Deciphering the Impact of BigTech Consumer Credit

Lei Chen
Southwestern University of Finance and Economics
leichen@swufe.edu.cn

Wenlan Qian
National University of Singapore
wenlan.qian@nus.edu.sg

Albert Di Wang
The University of Texas at Austin
albert.di.wang@utexas.edu

Qi Wu
City University of Hong Kong
qiwu55@cityu.edu.hk

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Abstract

This study evaluates the impact of BigTech credit on consumer spending, utilizing a unique dataset from a prominent BigTech ecosystem. In a nearly randomized context, we observe a 19% monthly increase in online spending among credit recipients. This increase is more pronounced for individuals with limited access to traditional financial credit, highlighting the role of BigTech credit in supporting financial inclusion. Moreover, the impact of credit is more notable in areas with more advanced logistics, illustrating the synergy between the financial and non-financial sectors of BigTech firms. Our analysis indicates that the uptick in consumption can be attributed to an increased frequency of purchases rather than to higher order values. Examining order-item level data, we find that credit recipients diversify their buying to include a wider variety of products and brands. Importantly, the provision of credit does not lead to a corresponding increase in discretionary spending or item pricing, and the heightened spending is not associated with increased delinquency, suggesting no overspending associated with BigTech credit.

Keywords: FinTech, Consumption, BigTech, BNPL, Consumer Credit, Consumer Behavior, Big Data

1. INTRODUCTION

Over recent years, BigTech firms, whose primary business is technology-related services, such as e-commerce, search engines, social media, hardware, and software, have expanded their presence in the domain of credit services. Since 2018, the lending totals of BigTech firms have outstripped the lending volumes of other FinTech entities like peer-to-peer and marketplace lending platforms, surpassing $700 billion globally by 2020 (Beck et al., 2022; Cornelli et al., 2023). While there is a rich vein of academic work focusing on BigTech's financing of small businesses (Hau, Huang, Shan, and Sheng, 2019; Huang et al., 2020; Chen, Huang, Lin, and Sheng, 2022; Hau et al., 2022; Gambacorta, Huang, Li, Qiu, and Chen, 2023), there remains a scarcity of studies examining their role in consumer finance—a realm where they are thought to have substantial influence (Stulz, 2022). In particular, there has been a gap in the literature regarding how exactly BigTech credit, and more broadly FinTech credit, impacts consumer activities, largely due to data constraints.

This paper seeks to bridge that research gap with a detailed, novel dataset from a leading BigTech firm administering one of the world's most prominent business-to-consumer (B2C) e-commerce platforms. The platform caters to nearly 600 million active users and generates net revenues surpassing 1,000 billion RMB, or approximately 150 billion US dollars, in 2023.

Our dataset intertwines different types of granular information within the firm's ecosystem, including consumer demographics, online activity metrics on the e-commerce platform (including page views, order placements, and purchase records), and credit data (details on credit issuance, utilization, and defaults). This unique dataset presents a significant opportunity to take a closer look and perform a comprehensive analysis on the precise effect of BigTech credit on consumer behavior, as the key to BigTech lending's success—compared to traditional banks and other

FinTechs—is their proprietary access to detailed user data within their established ecosystems such as e-commerce, social media, and internet search (Bank for International Settlements, 2019; Financial Stability Board, 2020; Liu, Lu, and Xiong, 2022).

Specifically, our analyses are built on two datasets. The first dataset is on the monthly basis (i.e., the monthly data), encompassing data on spending amounts, order volumes, and average prices per order. The second dataset is on the order-item level (i.e., the detailed data), offering granular details on consumer purchases, such as individual items bought and their respective transaction prices.

For empirical identification, we utilize reject inference (RI), a method employed by the BigTech firm in our study to enhance its AI credit assessment model. Specifically, RI randomly selects a group of applicants who are initially rejected and grants them credit. Consequently, the subset of RI-approved applicants becomes more comparable to those outright rejected than to those approved directly (for more details, see Section 3.2). We harness this RI methodology for our analysis, creating a distinction between consumers initially declined but later accepted via RI (treatment group) and those consistently rejected by both the AI model and RI (control group). Employing this framework in a stacked cohort difference-in-differences (DiD) analysis using our proprietary dataset, we are able to draw causal implications regarding the impact of BigTech credit on consumer behaviors.

Using the monthly data, our research indicates that consumers granted BigTech credit exhibit an approximate 19% increase in spending per month post-credit application relative to non-credit recipients. This augmented spending trajectory sustains over the subsequent twelve months, showcasing the enduring effect of BigTech credit on consumer expenditure. Through the implementation of alternate model specifications and sample selection methods, we affirm the robustness of our results.

We conduct two sets of cross-sectional analyses to investigate the influence of BigTech credits on consumer spending, with a particular emphasis on financial inclusion and the synergy between the firm's financial and non-financial operations. Our first analysis reveals that BigTech credits significantly stimulate spending, particularly for younger consumers, those with lower AI-generated credit scores, and individuals residing in areas with underdeveloped credit card sectors. This suggests that people who likely encounter greater difficulties in obtaining traditional credit experience the most substantial benefits from BigTech credits.

The second analysis demonstrates that the spending boost associated with credit availability is more pronounced in regions with advanced logistical infrastructures, which facilitate faster delivery of goods. This finding highlights a distinctive feature of BigTech companies, setting them apart from other FinTech firms: the symbiosis between their financial services and underlying non-financial business activities, as noted by Cornelli et al. (2020). Essentially, the effectiveness of BigTech credit is contingent upon the efficiency with which consumer demand is met, especially concerning the core offerings of the BigTech firm, such as the procurement and delivery of products in this context.

Next, we explore the mechanisms by which credit influences an increase in consumer spending. Monthly spending on the e-commerce platform is determined by two factors: the average spending per order and the number of orders placed within the month. Our findings reveal that while the provision of credit slightly increases the average spending per order by 3.5%, it significantly enhances the number of orders by 20%. This indicates that BigTech credit primarily stimulates spending through an increase in purchase frequency.

Shifting to the order-item-level data, we note that BigTech credit's availability heightens consumers' propensity for variety seeking. In particular, credit recipients are inclined to purchase a more diverse array of products from different categories, selecting items from a broader spectrum of brands and shopping across a multitude of distinct stores. This heightened appetite for variety raises concerns about the potential for consumers with BigTech credit to overspend. To address these concerns, we perform various analyses to illuminate the matter.

First, we manually categorize the products into discretionary and non-discretionary types. Our analysis reveals no evidence that access to BigTech credit results in an increase in discretionary spending. Additionally, we classify products into daily-use and necessities categories. We demonstrate that credit significantly boosts spending in both these categories. This suggests that BigTech credit primarily enhances spending on daily-use and necessity items, rather than discretionary purchases.

Second, we examine the price of products within each order. We uncover that BigTech credit's impact on the price of items purchased is negligible, implying that the credit does not sway consumers to opt for higher-priced goods within the same shop, brand, or/and category.[1] Furthermore, we ascertain that BigTech credit does not elevate the number of products bought per order neither. Since the spending per order can be viewed as the product of quantity and the price of items in an order, these outcomes also affirm earlier observations from the user-month data—that the monthly average order amount does not escalate with BigTech credit.

Our third analysis focuses on delinquency, utilizing various definitions to assess the situation. We find that the delinquency rate is relatively low. For instance, the monthly balance of loan

[1] Our results reveal that credit receipts improve their consumption set through product variety rather than product quality, as indicated by the item price within the same shop, brand, and category. Correspondingly, Butler, Demirci, Gurun, and Tellez (2024) demonstrate that consumers become more price-sensitive and alter their consumption set to smooth consumption in response to financial shocks.

principal overdue by more than 90 days, when divided by the total monthly balance of the consumer credit loan principal, fluctuates between 0% and 1.6%. This rate is on par with other major BigTech firms and is notably lower than those observed in traditional consumer credit providers, such as commercial banks in China. Furthermore, we observe no significant difference in the propensity for delinquency between consumers who experience substantial changes in spending and those with minor changes following credit approval. Synthesizing the insights garnered from these three analyses, we conclude that there is no concrete evidence to validate the concerns that BigTech firms' credit services contribute to excessive consumer spending.

Our paper offers several key contributions to the literature. Primarily, we enhance the burgeoning research surrounding BigTech finance. BigTech corporations are uniquely positioned to rival traditional banks and conventional FinTech platforms in extending credit, capitalizing on their data-rich environments, advanced technology, and extensive scale (Hau, Huang, Shan, and Sheng, 2019; Stulz, 2022; Li and Pegoraro, 2023). Emerging literature underscores BigTech's role in business lending, demonstrating that BigTech entities bolster financial inclusion and enhance the performance of Micro and Small-Sized Enterprises (MSEs) (e.g., Hau, Huang, Shan, and Sheng, 2019; Huang et al., 2020; Beck, Gambacorta, Huang, Li, and Qiu, 2022; Chen, Huang, Lin, and Sheng, 2022; Hau et al., 2022; Liu, Lu, and Xiong, 2022; Gambacorta, Huang, Li, Qiu, and Chen, 2023). While BigTech's potential in consumer finance is noted (Stulz, 2022), related research is sparse, possibly due to data scarcity. Two contemporaneous works, by Ouyang (2023) and Bian et al. (2023), are the exceptions.[2] Our research seeks to demystify the precise mechanisms through

[2] Our study distinguishes itself from these works in several respects. Both studies concentrate on the payment services of BigTech, the entry points for these entities into the financial sector (Liu, Lu, and Xiong, 2022). Specifically, Ouyang (2023) illustrates, through an exogenous shock to cashless payment activities, that the adoption of cashless payment facilitates access to BigTech consumer credit; Bian et al. (2023) showcase how embracing internal payment solutions, particularly buy-now-pay-later (BNPL) models, extends credit to typically underserved consumers. In contrast, our investigation delves into the influence of BigTech credit on consumer activity in-depth. While both works skim the surface of credit's impact on spending, our unique, granular order-item level purchase data enables us to present various new findings that explain how BigTech credit exerts its influence. Moreover, they

which BigTech credit stimulates consumer spending by executing an array of detailed analyses leveraging data not previously available to researchers.

As the financial activities of BigTech are considered a particular subset of FinTech innovations (Frost et al., 2019), our paper contributes to the expanding research on FinTech lending, especially concerning consumer credit. Previous studies, on the one hand, have largely agreed that FinTech firms, including peer-to-peer or marketplace lending platforms, can serve as alternatives or complements to traditional bank lending by providing credit to financially constrained borrowers or those without credit histories, thereby promoting financial inclusion; on the other hand, these studies still debate regarding the economic impact of FinTech lending, particularly in terms of default rates (e.g., Tang, 2019; Agarwal, Alok, Ghosh, and Gupta, 2021; Bao and Huang, 2021; Chava, Ganduri, Paradkar, and Zhang, 2021; Di Maggio and Yao, 2021; Di Maggio, Ratnadiwakara, and Carmichael, 2022; Wang and Overby, 2022). Yet, these studies do not address the effects of FinTech or BigTech credit on consumer behaviors.

Further, the BigTech credit we examine is an example of Buy-Now-Pay-Later (BNPL), a fast-growing FinTech payment option which provides short-term credit for retail purchases. Therefore, our study is also an addition to this emerging field of research (e.g., deHaan et al., 2022; Berg et al., 2022; Di Maggio, Katz, and Williams, 2022; Bian, Cong, and Ji, 2023; Guttman-Kenney et al., 2023). Most importantly, instead of providing BNPL as a one-time service at checkout, an increasing number of major retailers worldwide are shifting towards offering a full-service online

analyze Alibaba's BigTech consumer credit product, Huabei, which is accessible beyond Alibaba's e-commerce ecosystem. Our study, however, examines a BigTech consumer credit service that is utilized exclusively within the company's own e-commerce platform. As Alibaba and the firm we study exemplify two different BigTech lending models, their research and ours are mutually informative and complementary.

shopping experience and integrate BNPL into their self-contained ecosystem.[3,4] This shift suggests that data in the hands of retailers can be used to inform the design of user interfaces and user experiences to guide consumers towards desired actions, a practice known as data harvesting (CFPB, 2022; Consumer Reports, 2023). Consequently, our research is timely, as we leverage proprietary, highly-granular data on consumers' digital footprints and shopping patterns to demonstrate that BNPL offered by a leading e-commerce do not necessarily encourage overspending or lead to over-indebtedness among consumers.

