Deciphering the Impact of BigTech Consumer Credit*

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Abstract

Over the past decade, large technology companies (BigTechs) have become increasingly active in the credit market. Leveraging proprietary data from a leading e-commerce BigTech and a novel reject inference setting where applicants initially rejected by automated underwriting are randomly approved, we investigate how BigTech credit complements the company's core business. We identify three main channels of complementarity. First, BigTech credit significantly enhances consumer engagement with the core business across the entire shopping cycle, leading to notable increases in visits, orders, net spending, and customer retention. Second, it improves operational predictability by reducing the volatility of consumer browsing traffic and transaction volume. Third, BigTech credit boosts consumption across nearly all product categories and increases product variety in recipients' purchases, helping reduce revenue concentration risk for the core business. Importantly, credit recipients exhibit low default rates compared to traditional credit card users, and we find no evidence that the spending increases driven by credit access lead to consumer delinquencies. Instead, they seem to actively manage their liquidity by purchasing interest-free products and entering into longer installment plans. Together, these findings show that BigTech credit stimulates and stabilizes consumer activity without compromising borrower financial health, providing substantial operational and financial benefits to the core business. Our research enriches the understanding of BigTech ecosystems, highlighting their unique business models, and holds important implications for the evolving landscape of BigTech regulation.

Keywords: BigTech, FinTech, Consumer Credit, E-commerce, Business Complementarity, China

1. INTRODUCTION

BigTechs are large technology companies with established digital platforms and extensive customer networks (Financial Stability Board, 2019). Examples include Amazon and Meta in North America, Mercado Libre in Latin America, and Alibaba and Samsung in East Asia. In recent years, these firms have expanded into financial services, creating a distinct segment within the broader financial technology (FinTech) sector. Unlike typical FinTech companies that innovate primarily within finance, BigTechs originate from non-financial domains such as e-commerce, social media, and search engines. They integrate financial services strategically into their broader digital ecosystems rather than offering them in isolation. While it is well established that competitive advantages from BigTechs' core operations drive their success in finance (e.g., Stulz, 2022), less is known about how these financial services, in turn, benefit their core businesses. We address this gap using highly granular data from a field experiment conducted by a major BigTech company.

We focus on credit extension, a service BigTechs have increasingly offered. Global BigTech lending volumes grew rapidly from $11 billion in 2013 to $572 billion in 2019 (Cornelli et al., 2023), representing more than twice the combined volumes of all other FinTech firms. This growth stems from BigTechs' ability to embed lending deeply within their non-financial ecosystems, leveraging superior technology infrastructure, vast user bases, valuable data, and abundant financial resources (Berg, Fuster, and Puri, 2022; Liu, Lu, and Xiong, 2025). By investigating how these credit offerings enhance core business activities, we shed light on the effects of financial services on core operations, which is crucial for a comprehensive understanding of BigTechs' innovative models and associated risks (citations).

Despite its importance, answering our research question faces two main challenges. First, it demands granular data not only on credit applications and approvals within a BigTech's lending arm but also on user activities in the core business such as platform engagement and transactions, which generate the firm's primary revenue and value. Second, lending decisions are highly endogenous: users self-select into applying for credit, and BigTechs approve applications based on user profiles and histories. As a result, simple comparisons between credit recipients and non-recipients would produce biased estimates of credit's impact on core business metrics.

To address the first challenge, we employ an unprecedented micro-level proprietary dataset from one of the world's largest e-commerce BigTechs. This BigTech extends unsecured revolving credit to its core business users. Approved consumers later use the credit for purchases on the e-commerce platform and receive monthly credit bills detailing the debt due for that month. We source anonymized data from this company's core and lending businesses and link them using internal user account identifiers. The data include detailed information on user demographics (e.g., age, gender, and location), browsing and purchasing behavior (e.g., timing and content of visits and purchases), payment details (e.g., amount spent, discounts received, cancellations, and credit usage), and credit management (e.g., application history, approval decisions, internal credit scores, credit limits, interest rates, monthly bills, repayment behavior, and delinquencies).

To address the second challenge, we utilize a novel field experiment conducted by the BigTech, namely a reject inference (RI) program in which credit applicants initially rejected by the BigTech's auto-underwriting system (hereafter, AI model) are randomly approved. Typically, the AI model's training data include only approved applicants, whose delinquency outcomes can be observed, potentially causing bias when the model is applied to all applicants. To mitigate this, the BigTech randomly approves some AI-rejected applicants, observes their delinquencies, infers counterfactual delinquencies for the remaining rejected applicants, and incorporates these inferred data into the training data. In our study, we leverage this exogenous variation in credit granting within the RI setting for identification: AI-rejected but RI-approved applicants form the treatment group, while the remaining AI-rejected applicants serve as the control group. By grouping users who applied in the same calendar week into cohorts, we apply the stacked cohort difference-in-differences (stacked DiD) method (Goodman-Bacon, 2021; Baker, Larcker, and Wang, 2022) to estimate the causal effects of BigTech credit on consumer activity within the core business.

We examine how BigTech credit enhances the company's core business by analyzing consumer activities, recognizing that the core business derives its revenue and value from these activities. We start with a framework tracing the e-commerce shopping cycle across three stages: engagement, transaction, and retention. The engagement stage represents the initial phase, focusing on visit frequency and visit-to-purchase conversion. The transaction stage encompasses the core purchasing activities that drive monetary value, measured by net monthly spending and its four key components: number of orders placed, discounts received, cancellations initiated, and net spending per order. The retention stage captures users' likelihood of returning to the platform after a previous shopping experience. We find that access to BigTech credit significantly boosts consumer activity across all three stages, with particularly strong increases in visit frequency, orders placed, net spending, and retention, rising by 20.3%, 31.2%, 28.6%, and 23.6%, respectively.

A second dimension of the benefits BigTech credit brings to the company's core business is its ability to reduce the volatility of consumer activity, a critical managerial concern for retailers (Esteban-Bravo, Vidal-Sanz, and Yildirim, 2017; Chuang, Oliva, and Heim, 2019). Highly volatile consumer behavior can disrupt inventory planning, resulting in either excess inventory and increased costs or stockouts and lost sales. Smoothing consumer activity not only improves operational efficiency and profitability (Li, 2023), but also reduces a firm's risk of cash flow shortfalls (Minton and Schrand, 1999). Our analysis shows that access to BigTech credit significantly reduces the volatility in visit frequency, orders placed, and net spending by 4.4%, 5.7%, and 3.6%, respectively, with all effects statistically significant at the 1% level. These findings suggest that BigTech credit not only boosts consumer activity but also enhances its stability and predictability, providing important operational and financial benefits to the core business.

A third way in which BigTech credit complements the company's core business is by promoting consumption variety. When consumers purchase diverse products from a single retailer, it signals successful attraction of loyal, valuable one-stop shoppers. This diversified purchasing pattern strengthens customer retention and enables retailers to capture larger shares of consumer spending (Klemperer and Padilla, 1997; Thomassen et al., 2017). For e-commerce platforms, this is particularly vital as their advantage lies in offering broader product selections than brick-and-mortar stores (Brynjolfsson, Hu, and Smith, 2003; Quan and Williams, 2018). To assess this effect, we examine four measures of consumption variety based on unique product, brand, shop, and category identifiers. We find that access to BigTech credit significantly increases variety across all measures, expanding consumers' consumption variety by approximately 30%.

Collectively, the preceding evidence demonstrates that the BigTech's financial services effectively complement the company's core business. However, for these benefits to endure, it is crucial that the lending operations themselves are sustainable. If BigTech's credit services were to encourage reckless borrowing or result in high default rates, the value they add to the core business could be short-lived.

To address this concern, we conduct two sets of analyses. First, we examine whether access to BigTech credit leads to conspicuous consumption. Using detailed order-item level data and various fixed effects structures, we find no evidence that BigTech credit prompts consumers to purchase more expensive items, choose higher-end brands, or shop at more upscale stores. Second, we assess indebtedness associated with BigTech credit. We find that the 90-day delinquency rate averages just 1.0% over the sample period, lower than the 1.4% to 3.3% range reported for major national commercial bank credit cards in these banks' 2020 annual reports. Moreover, consumers who substantially increase their spending after receiving credit do not have higher default rates compared to those whose spending rises more modestly, indicating that credit-induced increases in spending do not negatively impact consumers' financial health. Overall, these findings suggest that the lending operations are sustainable.

To supplement these findings, we investigate the mechanisms driving these behavioral changes and quantify their economic significance. Our analysis indicates that the primary channel is the relaxation of consumer liquidity constraints, as the credit's effects are strongest for more financially constrained users. While we consider alternative explanations like targeted marketing, we find they are not the main drivers. Finally, we document a high marginal propensity to spend from the initial credit line, confirming that the BigTech's integrated model is highly effective at converting credit into immediate platform spending.

Our paper makes three key contributions. First, while review articles and regulators consistently emphasize the interplay between BigTechs' financial services and their core businesses as a distinct feature setting them apart from other FinTech companies (Berg, Fuster, and Puri, 2022; Financial Conduct Authority, 2022), recent literature has largely focused on how the strengths from core businesses contribute to BigTechs' rise in finance. For example, theoretical research on lending services highlights BigTechs' unique advantages in extending credit within their ecosystems, such as by controlling agents' revenue streams or obtaining "digital collateral" from proprietary settlement ledgers (Li and Pegoraro, 2023; Brunnermeier and Payne, 2025). Empirically, Liu, Lu, and Xiong (2025) find that integrating lending into a BigTech's core business reduces nonmonetary borrowing costs, such as time and effort, aiding in meeting short-term liquidity needs of small and medium-sized enterprises (SMEs) within its ecosystem. Similarly, Hau et al. (2024) show that BigTech credit's growth-boosting effect on SMEs is most pronounced for those with high information asymmetry and limited collateral, reflecting BigTechs' information advantage from analyzing transaction data on their core platforms. In contrast to these studies, we provide comprehensive empirical evidence of the reverse relationship: how BigTech lending reinforces the core business. Together with other research, we draw a more complete picture of the mutually reinforcing relationship between BigTechs' financial and core operations, deepening the understanding of their unique lending model.

Second, as BigTechs have come to dominate the FinTech lending market in recent years (Berg, Fuster, and Puri, 2022; Cornelli et al., 2023), a nascent literature on BigTech credit has begun to emerge. This research mostly focuses on the impact of BigTech credit on merchants or SMEs (e.g., Chen et al., 2022; Hau et al., 2024; Liu, Lu, and Xiong, 2025). In contrast, despite BigTechs' presumed substantial impact on consumer finance (Stulz, 2022), empirical evidence on consumer response remains limited, presumably due to the lack of high-quality data and clean identification strategies. By leveraging unique, granular data from a leading e-commerce BigTech and utilizing the RI setting for identification, our paper provides new insights into consumer responses to BigTech credit.

More broadly, we contribute to the research on the real effects of FinTech. Recent studies demonstrate that FinTech can stimulate entrepreneurial growth and merchant profitability (e.g., Agarwal et al., 2019; Gopal and Schnabl, 2022; Berg et al., 2025) and help consumers make better financial decisions (e.g., D'Acunto, Prabhala, and Rossi, 2019; Fuster et al., 2019; Gargano and Rossi, 2024; Rossi and Utkus, 2024; Agarwal et al., 2024; Parlour, Rajan, and Zhu, 2022). However, other research highlights potential downsides, suggesting that FinTech may also fuel excessive consumption and over-indebtedness (Buchak et al., 2018; Chava et al., 2021; Di Maggio and Yao, 2021; Wang and Overby, 2022). Our research adds to this literature by showing that BigTech credit, as a subset of FinTech, can generate substantial positive real effects for the BigTech firm without inducing conspicuous consumption or elevated delinquency risks.

Regulators worldwide are closely monitoring BigTechs due to their dominance in technology sectors and growing influence in finance. Some have adopted, or are considering, entity-based regulatory frameworks that impose consolidated oversight at the group level to address challenges from BigTechs' conglomerate structures and integrated models (e.g., Financial Conduct Authority, 2022; European Supervisory Authorities, 2022). Regulating BigTechs also requires enhanced collaboration among financial and non-financial authorities, including those focused on competition, data protection, cybersecurity, and consumer protection.[1] Thus, our research on the interplay between BigTechs' financial and non-financial activities is timely and pertinent for regulators. Moreover, our finding that BigTech financial services enhance core businesses is especially relevant for competition authorities concerned about entry barriers in sectors like e-commerce, social media, and search engines. Last, this self-reinforcing feedback loop, where strengthened core activities further bolster financial services, implies that financial regulators must consider ecosystem dynamics to accurately assess BigTechs' systemic impact on the financial sector. Additional background on BigTech regulation is provided in Section 2.1.

[1] See Agur, Ari, and Del'Ariccia (2025) for a model of how BigTechs exploit payment data for credit advantages, creating privacy tradeoffs and a rationale for regulating intrusive practices.

