in θ reflect limitations on BigTech's ability to utilize user data, thereby diminishing the credit benefits derived from cross-business synergies. Our quantitative analysis focuses on two main dimensions: societal green losses and BigTech losses. Societal green losses are measured by the percentage decline in the equilibrium green capital stock under varying levels of data-sharing restrictions. BigTech losses are further decomposed into two components: (1) the soft information value loss, measured by the increase in the equilibrium default probability, and (2) the net profit loss from lending services. Both losses are expressed as percentage differences between the steady-state outcomes under the new regulatory scenarios and those in our baseline analysis.

Table 8 presents the losses across three categories—BigTech Credit Value Loss, BigTech Soft Information Value Loss, and Green Value Loss—under varying degrees of data-sharing restrictions, ranging from 10% to 100%. To interpret these restrictions, a 10% reduction in data sharing means that the parameter θ decreases from its baseline value of 0.65 to 0.59. In our model, we first calculate the steady-state equilibrium without any data-sharing restrictions (i.e., $\theta = 0.65$), then assess the percentage changes as the restriction intensifies (e.g., $\theta = 0.59$ for a 10% restriction). Our results in Table 8 yield three main insights. First, data-sharing restrictions substantially affect BigTech's profits. The BigTech Credit Value Loss increases sharply as restrictions tighten, rising from 3.12% at a 10% restriction to 24.35% under a complete (100%) restriction. This profit loss stems from two primary channels: (1) a reduction in borrowing due to lower credit limits and (2) declining bond prices caused by higher default rates. These findings highlight the pivotal role of soft information integration in BigTech's credit services. Restricting the use of soft information weakens BigTech's ability to accurately assess creditworthiness and expand lending, thereby reducing profits.

Second, the BigTech Soft Information Value Loss increases more gradually, growing from 1.68% at a 10% restriction to 14.89% at a 100% restriction. This pattern underscores the importance of soft information—derived from users' green actions—in mitigating default risks. For instance, with a 10% data-sharing restriction, the increase in default rates accounts for 53.8% of the total lending loss (i.e., 1.68% out of 3.12%). When the restriction reaches 100%, this proportion rises to 61.1%. These results emphasize that, beyond their social value, green actions play a crucial role in BigTech's lending profitability by lowering default probabilities.

Third, our primary variable of interest, societal green losses, increases significantly as data-sharing restrictions tighten, rising from 4.15% to 31.64%. The green value loss reflects the decline in societal welfare due to reduced green capital investments, which are incentivized by BigTech's integrated credit offerings. During our sample period, the average green capital stock over four years is 68,181 grams.[14] Under a 10% reduction in Ant Forest's data-sharing policy, annual green energy production per user would decrease by 707.37 grams every year, roughly equivalent to the carbon absorption of a tree over 14 days.

Given Ant Forest's user base exceeding 600 million, the aggregate green losses associated with even a modest restriction are considerable. When valued using current European carbon prices,[15] the economic cost of a 10% data-sharing restriction amounts to 56.07 million US dollars per year (approximately 392.52 million *yuan* per year). Under a 100% restriction, this cost escalates to 427.52 million US dollars per year (around 2.99 billion *yuan* per year). On an individual level, the average green value per user is 0.71 US dollars per year (approximately 4.99 *yuan* per year). This relatively modest average stems from the fact that only a small fraction of Ant Forest users face significant credit constraints. As shown in Panel B of Table 1, just 3.5% of users are severely constrained (i.e., with a credit usage rate exceeding 80%). Among these users, however, the average green value increases sharply to 20.29 US dollars per year (about 142 *yuan* per year), representing a substantial economic benefit.

These findings underscore that stricter data-sharing policies significantly undermine BigTech's capacity to promote green initiatives, leading to notable reductions in green investments and substantial societal costs. More importantly, while the BigTech Credit Value Loss can be partially mitigated through looser lending standards (i.e., increasing the parameter λ), the Green Value Loss is not fully recoverable through alternative policy measures—a point we explore further in the next section.

4.5 Welfare Analysis and Policy Implications

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 welfare, which represents the lifetime utility of a typical platform user, and total welfare, which is the sum of consumer welfare and the profits generated by the BigTech platform. Through this welfare analysis, we reinforce the argument that a data-sharing

[14] For users with positive credit usage and active Ant Forest accounts, we calculated the average monthly green energy production (Scope 2) and multiplied it by 48 months to estimate the average green capital stock.

[15] As of February 2025, the carbon price in advanced EU countries like Switzerland is 132.12 US dollars per ton of emissions. This value is sourced from the World Bank's Carbon Pricing Dashboard (https://carbonpricingdashboard.worldbank.org/compliance/price). We adopt the European price due to the maturity of its carbon trading market, which more accurately reflects the true green value (e.g., Lina Meng, Pengfei Liu, Yinggang Zhou and Yingdan Mei, 2025).

policy framework is more advantageous than other approaches.