2. RELATED LITERATURE

The activities of BigTech in finance can be considered a particular subset of broader FinTech innovations (Frost et al., 2019). Thus, this section begins with a review of the literature on BigTech credit. We then move on to a review of FinTech-related research, with a focus on the segment of FinTech consumer lending, as it is closely related to our research. For a comprehensive review of FinTech literature, we refer the readers to Allen, Gu, and Jagtiani (2021) and Berg, Fuster, and Puri (2022).

2.1 BigTech Credits

2.1.1 The Macro Drivers of BigTech Credit

[3] There are two main BNPL models: the pure-play merchant partner model and the app-driven model. The pure-play merchant partner model involves BNPL providers partnering with merchants to integrate their solution into the merchant's payment infrastructure, utilizing the existing bank card network. The app-driven model strengthens the relationship between the consumer and the BNPL lender, as consumers often start and complete their purchase journey within the lender's self-contained ecosystem. This model has the potential to significantly impact consumer behavior, increasing the likelihood of habitual BNPL usage (CFPB, 2022), and is also adopted by the firm we study.

[4] Di Maggio, Katz, and Williams (2022) note that this shift implies that BNPL providers can leverage substantial amounts of proprietary data on customer's shopping and spending patterns, making BNPL increasingly distinct from standard credit cards. They also highlight other distinguishing features of BNPL compared to standard credit cards. First, instead of offering a revolving line of credit, BNPL products are structured as installment loans with a down payment due at sale and a fixed repayment schedule. Second, BNPL loans are offered through retailers and tied to the purchase of a particular product. Third, BNPL companies often provide more lenient lending terms, with no or limited credit checks, often zero interest, minimal fees, and no or limited negative reporting to credit bureaus. BNPL companies make money by charging merchants fees of around 5-8%, significantly higher than the 2-3% charged by credit card companies.

Several papers assess the economic and institutional factors driving the growth and adoption of BigTech credit using country-level data. Cornelli et al. (2020) and Cornelli et al. (2023) find that the volume of both FinTech and BigTech lending is larger in countries with higher GDP per capita, where banking sector mark-ups are higher, banking regulation is less stringent, business operations are easier, investor protection disclosure and judicial system efficiency are more advanced, and bond and equity markets are more developed. This suggests that these alternative credits complement more traditional credit markets, rather than substitute for them. Similarly, Frost, Gambacorta, Huang, Shin, and Zbinden (2019) find that the drivers of BigTech credit are similar to those of FinTech credit in terms of economic activity, financial regulation, and competitiveness.

2.1.2 The Advantage of BigTech Firms in Credit Provision

Hau, Huang, Shan, and Sheng (2019) argue that due to both cheaper (online) distribution channels and better credit analysis based on abundant data generated on their own trading platforms, BigTech firms have the capacity to compete with traditional banks for credit provision. Stulz (2022) claims that BigTech firms have potentially big advantages compared to banks and to FinTech firms, including the technical know-how and up-to-date systems that FinTech firms aspire to, the scale of large banks, absence of the legacy nor the organizational issues that banks have, and most importantly the access to data that neither banks nor FinTech firms have, which allow them to replace traditional banks, especially in consumer finance. Li and Pegoraro (2023) theorize that a unique feature of the BigTech platform is that it is the monopolistic provider of a valuable marketplace, allowing it to lend to small businesses of high credit risk, who are traditionally denied credits by banks.

Supporting the conjecture that BigTech firms have information and modeling advantages, Huang et al. (2020) find that BigTech firms can better predict loan defaults during both normal times and periods of large exogenous shocks than banks; Gambacorta et al. (2023) show that BigTech credit performs better than bank credit on average ex-post in terms of defaults and firm performance.

2.1.3 BigTech Credit Offered to Micro, Small-Size Enterprises (MSEs)

Several studies have focused on BigTech credit extended to Micro and Small Enterprises (MSEs). Building on the advantages of BigTech firms identified earlier, these studies highlight the potential for BigTech to complement traditional banks in promoting financial inclusion and improving the performance of MSEs. Notably, all of the literature in this area utilizes data from Mybank, a lending institution backed by Alibaba. Mybank provides credit to MSEs operating within Alibaba's ecosystem, encompassing online borrowers on platforms such as Taobao and Tmall, as well as offline borrowers utilizing the digital payment platform Alipay.[5]

In particular, Hau, Huang, Shan, and Sheng (2019) demonstrate that BigTech credit increases the availability of credit to borrowers with lower credit scores and provides relatively more credit to those with lower credit scores. Similarly, Huang et al. (2020) report that BigTech's proprietary information can complement or, when necessary, substitute credit history in risk assessment, enabling unbanked firms to access credit, particularly smaller firms in smaller cities. Beck, Gambacorta, Huang, Li, and Qiu (2022) find that transaction data generated through QR codes allows micro firms to obtain credit from both BigTech companies and banks, indicating that digital payment footprints contribute to financial inclusion by mitigating information asymmetry.

[5] Details about Alibaba Group and its ecosystem can be found in the papers reviewed in this section (e.g., Liu, Lu and Xiong, 2022).

Additionally, they note positive effects of access to BigTech credit on vendors' sales, even during the Covid-19 pandemic. Chen, Huang, Lin, and Sheng (2022) demonstrate that access to BigTech credit significantly reduces the sales volatility of MSEs, with a stronger effect observed for enterprises with fewer alternative sources of financing, as well as a reduced likelihood of bankruptcy or business exit for those with FinTech credit access. Hau et al. (2022) document that access to BigTech credit from the same e-commerce platform boosts the sales growth, transaction growth, and consumer satisfaction of small e-commerce firms. Liu, Lu, and Xiong (2022) reveal that the lending model of BigTech firms differs from that of conventional banks, as BigTech loans tend to be smaller with higher interest rates, and borrowers tend to repay them far earlier and more frequently, focusing on short-term liquidity needs rather than long-term financing. Gambacorta, Huang, Li, Qiu, and Chen (2023) find that BigTech credit does not correlate with local business conditions and house prices, unlike cyclical bank credit, suggesting that it reduces the importance of the collateral channel and makes lending more responsive to changes in firms' business activities.

2.1.4 BigTech Credit Offered to Consumers

In contrast to the extensive research on BigTech business credits, there are fewer studies on BigTech consumer credits. Ouyang (2023) demonstrates that the adoption of cashless payments, such as Huabei offered by Alibaba's Alipay, enhances individual consumers' access to credit, particularly for those who were previously financially underserved. Furthermore, Ouyang's findings contradict Huang's (2022) theory, as they do not indicate that increased payment flow leads to a rise in compulsive spending, such as on items like cigarettes, games, lotteries, or live streaming services.

2.2 FinTech Consumer Credit

Based on data from FinTech firms in various countries (e.g., the US, Germany, and India), multiple studies have reached a consensus that unconventional data play a crucial role in enabling FinTech firms to evaluate consumer credit risk, thereby promoting financial inclusion. Berg, Burg, Gombović, and Puri (2020) demonstrate that even basic online interactions, such as accessing or registering on an e-commerce website, influence credit access and decrease default rates. Similarly, Agarwal, Alok, Ghosh, and Gupta (2021) illustrate that alternative credit scoring based on mobile and social footprints can extend credit access to individuals without traditional credit scores without negatively impacting default outcomes, with the greatest benefit seen for underprivileged borrowers. Bao and Huang (2021) find that FinTech companies are more inclined to broaden credit access for new and financially constrained borrowers following the onset of the COVID-19 pandemic, underscoring the advantages of FinTech credit during a crisis.[6] Moreover, Di Maggio, Ratnadiwakara, and Carmichael (2022) report that utilizing alternative data to assess borrowers' creditworthiness leads to expanded credit access, particularly for individuals with limited credit histories and lower credit scores, without an increase in default rates. Additionally, Ghosh, Vallee, and Zenga suggest that consumers who rely more on cashless payments are more likely to obtain loans with lower interest rates and higher amounts, and are also less likely to default.

Several studies have delved into the dynamics and distinctions between banks and FinTech firms in the consumer credit market. Tang (2019) finds that peer-to-peer (P2P) lending serves as a substitute for bank lending for infra-marginal bank borrowers, while also complementing bank lending for small loans. In contrast, Di Maggio and Yao (2021) reveal that FinTech lenders are inclined to extend credit to high-risk borrowers who may have been turned down by traditional

[6] However, the authors also note that in stark contrast to bank loans, which show no significant change, the delinquency rate of FinTech loans triples after the pandemic outbreak, indicating the potential fragility of such institutions.

lenders due to a lack of soft information, and that the pricing strategies of FinTech lenders are likely to consider this adverse selection. Chava, Ganduri, Paradkar, and Zhang (2021) document that consumers borrowing from marketplace lending platforms tend to have lower credit scores and higher default rates in the long run compared to similar bank loan applicants, indicating that FinTech lenders face greater information frictions than banks, which engage in relationship lending to access unique borrower information (e.g., transaction history, soft information) and build relationship capital. Additionally, Balyuk (2023) demonstrates that banks expand credit access for consumers who have obtained FinTech loans, highlighting the potential of FinTech to mitigate imperfections in the consumer credit market and generate information spillovers to traditional credit intermediaries.

Some researchers have found evidence suggesting that FinTech lending may potentially worsen, rather than improve, the financial health of borrowers. For instance, Di Maggio and Yao (2021) demonstrate that FinTech borrowers experience delinquency at significantly higher rates, with these borrowers using the additional credit not for consolidating existing debt but to support additional expenditures. Similarly, Wang and Overby (2022) utilize a DiD approach to reveal that state approval of a major online lending platform to issue peer-to-peer loans results in an increase in bankruptcy filings.

Buy-Now-Pay-Later (BNPL)

A segment of FinTech consumer credit is the Buy-Now-Pay-Later (BNPL) model, offering a short-term credit option that enables consumers to defer payments at the point of sale. BNPL typically represents itself as an interest-free loan repaid in one or more installments and, as a relatively unregulated innovation, provides convenient access to credit for retail purchases. Instant decisions are made using alternative data without a hard credit check.[7]

There has been a growing interest in archival research on BNPL, reflecting its increasing popularity and usage. Driven by widespread concerns about potential misuse of BNPL due to its ease-of-use and ubiquity (e.g., CFPB, 2023; Johnson, 2023; Her Majesty's Treasury, 2023; Reed, Duckworth, and Brown, 2023), most academic studies on BNPL focus on how this FinTech innovation affects consumer welfare. Specifically, Di Maggio, Katz, and Williams (2022) demonstrate that BNPL leads to high consumption, particularly in the retail sector, even among consumers who are not liquidity-constrained. They conclude that BNPL increases the chances of negative outcomes such as overdraft fees, which reduces consumer price elasticity on covered items, leading to increased near-term spending possibly at the expense of longer-term liquidity. Additionally, deHaan et al. (2022) find that new BNPL users experience rapid increases in bank overdraft charges, as well as credit card interest and fees, suggesting that BNPL is detrimental to users' financial health. Moreover, using a stylized general equilibrium model, Huang (2022) shows that E-commerce platforms with an integrated consumer lending function are more inclined to provide credit than standalone banks. While the additional consumer credit might have positive externalities, it may also amplify the distortion of consumers' present bias. Guttman-Kenney et al. (2023) document that a significant minority of UK consumers use credit cards to fund their BNPL purchases, particularly among younger consumers and those residing in economically deprived areas, raising doubts about these consumers' ability to pay for BNPL.