2. INSTITUTIONAL BACKGROUND AND CONTEXT

2.1 BigTech Firms and Their Financial Expansion

BigTech firms are large technology companies with extensive, established customer networks (Financial Stability Board, 2019). Their core businesses include search engines, hardware and software development, e-commerce, social media, telecommunications and so on. Over the past decade, these companies have established a broad and diverse presence in the global financial sector. For example, U.S.-based technology giants such as Alphabet (Google), Amazon, Meta (Facebook), Apple, and Microsoft now offer a wide array of financial services, including current accounts, credit, payments, crowdfunding, insurance, and stablecoins. Major Chinese firms, such as Alibaba and Tencent, have expanded even further into financial services, including asset management. Similarly, companies like NTT Docomo and Rakuten (Japan), Vodafone (UK), and Samsung (South Korea) are also deeply embedded in the global financial ecosystem.

2.2 Distinct Advantages and Business Model of BigTechs

When BigTechs use their platforms to provide financial services, they can be considered a subset of FinTech firms. However, BigTechs enjoy several distinct advantages over traditional FinTechs, such as vast customer networks, strong brand recognition and trust, and exclusive access to proprietary customer data generated through their core businesses. Additionally, BigTechs typically possess robust financial resources, easy access to low-cost capital, and advanced technological capabilities for processing and analyzing big data (Financial Conduct Authority, 2023).

As Figure 1 illustrates, when BigTechs leverage these strengths to launch financial services, they can rapidly scale their offerings and attract users from their existing customer base. These financial services create a feedback loop that strengthens their core businesses by deepening customer engagement, generating additional data, and enhancing the overall value proposition of their platforms. This creates a self-reinforcing cycle where non-financial businesses provide the foundation and resources for financial expansion, while financial services strengthen the core business (Financial Stability Board, 2019). Due to this unique ecosystem operation that integrates both financial and non-financial offerings, BigTechs have been described as “tech conglomerates,” “neo-conglomerates,” or technology-enabled “mixed activity groups” (Financial Conduct Authority, 2022; European Supervisory Authorities, 2022).

2.3 Regulatory Challenges Posed by BigTechs

The distinctive business model and comparative advantages of BigTechs pose significant challenges for regulators. Specifically, traditional regulatory frameworks target specific activities (e.g., banking regulations for banks, telecommunications rules for telecoms). In contrast, BigTechs operate across multiple sectors, creating regulatory gaps. When a BigTech wields substantial market power across multiple sectors, significant risks and distortions may arise that activity-specific regulations cannot adequately address.[2] In response, regulators around the world are increasingly adopting an entity-based approach, imposing requirements at the group (consolidated) level, regardless of how financial and non-financial activities are structured across subsidiaries.[3] Consistent with this approach, effective oversight will require coordinated efforts among financial, data protection, cybersecurity, consumer protection, and competition authorities (European

[2] For example, a BigTech might comply with banking regulations for its payment services while simultaneously using data from those services to gain unfair advantages in unrelated markets such as e-commerce or advertising. Likewise, a BigTech dominant in search or social media may adhere to marketplace and privacy rules, yet still leverage its vast data resources to offer preferential credit terms or build significant off-balance-sheet leverage, potentially distorting credit markets and amplifying systemic risk.

[3] In the U.S., new legislative proposals and antitrust reforms target anti-competitive practices by these large, multi-sector platforms. China has introduced guidelines and regulations for internet companies, required firms like Ant Group and Tencent to become financial holding companies, and imposed new rules on non-bank payment providers. Similarly, the EU’s proposed Digital Markets Act and Digital Services Act establish comprehensive requirements for governance, risk management, and supervision of BigTech “gatekeepers.” (See also Crisanto et al., 2021; Bains, Sugimoto, and Wilson, 2022; Tierno, 2022)

Supervisory Authorities, 2024).

2.4 The Lending Business of BigTechs

BigTechs extend credits to their users either directly through financial services subsidiaries or in partnership with traditional financial institutions. Notable examples include the lending activities of Alibaba's Ant Group and Tencent's WeBank in China, Amazon's lending operations in the U.S., U.K., and other countries, Google's lending initiatives in India, Vodafone and Safaricom's joint services in Africa, Grab and Go-Jek's offerings in Southeast Asia, and Mercado Libre's lending platform in Latin America.

BigTech lending has grown dramatically since 2013. Starting from $11 billion, it surpassed the outstanding credit issued by other FinTechs in 2018, reaching $375 billion compared to the $300 billion combined balance of all other FinTechs. This gap widened further to $572 billion versus $200 billion in 2019 (Cornelli et al., 2023). In China alone, BigTech credit grew 37% in 2021, nearly triple the 13% growth rate of bank credit (De Fiore, Gambacorta and Manea, 2024).

2.5 The BigTech Under Study

The BigTech company we study is headquartered in China. As an emerging economy that tends to be more open to disruption than established markets like the U.S., it offers researchers unique opportunities to explore financial innovation in rapidly evolving markets (Goldstein, Jiang and Karolyi, 2019).

The company's core business is e-commerce. As a comprehensive "one-stop shop," it offers a wide range of products, such as consumer electronics, home appliances, groceries, apparel, cosmetics, books, and more, and provides services throughout every province in mainland China.

The company invests heavily in digital technologies, including big data analytics and personalized product recommendations, as well as logistics innovations such as automated warehouses, autonomous delivery vehicles, and drones. With annual revenues exceeding $100 billion, it ranks among the world's largest e-commerce platforms.

The company operates a financial services division that runs in parallel with its core e-commerce business. This division offers unsecured revolving credit among other financial services to existing users of the e-commerce platform and non-users, the latter of whom are attracted by credit access and converted to e-commerce platform users. Consumers apply for BigTech credit via a streamlined, one-click online application. The company's proprietary AI model evaluates each application and, if approved, assigns an initial credit limit and interest rate within minutes.

This credit product is fully integrated into the e-commerce platform, allowing users to select it as a payment method at checkout and choose from available installment plans. Monthly bills are issued by the company, which consumers can repay in full or refinance through 3-, 6-, 12-, or 24-month installment plans for any unpaid balance not already on a plan. The company regularly evaluates credit users to determine whether to adjust their credit limits and interest rates.

3. THE SETTING FOR IDENTIFICATION

3.1 Introduction to the Reject Inference Program

The company launched a filed experiment, namely, the reject inference (RI) program between April and September 2020. During this period of time, the company's proprietary AI model makes real-time approval decisions upon receiving credit applications as usual. However, among applicants rejected by the AI model, a randomly selected group is funneled into the RI program and being approved for BigTech credit. They receive notifications informing them of their credit account approval within minutes like other AI-approved appliants, along with the assigned credit limit and interest rate.

The company employs this program for two purposes. First, the program addresses the bias that arises when a credit granting model is trained solely on accepted applicants (Anderson, 2007; Thomas, Crook, and Edelman, 2017). The architecture of the automated underwriting system is presented in Figure 2. As the left branch of the figure shows, the BigTech company uses a proprietary AI model to decide which applications to approve or reject, and relies on the approved ones' realized delinquencies to train and improve the AI model's predictive power. While this credit granting and data production loop help improve the model over time, it has a critical limitation: the model is trained only on approved applicants, yet it is applied to all applicants. To address this issue, the company needs to train the AI model on rejected applicants' delinquencies as well. As shown in the right branch of the figure, the company randomly extends credit to a representative sample of applicants that are AI-rejected. The realized delinquencies collected from this AI-rejected but RI-approved group enables the inference of counterfactual delinquencies for the rest AI-rejected applicants. The company incorporates these realized and inferred delinquencies of AI-rejected applicants in training to help debias the AI model.

Second, the RI program helps evaluate the effectiveness of the company's current credit granting policy. Credit providers routinely face a trade-off between the benefits of approving more applicants and the potential costs of doing so. In the BigTech context, this trade-off is more complex: approved users are not only borrowers but also customers of the core business. The benefits of approval extend beyond interest income to include increased spending and engagement on the e-commerce platform. Similarly, the costs include not only potential loan defaults and capital costs for the lending business, but also broader impacts on the e-commerce platform such as increased customer service expenses, higher rates of product returns, and the risk of damaging the brand's reputation if credit is extended to unsuitable users. These broader considerations are essential for the operations of the BigTech company. The RI program creates a setting for the company to evaluate its current credit policy on marginal applicants who are currently excluded from the system.

3.2 The RI Program's Features and Implications

To debias the AI model and enable unbiased evaluation of the current lending policy (as discussed in Section 3.1), the RI program is designed to mirror a randomized controlled trial (RCT), akin to field experiments by Aydin (2022) at a retail bank and Karlan and Zinman (2010) at a consumer finance company. Specifically, three core features ensure the rigor of the RI program. First, randomization is achieved by extending BigTech credit to a representative sample of applicants initially rejected by the AI model. Second, sole manipulation is ensured, with no other exogenous interventions applied to RI-approved applicants. Both features enable any observed changes in outcomes to be attributed directly to receiving BigTech credit.[4] Third, blinding is satisfied, as all credit approvals, whether by the AI model or through the RI program, deliver indistinguishable notifications within minutes after applications, ensuring RI-approved applicants remain unaware of their initial rejection or random selection into the program. This further reduces the risk of these consumers altering their behaviors due to awareness of being studied or selected experimentally.

We leverage these features to identify the causal effects of BigTech credit, designating AI-rejected but RI-approved applicants as the treatment group and the remaining AI-rejected applicants as the control group. RI is a critical tool for credit providers using scoring models and has been widely adopted by FinTechs and traditional banks for model improvement (Anderson,

[4] All platform-initiated actions, such as credit limit and interest rate assignment, targeted advertising, and customer support, remain independent of the RI program and follow standard operating procedures. Accordingly, the treatment effects of BigTech credit estimated in this setting are conditional on the company's existing operational practices including credit limit and interest rate policies. While we note this as an important caveat, the company's leading position in the e-commerce industry suggests that our findings are broadly generalizable.

2007; Thomas, Crook, and Edelman, 2017). However, despite its prevalence, this exogenous variation has not been exploited for causal inference in empirical research. To our knowledge, we are the first to do so.

Beyond mimicking an RCT, the RI program targets marginal consumers, aligning with its second purpose of evaluating the current credit policy. This feature yields two key implications. First, it reveals the marginal effects of policy changes, highlighting untapped potential, namely, how much additional value the core business (e.g., e-commerce) could gain from slightly expanding credit access. If marginal approvals yield significant boosts in platform spending and engagement that outweigh default risks, it underscores financial services as a growth lever for non-financial operations. Thus, the RI program offers a powerful setting to examine how lending enhances BigTechs' core businesses. Second, since FinTech lenders are typically more inclusive and tend to offer credit to riskier consumers than traditional institutions do (Bao and Huang, 2021; Di Maggio and Yao, 2021), these AI-rejected borrowers are likely underserved by conventional credit markets. Analyzing their post-approval behaviors aligns with our goal of assessing BigTech business model sustainability, as these marginal borrowers may be more vulnerable to over-indebtedness and financial distress.

3.3 The Implementation of the RI Program

We describe the implementation of the RI program in Figure IA1 in the Internet Appendix. This figure tracks weekly metrics of the program between April and September 2020: the size of the RI pool (AI-rejected applications, Panel A), internal credit scores of RI applicants (Panel B), RI approval rates (Panel C), initial credit limits (Panel D), and initial interest rates for RI-approved applicants (Panel E). Panel A shows that AI-rejected application volume is fairly stable over time, representing 2-5% of the pool each week, with no clustering around specific events, which mitigates concerns about time-specific shocks. Panel B reveals that applicant quality is stable, with internal credit scores narrowly ranging from 677 to 685 (about 1% variation). The company initially adopted a conservative credit policy, with the RI approval rate rising from 14% in April to 28% by September, and the initial credit limit increasing from 290 to 340 RMB. The initial monthly interest rate declined from 1.17% to 1.13% over the first six weeks and then stabilized. On average, the initial credit limit and monthly interest rate during the RI period were 328 RMB and 1.12%, respectively.[5] To put the initial credit limit and interest rate in context, average monthly spending in our sample was 190 RMB, while monthly per capita disposable income in China in 2020 was 2,682 RMB. In 2020, China's central bank capped credit card annual interest rates at 18.25%, with a lower limit of 12.775%. Interest rates for FinTech credit products, such as peer-to-peer (P2P) lending, ranged more widely from 8% to 24% (Deer, Mi, and Yu, 2015).[6]

3.4 Identification Strategy

To estimate the treatment effects of BigTech credit, we employ a stacked cohort difference-in-differences (stacked DiD) approach. Specifically, consumers who applied in the same week and were rejected by the AI model are grouped into the same cohort. Within each cohort, we compare outcomes before and after credit approval for AI-rejected but RI-approved consumers (treatment group), relative to the remaining AI-rejected consumers (control group).