The analysis of the data-sharing policy follows the same methodology as in the previous 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%,[16] 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. For consistency in comparisons, we rescale the values by normalizing China's score to 1.0.[17] 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.[18] This approach enables us to compare the relative effectiveness of different policy tools across countries with varying levels of climate perception.

Graphs (a) and (b) in Figure 6 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 6, 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

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

green activity may offer environmental benefits, it places a heavy burden on consumers, as household 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 6, 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, according to the purple dotted lines in Figure 6, our proposed data-sharing policy effectively enhances both consumer and total welfare, with even greater effectiveness in countries with low climate perception. This feature can be attributed to the fact that our proposed solution is both incentive-compatible and selective, targeting users most in need of credit relaxation. For oil-producing and developing countries such as China, Malaysia, and Indonesia, our policy proves particularly effective, as it provides stronger incentives for households with low intrinsic green values to participate in green activities. Additionally, this policy boosts BigTech's profits by allowing household to have higher borrowing limits, thereby increasing BigTech's earnings. This outcome underscores the long-term sustainability of our data-sharing policy. In contrast to the other approaches, our proposed data-sharing policy does not face these same limitations, offering a scalable, sustainable solution that aligns environmental goals with consumer welfare and economic growth. For countries like China, where platforms such as Alipay and Tencent play significant roles in economic activities, regulators may consider adopting a unified approach that links profit-driven activities with those that contribute to public goods, such as environmental sustainability.

Our last finding here 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,[19] 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 developed by Alipay and a key component of China's BigTech ecosystem. Using 48 months of data, we show that individuals strategically engage in eco-friendly behaviors to improve their credit limits, especially when nearing borrowing constraints. These green actions not only benefit users by enhancing their financial standing but also generate soft information value for the platform. This soft information value becomes particularly significant under data-sharing restrictions imposed by regulations like the Personal Information Protection Law (PIPL), as it allows Ant Forest to assess creditworthiness internally. To establish causality, we leverage exogenous shocks to credit line usage in China, focusing on the 2020 Double 11 shopping festival and the unexpected regulatory shock of Alipay's IPO suspension. Additionally, we quantify the potential green losses resulting from restrictions on BigTech's data-sharing capabilities, shedding light on the broader implications of such regulatory changes.

Our results demonstrate that BigTech platforms like Ant Forest effectively influence user behavior by linking eco-friendly actions to financial incentives through credit limit adjustments. Users nearing

[19]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.

their credit limits are more likely to engage in green behaviors to improve their creditworthiness. This highlights the interplay between financial and environmental incentives, where green actions are strategically used to address credit needs. Our study emphasizes the transformative potential of personal carbon accounts on BigTech platforms to drive sustainable behaviors through innovative business models and policy frameworks. The personal-carbon-account-linked credit-limit approach offers a sustainable alternative to traditional ESG policies, enabling BigTech to incentivize green actions while creating data-driven value. In addition, in markets without established BigTech ecosystems, policymakers could integrate personal carbon accounts into existing credit reporting systems, aligning financial institutions with low-carbon goals and expanding access to sustainable finance. These insights underscore the potential of data-driven models to deliver both environmental and economic benefits, paving the way for global low-carbon economies.

One limitation of our proposed financial rewards 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: **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.

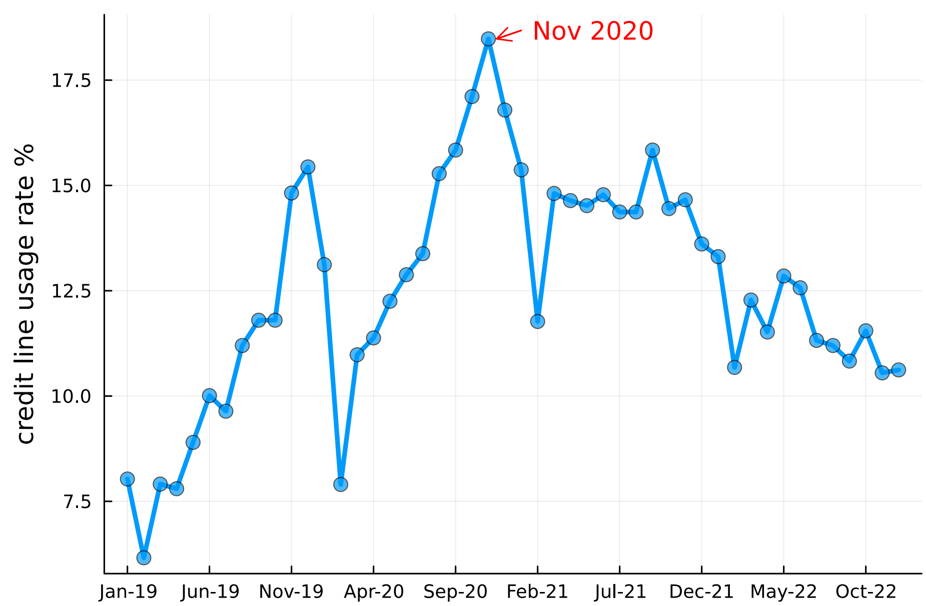

Figure 3: **Financial Frictions and Green Actions: The Impact of Gender and Age**