[7] The popularity of BNPL has surged due to the increasing global trend of online shopping, particularly during the Covid-19 pandemic, where cashless payments are preferred. For instance, a survey by the Consumer Financial Protection Bureau (CFPB) in 2023 revealed that 17% of respondents had made at least one purchase using BNPL between February 2021 and February 2022. This surge in demand has led to BNPL providers experiencing high transaction volume and value. According to CB Insights (2021) and Research and Markets (2023), global BNPL payments are projected to surpass $527 billion by 2023 and reach $1 trillion by 2025.

In contrast, some research show that on average, consumers are using BNPL responsibly. Papich (2023), by exploiting geographic and temporal variation in the availability of BNPL at Walmart in the US, offers causal evidence that although BNPL access leads consumers to increase their utilization of other forms of credit, consumers' ability to repay their debts actually improves with BNPL access. Using Chinese data, Bian, Cong, and Ji (2023) demonstrate that BNPL significantly boosts consumer spending; yet, consumers, particularly those who solely rely on BNPL for credit access, exercise caution to avoid overspending and becoming overly indebted.[8]

Different from the above research, Berg et al. (2023) contribute to the debate on BNPL from a merchant's viewpoint. Using experimental data from a German online furniture retailer, they find that BNPL increases the merchant's sales by 20%, attributed to both the intensive and extensive margin. Additionally, Berg et al. (2023) demonstrate that BNPL costs arising from payment defaults are considerably lower than the costs associated with other popular payment methods, which the authors believe explains the global surge in BNPL popularity in e-commerce.

3. BACKGROUND, IDENTIFICATION STRATEGY, AND DATA AND SAMPLE

3.1 Background

3.1.1 The Company and Its Consumer Finance Service

Our proprietary data is sourced from a leading B2C online retailer in China, which boasts a diverse product lineup encompassing electronics, appliances, clothing, cosmetics, books, groceries, and more. In 2023, the company caters to nearly 600 million active users and records net revenues

[8] Bian, Cong, and Ji (2023) adopt a broader perspective by examining e-wallets that offer external payment options (such as linked debit and credit cards) where e-wallets act as a conduit to banks, as well as internal payment options (e.g., e-wallet balance, e-wallet savings, and BNPL) where e-wallets operate as an independent ecosystem. Their findings reveal that BNPL crowds out other e-wallet payment options and expands FinTech credit to underserved consumers.

exceeding 1,000 billion RMB, equivalent to 150 billion US dollars, positioning it among the world's largest retailers.[9]

The retailer has expanded into the lending sector, operating a division that provides consumer credit for online purchases. To access this credit, consumers must submit an application. The credit product is seamlessly integrated into the company's e-commerce platform, allowing approved consumers to select it as a payment method at checkout. Customers can then utilize their approved credit limit and select their preferred installment plan.[10]

The credit application process is designed to be swift and efficient. Initiated with a single click, the company's proprietary AI model promptly generates key outputs: a credit score, an application decision, and a designated credit limit. The credit score, invisible to the applicant, offers a thorough assessment of the applicant's credit risk, with higher scores signifying a lower risk of delinquency or default. The application decision is straightforward, resulting in either approval or rejection. Upon approval, consumers are allocated an initial credit limit, which represents the maximum they can charge to their revolving consumer credit account.[11]

3.1.2 The company's Reject Inference (RI) program

Since 2020, the company has been piloting a Reject Inference (RI) program aimed at enhancing the quality of its AI model. Figure 1 illustrates the rationale behind the RI program and its operational mechanism.

[9] Driven by the development of digital technologies and the rapidly expanding consumer market, China has witnessed significant growth in online retail sales, consistently ranking first worldwide (UNCTAD, 2021). By 2022, the total online retail sales in China reached nearly 13.8 trillion RMB or 2 trillion US dollars (National Bureau of Statistics of China, 2023).

[10] Before choosing to utilize the credit option, customers can view the applicable interest rates based on their credit assessment and selected repayment plan. Furthermore, after choosing to utilize the credit option, customers can track their credit account, monitor their current balance, and manage their repayment schedule through a credit management platform.

[11] For rejected consumers, their credit scores are re-evaluated based on the latest shopping behaviors whenever they submit a new application. The credit limit for approved consumers, on the other hand, is periodically updated based on both the latest shopping behaviors and repayment behaviors.

Insert Figure 1 about here

In the context of AI-driven credit approval, all applications are initially processed by AI, with subsequent repayment or default outcomes used to refine the AI model. This iterative process is designed to improve the AI's predictive accuracy for future credit decisions. However, a notable challenge arises: the training data is biased, as it includes only outcomes from approved applications (as shown on the left branch of Figure 1). This bias is problematic when the AI model is applied to the entire applicant pool.

To mitigate this, companies utilizing AI for credit approval seek to incorporate the outcomes of rejected applications into their training datasets. This is achieved through a technique known as reject inference, which infers the potential outcomes for applicants whose credit requests were initially denied. The process involves selecting a random subset of these individuals for credit approval, monitoring their subsequent performance, and using this data to infer outcomes for the remaining rejected applicants (as indicated on the right branch of Figure 1).

At the company under examination, the RI program introduces a real-time filter that operates before the AI model conveys its final decision to the consumer. Theoretically, this filter covertly converts a random subset of initially rejected applicants into RI-approved applicants. These RI-approved applicants are then granted a modest initial credit limit, typically under 500 RMB. Importantly, RI-approved applicants are not aware that they receive credit as a result of the RI program. Subsequently, the company closely monitors the credit behavior of these applicants, using the collected data to infer the potential performance of other rejected applicants. By analyzing the actual and inferred credit behaviors of AI-approved, RI-approved, and rejected applicants, the company refines the training of its proprietary AI model, thereby enhancing its accuracy and efficacy in assessing credit risks across a broader spectrum of applicants.[12]

3.2 Our Identification Strategy

The inability of the AI model to distinguish between RI-approved and rejected applicants, coupled with the RI program's aim to represent the entire population rather than focusing solely on profit maximization, provides a unique opportunity to examine the influence of BigTech credit on consumer behavior.

Our analysis is centered on a comparison of outcome variables between two distinct groups: the treatment group, which includes consumers initially rejected by the AI model but subsequently approved by the RI program (referred to as RI-approved applicants), and the control group, consisting of consumers rejected by both the AI model and the RI program (referred to as rejected applicants).[13] Fundamentally, our methodology parallels the field experiment conducted by Karlan and Zinman (2010).[14]

This comparative approach takes advantage of the inherent randomness within the selection process, thereby bolstering the basis for causal inferences within a DiD framework. The integration of randomness serves to mitigate biases and enhances the probability that any observed differences

[12] Although RI is a common practice, particularly among FinTech and BigTech firms, its application remains largely unexplored in academic settings. By implementing RI, we bridge a gap in literature that often focuses solely on loans directly approved by machine-learning algorithms, constrained by data availability. Additionally, our study reveals that consumers initially declined but subsequently accepted via RI—the treatment group—demonstrate increased spending without signs of overspending or excessive indebtedness. This suggests that RI not only augments the predictive precision of credit models but also promotes fairer distribution of FinTech and BigTech credit, potentially advancing financial inclusion.

[13] Previous studies in this domain have often compared the spending behavior between approved and rejected applicants. However, these studies encounter limitations due to endogeneity issues, as individuals with higher incomes are more likely to be approved and also tend to spend more. Consequently, the true impact of FinTech/BigTech credit on consumer spending behavior may not be accurately captured.

[14] In their study, loan officers at a microlender in South Africa are randomly prompted to reconsider marginal loan applications they would have otherwise declined. This allows the researchers to measure the causal effects of credit access by monitoring the behavior and outcomes of both the treatment group (325 reconsidered applicants) and the control group (462 applicants who remained rejected).

post-treatment are a result of the treatment rather than extraneous factors (Bertrand, Duflo, and Mullainathan, 2004; Roth, Sant'Anna, Bilinski, and Poe, 2023). It is crucial to highlight that the method by which RI-approved applicants are selected at the retailer is a proprietary business secret, and the exact process is not disclosed. To verify the extent to which RI-approved applicants and rejected applicants are comparable, we will conduct a sanity check in the subsequent section.

Our analysis accounts for the staggered nature of credit applications and decisions across various consumers, employing a stacked cohort DiD analysis over a panel of individual-month observations. The regressions are specified as follows:

$$Outcome_{i,c,t} = \beta \times Treatment_i \times Post_{t,c} + \alpha_i + \delta_{t,c} + \varepsilon_{i,c,t} \quad (1)$$

Here, i denotes the consumer, c represents the cohort (with each cohort corresponding to applications made each month over a six-month period), t signifies the calendar month, α_i captures individual fixed effects for time-invariant characteristics, $\delta_{t,c}$ accounts for month-cohort fixed effects for cohort-specific time trends, and *Outcome* encompasses variables measuring consumer activity such as spending, visits, and purchase prices. *Treatment* is a binary variable indicating RI-approved applicants, and *Post* is a binary variable for the application month and subsequent months. β captures the average treatment effect on consumer behavior post-credit approval.

We estimate Equation (1) using both Ordinary Least Squares (OLS) and Poisson regression methods. While OLS is commonly applied, recent studies have questioned the interpretability of results from log transformations of non-negative dependent variables (Silva and Tenreyro, 2006; Campbell and Mauand, 2021; Chen and Roth, 2023). Thus, we also opt for Poisson regression, which provides valid semi-elasticity estimates and standard errors for continuous outcome variables with right-skewed distributions, including a high frequency of zero values (Silva and

Tenreyro, 2011; Cohn, Liu, and Wardlaw, 2022). To address potential cross-sectional and serial correlations, we cluster standard errors by individual and month-cohort.

3.3 Data and Sample

We draw upon several databases from the company to constitute our sample. The sample selection criteria are detailed in Table A1 of the online Appendix.

The primary dataset pertains to credit applications. From approximately 6 million consumer credit applications received by the company from 5 million unique consumers over a six-month period (April 1, 2020, to September 30, 2020), we randomly select 10% of these applications, excluding individuals with incomplete demographic information.

Subsequently, we merge the application data with outcome data, which includes information on visits, order placements, and consumption and so on. This merged dataset covers the period from April 1, 2019, to March 31, 2021, and is highly granular, providing details such as the items purchased and their prices. We aggregate the outcome variables at the monthly level for the organization of the sample, while maintaining all information at the order-item level for subsequent analyses (see below). For applicants from the first cohort (i.e., April 2020), there is a maximum of 12 monthly observations before and after the application. For those from the last cohort (i.e., September 2020), there are up to 18 monthly observations before and 6 after the application. However, not all applicants have 24 monthly observations from April 2019 to March 2021 if they open their shopping account after April 2019; in these cases, the observations start from their registration month through March 2021.[15]

[15] Our sample period for studying credit's influences spans from six months before to twelve months after credit applications, much longer than prior studies (e.g., one month in Berg et al., 2022, and two months in Bian, Cong, and Ji, 2023). This extended timeframe is crucial as it helps to determine whether BigTech credit or BNPL's boosting effect on spending is is temporary or persistent. A sufficiently long sample period is also preferable when studying any adverse consequences of Fintech/BigTech credit or BNPL product, such as overspending and delinquency.

Next, we integrate the dataset with information on credit utilization and delinquency. We then exclude inactive applicants who have zero monthly spending in more than one-third of their pre-application sample months. Following this step, there are 635,919 and 2,412,557 use-month observations for the RI-approved and rejected applicants, respectively (i.e., our treatment and control groups).