To avoid bias from time-varying treatment effects (Goodman-Bacon, 2021; Baker, Larcker, and Wang, 2022) and ensure clean separation between groups, each applicant is included in only

[5] Section 7 presents week-by-week analyses to demonstrate the robustness of our results across both the early and later phases of the RI program.

[6] Their interviews and surveys of major Chinese P2P lending platforms revealed that CreditEaseAct charged a flat 12% plus additional fees based on loan type and risk, Dianrong.com offered rates between 8% and 20%, and most Paipaidai borrowers paid between 8% and 18%. It is important to note that the Chinese government began tightening regulation of P2P lending platforms in 2016, following a series of industry-wide defaults and scandals. In 2018, after several high-profile platform failures, authorities required non-compliant P2P platforms to exit the market. By 2020, nearly all P2P lending platforms in China had shut down as a result of this regulatory crackdown.

one cohort. Specifically, we do not reuse individuals from earlier cohorts in later ones (whether treated or control), even if a control group member submits applications again in a later week. Additionally, we exclude treated applicants who ever held BigTech credit before the RI program, as well as control applicants who are later approved by the AI model or RI program within our sample period, to prevent contamination from switching between groups.[7]

When constructing each cohort, we match treated and control applicants based on their application histories to account for underlying credit needs, as detailed in Section 4.2. The staggered rollout of treatments across cohorts helps rule out many alternative explanations for our findings. Any confounding factor would need to vary not only over time but also across individuals, in lockstep with the treatment events (approved applications) observed in our study. We estimate the following model using a panel dataset of individual-month observations:

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

where i represents the consumer, t the calendar month, c the cohort, α_i individual fixed effects controlling for time-invariant consumer characteristics, and $\delta_{c,t}$ cohort-calendar month fixed effects controlling for consumer-invariant calendar month characteristics. $Outcome$ denotes a series of variables designed to assess the extent to which the BigTech's lending business enhances its core business. $Treated$ is a binary variable indicating RI-approved applicants, and $Post$ is a binary variable taking the value of one for the application month and subsequent months. The coefficient β captures the average treatment effect of BigTech credit on $Outcome$. We estimate the coefficient using Poisson regressions to obtain valid semi-elasticity estimates (Cohn, Liu, and Wardlaw, 2022; Chen and Roth, 2023).[8] To address potential serial and cross-sectional

[7] Very few people had previously received BigTech credit but later closed their accounts, resulting in no active credit before being granted credit again through the RI program.

[8] These studies suggest that log-transforming non-negative dependent variables can introduce bias, especially when the data are right-skewed or contain a high frequency of zeros. In our setting, variables such as monthly order count

correlations, we employ two-way clustered standard errors at the individual and cohort-calendar month levels. Definitions of all variables are provided in Appendix A. In some analyses, we use order-level data and adjust the variable definitions and fixed effects structures in Equation (1) accordingly, as detailed in relevant sections.

4. SAMPLE CONSTRUCTION AND DESCRIPTION

4.1 Data and Sample

We source anonymized data from multiple operational units of the BigTech company, including its core e-commerce and lending businesses, and link them using internal user account identifiers. The dataset includes rich information on user demographics (age, gender, and location), browsing and purchasing behavior (visit and purchase timing and content), payment details (amount spent, discounts received, cancellations, and credit usage), and credit management (application history, internal credit scores at application, approval decisions, credit limits, interest rates, monthly bills, repayment behavior, and delinquencies).

We begin sample construction with applicants who applied for BigTech credit between April and September 2020 and were initially rejected by the AI model, i.e., the RI applicants pool. The company provided access to a random sample of this pool, and we further restrict the sample to applicants that have complete demographic information (e.g., gender, account age, user age, and location) and are active on the platform (Agarwal, Qian, and Zou, 2021).[9] For each applicant, we construct monthly observations spanning April 2019 to March 2021 by aggregating their activities within the BigTech ecosystem at the monthly level. Each individual can have up to 24 monthly

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or spending may take a value of zero when no purchases occur. To address this, we primarily use Poisson regressions. Nevertheless, all results remain robust when estimated using OLS regressions.

[9] We consider consumers active if they have browsing activities in more than half of pre-application sample months. Our findings are robust to other definitions or dropping this filter (results untabulated).

observations in total.[10] For applicants applied in the first month of the RI period, we observe up to 12 months before and 12 months after application. For those applied in the last month of the RI period, we observe up to 17 months before and 7 months after application. As described in Section 3.4, we group applicants who applied in the same calendar week into the same cohort. For each cohort from April to September 2020, RI-approved applicants are assigned to that cohort's treatment group, while the remaining AI-rejected applicants form the control group.

It is important to note that our sample period spans from 17 months before to 12 months after BigTech credit applications. This long timeframe is crucial for three reasons. First, it allows for a long pre-event period to detect any potential differences across the treatment and control groups. Second, it helps determine whether any observed effects are temporary or persistent. Third, it leaves enough post-event time for any potential adverse consequences to surface.

In some sections, we aggregate user activities at the weekly level to construct a user-week sample when we try to capture more timely reactions. For a 10% random subsample of the sample users, we even obtain their order-item level shopping history for more detailed analysis (hereafter, detailed subsample). These samples are described in detail in corresponding sections.

4.2 Propensity Score Matching

As elaborated in Section 3, one principle behind RI is randomness. However, the specific process used by the company to select RI-approved applicants is proprietary and has not been disclosed to us. Therefore, we conduct a series of sanity checks to assess the randomness of the selection. Specifically, we perform *t*-tests to compare treated and control applicants across various dimensions, including credit status (application history and internal credit score), demographics

[10] Note that some consumers opened their e-commerce accounts after April 2019. Then, their monthly observations start from their account registration month to March 2021, resulting in fewer than 24 monthly observations for each of them in our sample.

(gender, age, account age, and location), and browsing and purchasing behavior (visit and purchase frequency, spending amount, discount rates, cancellation rates, and use of platform points).

As shown in Table IA1 Panel A of the Internet Appendix, while we observe statistically significant differences across many dimensions for treated and control applicants in the pre-period (likely due to the large sample size), these differences are generally modest in economic magnitude. Most notably, the difference in internal credit scores, a key determinant in the AI's credit-granting decisions, is only 4.5, with an average of approximately 686. Internal credit scores created by the BigTech under study are derived from tens of thousands of variables, encompassing demographics, online behaviors, credit bureau data, digital footprints, and more. The small difference in scores suggests that treated and control applicants are highly comparable, even along dimensions that are not observed here.

However, we do note that RI-approved applicants tend to have newer e-commerce accounts and lower overall platform activity in the pre-period, as indicated by fewer visits, fewer orders, and lower spending. To mitigate these observed differences (even economically modest ones), we employ nearest-neighbor propensity score matching without replacement (PSM) to pair each treated applicant with one control applicant within the same cohort. The PSM procedure balances key characteristics, including demographics, demand for BigTech credit, credit risk, consumption level, and online shopping behavior. Post-matching differences are negligible and presented in Table IA1 Panel B of the Internet Appendix.[11]

Ultimately, our sample includes 59,904 treated and 59,904 control applicants with 1,296,335 and 1,290,315 monthly observations, respectively.

[11] For a detailed list of variables used in PSM as well as the logistic regression results, please refer to Table IA1 Panel C of the Internet Appendix. Despite the extensive list of matching variables, pseudo R-squared of the regression is only 0.077, further testifying the randomness of credit approval in the RI program.

4.3 Who Are These BigTech Credit Applicants?

We present summary statistics of key variables in Table 1. According to Panel A, approximately 66% of applicants in our sample, are male, with an average age of around 29 years old and an average registration duration on the e-commerce platform of roughly 31 months. We present more detailed demographic information of geographic and age distributions in Figure IA2 in the Internet Appendix.

Panel A of Figure IA2 displays their geographic distribution based on shipping addresses. Guangdong province has the highest number of applicants, consistent with its status as the province with the largest population and the highest number of mobile internet users in China. Shandong, Sichuan, Jiangsu, and Henan also report high applicant volumes, aligning with their population sizes and digital user bases. This geographic distribution is broadly consistent with 2019 provincial population data from the National Bureau of Statistics and mobile internet user data from the China Digital Economy Research Database (citations needed? From databases, maybe insert a footnote for the links?).

Panel B shows the age distribution of applicants. Individuals aged 20-29 make up the largest segment, while those over 50 account for the smallest share. This pattern is consistent with the age distribution of internet users reported by the China Internet Network Information Center (2019). It also reflects the fact that the “post-90s” (born after 1990) and “post-00s” (born after 2000) generations have the highest rates of online shopping in China (China Internet Network Information Center, 2024). Overall, these descriptive results support that our sample applicants are representative of China’s population and internet users in terms of geographic and age distributions.

4.4 What Do These BigTech Credit Applicants Purchase?

Like any large e-commerce platform, the company under study employs a multi-level product categorization scheme. The broadest level (Level 1) comprises more than 70 categories, while the most detailed (Level 3) includes more than 5,000 categories. This diverse set of categories highlights the wide range of products available on the platform, underscoring its role as a comprehensive one-stop e-commerce destination.

To better illustrate the types of products typically purchased by BigTech credit applicants in our sample, we used a Large Language Model (LLM), specifically GPT-4o-mini, to consolidate the Level 1 categories into broader, more intuitive groups consistent with common e-commerce classification schemes. The LLM organized these categories into ten overarching product groups: Automotive & Industrial, Baby & Mother Products, Beauty, Personal Care & Health, Books, Education & Entertainment, Electronics & Digital Products, Fashion & Accessories, Food & Beverage, Home & Living, Jewelry & Watches, and Sports, Toys & Outdoor.

We present BigTech credit applicants' purchase frequency across these ten product groups in Figure IA3 in the online Appendix. It shows the distribution of purchase frequency, with Electronics & Digital Products accounting for the largest share at 24.7%, followed by relatively similar shares for Food & Beverage (15.9%), Home & Living (15.7%), and Beauty, Personal Care & Health (15.7%). Jewelry & Watches has the lowest purchase frequency, representing only 1.5%.

5. HOW DOES BIGTECH CREDIT COMPLEMENT THE CORE BUSINESS?

5.1 Impact on E-commerce Shopping Cycle

5.1.1 Constructs and Measurements

To understand how BigTech credit enhances the company's core e-commerce operations, we first analyze its effects on different stages throughout the entire shopping cycle: engagement, transaction, and retention.

The engagement stage represents the initial phase, focusing on how often a user interacts with the platform (i.e., website traffic) and how effectively these interactions convert into actual purchases. We measure engagement using two metrics: $Visits$, which tracks the number of product-page visits in a given month, and $Conversion$, which quantifies the proportion of every 10 visits ending up with purchases.

The transaction stage captures the core purchasing activities that generate revenue for the platform. We assess this with a consumer's net monthly spending ($Spending$), representing expenditure for the user and a revenue stream for the core business. This metric comprises of four underlying components: the number of orders placed ($Orders$), the discount as a percentage of the total order amount ($Discount$), the cancellation rate as a percentage of the total order amount ($Cancellation$), and the net spending per order after accounting for discount and cancellation ($SpendingPerOrder$). Together, these components determine the BigTech's monthly revenue stream from its core business transactions.

The retention stage measures whether a user returns to the core business after a previous shopping experience. Accordingly, we define $Retention$ as a binary indicator equal one if a consumer continues shopping on the platform in one quarter following their last purchase in a given calendar quarter.

This three-stage framework provides a comprehensive view of the consumer activities that are critical to the core business operations, allowing us to systematically evaluate how BigTech credit influences platform engagement, purchasing decisions, and customer loyalty throughout the entire shopping cycle on the e-commerce platform.

Summary statistics that profile the shopping cycle on the platform are presented in Table 1, Panel B. On average, users visit the product pages on the platform 63.5 times per month, with approximately 6.6% of visits resulting in actual purchases. When users make purchases, they place an average of 1.4 orders per month. The average discount percentage and cancellation rate is 18% and 25% of the order value, respectively. After accounting for discounts and cancellations, net monthly spending per consumer averages 192 RMB. On average, 29% users continue shopping on the platform after one quarter following their last purchase.

5.1.2 Generalized and Dynamic DiD Estimations

We report in Table 2 and visualize in Figure 3 the generalized DiD estimates from Poisson regressions based on Equation (1). The results indicate that, visit frequency, number of orders, net monthly spending, and the likelihood of continued platform use increase by 20.3%, 31.2%, 28.6%, and 23.6%, respectively, following credit access. While BigTech credit also displays statistically significant effects on $Conversion$, $Discount$, $Cancellation$, and $SpendingPerOrder$, the magnitudes are small. Event studies presented below confirm that these small effects are not economically meaningful in the long run.