Notes: This figure illustrates the relationship between credit usage rates and green energy production for users across different demographic groups. The baseline regression model is specified as follows:

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

where, $Constraint^{20-40}_{i,t-1}$, $Constraint^{40-60}_{i,t-1}$, $Constraint^{60-80}_{i,t-1}$, and $Constraint^{over80}_{i,t-1}$ are dummy variables indicating the credit usage rate of user i in the previous month $(t-1)$. The 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%. These coefficients are plotted here, with the shaded area representing the 95% confidence intervals. Graph (a) shows the coefficients for the full sample, female subsample, and male subsample. The gray solid line represents the results for the entire sample, while the red dashed line and green dotted line correspond to the female and male subsamples, respectively. Graph (b) displays the coefficients for the full sample, young subsample, and old subsample, with the threshold for "old-young" set at 30. The gray solid line represents the results for the full sample, while the purple dashed line and yellow dotted line correspond to the young and old subsamples, respectively.

(a) gender

(b) age

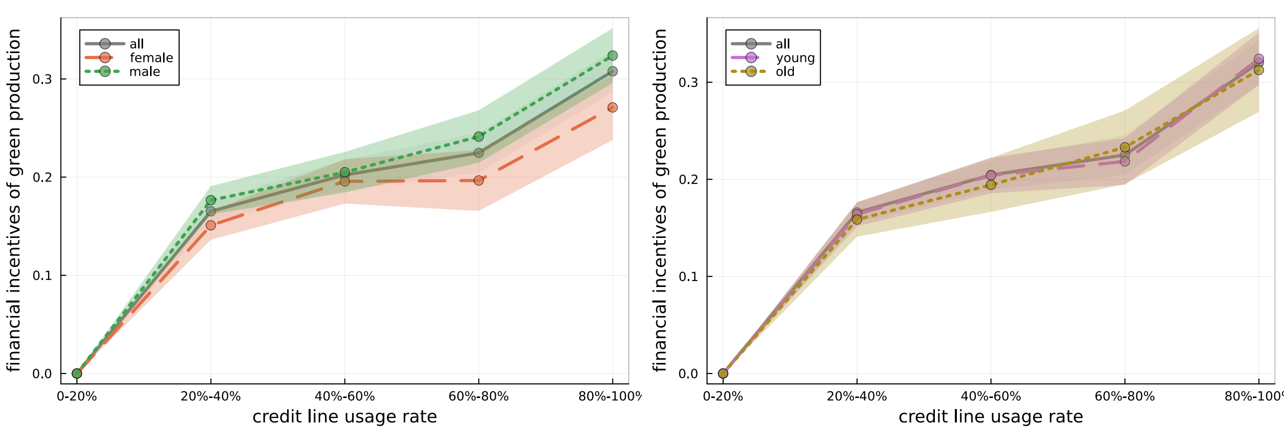

Figure 4: **Dynamic Effects of Increased Credit Usage on Green Actions**

Notes: This figure presents the results of a Difference-in-Difference event study. The identification strategy leverages the 2020 Double 11 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:

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

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 increased by at least 50% in October–December 2020 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 Double 11 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.