We proceed with a sanity check to evaluate the randomness of the group selection. As detailed in Table A2 of the online appendix, despite statistically significant differences in certain dimensions due to the large sample size, most of these discrepancies are economically trivial. Notably, the credit score discrepancy is a minor 0.65 points, which is insignificant when compared to the average scores of 689 and 688 for the two groups, respectively. This result has a important implication: the credit score, a critical factor in the AI's decision-making for credit applications, confirms the distinguishability of RI-approved and rejected applicants. This score is calculated from a comprehensive set of factors, encompassing users' demographic details, online behaviors, credit bureau reports, digital footprints and more, as highlighted by the company's financial division CEO in a 2017 interview mentioning the use of over 30,000 variables in their AI model. Consequently, the comparability between RI-approved and rejected applicants across numerous dimensions, many of which are unobservable to researchers, should exceed that between AI-approved applicants and the broader applicant pool.

Nevertheless, we observe some evidence suggesting that RI-approved applicants might be less active than their rejected counterparts in our sample, as indicated by shorter account ages, fewer visits and orders, and lower spending levels. This hints that the selection between these two groups may not be entirely random, even though their comparability across numerous dimensions is already highly significant, with many of these dimensions being unobservable to researchers.

To further bolster comparability, we implement nearest-neighbor propensity score matching (PSM) for each month, ensuring that each treated applicant is paired with a control applicant who submitted their credit application in the same month and shares the most analogous characteristics. This methodology involves executing a logistic regression model for each month to forecast credit application approval based on variables such as age, gender, credit score, account age, average number of visits, orders placed, spending amount, discount rate, cancellation rate, and spending. For a thorough explanation of these variables, please refer to Appendix A.

Ultimately, our sample includes 60,882 applicants, evenly divided between the treatment and control groups. At the user-month level, there are 1,260,930 observations, with 635,919 and 625,011 observations belonging to the treatment and control groups, respectively. As shown in Table A2, all differences between the two groups are negligible. Additionally, we calculate the Pearson correlation coefficients for the credit limit and each variable used in PSM and regress the credit limit on these variables. As Table A3 of the online appendix indicates, the coefficients are mostly insignificant, and the R-squared value from the regression is only 3%, confirming the randomness of the initial credit limit assignment.

Table 1 offers a comprehensive overview of the key variables. Panel A details the demographic profile of the 60,882 applicants. Around 65% of the applicants are male, with an average age of about 31 years. On average, the account age for these applicants stands at roughly 30 months. For the treatment group, the average initial credit limit is set at 331 RMB, with the highest limit capped at 500 RMB. The conservative credit limit is intentional, reflecting the initial rejection by the AI model. Given the perceived risk, it would be imprudent for the company to extend a high credit line to these individuals at the outset.

Moving to Panel B, summary statistics are presented for variables that vary on a monthly basis. Metrics such as monthly visits, orders, and spending are based on 1,260,930 individual-month observations. However, only about 711,815 observations are available for the other three variables due to months with no activity, which results in the absence of denominators for calculating these values.

Insert Table 1 about here

To discern the impacts of credit on consumer activity, particularly the potential for overspending, we further create a more detailed and granular dataset. Given the vast size of the data, we randomly select 10% of the treated applicants and their corresponding matched control applicants from the aforementioned procedures. We then gather specific information on every purchase made by these consumers, including the timing of purchases, specific items purchased, quantities or amounts bought, and the corresponding purchase prices.

4. RESULTS

4.1 The Effects of BigTech Credits on Spending

4.1.1 The baseline results

To demonstrate the impact of BigTech credit, we start with spending, which is a key outcome. Specifically, we compare the variable *Spending*—the total out-of-pocket consumption for a consumer in a specific calendar month—between the treatment and control groups. Figure 2 shows that both groups have similar spending levels, ranging from 230 RMB to 350 RMB, prior to credit application. The most noteworthy change in spending patterns occurs when the treatment group's credit applications are approved. Compared to the previous month ($Month_{-1}$), consumers who are granted credit experience a substantial increase in their monthly spending, with an approximately 21% rise to 401 RMB in the application month ($Month_0$). Conversely, consumers who do not receive credit see relative small increase in their monthly spending during the application month (7%). Interestingly, consumers in the treatment group consistently spend more than their counterparts in the control group, indicating the long-lasting impact of credit on consumption.

Insert Figure 2 about here

Figure 2 provides initial evidence supporting the parallel hypothesis underlying the DiD method. To formally test this hypothesis, we employ a dynamic model. We replace $Treatment_i \times Post_{t,c}$ in Eq. (1) with a series of interaction terms between $Treatment_i$ and $Month_t$, where t ranges from -17 to +11. As presented in Figure 3, the coefficients of most interaction terms are both insignificant and of small magnitude for the periods preceding the application month. However, in contrast, the interaction terms consistently exhibit a positive and statistically significant impact since the credits are granted. The results from Figure 3 verify the patterns observed in Figure 2, conditioning on certain fixed effect structures, and strongly support the notion that credits enhance consumer spending.

Insert Figure 3 about here

In Table 2, we present the results of estimating Eq (1). Column 1 employs OLS regression, while Column 2 uses Poisson regression. Regarding Column 1, in comparison to consumers who do not receive credits, consumers who are granted credits spend approximately 65 RMB more per month after their credit applications, which is statistically significant at the 1% level. Consistent with the findings in Figure 1, Column 2 demonstrates that consumers in the treatment group, when compared to consumers in the control group, experience a significant 19% increase in their monthly spending following the granting of credit (significant at the 1% level).

Insert Table 2 about here

We conduct a series of robustness tests to validate our main finding. The first test uses an alternative definition in which *Spending* represents the total consumption for a consumer in a specific event month, rather than in a specific calendar month. The second test excludes the application month from our sample. These two robustness tests mainly aim to eliminate any potential confounding factors from the application month, where some purchases occur before the credit is granted, while others happen afterward. The other three tests employ alternative identification methods, including the traditional staggered DiD approach with time fixed effects and individual fixed effects, the regular cohort approach, which addresses the issue of multiple treatment timings as described by Bertrand, Duflo, and Mullainathan (2004), and the state-of-the-art approach proposed by Callaway and Sant'Anna (2020), which addresses both cohort- and time-varying treatment effects. We find that our inferences remain consistent across all approaches, further strengthening the robustness of our findings. We present the results in the online Appendix Table A4.

4.1.2 The Heterogeneity in the Effect of BigTech Credits on Spending

We proceed with two sets of cross-sectional analyses to explore the variability in the effects of credits on our primary outcome of interest, *Spending*.

Our initial cross-sectional analysis is designed to demonstrate the role of BigTech credit in fostering financial inclusion. We employ the following model:

$$Spending_{i,c,t} = \beta \times Treatment_i \times Post_{t,c} \times FinancialInclusion_i + \alpha_i + \delta_{t,c} + \varepsilon_{i,c,t} \quad (2)$$

Here, *FinancialInclusion* encompasses a set of variables that capture the potential exclusion or marginalization of consumers by traditional credit systems. To maintain simplicity and ensure the validity of interpretability from log transformations of non-negative dependent variables, we report results from the Poisson model only.

We begin by examining the age of the applicant. We assume that consumers under 22 years old, a typical age for college graduates, are more likely to face challenges in securing credit from traditional financial institutions. This is typically due to a higher probability of unemployment and an absence of established credit history. Furthermore, we factor in the credit score generated by the AI model, which offers an extensive evaluation of a borrower's propensity to repay loans on time. This assessment is derived from numerous variables, both within and external to the firm's ecosystem, including credit bureau reports that banks heavily rely on for credit decisions. Consequently, it is reasonable to expect that this AI-derived score would correlate positively with those from traditional financial systems. As a result, individuals with lower credit scores from BigTech firms may face increased difficulty in accessing traditional credit services.

Next, we assess the accessibility of bank credit using the "Regional Bank Credit Card Development Vitality Index" (UPD Index), as reported by China UnionPay, the official organization for bank cards in China. This index, which evaluates the credit card industry's development covers factors including income capacity, risk management, scale, user loyalty, growth velocity, and credit limit administration. The UPD Index is updated monthly for each province in China, with lower scores indicating less developed credit card sectors. We determine each consumer's province utilizing their delivery addresses prior to credit application, positing that consumers in provinces with lower UPD Index scores may experience increased challenges in securing bank credit.

As Table 3, Column 1, illustrates, the *F*-test indicates that the coefficient for the interaction of *Treatment*×*Post*×*YoungAge* is significantly larger than that for *Treatment*×*Post*×*OtherAge*. This suggests that BigTech credits significantly bolster spending for consumers under 22 years old—presumably unemployed—more so than for other age groups. Column 2 further reveals that the impact of credits on spending is heightened for those more likely to be excluded by traditional systems. Specifically, individuals with lower credit scores witness a 37% increase in spending upon receiving credits, which is 25 percentage points higher than the increase among those with higher credit scores—a difference that is statistically significant at the 1% level. Our findings are consistent when considering the development of the bank credit card system, as shown in Column 3. Collectively, these results underscore the significant role of BigTech credit in advancing financial inclusion.

Insert Table 3 about here

A distinguishing feature of BigTech is the interplay between financial services and its underlying non-financial business operations, as highlighted by Cornelli et al. (2020). Therefore, our second set of cross-sectional analyses aims to investigate the potential synergy between the credit and external infrastructure that could influence the non-financial business of the BigTech firm.

Should such synergy exist, we would anticipate a more pronounced stimulative effect of BigTech credit on spending when there is more advanced external infrastructure that enables the e-commerce platform to better meet consumer needs. Our model reflects this hypothesis:

$$Spending_{i,c,t} = \beta \times Treatment_i \times Post_{t,c} \times Infrastructure_i + \alpha_i + \delta_{t,c} + \varepsilon_{i,c,t} \quad (3)$$

In this model, *Infrastructure* encompasses variables that measure the development of external infrastructure potentially affecting the non-financial facets of a BigTech firm's operations.

The first infrastructure type we examine is logistical. Table 3, Panel B, Column 1, compares the spending effects of credits among consumers in the top 5 provinces with the highest per capita total expressway lengths to those in the bottom 5 provinces. Consumers in the top provinces exhibit a 27% increase in spending, which is significantly higher than the less than 14% increase observed in the bottom provinces at the 10% significance level. These findings imply that the effectiveness of BigTech credit is contingent upon the promptness with which consumer demands are met, specifically for core services like product procurement and delivery offered by e-commerce in our case. This aligns with the idea that the integration of financial services with non-financial business activities is a distinctive characteristic of BigTech, setting it apart from other FinTech entities.

We also consider Internet infrastructure, examining whether it moderates the impact of credits on spending. As Column 2 (Column 3) of Table 3 indicate, there is no significant difference in the effects of credits on spending between consumers in the top 5 provinces with the highest mobile Internet penetration rates (broadband access rate) and those in the bottom 5 provinces. This implies that Internet infrastructure does not significantly influence the spending impact of credits. A potential rationale for this observation is that utilizing the e-commerce platform necessitates only a basic Internet connection, which all consumers in our sample possess.

4.2 Deciphering the Effects of BigTech Credits on Spending

4.2.1 The Effects of BigTech Credit on the Elements underlying Spending

Relying on the detailed data obtained from the e-commerce platform, this section delves into the mechanisms through which credits drive an increase in consumer spending. The monthly spending on the e-commerce platform is determined by two factors. The first factor is the average spending per order and the second factor is the number of orders placed in the month.

Correspondingly, we break down our principal dependent variable, *Spending*, into two components: *Orders* and *OrderSpending*. *Orders* equals to the total number of orders made by a consumer in a given month. *OrderSpending* reflects the average spending amount per order for a consumer in a specific month. Therefore, *Spending* used in previous tests is essentially the product of *Orders* and *OrderSpending*.