We present the dynamic effects of BigTech credit using event study analyses in Figure 4. Each panel in this figure displays estimated treatment effects by month relative to the credit application month (month 0), along with the corresponding 99% confidence intervals. Across all outcomes, the pre-treatment estimates are centered around zero, supporting the parallel trends assumption underlying our DiD framework. For $Visits$, $Orders$, $Spending$, and $Retention$, we observe a substantial and immediate positive shift following credit approval. These effects are persistent, remaining statistically and economically significant for all observed post-treatment periods, extending up to 6 months for $Retention$ and 12 months for other outcomes.

However, we observe no meaningful increases in visit-to-purchase conversion rates or order value following BigTech credit access, nor any persistent alterations in consumers' sensitivity to discounts or cancellations. For $Conversion$ and $SpendingPerOrder$, we observe mild upward trends following credit access, but the effect sizes are small and the confidence intervals frequently include zero. $Discount$ initially decreases after treatment but gradually returns to baseline, while $Cancellation$ shows a temporary spike immediately after credit approval, followed by a steady decline toward zero.

Overall, the results suggest that BigTech credit strengthens the company's core business by fundamentally transforming consumer behavior across all three stages of the shopping cycle. It significantly increases platform engagement through more frequent visits, boosts transaction value primarily by raising order frequency rather than order size, and meaningfully enhances customer retention. While BigTech credit induces short-term fluctuations in discount usage and cancellation behavior, these dissipate over time, underscoring that it does not foster lasting changes in consumers' discount sensitivity or impulsiveness.

5.2 Impact on Traffic and Transaction Volatility

5.2.1 Constructs and Measurements

The previous results demonstrate that BigTech credit increases the overall level of consumer activity throughout the shopping cycle on the platform. This section further examines the impact of BigTech credit on the volatility of consumer activity. Consumer activity volatility poses major challenges for retailers, disrupting inventory planning and operational efficiency, and resulting in either excess inventory or stockouts (Esteban-Bravo, Vidal-Sanz, and Yildirim, 2017; Chuang, Oliva, and Heim, 2019). Smoothing consumer activity enhances efficiency and profitability and helps stabilize cash flows (Minton and Schrand, 1999; Li, 2023).

We measure consumer activity volatility at the individual level. While volatility is calculated for each consumer, reductions in individual volatility should translate into lower aggregate volatility for the platform. According to the law of large numbers, stabilizing consumption across many users reduces overall demand variance, especially when user behaviors are not highly correlated. This, in turn, helps mitigate amplification effects such as the bullwhip effect in supply chains, where small changes in consumer demand can result in large upstream fluctuations (Lee, Padmanabhan, and Whang, 1997).

Following the same logic as our user-month panel, we construct a user-week panel for the stacked DiD analysis, covering 24 weeks before and 24 weeks after the BigTech credit application week. The observation window is chosen to maintain a manageable sample size. Volatility in a given week is measured using a 12-week window prior to that week. Specifically, we calculate volatility as the standard deviation of a given activity over the prior 12 weeks, normalized by the mean activity level during the same period. This normalization enables straightforward comparisons of volatility before and after credit access, which influences consumers' absolute activity levels. We focus on three key activities that exhibit consistent and significant changes following credit approval, and create three user-week level variables, $VisitVolatility$, $OrderVolatility$, and $SpendingVolatility$. Summary statistics for them are reported in Table 1, Panel B.

5.2.2 Generalized and Dynamic DiD Estimations

Using the three volatility measures as dependent variables, we estimate the effects of BigTech credit based on Equation (1), with results reported in Table 3. The interaction terms ($Treated \times Post$) consistently show negative coefficients, all significant at the 1% level. In term of economic magnitudes, access to BigTech credit lowers the volatility of visit frequency, order volume, and spending amounts by 4.4%, 5.7%, and 3.6%, respectively.

We also conduct dynamic DiD estimations to examine how BigTech credit affects the volatility of consumer activity over time. Figure 5 displays the estimated treatment effects for

$VisitVolatility$, $OrderVolatility$, and $SpendingVolatility$. As we require 12 weeks of observations to create the volatility measures, we only have 12 pre-treatment event weeks. We use week –1 as the reference period and omit the transition period during which volatility calculations straddles both pre- and post-treatment weeks. The plots confirm the parallel trends assumption for our stacked DiD design. In all three panels, we observe a distinct and sustained decline in volatility following the receipt of BigTech credit: treatment effects for visit, order, and spending volatility drop below zero and remain negative. Notably, the volatility-reducing effects persist for at least 24 weeks (approximately six months) after credit is granted.

Overall, BigTech credit helps stabilize consumer behavior and reduce the volatility of user traffic and transactions, which may contribute to greater efficiency in the platform's inventory management. These findings also suggest that BigTech credit deepens user engagement with the company's ecosystem, encouraging users to view the platform as a regular, trusted destination rather than an occasional shopping venue.

5.3 Impact on Variety of Consumption Set

5.3.1 Constructs and Measurements

Another important benefit of BigTech credit for the company's core business is that it may encourage consumers to buy a wider range of products from its platform. Greater purchase variety suggests the platform is attracting loyal, one-stop shoppers and capturing more consumer spending (Klemperer and Padilla, 1997; Thomassen et al., 2017). This effect may be especially significant for e-commerce platforms, whose strength lies in broad product selection compared to traditional brick-and-mortar stores (Brynjolfsson, Hu, and Smith, 2003; Quan and Williams, 2018).

We construct four user-month level metrics to proxy for consumption variety using order-item data: $SKUs$, $Brands$, $Shops$, and $Categories$. An SKU (stock-keeping unit) is a unique alphanumeric identifier assigned to each distinct product in the e-commerce platform's inventory, representing the most granular level of product differentiation.[12] For example, each specification of an iPhone 16 (the combination of color, RAM, and CPU configuration, etc.) corresponds to a different SKU. $SKUs$ captures the number of unique products purchased by a consumer within a given month. $Brands$ and $Shops$ count the number of distinct brands and stores from which a consumer makes purchases during the month, respectively. $Categories$ reflects the number of unique product groups (the 10 overarching product groups described in Section 4.4) from which a consumer purchases in that month.[13] As shown in Table 1, Panel B, an average consumer purchases 1.82 unique products from 1.27 brands and 1.27 shops, spanning 0.79 product categories per month on the platform.

5.3.2 Generalized and Dynamic DiD Estimations

We conduct a series of stacked DiD analyses using Equation (1), replacing the dependent variable with each of the four variety measures. The results, presented in Table 4, consistently reveal economically and statistically significant increases (approximately 30%) across all metrics following the receipt of BigTech credit.

Similar to its impact on other core business outcomes, BigTech credit leads to an immediate and persistent increase in consumption variety. Figure 6 presents the dynamic DiD estimates for the four variety measures. All panels support the parallel trends assumption underlying our stacked DiD approach and reveal a clear, sustained expansion in the consumer consumption set following the receipt of credit. This expansion remains throughout all 12 months post-treatment.

Overall, the evidence clearly illustrates that BigTech credit bolsters the firm's e-commerce

[12] The order-item data is used for regression analysis in Section 6.1. Here we just leverage the granularity of it to construct measures for consumption variety. Please refer to that section for a detailed introduction to the order-item data.
[13] Our inference remains robust when we use the more detailed product categories originally employed by the platform.

core by encouraging consumers to explore and purchase a broader array of products. These findings highlight how embedded credit services amplify platform stickiness and revenue potential, contributing to a virtuous cycle within the BigTech's ecosystem.

6. IS THE BIGTECH CREDIT SERVICE SUSTAINABLE?

While the findings in the previous section demonstrate that the lending business effectively complements the company's core operations, the long-term value of these benefits hinges on the sustainability of the credit service. If BigTech credit mainly encouraged reckless borrowing and led to high default rates, the value they add to the core business could be short-lived. In particular, the observed increase in spending following credit approval may raise concerns about excessive or conspicuous consumption. Similarly, the observed expansion in consumption variety could reflect impulse buying, as consumers may seek variety to fulfill psychological or emotional needs (e.g., Ratner and Kahn, 2002; Yoon and Kim, 2018). Both patterns could undermine consumer well-being and threaten the sustainability of BigTech's business model. In this section, we assess the sustainability of the credit service through the following two sets of analyses.

6.1 Purchase of Higher-end Products

A potential sign of unsustainability in the credit service is if recipients begin to engage in conspicuous consumption. To explore this possibility, we first investigate whether consumers, after receiving BigTech credit, start opting for higher-end versions of products that *they used to buy* and *serve the same function* (i.e., whether they switch to a pricer product/brand/shop when buying from the same most detailed product category, or Level 3 product category, after receiving BigTech credit).

We compile an order-item sample and construct several measures for this analysis. Specifically, for the users in our user-month panel, we collect all of their orders during the sample period. Each order may contain multiple items, and for each item, we observe the unit price and quantity purchased. Given the enormous size of the order-item dataset, we randomly draw a 10% subsample of users to construct the order-item sample used for regression analyses. This yields a total of 578,392 order-item observations, with summary statistics presented in Panel C of Table 1. As shown, the average unit price of an order-item is 229.26 RMB.

We start with examining whether the prices of items purchased by treated consumers increase after receiving credit. The dependent variable in our analysis is $ItemPrice$, defined as the unit price of an item in a specific order. Table 5 presents the results. In Column 1, we include fixed effects for user, shop, brand, product category, and cohort-date. This specification allows us to detect indulgent consumption upgrades by comparing $ItemPrice$ within the same user while holding the shop, brand, and product category constant. In Column 2, we replace the user and product category fixed effects with a user-product category fixed effect. This alternative approach focuses on changes in an individual consumer's purchasing behavior within a specific product category. For instance, if treated consumers switch from purchasing regular milk to organic milk after receiving credit, this upgrade would be captured by the DiD estimate. Under both specifications, the interaction term $Treated \times Post$ is statistically insignificant, suggesting that access to BigTech credit does not lead consumers to purchase more expensive items.

We also construct two additional variables to capture the quality of products consumers purchase: $BrandRank$ and $ShopRank$. Specifically, we calculate the average unit price of all unique products associated with each brand (or shop) and then rank the brands (or shops) based on their average unit price in percentile terms, from most to least expensive. For example, Apple MacBook laptops are likely to have a higher average unit price than Acer and would therefore receive a higher brand rank. Using the same fixed effects structures as before, we examine whether consumers upgrade their product choices within the same product category after receiving credit. As shown in Columns 3 through 6 of Table 5, the coefficient on $Treated \times Post$ remains statistically insignificant across all specifications. This suggests that access to BigTech credit does not lead consumers to select higher-end brands or shop at more premium stores for items serving the same function.

Overall, these findings are inconsistent with the notion that BigTech credit leads to conspicuous spending by encouraging purchase of higher-end products.

6.2 Delinquency of BigTech Credit Users

Another key indicator of the potential unsustainability of the company's credit service is the frequency with which consumers become delinquent on their monthly credit bills. To assess this, we restrict our user-month sample to post-treatment observations of treated consumers only, as only these users are granted BigTech credit and have observable delinquency outcomes during the post-treatment period.

First, we show that the overall delinquency rate among treated consumers is relatively low. We define the monthly delinquency rate as the balance of loan principal overdue by more than 90 days, divided by the total balance of consumer credit loan principal issued by the lending business. This definition is consistent with that used by traditional credit card issuers, such as commercial banks. We find an average delinquency rate of 1.0% across our sample period, compared to a range of 1.4% to 3.3% for major Chinese commercial banks' credit card businesses in 2020, according to their annual reports. This relatively low delinquency rate contradicts the notion that the BigTech credit service lead to higher levels of consumer over-indebtedness than traditional credit providers.

Second, we provide user-level evidence by examining whether the spending increases induced by BigTech credit lead to user delinquencies. If BigTech credit were unsustainable due to excessive spending it triggers, we would expect consumers experiencing larger treatment effects to exhibit a higher likelihood of default. To test this hypothesis, we calculate the BigTech credit-induced growth rate of spending for each treated consumer by comparing the average monthly spending before and after treatment, relative to the matched control consumer. We then categorize treated consumers into high and low spending effect groups based on the sample median of the growth rate. The indicator variable $HighSpendingEffect$ equals one for the high spending effect group and zero otherwise.

We define two variables to proxy for delinquency outcomes at the user-month level: $Delinquent60Day$ and $Delinquent90Day$, which are set to one if a consumer is delinquent on any monthly credit bill for more than 60 and 90 days, respectively. Univariate analysis (results untabulated) indicates that the mean of $Delinquent60Day$ ($Delinquent90Day$) is 0.013 (0.009) for the high spending effect group, and 0.014 (0.010) for the low spending effect group, with all differences insignificant at conventional levels. We further analyze the correlation between these delinquency indicators and the group indicator $HighSpendingEffect$ by regressing the former on the latter. Table 6 shows that the coefficient for $HighSpendingEffect$ is not significant, indicating no significant difference in the likelihood of default between consumers who experienced substantial spending increases and those with minor increases after receiving BigTech credit. These findings provide further evidence against the idea of BigTech credit worsening consumers' financial health.[14]

7. SUPPLEMENTARY ANALYSIS AND FURTHER DISCUSSION

7.1 Detecting The Major Mechanism

[14] In untabulated analysis, we show that consumers experiencing substantial spending tend to make careful financial choices. At purchase, they opt for longer loan terms and lower service fees, and after purchase, they actively refinance and repay larger portions of their bills. These behaviors reflect sophisticated financial management, enabling higher spending without increased delinquency.