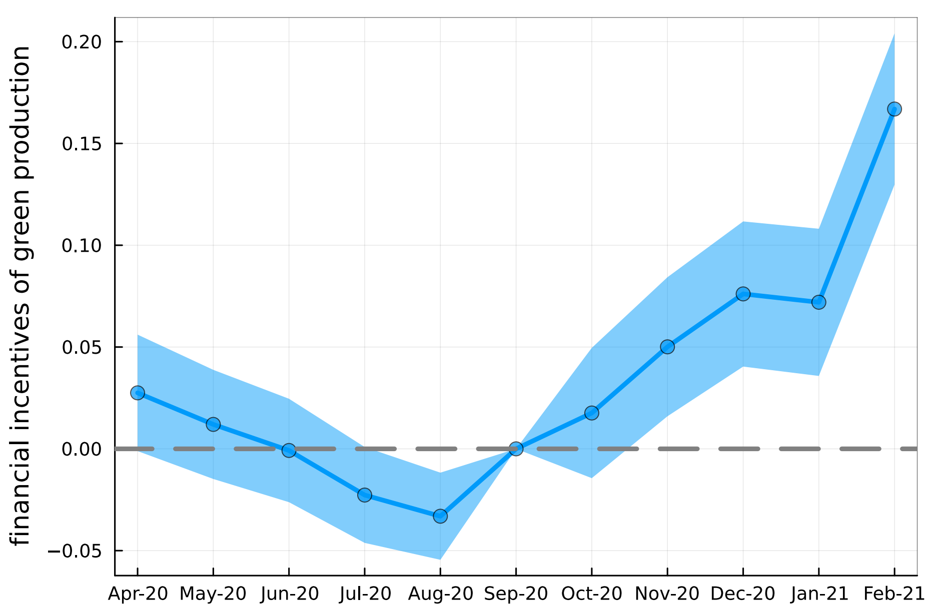

Figure 5: **Quantitative Performance: Model v.s. Data**

Notes: This table 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

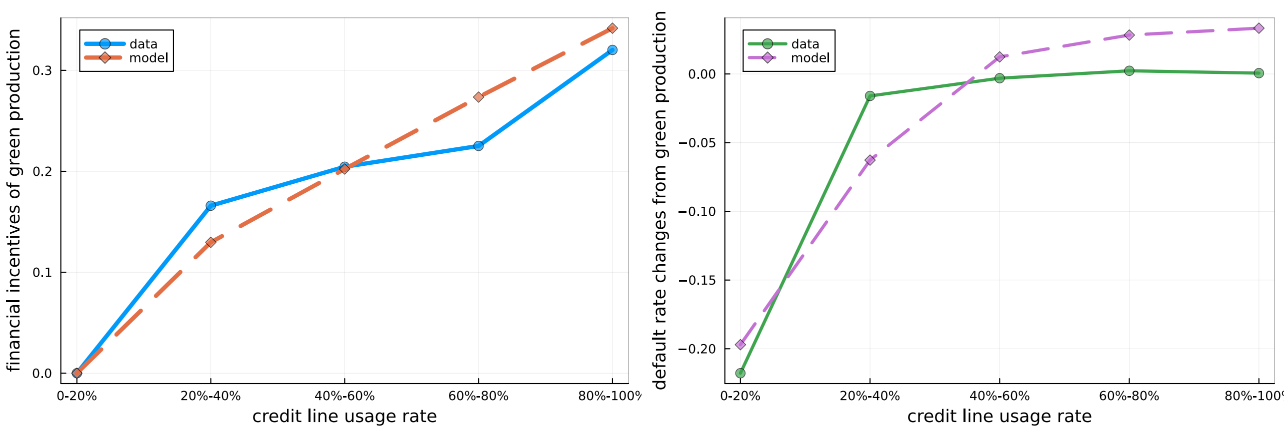

Figure 6: **Welfare Analysis**

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 welfare target is the lifetime utility of the representative platform user, excluding profits generated by the BigTech platform. Meanwhile, the total welfare is the sum of consumer welfare and platform profits. The impact of our proposed data-sharing 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 A4 in the appendix.

(a) consumer welfare (b) total welfare

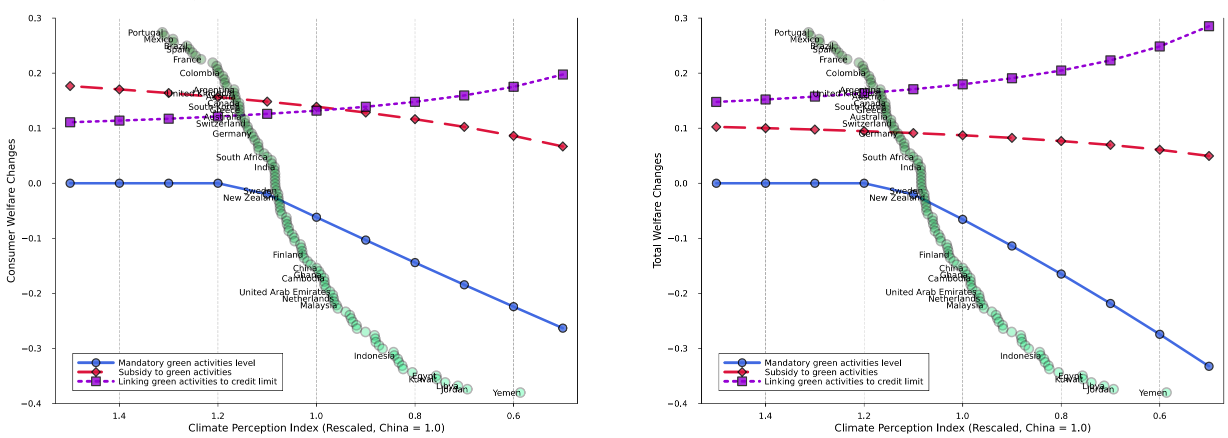

Table 1: **Descriptive Statistics**

Notes: Panel (A) provides the summary statistics for our ful 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
	city	3,945,168	-	-	-	-	-
Green Behaviors	green energy production (Scope 1)	3,945,168	1,262	1,546	0	655	7,156
	green energy production (Scope 2)	3,945,168	1,200	1,501	0	611	6,965
	green energy production (Scope 3)	3,945,168	111	225	0	0	1,202
	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 reserve 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
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) (Scope 2)	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: **Initial Evidence for Green Behaviors and CreditLimit**