We proceed to estimate Eq. (1), substituting the dependent variable with *OrderSpending* and *Orders*, respectively, and we present the findings in Table 4. In Column 1, the interaction term *Treatment* × *Post* displays a positive sign (significant at the 1% level). However, the association between *Treatment* × *Post* and *OrderSpending* is not economically significant. The grant of credit only escalates the average order spending by 3.5%. In Column 2, the interaction term *Treatment* × *Post* continues to display a positive sign (significant at the 1% level), suggesting that credits positively influence consumers' frequencies of placing orders. Moreover, such an influence is economically significant as the grant of credit boosts the number of orders by 20%. Therefore, it is obvious that BigTech credit enhances spending mainly through an increase in the frequencies of making purchases rather than an increase in the average spending amount per order.

Further, there are two steps for consumers to place orders. Initially, consumers engage in visiting or browsing, where they search for products they intend to purchase within the month. Following this, the second step involves placing the order upon these visits, a process referred to as conversion. Therefore, we further decompose *Orders* into *Visits* and *Conversion*. *Visits* denote the total number of visits a consumer makes in a given month. *Conversion* is determined as the number of orders normalized by $10 \times$Visits, serving as a measure of the retailer's effectiveness in converting visitors to consumers. We substitute the dependent variable of Eq. (1) with these two variables and present the results in Columns 3 and 4, respectively. We find that the interaction term *Treatment* × *Post* are positive and significant at the 1% levels in both columns, suggesting that credits positively influence consumers' willingness to visit the shopping platform and the conversion of visits into purchases.

Insert Table 4 about here

4.2.2 BigTech Credits and Purchasing Variety Seeking

As elaborated in Section 3.3, we obtain highly-granual information regarding every order for 10% of the treated applicants and their corresponding matched control applicants from our main sample. This information contains details such as the timing of purchases, the specific items purchased, the quantity or amount bought, and the corresponding purchase price. In this subsection (4.2.2) and the following sub-sections (Sections 4.2.3-4.2.4), we aim to shed light on the effects of BigTech credit on several aspects the consumption using this detailed data set.

The first aspect of the consumption is variety seeking. Variety seeking refers to the tendency of consumers to seek out and purchase a diverse range of products or brands within a certain category rather than consistently sticking to one choice. Investigating whether Bgtech credit users engage in more variety seeking can provide insights into the diversity of their spending patterns and shed light on the broader impact of credit on consumer decision-making processes.

Specifically, we conduct a sequence of stacked DiD analyses using Eq. (1), substituting the dependent variable with each of the following metrics: *SKUs*, *Categories*, *Brands* and *Shops*.

SKUs refers to the number of unique products that a consumer purchases within a specific month. *SKUs* are unique alphanumeric codes or numbers assigned to each product or item in a retailer's inventory. In our dataset, *SKUs* provide the most precise identification of products, even accounting for differences in attributes such as weight and color, which result in distinct SKUs.

Categories represents the number of unique product categories that a consumer purchases within a specific month. The e-commerce in our study categorizes products into three levels. The broadest category encompasses 73 categories, including electronics, personal care, sports, toys, and more. In contrast, the finest category consists of 5,067 categories. While the main paper presents results based on the broadest category, our findings remain consistent when utilizing the other two more detailed categories (results untabulated).

Additionally, we evaluate two additional variables: *Brands* and *Shops*. These variables signify the number of brands or shops from which a consumer makes purchases within a specific month.

Based on the findings presented in Table 5, the interaction term *Treatment* × *Post* consistently exhibits a positive coefficient across all four columns, indicating a statistically significant relationship at the 1% level. This outcome suggests that the provision of credits amplifies customers' inclination for variety seeking. Specifically, customers tend to purchase a higher number of distinct products, across a wider range of categories, from a greater number of diverse brands, and across multiple distinct shops.

As variety seeking may be driven by a desire for novelty and excitement, the above findings raises concerns that the inclination towards seeking variety in spending behaviors facilitated by BigTech credit might suggests a heightened propensity for individuals to engage in excessive or unplanned purchases beyond their financial means. To explore this, we carry out a series of analyses to illuminate the issue in the upcoming sections.

Insert Table 5 about here

4.2.3 BigTech Credits and Spending: Discretionary versus Necessary Spending

In this section, we utilize the detailed dataset to categorize consumers' purchases as either discretionary or necessary. We achieve this by manually assessing the product category of each purchased item. The discretionary category encompasses a wide range of products, including Digital, Sports & Outdoors, Gifts, Books, Music, Movies & TV, Cultural & Entertainment, Local Living/Travel, Watches, Digital Content, Jewelry & Accessories, Toys & Musical Instruments, Automotive Accessories, Pet Supplies, Alcohol, Automotive, Agricultural Supplies & Gardening, Stamps & Coins, and Art. To quantify discretionary spending, we introduce a variable called *DiscretionSpending*, which represents the total expenditure on discretionary items by a consumer within a given calendar month. Additionally, we define two more variables: *DailyuseSpending* and *NecessitySpending*, which measure the consumption on daily use items and necessity items, respectively, for a consumer within the same time frame. For details on the product categories classified as daily use and necessity items, please refer to Appendix A.

Table 6 presents the results of Poisson regression analyses with *DiscretionSpending*, *DailyuseSpending*, and *NecessitySpending* as the dependent variables. Our findings indicate that the interaction term Treatment × Post is not significantly related to *DiscretionSpending* (Column 1), suggesting that the provision of credits does not stimulate an increase in spending on discretionary items. Conversely, Columns 2 and 3 reveal a positive and significant relationship (at the 5% or 1% level) between Treatment × Post and both *DailyuseSpending* and *NecessitySpending*. This suggests that the primary impact of credits on consumer spending is observed in the realms of daily use and necessity items. In summary, these findings are against the notion that the credit leads to irresponsible spending on non-essential items.

Insert Table 6 about here

4.2.4 **BigTech Credits and Price of Items Purchased**

Using monthly data, Table 4 has shown that the increase in customer spending is primarily driven by an increase in the number of orders placed, rather than an increase in spending per order, which provides preliminary evidence that the credits do not incentivize consumers to purchase more expensive items. However, *OrderSpending* in Table 4 is calculated as the average spending amount per order, thus containing noise.

In this section, we introduce *ItemPrice*, a variable that represents the average price of the items purchased in an order. An analysis of the relation between credit granting and *ItemPrice* directly speak to the issue of whether credit exacerbate consumers' inclination to buy more expensive items. We use *ItemPrice* as the dependent variable in Table 7. This analysis consistently incorporates customer and date-cohort fixed effects. Furthermore, we incorporate shop, brand, or category fixed effects in Columns 1 through 3, respectively, and include all three types of fixed effects in Column 4.

The interaction term *Treatment* × *Post* yields insignificant results in all columns. This suggests that credits have little effect on the price of products purchased in an order. In other words, there is no evidence to indicate that credits lead to purchase upgrades within the same shop, brand, or category. This finding corroborates with the previous result from Table 4, Column 1, that credit does not increase the average spending amount per order in a given month.[16]

In conjunction with the findings presented in Tables 5 and 6, we conclude that credit precipitants are not inclined towards overspending. Despite having a wider array of shopping options, they do not tend to buy more expensive or discretionary items.

Insert Table 7 about here

4.2.5 Credits Usage and Delinquency

We analyze the usage of credit and the delinquency rate over time. Table 8 shows that the average credit limit has been increasing steadily since the credit's issuance, rising from 371 RMB to 2899 RMB one year after approval. This trend suggests that the e-commerce company closely monitors consumer behavior and likely raises credit limits for consumers approved for RI based on their increased shopping activity and strong creditworthiness. Additionally, the proportion of

[16] In untabulated result, we also use *ItemQuantity,* which measures the number of items purchased in an order, as the dependent variable. Notably, the interaction term Treatment * Post also yields insignificant results. Since the spending per order can be viewed as the product of *ItemQuantity* multiplied by *ItemPrice*, these outcomes also affirm earlier observations from the user-month data—that the monthly average order amount does not escalate with the credit. They further confirm that the credit's positive effect on overall spending is primarily driven by an increase in the frequency of order placement by the recipients.

the credit line utilized remains relatively stable, fluctuating between 12% and 15% for most of the observed period.

Insert Table 8 about here

More importantly, we examine the delinquency rate using multiple definitions. The first two measures capture overall delinquency at the firm level. Specifically, we calculate the balance of loan principal overdue by more than 30 days or 90 days, divided by the total balance of the consumer credit loan principal facilitated through the company's platform (denoted as $Delinquency_{Firm30}$ and $Delinquency_{Firm90}$, respectively). These calculations are performed monthly. The significant advantage of these variables is that their definitions align with those used by traditional credit card issuers, such as commercial banks, and other BigTech firms in China, including Alibaba. This consistency aids in comparisons.

We observe a steady increase in both $Delinquency_{Firm30}$ and $Delinquency_{Firm90}$ over time, which parallels the pattern of the average credit limit's change. It is worth noting that the credit limit increases significantly more rapidly than the delinquency rate, which indicates effective credit management by the firm. $Delinquency_{Firm30}$ varies between 0% and 4.1%, while $Delinquency_{Firm90}$ ranges from 0% to 1.6% during our sample period. For reference, $Delinquency_{Firm30}$ for Alibaba's consumer product, Huabei, fluctuates between 1.8% and 3.0%, and $Delinquency_{Firm90}$ between 1.2% and 2.2%.[17] Furthermore, according to the annual reports of major commercial banks in China, their delinquency rate (using the same definition as our $Delinquency_{Firm90}$) in 2020 ranges from 1.4% to 3.3%. Thus, it is evident that the delinquency rate

[17] Source: Ant Group's IPO prospectus available at http://static.sse.com.cn/stock/information/c/202008/e731ee980f5247529ea824d20fcdb293.pdf.

of the BigTech firm in our study is comparable to other major BigTech players and is lower than that of commercial banks issuing traditional credit cards.

Additionally, we introduce three dummy variables that are constructed on the consumer level: $Delinquency_{Individual0}$, $Delinquency_{Individual30}$, and $Delinquency_{Individual90}$. These three variables equal one if the consumer's credit payment is more than zero days, 30 days, and 90 days overdue in a particular month, respectively, and zero otherwise. $Delinquency_{Individual0}$ does not exhibit a monotonic trend, with the lowest value observed in the second month after credit approval (5.8%) and the highest in the ninth month (8.0%). $Delinquency_{Individual30}$ and $Delinquency_{Individual90}$ show a steady increase over time, ranging from 0% to 4.0% and 0% to 2.4%, respectively. For comparison, Berg et al. (2023) study a German retailer offering BNPL services and report that the proportion of accounts more than 42 days overdue is slightly under 2%.[18] Thus, the delinquency rate at our firm is also comparable to that reported by Berg et al. (2023).

We also conduct a Logit regression analysis where the dependent variable is $Delinquency_{Individual30}$, and the independent variables consist of a series of interaction terms between $Spending_{IncreaseHigh}$ and month indicators. $Spending_{IncreaseHigh}$ is a binary indicator that equals one for consumers whose credit-boosted spending increase exceeds the median among all consumers receiving credit, in comparison to their matched counterparts in the control group (see Appendix A for detailed definition). The regression is designed to assess whether changes in spending associated with credit influence the likelihood of delinquency. Column 1 of Table 9 indicates that none of the interaction terms are significant at conventional levels, suggesting no

[18] Berg et al. (2023) describe a process whereby a reminder is emailed to the BNPL consumer on the payment due date, with a grace period of 14 days before imposing a late payment fee. A second reminder with a penalty fee follows, and after another 14 days, a final reminder is sent by mail. After an additional 14-day period without payment, the account is referred to a debt collection agency and is deemed delinquent, indicating that accounts more than 42 days overdue are considered delinquent.

discernible difference in delinquency likelihood between consumers with substantial spending changes and those with minor changes upon receiving credit.