7.1.1 The relaxation of liquidity constraints?

First, we provide direct evidence that the relaxation of liquidity constraints is likely to be a primary mechanism driving our main findings. For this purpose, we extend our stacked DiD model to a triple-difference (DDD) specification to test whether the causal effects of BigTech credit are more pronounced for consumers facing greater ex-ante financial constraints. We employ two distinct proxies for liquidity constraints. Following Constantinides, Donaldson, and Mehra (2002), we use consumer age, as younger consumers face greater credit constraints due to limited savings and a lack of credit history. We also use the firm's internal credit score, as prior research indicates that individuals with low credit scores face greater difficulty accessing traditional loans despite their higher borrowing propensity (e.g., Agarwal et al., 2018).[15] We then examine whether the treatment effect varies across these groups for three key outcome variables: net monthly spending ($Spending$), the volatility of net spending ($SpendingVolatility$), and the number of unique products purchased ($SKUs$). Each of these variables corresponds to one of the three core dimensions through which BigTech credit enhances the firm's business: boosting activity level, reducing its volatility, and promoting consumption variety. In untabulated analyses, we find that the inference remains unchanged when we use other variables as in Tables 2-4.

Table 7 Panel A presents our results. In these models, $YoungAge$ and $LowCreditScore$are indicator variables equal to one if an applicant's age or internal credit score at the time of credit application, respectively, is below the sample median, thereby proxying for higher liquidity constraints. The coefficient on our key parameter of interest (i.e., the triple-interaction term) is statistically significant and carries the expected sign across all specifications. The results show that

[15] There is no single, official, publicly available credit score for individuals in China similar to credit scores like FICO in the United States. The internal credit scores generated by the BigTech company use numerous variables within and external to the firm's ecosystem, including credit bureau reports that banks heavily rely on.

the positive impacts of credit on $Spending$ and $SKUs$, as well as the negative (i.e., stabilizing) impact on $SpendingVolatility$, are all significantly stronger for younger and lower-credit-score applicants. This provides consistent and robust evidence that the relaxation of liquidity constraints is a central mechanism driving the effects documented in our main analysis.

To further substantiate that our results stem from the relaxation of liquidity constraints, we examine patterns in credit usage among treated applicants. Specifically, we compare the high-spending effect group (those experiencing above-median increases in net spending post-credit as defined in Section 6.2) to the low-spending effect group (those with below-median increases). We find that the high-spending effect group is significantly more likely to select interest-free products and opt for longer installment terms (results untabulated). This behavior indicates active management of credit to optimize cash flow, defer payments, and afford larger purchases without incurring high interest costs, all of which are indicative of liquidity relief. These results provide additional evidence that BigTech credit unlocks consumer activity by alleviating binding financial constraints. In contrast, such patterns would be less pronounced if spending increases were driven merely by passive responses to targeted advertising, an alternative mechanism which we discuss in the following sub-section.

7.1.2 The Effects of Marketing?

This subsection addresses the concern that our main findings might be driven by targeted marketing. It is plausible that BigTech's marketing algorithms use credit status as an input, leading our treatment group to receive more targeted promotions. While our RI design exogenously assigns credit, it does not alter subsequent, standard operational procedures like marketing. Therefore, our estimates could be interpreted as the total causal effect of BigTech credit within its integrated ecosystem. This captures the combined impact of relaxed liquidity constraints and any bundled platform synergies, such as enhanced marketing, that result from credit approval. [16]

First, we note that this bundled nature, rather than being a limitation, is a central and defining feature of the BigTech model. Unlike traditional financial institutions, BigTechs possess the unique ability to seamlessly integrate financial services with their core commercial platforms, and the synergy we document arises precisely from this integration. By measuring this holistic, bundled effect, we can accurately capture the competitive advantage of BigTech lending. Also, teasing out the downstream effects of marketing is unnecessary from a policy perspective, as understanding how credit access amplifies the power of the core platform is crucial for competition authorities concerned with market concentration and for financial regulators assessing the systemic implications of the self-reinforcing feedback loop between a BigTech's financial and non-financial operations.

Nevertheless, we rule out the possibility that marketing is the key driver of the change in consumer behavior. A large body of marketing literature documents that while targeted advertising can generate immediate increases in consumer engagement and sales, it rarely translates into sustained changes in consumer behavior (e.g., Sahni, Zou, and Chintagunta, 2017; Sahni, Narayanan, and Kalyanam, 2021; Li et al., 2021). Moreover, marketing inducements (e.g., limited-time flash sales, seasonal promotions, or special coupons attached to credit approval) are often ephemeral by design. They tend to create a short-term lift and lose relevance shortly . In stark contrast, our dynamic analyses (Figures 4-6) reveal a remarkably stable and persistent treatment effect. This is consistent with a more fundamental change driven by continuous access to liquidity, as demonstrated in Section 7.1.1.

[16] This approach is not unique to the setting of BigTech credit. The estimated impacts of traditional credit cards, for example, also implicitly include the influence of bundled rewards programs and associated marketing that accompanies card usage.

To provide more direct evidence that marketing is not a major mechanism, we test whether the treatment effect is larger for individuals most likely to be targeted by marketing. Since data from user activities facilitates user profiling and enhances marketing (e.g., Trusov, Ma, and Jamal, 2016; Sun et al., 2024), we create two indicators, namely $HighVisits$ and $HighOrders$, each of which equals one if the consumer's historical visit frequency and number of orders are above the sample median, and zero otherwise. Again, we use a DDD specification, interacting the standard treatment effect ($Treat \times Post$) with theses indicators.

Panel B of Table 7 presents results that are inconsistent with the marketing explanation. We find that the coefficients on the triple-interaction terms are negative and statistically significant for both net spending (columns 1-2) and purchase variety (columns 5-6), and positive and significant for spending volatility (column 3). These results suggest that the impact of BigTech credit is actually dampened for users with a larger volumn of digital footprints, the very users who are the most likely targets of marketing. Instead, it is consistent with the view that the effect is more pronounced for users who face greater liquidity constraints, thus displaying lower visits and ordering in the first place.

7.1.3 Spending Shifting from Other Platforms

A potential alternative interpretation of our results is that the observed increase in consumer spending represents not incremental consumption, but a reallocation of spending from competing platforms or retailers (i.e., a within-period, across-platform shift rather than an inter-period one). We acknowledge that our dataset, which is confined to the BigTech's ecosystem, prevents us from directly observing such shifting behavior. However, for our primary research question concerning the benefits to the BigTech's core business, this distinction is of secondary importance. Whether the spending is newly generated or captured from competitors, the resulting increase in platform engagement, transactions, and retention constitutes a direct and significant benefit to the firm.

Furthermore, the spending-shifting hypothesis is not mutually exclusive with our main explanation of relaxed liquidity constraints; in fact, it can be viewed as evidence supporting it. A rational consumer would only alter their purchasing patterns to concentrate spending on this platform if doing so provides a superior value proposition. Given that we find no evidence of systematic product discounts for credit users (see Section 5.1), the most plausible driver for such a shift is the provision of cheaper or more convenient credit relative to the consumer's outside options. If consumers reallocate spending to leverage the BigTech's credit, it is precisely because this financial service relaxes their overall budget constraint more effectively. Thus, spending shifting, if it occurs, is a channel through which the benefits of relaxed liquidity are realized on the platform, reinforcing our conclusion that the financial service creates value for the core business.

7.2 Marginal Propensity to Spend

Having established that the relaxation of liquidity constraints is the primary mechanism, we now quantify the economic magnitude of this effect by estimating the marginal propensity to spend (MPS) out of the initial credit line. This analysis reveals how much additional spending the BigTech platform captures for every dollar of credit extended.

To estimate the MPS, we extend our DiD model with a continuous variable, employing a DDD specification. The model interacts the treatment effect ($Treat \times Post$) with the initial credit limit granted to treated consumers, measured in 100 RMB increments. To isolate the immediate impact and avoid confounding effects from subsequent credit limit adjustments, we conduct the analysis over a short window. We present two specifications in Table IA2: the first includes the month of credit granting and the subsequent month (column 1), while the second further excludes the month of credit granting to better mitigate potential biases from the staggered timing of credit approval within it (column 2).

The results demonstrate a substantial and immediate spending response. Focusing on column 2, our estimates imply a monthly MPS of approximately 0.15. This indicates that for every 100 RMB of credit granted, consumer spending on the platform increases by about 15 RMB in the first month. This figure is economically significant, as our estimated monthly MPS rivals or even exceeds the annual MPS of 0.10–0.14 for traditional credit cards found by Gross and Souleles (2002) and the quarterly MPS of 0.11 documented by Aydin (2022). This underscores the powerful and rapid effect of BigTech credit in stimulating consumption, an effect likely amplified by its seamless integration within an e-commerce ecosystem where spending opportunities are readily available.

8. CONCLUSION

In recent years, BigTechs have surpassed other FinTechs in global lending volume, leveraging competitive advantages from ecosystems that seamlessly integrate their lending and core businesses. While prior research has explored how the core business supports the lending arm, much less is known about the reverse relationship. This gap likely stems from two main challenges: first, the difficulty of obtaining comprehensive, granular data within a BigTech ecosystem, especially from core financial operations; second, the endogeneity of BigTech credit granting.

To address these challenges, we utilize a proprietary order-level dataset from a major e-commerce BigTech and employ a reject inference setting in which applicants initially rejected by AI-driven underwriting are randomly approved for credit. This approach enables an in-depth analysis of BigTech credit's impact and allows us to use a stacked cohort difference-in-differences identification strategy.

Our study provides comprehensive evidence that BigTech credit complements and reinforces the core e-commerce business. Access to BigTech credit fundamentally transforms consumer behavior across the entire shopping cycle, increasing visits, orders, and net spending by 20.3%, 28.6%, and 31.2%, respectively. Beyond these aggregate effects, BigTech credit stabilizes consumer activity by reducing volatility by 3.5–5.5%, and promotes greater consumption variety, with recipients diversifying across approximately 30% more products, brands, and merchants.

Importantly, these benefits appear sustainable. Despite concerns about potential over-indebtedness, we find no evidence of conspicuous consumption or elevated default rates among credit recipients. The overall default rate is just 1.0%, lower than that of traditional bank credit cards, and consumers who increase their spending the most after receiving credit maintain strong repayment discipline through sophisticated financial management strategies.

By illustrating the reciprocal benefits of financial services to core operations, our study complements existing research to provide a complete picture of the mutually reinforcing relationship that defines the BigTech lending model and its competitive advantages. Our findings hold important implications for evolving regulatory frameworks that govern BigTechs' operation and expansion, especially the recent calls for entity-based oversight and cross-authority collaboration.

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Appendix A. Variable Definitions

Notes: This table provides the definitions of variables used in this study.

Variables of Bigtech Credit Granting	
Treated	A dummy variable that equal one if a consumer's credit application is rejected by the AI but approved for reject inference, and zero if the application remains rejected by the AI.
Post	A dummy variable that qequal one if a calendar month is the month a consumer applies for BigTech credit or any subsequent months, and zero otherwise.
Outcome Variables Used in the Tests of Complementarity	
Visits	The total number of product page visits made by a consumer in a month.
Conversion	The number of orders placed by a consumer in a month scaled by 10 * *Visits*.
Orders	The number of orders placed by a consumer in a month.
Discount	The discount amount scaled by the order amount pre-discount pre-cancellation in a month.
Cancellation	The cancelled purchase amount scaled by the order amount pre-discount pre-cancellation in a month.
SpendingPerOrder	The average order value of the orders placed by a consumer in a month.
Spending	The total out-of-pocket consumption (i.e., canceled amount and discount are excluded) for a consumer in a month.
Retention	An indicator that equals one when a consumer continues shopping on the platform in the subsequent month, and zero otherwise.
VisitVolatility	The standard deviation of weekly number of product page visits made by a consumer over a 12-week period prior to week t and dividing it by the mean visit level for the same period.
OrderVolatility	The standard deviation of weekly number of orders placed by a consumer over a 12-week period prior to week t and dividing it by the mean orders level for the same period.
SpendingVolatility	The standard deviation of weekly net spending by a consumer over a 12-week period prior to week t and dividing it by the mean spending level for the same period.
SKUs	The number of unique products purchased by a consumer in a month.
Brands	The number of unique brands involved in a consumer's consumption in a month.
Shops	The number of unique shops involved in a consumer's consumption in a month.
Categories	The number of unique product categories involved in a consumer's consumption in a month.
Variables Used in the Tests of Sustainability	
ItemPrice	The price of an item purchased in an order.
BrandRank	Percentile ranking of each brand, calculated by averaging the unit prices of all stock-keeping units for each brand and ranking brands from most to least expensive.
ShopRank	Percentile ranking of each shop, calculated by averaging the unit prices of all stock-keeping units for each shop and ranking shops from most to least expensive.
Delinquent60Day (*Delinquent90Day)*	A dummy variable that equals one if a consumer's payment for a monthly credit bill is more than 30 days (90 days) overdue, and zero otherwise.
HighSpendingEffect	An indicator variable equal to one if a treated consumer's BigTech-induced spending growth rate, measured as the change in average monthly spending before and after treatment relative to the matched control, is above the sample median, and zero otherwise.
Variables Used in the Supplementary Tests	
YoungAge	A dummy variable that equals one if a consumer's age at the time of credit application is below the sample median, and zero otherwise.
LowCreditScore	A dummy variable that equals one if a consumer's credit score at the time of credit application is below the sample median, and zero otherwise.
HighVisit	A dummy variable that equals one if a consumer's number of product page visits over a 12-week period prior to credit application is above the sample median, and zero otherwise.
HighOrder	A dummy variable that equals one if a consumer's number of orders placed over a 12-week period prior to credit application is above the sample median, and zero otherwise.
Consumer Demographics	
Male	A dummy variable that equals one if a consumer is a male, and zero otherwise.