Notes: Panel A presents Ordinary Least Squares (OLS) regression estimates of credit limits on green energy production measures. Columns (1)-(2) use the Scope-1 measure, which includes all green activities. Columns (3)-(4) use the Scope-2 measure, excluding payment-related green energy production. Columns (5)-(6) adopt the Scope-3 measure, further excluding walking and public transport energy. Odd-numbered columns exclude controls, while even-numbered 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. Panel B presents additional robustness checks: Columns (3)-(4) replicate Panel A using Poisson regression, and Columns (5)-(6) apply an inverse hyperbolic sine transformation. The dependent variables are natural logarithm of credit limits for OLS regressions in Columns (1)-(2), the raw credit limits for Poisson regressions in Columns (3)-(4), and IHS transformation of credit limits in Columns (5)-(6). Panel C explores alternative green behaviors, including (1) energy stealing, (2) energy collection, (3) trees planted, (4) protected reserves count, and (5) reserve area. All continuous variables are winsorized at the 1% level. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Green Energy Production and Credit Limit

	ln(Credit Limit)					
Dependent Variable	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
green energy production (Scope 1)	0.0050***	0.0023***				
	(7.16)	(3.32)				
green energy production (Scope 2)			0.0043***	0.0017**		
			(6.00)	(2.41)		
green energy production (Scope 3)					0.0185***	0.0119***
					(5.25)	(3.40)
ln (total financial assets)		0.0010***		0.0010***		0.0010***
		(2.90)		(2.95)		(3.05)
ln (consumption amount)		0.0110***		0.0111***		0.0111***
		(33.49)		(33.58)		(33.48)
Observations	3,862,977	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	0.927
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

Panel B: Alternative Regression Settings

Dependent Variable	Credit Limit					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	Poisson	Poisson	IHS	IHS
green energy production (Scope 2)	0.0043***	0.0017**	0.003***	0.002***	0.0042***	0.0016**
	(6.00)	(2.41)	(7.50)	(5.00)	(5.64)	(2.20)
ln (total financial assets)		0.0010***		0.001***		0.0010****
		(2.95)		(2.59)		(2.69)
ln (consumption amount)		0.0111***		0.006***		0.0112***
		(33.58)		(15.00)		(32.89)
Observations	3,862,977	3,862,977	3,830,641	3,830,641	3,862,977	3,862,977
R-squared	0.927	0.927	-	-	0.925	0.925
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

Panel C: Alternative Measures of Green Behaviors

Dependent Variable	ln(Credit Limit)				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	OLS
green energy stealing	-0.0002				
	(-0.18)				
green energy collection		0.0003			
		(0.26)			
# Trees planted			0.0133***		
			(8.71)		
# of reserve protected				0.0037***	
				(5.47)	
area of reserve protected					0.0037***
					(5.47)
ln (total financial assets)	0.0010***	0.0010***	0.0010***	0.0010***	0.0010***
	(3.08)	(3.06)	(3.13)	(3.00)	(3.00)
ln (consumption amount)	0.0112***	0.0112***	0.0113***	0.0112***	0.0112***
	(33.45)	(33.63)	(33.61)	(33.38)	(33.38)
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
Control	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: **Borrowing Constraint and Green Behaviors: Total Green Energy Production**

Notes: This table examines the relationship between financial constraints and green enery 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 rest 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)				
Dependent Variable	(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 4: **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

Table 5: **Green Behavior's Soft Information Value for BigTech: The Role of PIPL Policy**

Notes: We focus the timeframe on the three months before and after the announcement of the PIPL (April 2021 to Feb 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)					
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
green energy production (scope 2)	0.0035***	0.0027**				
	(3.00)	(2.32)				
PIPL × green energy production (scope 2)	0.0055***	0.0056***				
	(7.27)	(7.38)				
Eco-high behavior			0.0031***	0.0022*		
			(2.60)	(-1.49)		
PIPL × Eco-high behavior			0.0053***	0.0054***		
			(6.75)	(6.85)		
Eco-low behavior					-0.0011	-0.0009
					(-0.20)	(-0.17)
PIPL × 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 6: **Green Behavior's Soft Information Value for BigTech: 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)-(4)) and default amount (Columns (5)-(8)) as dependent variables, with three different measures of green actions. 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 higher credit usage is associated with increased green behaviors. 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