For further exploration, when we substitute $Delinquency_{Individual0}$ for the dependent variable, we observe that most interaction terms become positive and significant (Column 2). This implies that consumers with significant spending increases post-credit approval exhibit a higher likelihood of delinquency when using the most stringent definition of delinquency. Notably, upon incorporating the repayment rate, refinancing rate, and refund rate as additional explanatory variables, the significance of the majority of interaction terms dissipates, and the Pseudo R-squared increases markedly from less than 1% to over 82% (Column 3). These findings indicate that users impacted by FinTech credit, who exhibit increased spending, are more likely to become delinquent in the short term (delinquency of 0+ days) but not in the long term (delinquency of 30+ days). This aligns with the consumption-smoothing function of FinTech credit, but it contradicts the notion that it exacerbates over-indebtedness. Notably, the disappearance of this correlation after controlling for explanatory variables suggests that individuals in the high-effect group possess a greater repayment capacity and utilize refinancing or refunds to avert more severe delinquency.

In summary, our findings demonstrate that consumers with access to BigTech credit do not increase their discretionary spending, do not purchase more expensive items than before, and do not exhibit a high delinquency rate. These results allow us to conclude that BigTech credit is not detrimental to consumers' financial health.

Insert Table 9 about here

5. CONCLUSIONS

Over recent years, BigTech firms renowned for their technology-related services, including e-commerce, search engines, social media, and hardware and software development, have ventured into the credit services sector. Despite this innovation, there remains a significant gap in the literature concerning the impact of BigTech credit and, more broadly, FinTech credit on consumer activities. Our paper endeavors to close this research gap by leveraging a detailed, novel dataset which integrates multiple granular dimensions of information from a leading BigTech' ecosystem.

Our research reveals that consumers who are granted BigTech credit demonstrate an approximate 19% increase in spending per month post-credit application, compared to non-credit recipients. Cross-sectional analyses indicate that individuals who likely face challenges in obtaining traditional credit, as well as those in areas with advanced logistical systems, show a more significant spending increase after receiving BigTech credit. These findings align with the objectives of financial inclusion and highlight the synergistic relationship between the financial and non-financial sectors of BigTech firms.

Delving into the drivers of spending increases, our data show that BigTech credit influences spending primarily by elevating the number of orders placed, rather than the amount spent per order. This is facilitated by increased visit frequency to the platform and improved conversion efficiency for purchases.

With access to order-item-level data, we observe that credit recipients tend to purchase from a wider range of product categories and select items from a broader array of brands, shopping across numerous distinct stores. However, this enhanced inclination toward variety-seeking does not equate to reckless spending as BigTech credit does not lead to higher discretionary spending or more expensive purchases, nor does it contribute to an uplifted delinquency rate.

In conclusion, our data suggest that BigTech credit augments consumer spending and encourages financial inclusion without precipitating over-indebtedness.

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Appendix A. Variable Definitions

Main Variables	
Spending	The total out-of-pocket consumption (i.e., canceled amount and discount are excluded) for a consumer in a specific calendar month. For the application month, the consumption on the application day and the day after application is excluded.
$Spending_{Discretionary}$/$Spending_{Dailyuse}$/$Spending_{Necessity}$	The spending on discretionary/daily-use/necessity items for a consumer in a specific calendar month. The discretionary category encompasses a wide range of products, including Digital, Sports & Outdoors, Gifts, Books, Music, Movies & TV, Cultural & Entertainment, Local Living/Travel, Watches, Digital Content, Jewelry & Accessories, Toys & Musical Instruments, Automotive Accessories, Pet Supplies, Alcohol, Automotive, Agricultural Supplies & Gardening, Stamps & Coins, and Art. The daily-use category includes Home Appliances, Apparel & Underwear, Beauty & Skin Care, Home & Daily Use, Kitchenware, Pet Products, Health & Wellness, Shoes, Prescription Medicine, Home Textiles, Household Cleaning & Paper Products, Personal Care and Bags & Leather Goods. The necessity category includes Apparel & Underwear, Mother & Baby, Food & Beverages, Home & Daily Use, Kitchenware, Health & Wellness, Mobile Phones & Communication, Shoes, Fresh Produce, Prescription Medicine, Household Cleaning & Paper Products and Personal Care.
$Spending_{IncreaseHigh}$	For consumers in the treatment group, we define their spending in the periods before and after credit application as a and b, respectively. Correspondingly, we identify the spending of their counterparts in the control group during the same periods as c and d. We then compute the formula [(b-a)-(d-c)]/a to measure the change in spending. $Spending_{IncreaseHig}$, is a dummy which equals one if the consumer's spending increase in the treatment group is above the median value, and zero otherwise.
Treatment	A dummy variable which is set to one if a consumer's credit application is rejected by the AI model but approved afterwards for the purpose of reject inference, and zero if the application is rejected by the AI model without being approved manually for reject inference.
Post	A dummy variable which is set to one if the calendar month is the month a consumer applies for credit or any of the subsequent months, and zero otherwise.
$Delinquency_{Firm30}$ ($Delinquency_{Firm90}$)	The monthly balance of loan principal overdue by more than 30 days (90 days), divided by the total monthly balance of the consumer credit loan principal facilitated through the company's platform.
$Delinquency_{Individual0}$ ($Delinquency_{Individual30}$/$Delinquency_{Individual90}$)	A dummy that equal one if the consumer's credit payment is more than zero days (30 days/90 days) overdue in a particular month, respectively, and zero otherwise.
Other Purchasing Characteristics	
Orders	The number of orders a consumer made in a specific month. For the application month, the orders made on the application day and the day after application are excluded.
OrderSpending	The average spending amount of the orders for a consumer in a specific month. For the application month, the orders made on the application day and the day after application are excluded.
Visits	The total number of visits made by a consumer in a given month. Each time a product page is browsed counts as one visit. For the application

	month, the visits on the application day and the day after application are excluded.
Conversion	The number of orders placed by a consumer in a specific month scaled by 10**Visits*.
SKUs	The number of unique product (i.e., stock keeping unit or SKU) a consumer purchases in a specific month.
Categories	The number of product category a consumer purchases in a specific month.
Brands	The number of brands a consumer purchases in a specific month.
Shops	The number of shops a consumer purchases from in a specific month.
ItemPrice	The average price of the items purchased in an order.
Variables used in Cross-sectional Analysis	
YoungAge (OtherAge)	A dummy that equals one if the consumer's age is (not) smaller than 22, and zero otherwise.
LowCreditScore (HighCreditScore)	A dummy that equals one if a user's credit score for the credit granting is below (above) the median, and zero otherwise.
LowUPDIndex (HighUPDIndex)	A dummy that equals one if a user resides in a province whose "Regional Bank Credit Card Development Vitality Index" (UPD Index), as reported by China UnionPay, is below (above) the median.
HighTotalRoad (RestTotalRoad)	A dummy that equals one if the consumer is (not) from a province in which total road length scaled by the population is among the top five provinces, and zero otherwise.
TopHighway (BottomHighway)	A dummy that equals one if the consumer is from a province in which expressway road length scaled by the population is among the top (bottom) five provinces, and zero otherwise.
TopMobileInternet(BottomMobileInternet)	A dummy that equals one if the consumer is from a province whose number of mobile Internet users scaled by the population is among the top (bottom) five provinces, and zero otherwise.
TopBroadband(BottomBroadband)	A dummy that equals one if the consumer is from a province where broadband access per capital is among the top (bottom) five provinces, and zero otherwise.
User characteristics	
Male	A dummy that equals one if the consumer is a male, and zero otherwise.
Age	The age of the consumer.
AccountAge	The number of months since the consumer register with the e-commerce.
CreditScore	The credit score assigned by the AI model of the e-commerce.
Applications	The number of prior applications of the consumer by the month.
CreditLimit	The initial credit limit granted to a consumer when her application is approved.
Discount	The total discount amount scaled by the total order amount by a consumer for a specific month.
Cancel	The total canceled amount scaled by the total order amount by a consumer for a specific month.
Other Variables	
$Month_n$	The n-th month after the credit granting. When n equals zero, it means the month in which the credit application is submitted.
RepayRate	The amount repaid scaled by bill amount.
RefinanceRate	The amount of spending switched from no installment payment to installment payment after seeing the monthly credit bill, scaled by the amount of spending with no installment payment in the bill.
RefundRate	The amount of credit spending canceled in the bill, scaled by the amount of spending with no installment payment in the bill.
CreditDue	A dummy variable that the amount due this month is not zero, and zero otherwise.

Figure 1. Reject Inference in BigTech Credit Granting

This figure illustrates the rationale behind the RI program conducted by the retailer, and its operational mechanism.

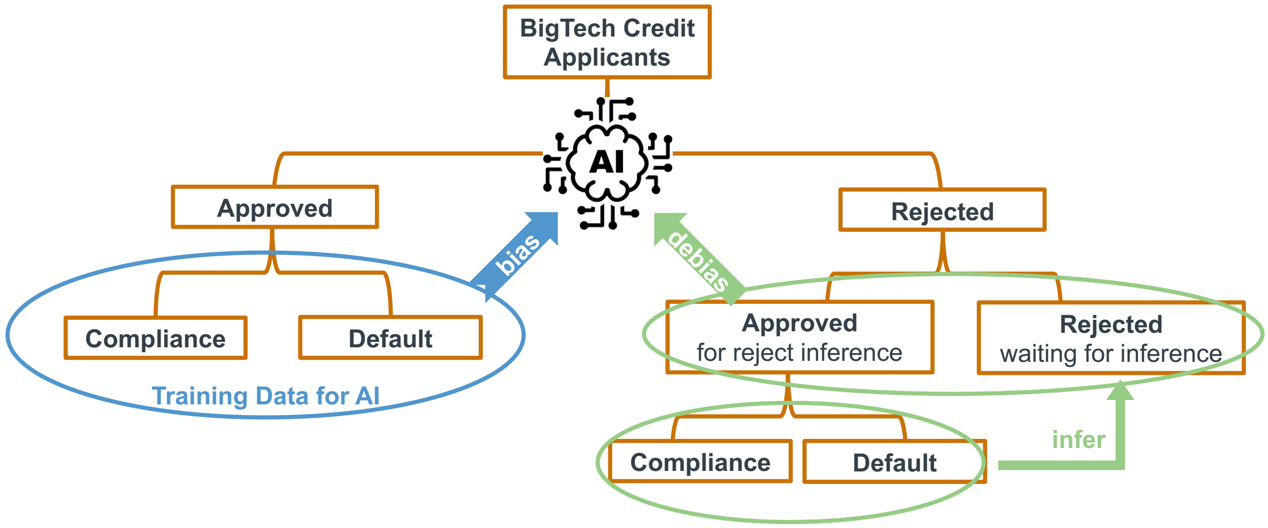

Figure 2. Univariate Analysis – Monthly Spending before and after Credit Application

This figure plots the monthly spending (i.e., Spending) before and after credit application for both treatment and control group. The vertical axis is the monthly spending measured in RMB. The horizontal axis is the number of months before or after the application, where 0 stands for the month of application.