Age	The age of a consumer measured in years.
AccountAge	The number of months since a consumer signed up with the e-commerce platform.

Figure 1. The Self-Reinforcing Feedback Loop of BigTechs

Notes: This figure depicts the self-reinforcing feedback loop of BigTech firms which explains how their core non-financial businesses and financial services mutually strengthen each other, creating a powerful competitive ecosystem.

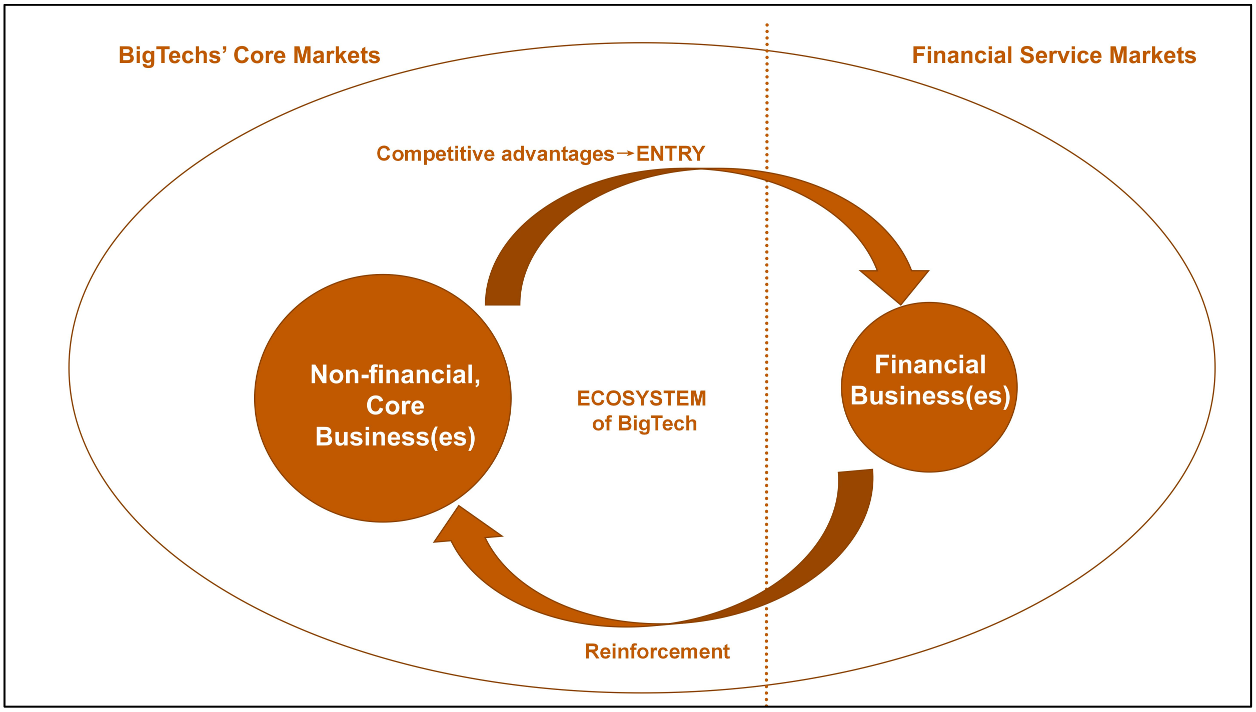

Figure 2. The Architecture of Auto-underwriting System

Notes: This figure presents the architecture of the BigTech's auto-underwriting system. BigTech credit applicants arrive and go through an AI model to get approved or rejected. The left branch represents the training data loop, where delinquency outcomes of approved applicants are used to improve the AI model. However, this data alone biases the model since outcomes exist only for approved applicants, yet the model applies to all. The right branch of the architecture depicts the process of reject inference (RI). BigTech selects a sample of AI-rejected applicants, extends credit to them, and uses their delinquency outcomes to infer outcomes for other rejected applicants. These realized or inferred outcomes are added to the training data to debias the AI model.

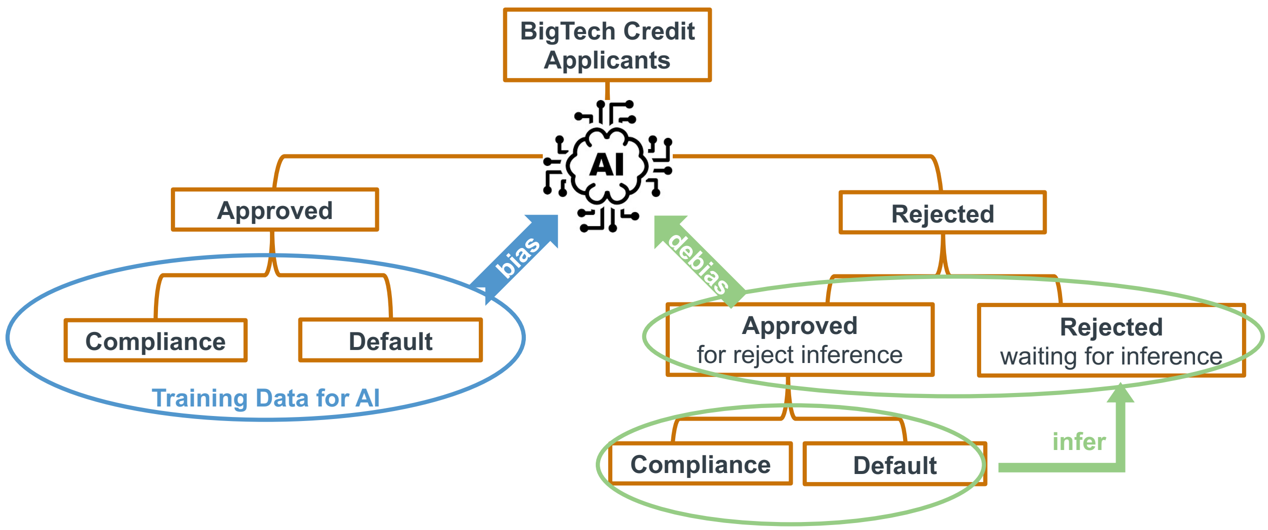

Figure 3. DiD Estimates of the Impact of BigTech Credit on Consumer Activities Over the Shopping Cycle

Notes: This figure presents the generalized DiD estimates of the impact of BigTech credit on consumer activities along the shopping journey. We plot treatment effects with 99% confidence intervals. The red dashed vertical line at zero serves as the reference point for no effect of BigTech credit. We perform a stacked cohort DiD analysis using the following specification: $Outcome_{i,t} = \beta * Treated_i * Post_{c.t} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}$, where c, i, and t is the subscript for cohort, consumer, and calendar month, respectively. α_i represents individual fixed effects, and $\delta_{c,t}$ represents month-cohort fixed effects. *Outcome* is either *Visits*, *Conversion*, *Orders*, *Discount*, *Cancellation*, *SpendingPerOrder*, *Spending* or *Retention*. Variable definitions are in Appendix A. The coefficients are estimated using Poisson regressions. We cluster standard errors by individual in all regressions.

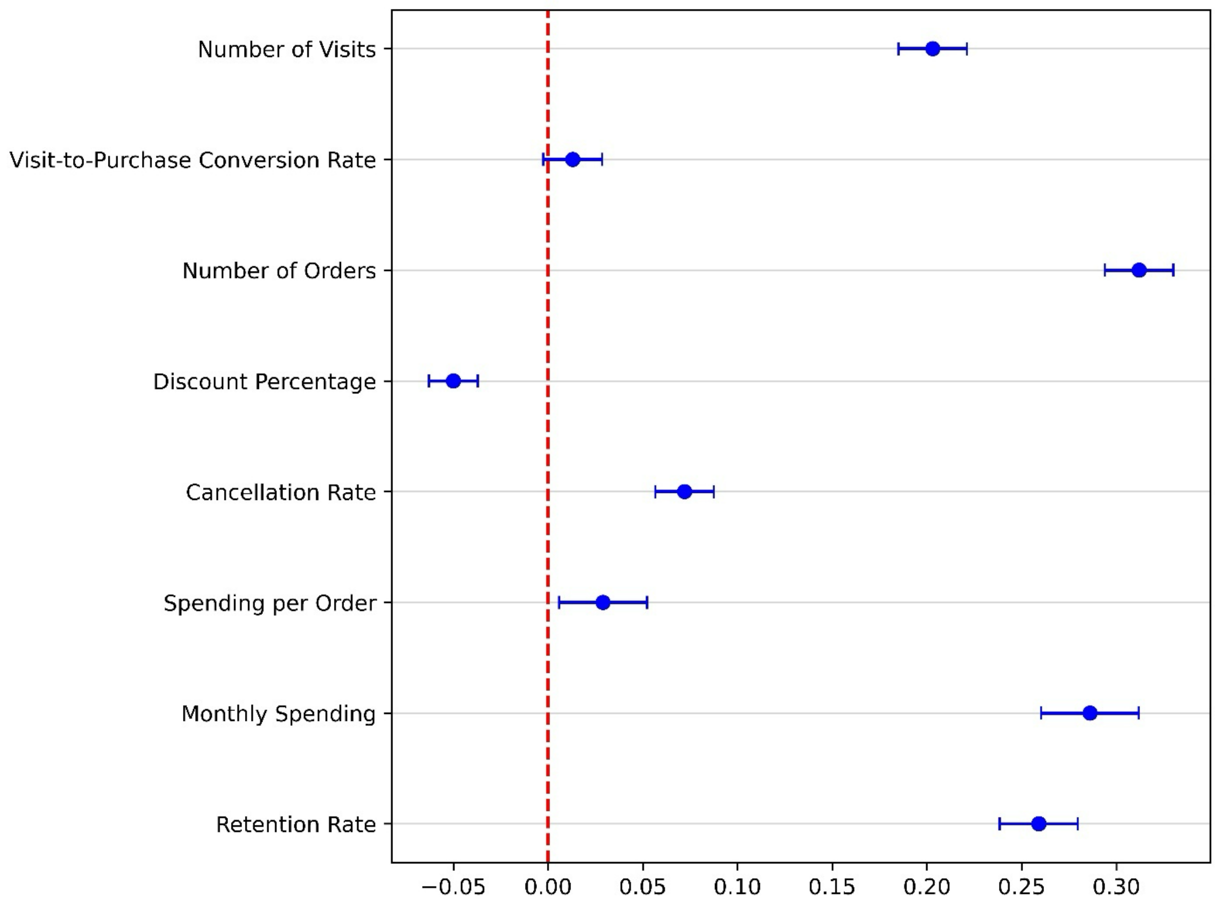

Figure 4. The Dynamic Impact of BigTech Credit on Consumer Activities Over the Shopping Cycle

Notes: This figure presents the dynamic impact of BigTech credit on consumer activities along the shopping journey. We plot treatment effects with 99% confidence intervals across months relative to credit application at month 0. We perform a stacked cohort DiD analysis using the following specification: $Outcome_{i,t} = \sum_{k=-17}^{-2} \beta_k Treated_i \times 1_{c,k} + \sum_{k=0}^{11} \beta_k Treated_i \times 1_{c,k} + \alpha_i + \delta_{c,t} + \epsilon_{i,t}$, where *i*, *t*, *c*, and *k* is the subscript for consumer, calendar month, cohort, and the month relative to the month of credit granting, respectively. α_i and $\delta_{c,t}$ represents individual and month-cohort fixed effects, respectively. *Outcome* is either *Visits*, *Conversion*, *Orders*, *Discount*, *Cancellation*, *SpendingPerOrder*, *Spending* or *Retention*. The last graph does not plot the estimates in the period in which calculating *Retention* requires combining data from both the pre- and post-credit periods. Variable definitions are in Appendix A. The coefficients are estimated using Poisson regressions. We cluster standard errors by individual in all regressions. The effect size in the first month post-treatment appears smaller because credit may be granted at any time during that month, causing the average effect to reflect a mix of partial and full exposure. The confidence intervals widen progressively toward the left and the right ends due to the decreasing sample size as the time approaches the two ends of the sample period.