Dependent Variable	Default Rate				Default Amount			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
green energy production	-0.4348***	-0.2096***			-32.20***	-17.17***		
	(-33.09)	(-20.01)			(-17.81)	(-11.75)		
green energy stealing			-0.0743***				-8.49***	
			(-5.25)				(-3.67)	
green energy collection				-0.1736***				-15.18***
				(-11.54)				(-6.74)
ln(total financial assets)		-0.1012***	-0.1053***	-0.1036***		-8.86***	-9.18***	-9.04***
		(-25.72)	(-26.55)	(-26.21)		(-12.63)	(-12.95)	(-12.78)
ln(consumption amount)		-0.9513***	-0.9649***	-0.9603***		-62.26***	-63.35***	-62.97***
		(-54.48)	(-54.39)	(-54.39)		(-27.02)	(-26.99)	(-27.00)
Observations	3,818,137	3,818,137	3,818,137	3,818,137	3,862,977	3,862,977	3,862,977	3,862,977
R-squared	0.240	0.267	0.266	0.267	0.229	0.239	0.239	0.239
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES	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 7: **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	1.31	0.12
γ	share parameter	0.71	0.07
ξ	elasticity of substitution	2.09	0.33
δ	green capital depreciation rate	0.18	0.04
ϕ	degree of green capital investment inflexibility	1.30	0.12
λ	degree of financial frictions	0.43	0.05
θ	degree of soft-info usage	0.65	0.08
η	repayment delay punishment	1.52	0.24

Moments	Model Counterpart	Data	Model
consumption volatility	$\sigma(c)$	0.35	0.42
average consumption-to-income ratio	$\frac{c}{y}$	0.60	0.53
median consumption-to-green-energy-production-ratio	$\ln(\frac{c}{\omega})$	0.56	0.66
median credit usage rate	$\frac{b}{\lambda \bar{y} \kappa^{\theta}}$	2.9%	3.4%
median green capital investment to credit limit	$\frac{\omega}{\lambda \bar{y} \kappa^{\theta}}$	0.05	0.08
mean of repayment delay probability	$\frac{\int \mathbb{1}_{b'>\bar{b}}}{\int \mathbb{1}_{b'>\bar{b}}+\int \mathbb{1}_{0<b'<\bar{b}}}$	0.99%	1.08%
correlation between credit limit and green energy production	$\mathrm{corr}(\lambda \kappa^{\theta} (1-\mu)^{\nu}, \omega)$	0.11	0.15
correlation between credit usage rate and green energy production	$\mathrm{corr}(\frac{b}{\lambda \kappa^{\theta}(1-\mu)^{\nu}}, \omega)$	0.20	0.22

Table 8: **Counterfactual Exercises**

Notes: This table summarizes the counterfactual analyses using our calibrated model to examine the welfare implications of changes in data-sharing policies. In our model, data-sharing restrictions are represented as a percentage reduction in θ from its baseline value of 0.65, 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 the 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.

Degree of Data Sharing Restriction	**10%**	**30%**	**50%**	**70%**	**90%**	**100%**
BigTech Credit Lending Loss	3.12%	6.15%	7.23%	10.84%	16.92%	24.35%
BigTech Soft Information Value Loss	1.68%	3.54%	4.83%	6.45%	10.12%	14.89%
Green Value Loss	4.15%	7.42%	9.67%	14.23%	21.85%	31.64%

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Online Appendix

(Not For Publication)

This version: March 14, 2025

Figure A1: **Time-series Overview of the Gross Merchandise Value (GMV) generated during the Double 11 Shopping Festival**

Notes: This figure illustrates the annual gross merchandise value (GMV) across major online shopping platforms during China's Double 11 Shopping Festival from 2009 to 2021. The data is sourced from Syntun (http://www.syntun.com.cn/datanews/hotspot.html).