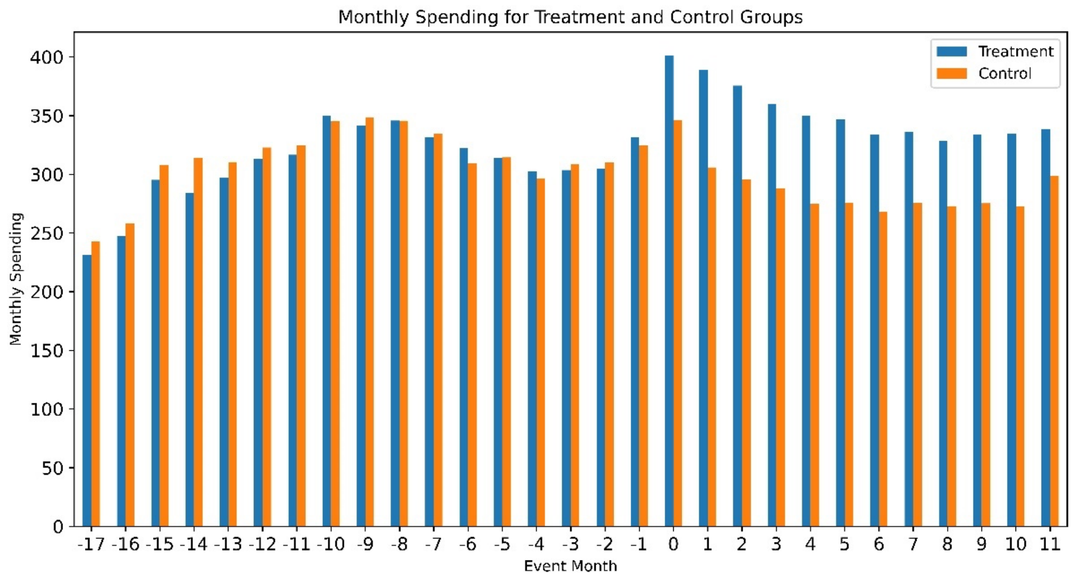

Figure 3. The Effect of Credit Granting on Spending – Event Study

These figures present the effect of credit granting on consumption. We perform a stacked cohort difference-in-differences analysis using the following specifications: $Spending_{i,c,t} = \sum_{t=-17}^{-2} \beta_t \times Treatment_i \times 1_{t,c} + \sum_{t=0}^{11} \beta_t \times Treatment_i \times 1_{t,c} + \alpha_i + \delta_{t,c} + \epsilon_{i,c,t}$, where t is the relative month where $t = 0$ demotes the month individual i applying for credit, $1_{t,c}$ is the indicator that equals one if the individual belongs to cohort c that has been treated in calendar month t and zero otherwise, and β_t captures the treatment effect of credit granting on consumption benchmarked on $t = -1$, i.e., the month prior to the application month. α_i represents individual fixed effects, $\delta_{t,c}$ represents month-cohort fixed effects. We estimate the model using Poisson regression. Variable definitions are in Appendix A. We cluster standard errors by both individual and calendar month in all regressions. All continuous variables are winsorized at 1% and 99% levels.

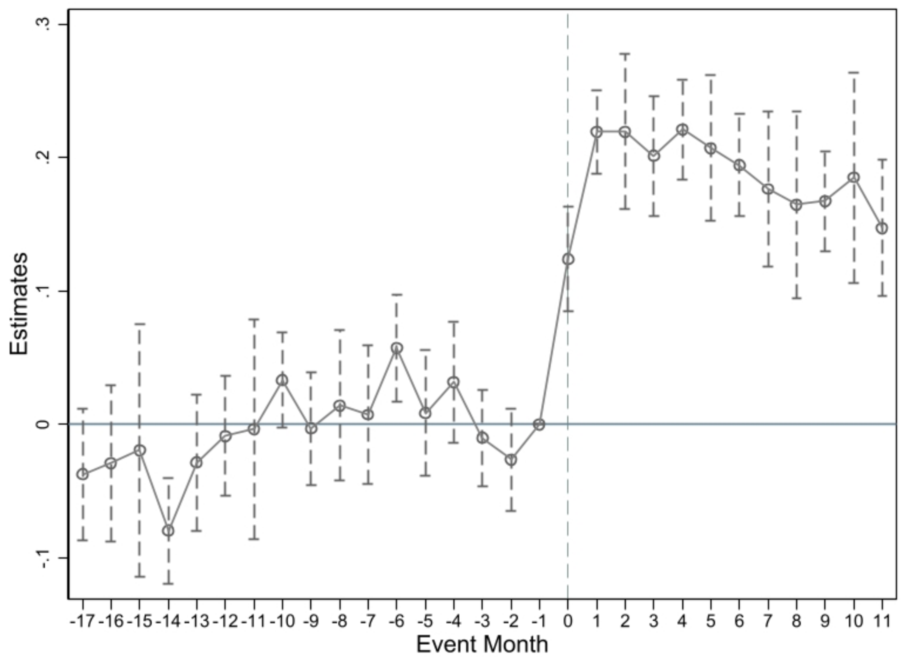

Table 1. Summary Statistics

Panel A. User Characteristics

	Count	Mean	Std.	25%	50%	75%
Male	60,882	0.65	0.48	0	1	1
Age	60,882	30.55	10.88	22	28	36
AccountAge	60,882	29.73	24.5	8	25	46
CreditScore	60,882	689.14	36.25	663	688	715
Applications	60,882	1.28	0.77	1	1	1
CreditLimit	30,441	331.04	172.41	200	400	500

Panel B. User-month Characteristics

	Count	Mean	Std.	25%	50%	75%
Spending	1,260,930	320.15	886.14	0.00	19.90	226.31
Orders	1,260,930	2.17	3.64	0	1	3
Visits	1,260,930	90.63	167.71	4	29	99
OrderSpending	711,815	154.32	288.07	29.90	69.90	147.21
Discount	711,299	0.19	0.19	0.02	0.15	0.31
Cancel	711,299	0.21	0.32	0.00	0.00	0.37

Table 2. The Impact of BigTech Credits on Consumer Spending

This table presents the impact of BigTech credit granting on consumption. We perform a stacked cohort difference-in-differences analysis using the following specifications: $Spending_{i,c,t} = \beta \times Treatment_i \times Post_{t,c} + \alpha_i + \delta_{t,c} + \varepsilon_{i,c,t}$, where i is the subscript for consumer, c is the subscript for cohort, t is the subscript for calendar month, α_i represents individual fixed effects, $\delta_{t,c}$ represents month-cohort fixed effects. Variable definitions are in Appendix A. Column 1 uses OLS regression and Column 2 uses Poisson regression. We cluster standard errors by both individual and calendar month in all regressions. All continuous variables are winsorized at 1% and 99% levels.

Dep. Var. = *Spending*	**(1)**	**(2)**
	OLS	**Poisson**
Treatment * Post	65.012***	0.190***
	(14.072)	(13.837)
Individual FE	YES	YES
Month-Cohort FE	YES	YES
Observations	1,260,930	1,260,930
Adjusted/Pseudo R-squared	0.224	0.377

Standard errors adjusted for clustering by individual and cohort-month
*** p<0.01, ** p<0.05, * p<0.1

Table 3. The Impact of BigTech Credits on Consumer Spending
– Evidence of Financial Inclusion and Complementarity between BigTech Financial and Non-Financial Services

This table presents the differential impact of BigTech credit granting on consumption. In Panel A, we perform a stacked cohort difference-in-differences analysis with group indicators using the following specification: $Spending_{i,c,t} = \beta \times Treatment_i \times Post_{t,c} \times FinancialInclusion_i + \alpha_i + \delta_{t,c} + \varepsilon_{i,c,t}$. In Panel B, we perform a stacked cohort difference-in-differences analysis with group indicators using the following specification: $Spending_{i,c,t} = \beta \times Treatment_i \times Post_{t,c} \times Infrastructure_i + \alpha_i + \delta_{t,c} + \varepsilon_{i,c,t}$. In both specifications, *i* is the subscript for consumer, c is the subscript for cohort, t is the subscript for calendar month, α_i represents individual fixed effects, $\delta_{t,c}$ represents month-cohort fixed effects. *FinancialInclusion* is a list of variables that measure the level of financial inclusion. *Infrastructure* is a list of variables that measure the level of logistic and internet infrastructure. Variable definitions are in Appendix A. We obtain the estimates using Poisson regressions. We perform Wald Chi-squared test to compare credit granting's effects between different groups, and report the p-value of the test in the last row. We cluster standard errors by both individual and calendar month in all regressions. All continuous variables are winsorized at 1% and 99% levels.

Panel A Financial Inclusion

Dep. Var.= *Spending*	(1)	(2)	(3)
Treatment * Post * YoungAge	0.439***		
	(12.466)		
Treatment * Post * OtherAge	0.130***		
	(9.015)		
Treatment * Post * LowCreditScore		0.369***	
		(16.188)	
Treatment * Post * HighCreditScore		0.113***	
		(6.759)	
Treatment * Post * LowUPDIndex			0.331***
			(4.950)
Treatment * Post * HighUPDIndex			0.214***
			(9.697)
Applicable Interactions	YES	YES	YES
Individual FE	YES	YES	YES
Month-Cohort FE	YES	YES	YES
Observations	1,260,930	1,260,930	483,674
Pseudo R-squared	0.377	0.377	0.376
p-value ($\beta_1 = \beta_2$)	**0.000**	**0.000**	**0.086**

Standard errors adjusted for clustering by individual and cohort-month
*** p<0.01, ** p<0.05, * p<0.1

Panel B Complementarity between BigTech Financial and Non-Financial Services

Dep. Var.= ***Spending***	(1)	(2)	(3)
Treatment * Post * TopHighway	0.270***		
	(4.113)		
Treatment * Post * BottomHighway	0.136***		
	(5.472)		
Treatment * Post * TopMobileInternet		0.206***	
		(9.803)	
Treatment * Post * BottomMobileInternet		0.220***	
		(5.098)	
Treatment * Post * TopBroadband			0.214***
			(6.890)
Treatment * Post * BottomBroadband			0.195***
			(3.779)
Applicable Interactions	YES	YES	YES
Individual FE	YES	YES	YES
Month-Cohort FE	YES	YES	YES
Observations	328,370	584,962	267,325
Pseudo R-squared	0.392	0.381	0.381
p-value ($\beta_1 = \beta_2$)	**0.058**	0.772	0.753

Standard errors adjusted for clustering by individual and cohort-month
*** p<0.01, ** p<0.05, * p<0.1

Table 4. The Impact of BigTech Credits on Consumer Spending

– An Analysis of the Mechanisms

This table presents the mechanisms that drive the increase in spending due to credit approval. We perform a stacked cohort difference-in-differences analysis using the following specification: $Mechanism_{i,c,t} = \beta \times Treatment_i \times Post_{t,c} + \alpha_i + \delta_{t,c} + \varepsilon_{i,c,t}$, where *i* is the subscript for consumer, c is the subscript for cohort, t is the subscript for calendar month, α_i represents individual fixed effects, $\delta_{t,c}$ represents month-cohort fixed effects. *Mechanism* is a list of variables that capture the mechanisms that drive the increases in spending, including *OrderSpending*, *Orders*, *Visits* and *Conversion*. Variable definitions are in Appendix A. We obtain the estimates using Poisson regressions. We cluster standard errors by both individual and calendar month in all regressions. All continuous variables are winsorized at 1% and 99% levels.

	(1)	(2)	(3)	(4)
Dep. Var.=	***OrderSpending***	***Orders***	***Visits***	***Conversion***
Treatment * Post	0.035***	0.203***	0.116***	0.079***
	(3.255)	(19.655)	(11.427)	(8.751)
Individual FE	YES	YES	YES	YES
Month-Cohort FE	YES	YES	YES	YES
Observations	709,636	1,260,930	1,258,210	1,038,746
Pseudo R-squared	0.341	0.264	0.511	0.161

Standard errors adjusted for clustering by individual and cohort-month
*** p<0.01, ** p<0.05, * p<0.1

Table 5. The Impact of BigTech Credits on Purchasing Variety

This table presents the impact of credit granting on purchasing characteristics based on the order-item level data. We perform a stacked cohort difference-in-differences analysis using the following specification: $PurchasingVariety_{i,c,t} = \beta \times Treatment_i \times Post_{t,c} + \alpha_i + \delta_{t,c} + \varepsilon_{i,c,t}$, where i is the subscript for consumer, c is the subscript for cohort, t is the subscript for calendar month, α_i represents individual fixed effects, $\delta_{t,c}$ represents month-cohort fixed effects. *PurchasingVariety* is a list of variables that measure purchasing variety, including *SKUs*, *Categories*, *Brands*, *and Shops*. Variable definitions are in Appendix A. We use a random sub-sample of consumers with detailed order-level data for the tests. We obtain the estimates using Poisson regressions. We cluster standard errors by both individual and calendar month in all regressions. All continuous variables are winsorized at 1% and 99% levels.