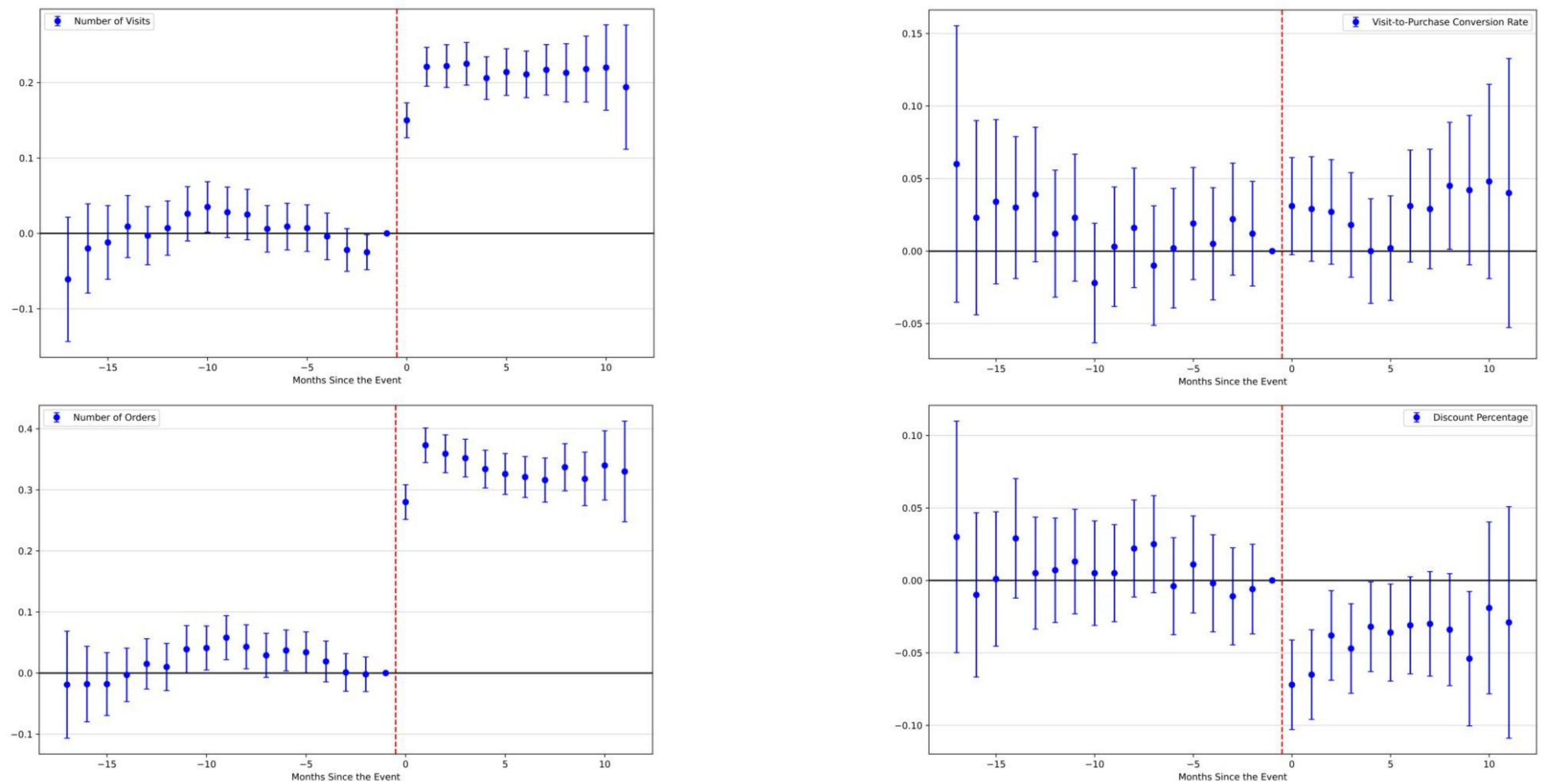

Figure 4. The Dynamic Impact of BigTech Credit on Consumer Activities Over the Shopping Cycle (continues)

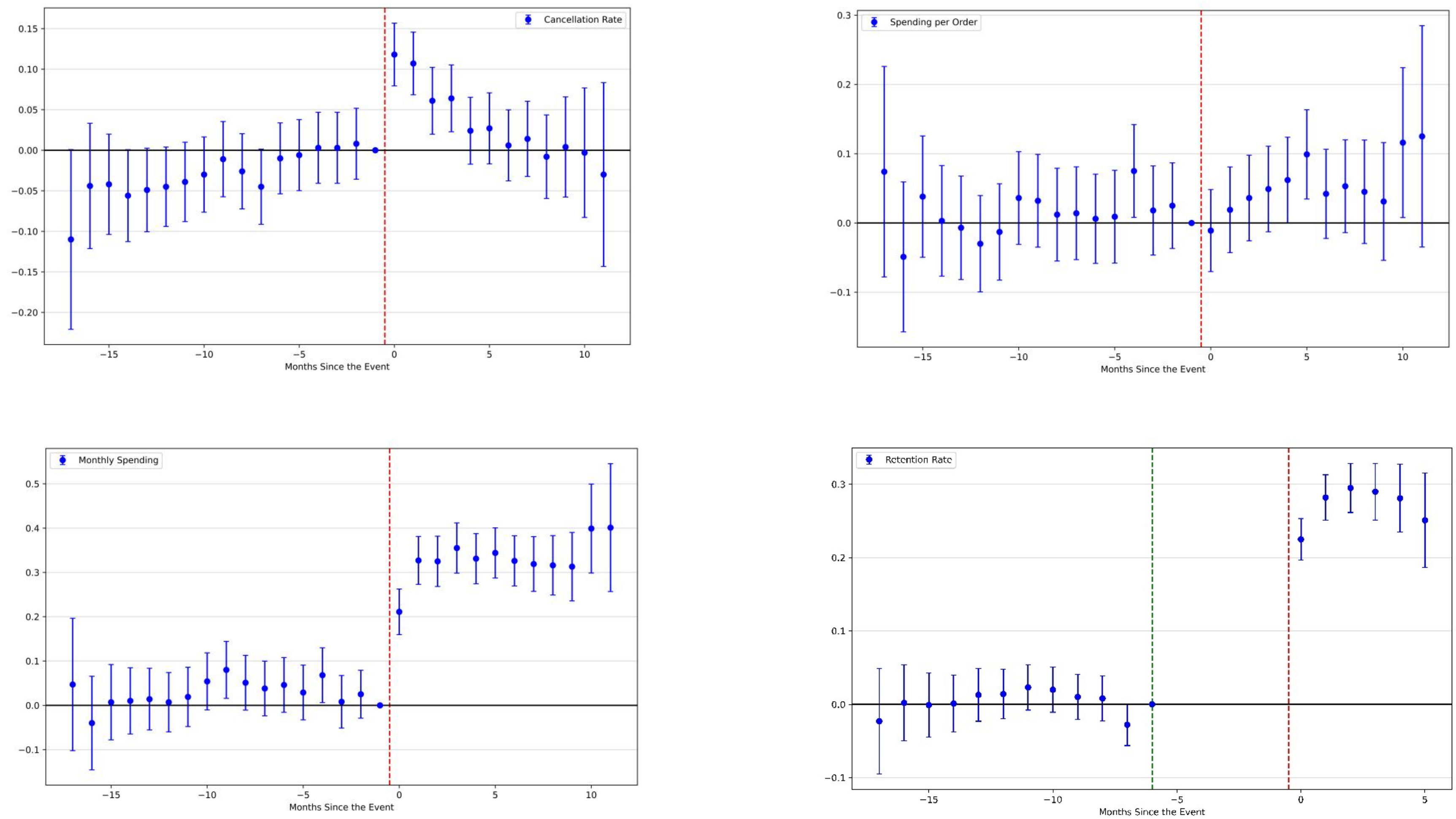

Figure 5. The Dynamic Impact of BigTech Credit on the Volatility of Consumer Activity

Notes: This figure presents the dynamic impact of BigTech credit on the volatility of consumer activity. We plot treatment effects with 99% confidence intervals across weeks around credit application at week 0. We perform a stacked cohort DiD analysis using the same specification as in Figure 4, except k is the subscript for the week relative to the week of credit granting, ranging from -8 to 23, and the dependent variable is replaced by either *VisitVolatility*, *OrderVolatility* or *SpendingVolatility*. We do not plot the estimates in the period in which calculating volatility measures requires combining data from both the pre- and post-credit periods. Variable definitions are in Appendix A. The coefficients are estimated using Poisson regressions. We cluster standard errors by individual in all regressions.

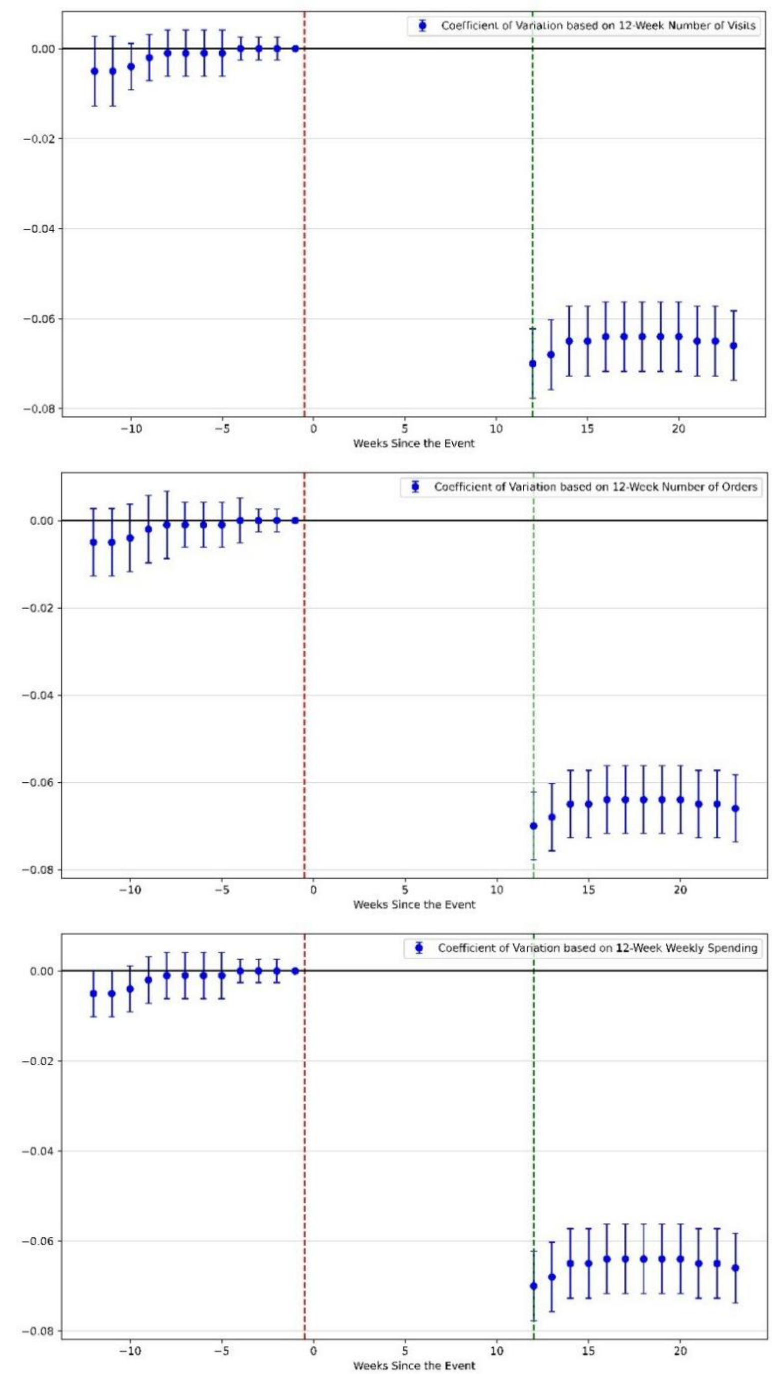

Figure 6. The Dynamic Impact of BigTech Credit on Consumption Variety

Notes: This figure presents the dynamic impact of BigTech credit on consumption variety. We plot treatment effects with 99% confidence intervals across weeks around credit application at month 0 (indicated by the vertical red dashed line). We perform a stacked cohort DiD analysis using the same specification as in Figure 4, except the dependent variable is either *SKUs, Brands, Shops,* or *Categories*. Variable definitions are in Appendix A. The coefficients are estimated using Poisson regressions. We cluster standard errors by individual in all regressions. The confidence intervals widen progressively toward the left and the right ends due to the decreasing sample size as the time approaches the two ends of the sample period.