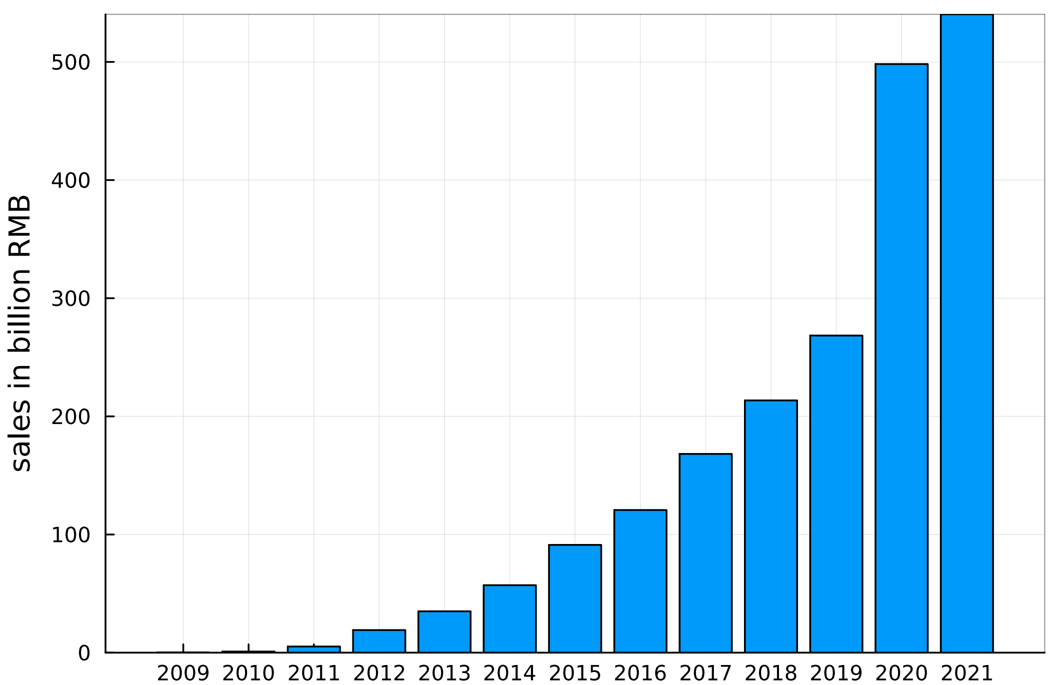

Figure A2: **Random Forest Regression Results on Credit Limit**

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.

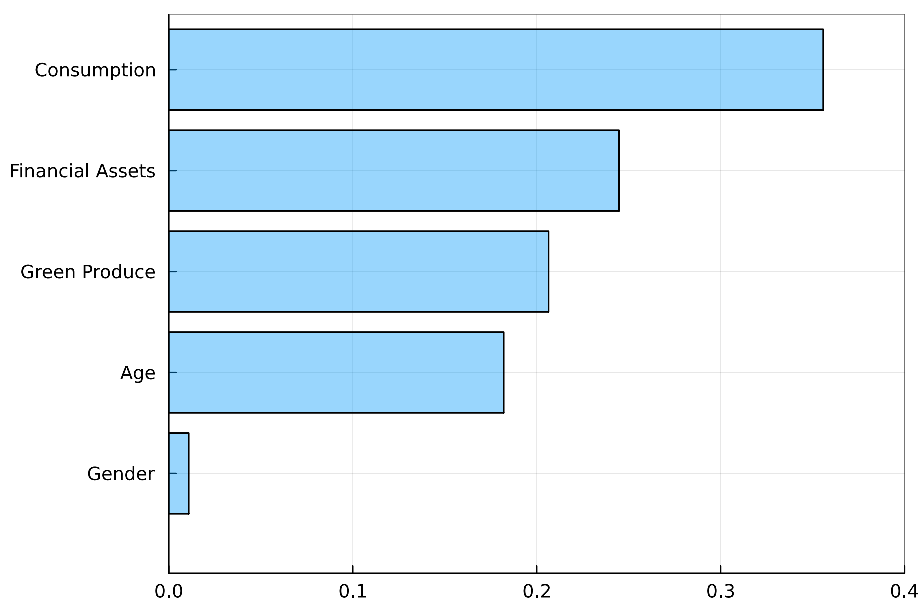

Figure A3: **Dynamic Effects of Increased Credit Usage on Green Actions**

Notes: This DiD specification utilizes data spanning from April 2020 to Feb 2021, treating September 2020 as the benchmark month. The regression model specification takes the same format as in Figure 4. 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.