	(1)	(2)	(3)	(4)
Dep. Var.=	***SKUs***	***Categories***	***Brands***	***Shops***
Treatment * Post	0.200***	0.180***	0.185***	0.194***
	(5.506)	(6.748)	(5.468)	(5.727)
Individual FE	YES	YES	YES	YES
Month-Cohort FE	YES	YES	YES	YES
Observations	125,324	125,324	125,211	125,139
Pseudo R-squared	0.324	0.206	0.285	0.284

Standard errors adjusted for clustering by individual and cohort-month
*** p<0.01, ** p<0.05, * p<0.1

Table 6. The Impact of BigTech Credits: Discretionary Spending versus Necessary Spending

This table presents the impact of credit granting on the spending on discretionary, daily use and necessity items. The unique observation is at the order-item level. We perform a stacked cohort difference-in-differences analysis using the following specification: $Spending_{Discretionary}/Spending_{Dailyuse}/Spending_{Necessity\ i,c,t} = \beta_1 \times Treatment_i \times Post_{t,c} + \beta_2 \times Treatment_i + \beta_3 \times Post_{t,c} + \varepsilon_{i,c,t}$, where i is the subscript for consumer, c is the subscript for cohort, t is the subscript for calendar day of the order. Variable definitions are in Appendix A. We use a random sub-sample of consumers with detailed order-item level data for the tests. We obtain the estimates using Poisson regressions. We cluster standard errors by both individual and calendar month in all regressions. All continuous variables are winsorized at 1% and 99% levels.

	(1)	(2)	(3)
Dep. Var.=	***Spending$_{Discretionary}$***	***Spending$_{Dailyuse}$***	***Spending$_{Necessity}$***
Treatment * Post	0.138	0.253**	0.175***
	(1.565)	(2.336)	(2.764)
Individual FE	YES	YES	YES
Month-Cohort FE	YES	YES	YES
Observations	111,560	121,518	122,868
Pseudo R-squared	0.390	0.670	0.394

Standard errors adjusted for clustering by individual and cohort-month

*** p<0.01, ** p<0.05, * p<0.1

Table 7. The Impact of BigTech Credits on the Price of Purchased Items

This table presents the impact of credit granting on the price of items purchased. The unique observation is at the order-item level. We perform a stacked cohort difference-in-differences analysis using the following specification: $ItemPrice_{i,c,t} = \beta \times Treatment_i \times Post_{t,c} + \alpha_i + \delta_{t,c} + \zeta_j + \varepsilon_{i,c,t}$, where i is the subscript for consumer, c is the subscript for cohort, t is the subscript for calendar month, α_i represents individual fixed effects, $\delta_{t,c}$ represents month-cohort fixed effects, and ζ_j denotes the shop/brand/category fixed effects for different columns.Variable definitions are in Appendix A. We use a random sub-sample of consumers with detailed order-level data for the tests. We obtain the estimates using Poisson regressions. We cluster standard errors by both individual and calendar month in all regressions. All continuous variables are winsorized at 1% and 99% levels.

Dep. Var.= *ItemPrice*	(1)	(2)	(3)	(4)
Treatment * Post	-0.020	-0.017	0.024	-0.015
	(-1.263)	(-0.978)	(0.973)	(-0.975)
Individual FE	YES	YES	YES	YES
Date-Cohort FE	YES	YES	YES	YES
Shop FE	YES	NO	NO	YES
Brand FE	NO	YES	NO	YES
Category FE	NO	NO	YES	YES
Observations	250,289	256,971	283,211	231,857
Pseudo R-squared	0.850	0.794	0.484	0.872

Table 8. Credit Usage and Delinquency

The table provides an overview of credit utilization and delinquency during the month when credit is granted and the subsequent months. Credit Limit refers to the mean credit limit available in a specific month. Utilization denotes the average extent to which the credit limit is put to use by the borrowers. $Delinqency_{Firm30}$, $Delinqency_{Firm9}$, $Delinqency_{Individual0}$, $Delinqency_{Individual30}$ and $Delinqency_{Individual90}$ are various indicators of delinquency, with their specific definitions elaborated in Appendix A.

Month	*Credit Limit*	*Utilization*	$Delinqency_{Firm30}$	$Delinqency_{Firm90}$	$Delinqency_{Individual0}$	$Delinqency_{Individual30}$	$Delinqency_{Individual90}$
0	370.77	12.3%	0.0%	0.0%	6.2%	0.0%	0.0%
1	449.98	12.4%	1.0%	0.0%	6.1%	1.2%	0.0%
2	624.65	12.7%	1.8%	0.0%	5.8%	2.1%	0.0%
3	897.12	13.0%	2.3%	0.2%	5.9%	2.1%	0.8%
4	1205.61	13.4%	2.7%	0.4%	6.4%	2.5%	1.3%
5	1460.67	13.6%	3.1%	0.7%	6.6%	2.7%	1.5%
6	1744.65	13.7%	3.5%	1.0%	7.1%	3.0%	1.7%
7	1943.09	14.1%	3.7%	1.2%	7.0%	2.9%	1.7%
8	2174.32	14.8%	3.9%	1.3%	7.5%	3.2%	1.7%
9	2310.47	15.1%	4.0%	1.4%	8.0%	3.4%	1.9%
10	2623.88	14.6%	4.1%	1.5%	7.8%	3.6%	2.4%
11	2899	12.7%	4.1%	1.6%	7.4%	4.0%	2.4%

Table 9. Credit Effect and Delinquency Likelihood

This table presents the comparison of the propensity for delinquency among credit recipients with marked increases in spending and those with minimal spending increases. Variable definitions are in Appendix A. We use a random sub-sample of consumers with detailed order-level data for the tests. We obtain the estimates using Logit regressions. We cluster standard errors by both individual and calendar month in all regressions. All continuous variables are winsorized at 1% and 99% levels.

	(1)	(2)	(3)
Dep. Var.=	***$Delinquency_{Individual30}$***	***$Delinquency_{Individual0}$***	***$Delinquency_{Individual0}$***
$Month_0$ * $Spending_{IncreaseHigh}$		-0.005	-0.134
		(-0.091)	(-1.301)
$Month_1$ * $Spending_{IncreaseHigh}$	-0.064	0.155***	0.237**
	(-0.624)	(3.234)	(2.325)
$Month_2$ * $Spending_{IncreaseHigh}$	0.022	0.198***	0.092
	(0.271)	(4.028)	(0.760)
$Month_3$ * $Spending_{IncreaseHigh}$	0.029	0.168***	0.148
	(0.373)	(3.463)	(1.220)
$Month_4$ * $Spending_{IncreaseHigh}$	0.051	0.245***	0.243**
	(0.696)	(5.182)	(2.073)
Month5 * $Spending_{IncreaseHigh}$	0.027	0.214***	0.009
	(0.382)	(4.600)	(0.071)
Month6 * $Spending_{IncreaseHigh}$	0.016	0.238***	0.172
	(0.232)	(5.267)	(1.490)
Month 7 * $Spending_{IncreaseHigh}$	0.067	0.266***	0.040
	(0.865)	(5.162)	(0.304)
Month8 * $Spending_{IncreaseHigh}$	0.112	0.296***	0.145
	(1.284)	(5.058)	(0.978)
Month9 * $Spending_{IncreaseHigh}$	0.102	0.248***	-0.255
	(1.023)	(3.663)	(-1.385)
Month10 * $Spending_{IncreaseHigh}$	-0.141	0.074	-0.378
	(-1.043)	(0.786)	(-1.475)
Month11 * $Spending_{IncreaseHigh}$	0.029	0.321**	0.484
	(0.144)	(2.165)	(1.044)
RepayRate			-7.873***
			(-145.088)
RefinanceRate			-5.275***
			(-46.175)
RefundRate			-3.544***
			(-41.014)
CreidtDue			-10.408***
			(-93.711)
Month-Cohort FE	YES	YES	YES
Observations	243,695	264,000	264,000
Pseudo R-squared	0.011	0.003	0.825

Deciphering the Impact of FinTech Credit

Online Appendix

Table A1. Sample Selection Procedure

		Approved for Reject Inference			Rejected by AI Model		
#	**Steps**	**# Users**	**# Apps**	**# User-Months**	**# Users**	**# Apps**	**# User-Months**
1	Select applications between 2020-04-01 and 2020-09-30	129,813	129,813	-	340,314	445,457	-
2	Drop applicants with missing demographic information	128,232	128,232	-	328,972	431,573	-
3	Create user-month panel from 2019-04 to 2021-03	128,232	128,232	2,789,975	328,972	431,573	9,704,460
4	Merge with shopping data to obtain visit and consumption information	128,232	128,232	2,789,975	328,972	431,573	9,704,460
5	Merge with credit data to obtain credit usage and outcomes	128,232	128,232	2,789,975	321,310	422,883	9,502,220
6	Drop inactive users by pre-application spending	30,441	30,441	635,919	83,938	110,473	2,412,557
7	Perform month-by-month PSM without replacement	30,441	30,441	635,919	30,441	30,441	625,011

Table A2. Balance Check for PSM Variables

	Variable	Mean (Approved for Reject Inference)	Mean (Rejected by AI Model)	Difference
Before Matching	Gender (male=1)	0.64	0.70	-0.06***
	User Age (years)	30.50	30.46	0.04
	Account Age (months)	29.74	36.68	-6.94***
	N Application	1.28	1.92	-0.64***
	Credit Score	**689.11**	**688.46**	**0.65*****
	Monthly Visits (pre-event 12mo avg)	89.94	108.69	-18.75***
	Monthly Orders (pre-event 12mo avg)	2.17	2.51	-0.34***
	Monthly Spending (pre-event 12mo avg)	**320.45**	**378.74**	**-58.28*****
	Discount Proportion (pre-event 12mo cum)	0.19	0.18	0.01***
	Cancel Proportion (pre-event 12mo cum)	0.27	0.30	-0.03***
After Matching	Gender (male=1)	0.64	0.65	0.00
	User Age (years)	30.50	30.60	-0.10
	Account Age (months)	29.74	29.73	0.01
	N Application	1.28	1.28	0.00
	Credit Score	**689.11**	**689.17**	**-0.06**
	Monthly Visits (pre-event 12mo avg)	89.94	89.76	0.18
	Monthly Orders (pre-event 12mo avg)	2.17	2.17	0.00
	Monthly Spending (pre-event 12mo avg)	**320.45**	**315.64**	**4.81**
	Discount Proportion (pre-event 12mo cum)	0.19	0.19	0.00
	Cancel Proportion (pre-event 12mo cum)	0.27	0.27	0.00

Table A3. Randomness of Initial Credit Limit Assignment

Initial Credit Limit	Pearson Correlation Coefficient
Gender (male=1)	-0.06
User Age (years)	0.07
Account Age (months)	0.05
N Application	-0.04
Credit Score	**0.15**
Monthly Visits (pre-event 12mo avg)	0.02
Monthly Orders (pre-event 12mo avg)	0.01
Monthly Spending (pre-event 12mo avg)	0.03
Discount Proportion (pre-event 12mo cum)	0.01
Cancel Proportion (pre-event 12mo cum)	-0.03
Adj. R2 (regress initial credit limit on all above variables)	**0.03**

Table A4. Effect Robustness of FinTech Credit on Consumer Spending

Dep. Var.= ***Spending***	(1)	(2)	(3)	(4)
	Excluding Event Month 0	Rolling-window Spending	Staggered DID	C&S DID (OLS)
Treatment * Post	0.200***	0.207***	0.193***	43.338***
	(14.337)	(16.190)	(12.680)	(6.300)
Individual FE	YES	YES	YES	-
Month-Cohort FE	YES	YES	NO	-
Month EF	NO	NO	YES	-
Observations	1,200,048	1,300,723	1,260,930	961,502
Pseudo R-squared	0.378	0.372	0.376	-