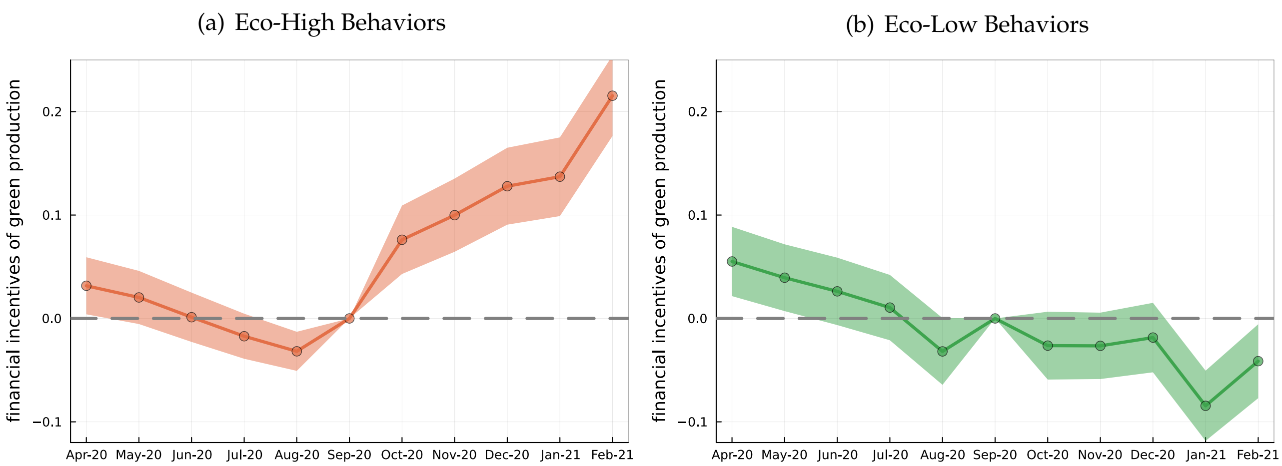

Figure A4: **Climate Perceptions Index**

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.

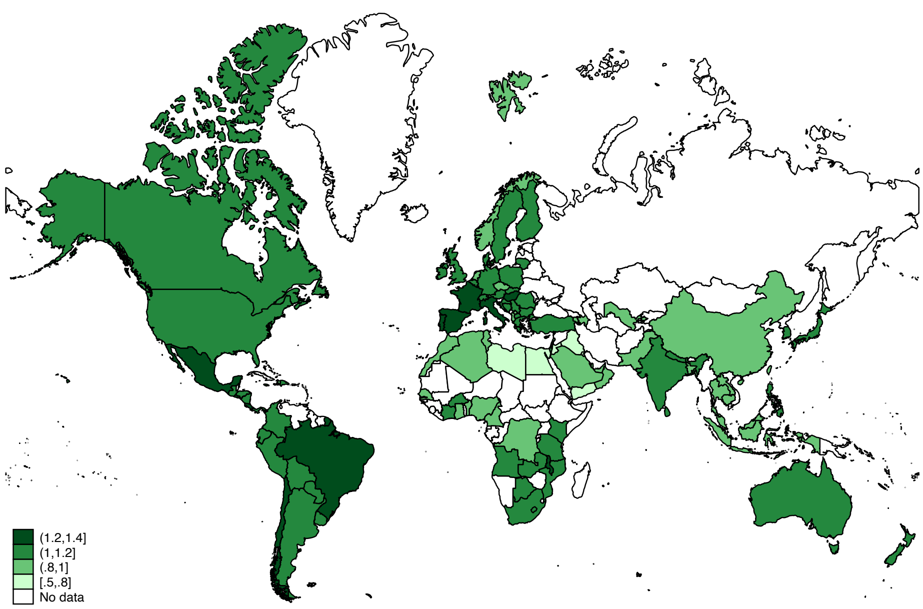

Table A1: **List of Eco-High Behaviors**

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.

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.

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: **Financial Inclusion Role of Green Behaviors**

Notes: This table presents a subsample analysis from Table 2, broken down by different city categories. Tier-1 cities refer to the top four cities in China: Beijing, Shanghai, Guangzhou, and Shenzhen. Tier-2 cities encompass both municipalities directly governed by the central government and provincial capitals. Specifically, tier-2 cities include Tianjin, Chongqing, Shijiazhuang, Harbin, Changchun, Shenyang, Hohhot, Taiyuan, Jinan, Zhengzhou, Hefei, Nanjing, Hangzhou, Nanchang, Fuzhou, Wuhan, Changsha, Nanning, Haikou, Chengdu, Guiyang, Kunming, Lhasa, Xi'an, Lanzhou, Xining, Yinchuan, Urumqi, Dalian, Qingdao, Ningbo, and Xiamen. Our definitions are based on the classification provided by the National Bureau of Statistics of China.

	ln(Credit Limit)			
	(1)	(2)	(3)	(4)
	Tier 1 Cities	Non Tier-1 Cities	Tier 1 and 2 Cities	Non-Tier 1 and 2 Cities
GreenProduce	0.0041	0.0016**	0.0004	0.0024***
	(1.33)	(2.14)	(0.30)	(2.87)
ln(Total Financial Assets)	0.0026*	0.0009***	0.0013**	0.0009**
	(1.78)	(2.58)	(2.11)	(2.11)
ln(Consumption Amount)	0.0152***	0.0109***	0.0124***	0.0106***
	(8.51)	(32.49)	(18.79)	(27.86)
Observations	208,868	3,654,109	1,184,964	2,678,013
R-squared	0.921	0.927	0.926	0.927
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
City*Year FE	YES	YES	YES	YES

Table A4: **Borrowing Constraint and Green Behaviors: Eco-High v.s. Econ-Low**

Notes: Here we extends the analysis in Table 3 to "Eco-High" and "Eco-Low" behaviors as alternative dependent variables.

	ln(Eco-High)			ln(Eco-Low)		
Dependent Variable	(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