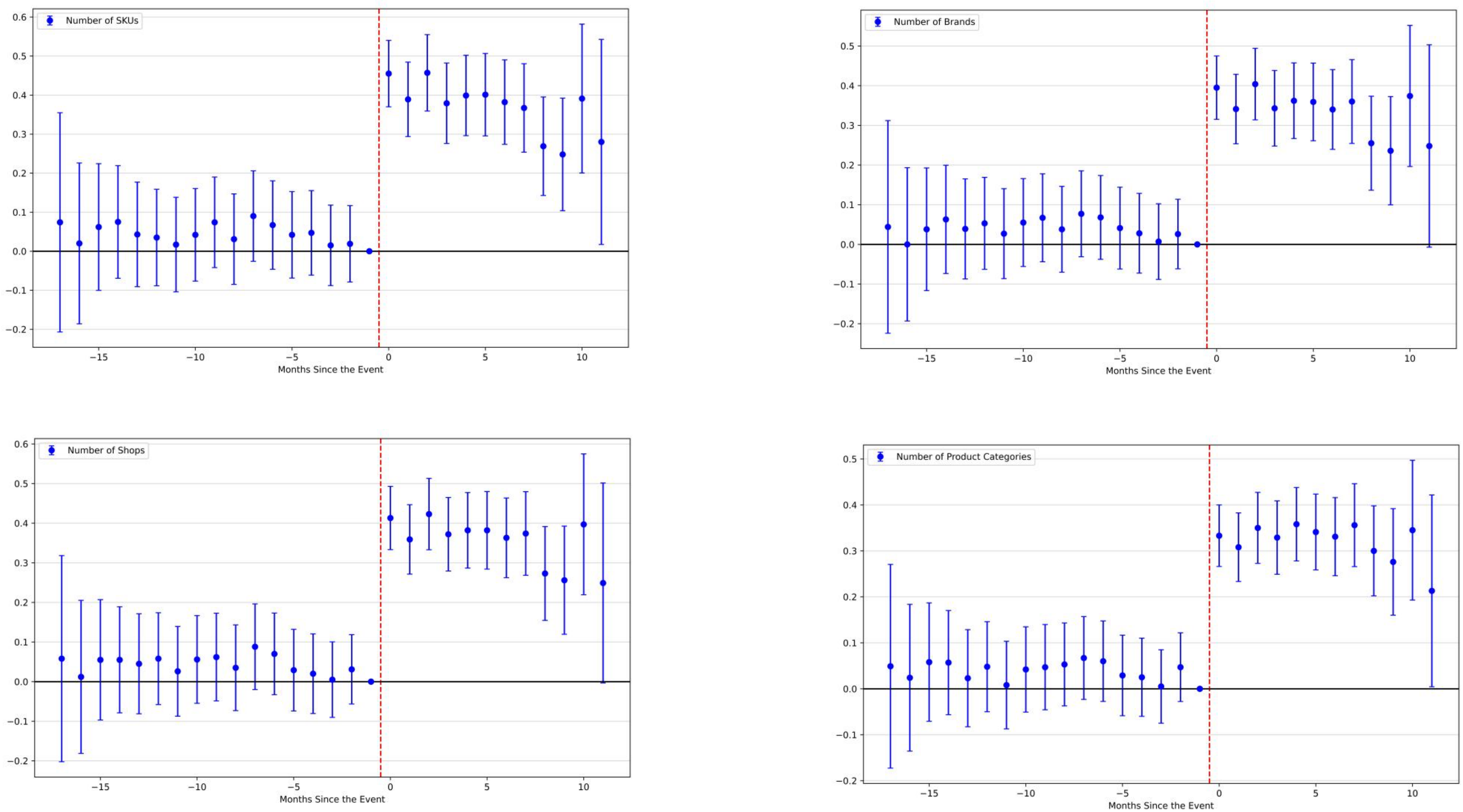

Table 1. Summary Statistics

Notes: This table presents summary statistics for the key variables used in this study. Panel A focuses on the demographics of applicants in our sample. Panels B and C provide summary statistics for the outcome variables used in the tests of complementarity and sustainability, respectively. Demographic variables are measured at the individual level; *VisitVolatility*, *OrderVolatility*, and *SpendingVolatility* are measured at the individual-week level; *ItemPrice*, *BrandRank*, and *ShopRank* are measured at the order-item level; all other variables are measured at the individual-month level. *Conversion*, *Discount*, *Cancellation*, and *SpendingPerOrder* are available only for months with non-zero orders placed or non-zero page visits made. *Retention* is available except the last six months of the sample period. *Delinquent30Day* and *Delinquent90Day* are available only for treated consumers. *SKUs*, *Brands*, *Shops*, *Categories*, *ItemPrice*, *BrandRank*, and *ShopRank* are available only for the detailed subsample. All continuous variables are winsorized at the 1% and 99% levels. Variable definitions are provided in Appendix A.

Panel A. Consumer Demographics

	Count	Mean	Std.	25%	50%	75%
Male	119,808	0.66	0.47	0.00	1.00	1.00
Age	119,808	28.88	10.37	20.00	27.00	34.00
AccountAge	119,808	31.03	22.07	12.52	26.87	45.24

Panel B. Outcome Variables Used in the Tests of Complementarity

	Count	Mean	Std.	25%	50%	75%
Visits	2,586,650	63.48	121.71	1.00	17.00	66.00
Conversion	1,054,639	0.66	0.89	0.18	0.37	0.76
Orders	2,586,650	1.35	2.62	0.00	0.00	2.00
Discount	1,059,987	0.18	0.20	0.00	0.13	0.30
Cancellation	1,059,987	0.25	0.36	0.00	0.00	0.49
Spending	2,586,650	192.00	609.45	0.00	0.00	94.00
SpendingPerOrder	1,061,223	155.09	316.00	22.80	62.80	139.30
Retention	1,781,543	0.29	0.45	0.00	0.00	1.00
VisitVolatility	6,290,107	1.77	0.73	1.22	1.66	2.24
OrderVolatility	4,449,221	2.31	0.85	1.64	2.24	3.32
SpendingVolatility	4,027,493	2,56	0.75	1.96	2.61	3.32
SKUs	253,664	1.82	3.49	0.00	0.00	2.00
Brands	253,664	1.27	2.31	0.00	0.00	2.00
Shops	253,664	1.27	2.30	0.00	0.00	2.00
Categories	253,664	0.79	1.18	0.00	0.00	1.00

Panel C. Outcome Variables Used in the Tests of Sustainability

	Count	Mean	Std.	25%	50%	75%
ItemPrice	578,392	229.26	726.44	9.90	36.90	99.90
BrandRank	546,094	0.55	0.29	0.32	0.54	0.81
ShopRank	546,484	0.52	0.29	0.29	0.48	0.77
Delinquent30Day	522,383	0.02	0.15	0.00	0.00	0.00
Delinquent90Day	522,383	0.01	0.10	0.00	0.00	0.00

Table 2. The Impact of BigTech Credit on Consumer Activities Over the Shopping Cycle

Notes: This table presents the effect of BigTech credit on the volatility of consumer activity. We perform a stacked cohort DiD analysis using the following specification: $Outcome_{i,t} = \beta * Treated_i * Post_{c.t} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}$, where c, i, and t is the subscript for cohort, consumer, and calendar month, respectively. α_i represents individual fixed effects, and $\delta_{c,t}$ represents month-cohort fixed effects. *Outcome* is either *Visits*, *Conversion*, *Orders*, *Discount*, *Cancellation*, *SpendingPerOrder*, *Spending* or *Retention*. Variable definitions are in Appendix A. The coefficients are estimated using Poisson regressions. We cluster standard errors by individual in all regressions. Standard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable =	*Visits*	*Conversion*	*Orders*	*Discount*	*Cancellation*	*Spending PerOrder*	*Spending*	*Retention*
*Treated * Post*	0.203***	0.013**	0.312***	-0.050***	0.072***	0.029***	0.286***	0.259***
	(0.007)	(0.006)	(0.007)	(0.005)	(0.006)	(0.009)	(0.010)	(0.008)
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Cohort-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,586,650	1,050,401	2,572,363	1,048,170	1,016,685	1,056,462	2,562,426	951,416
Pseudo R-squared	0.468	0.167	0.280	0.051	0.110	0.366	0.377	0.122

Table 3. The Impact of BigTech Credit on the Volatility of Consumer Activity

Notes: This table presents the effect of BigTech credit on the volatility of consumer activity. We perform a stacked cohort DiD analysis using the following specification: $Outcome_{i,t} = \beta * Treated_i * Post_{c.t} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}$, where c is the subscript for cohort, i is the subscript for consumer, t is the subscript for calendar week, α_i represents individual fixed effects, and $\delta_{c,t}$ represents week-cohort fixed effects. *Outcome* is either *VisitVolatility*, *OrderVolatility* or *SpendingVolatility*. Variable definitions are in Appendix A. The coefficients are estimated using Poisson regressions. We cluster standard errors by individual in all regressions. Standard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Dependent Variable =	*VisitVolatility*	*OrderVolatility*	*SpendingVolatility*
*Treated * Post*	-0.064***	-0.085***	-0.057***
	(0.003)	(0.003)	(0.002)
Individual FE	YES	YES	YES
Cohort-Week FE	YES	YES	YES
Observations	3,161,367	2,224,921	2,024,658
Pseudo R-squared	0.069	0.068	0.050

Table 4. The Impact of BigTech Credit on Consumption Variety

Notes: This table presents the effects of BigTech credit on consumption variety. We perform a stacked cohort DiD analysis using the following specification: $Outcome_{i,t} = \beta * Treated_i * Post_{c,t} + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}$, where c, i, and t is the subscript for cohort, consumer, and calendar month, respectively. α_i represents individual fixed effects, and $\delta_{c,t}$ represents month-cohort fixed effects. The dependent variable *Outcome* is one of four measures: *SKUs, Brands, Shops,* and *Categories*. Variable definitions are in Appendix A. We use the order-item data aggregated at the monthly level for this analysis. The coefficients are estimated using Poisson regressions. We cluster standard errors by individual in all regressions. Standard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable =	*SKUs*	*Brands*	*Shops*	*Categories*
*Treated * Post*	0.355***	0.316***	0.336***	0.296***
	(0.021)	(0.020)	(0.020)	(0.017)
Individual FE	YES	YES	YES	YES
Cohort-Month FE	YES	YES	YES	YES
Observations	252,623	252,388	252,531	252,623
Pseudo R-squared	0.289	0.270	0.272	0.194

Table 5. The Impact of BigTech Credit on Purchase of Higher-end Products

Notes: This table presents the impact of BigTech credit on purchase of higher-end products by consumers. The data used here is the order-item data with unique observations at the order-item level. We perform a stacked cohort DiD analysis using the following specification: $Outcome_{i,t,j,k} = \beta * Treated_i * Post_{c,t} + \varepsilon_{i,t,j,k}$, where c, i, t, j, and k is the subscript for cohort, consumer, calendar date, order and item, respectively. The dependent variable *Outcome* is one of three measures: *ItemPrice* , *BrandRank,* and *ShopRank*. Variable definitions are in Appendix A. The coefficients are estimated using Poisson regressions. We cluster standard errors by individual in all regressions. Standard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable =	*ItemPrice*	*ItemPrice*	*BrandRank*	*BrandRank*	*ShopRank*	*ShopRank*
*Treated * Post*	0.008	0.011	0.001	0.001	0.000	-0.001
	(0.013)	(0.016)	(0.001)	(0.001)	(0.002)	(0.002)
User FE	Yes	No	Yes	No	Yes	No
Product Category FE	Yes	No	Yes	No	Yes	No
User-Product Category FE	No	Yes	No	Yes	No	Yes
Cohort-Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Brand FE	Yes	Yes	No	No	Yes	Yes
Shop FE	Yes	Yes	Yes	Yes	No	No
Observations	507,382	492,835	509,083	494,743	511,519	497,811
Pseudo R-squared	0.753	0.763	0.101	0.101	0.103	0.105

Table 6. BigTech-induced Spending Growth and Consumer Delinquency

Notes: This table presents the correlation between BigTech-induced spending growth and consumer delinquency. The data used here is the individual-month observations for treated consumers after they receive BigTech credit. We perform OLS regressions using the following specification: $Outcome_{i,t} = \beta * HighSpendingEffect_i + \delta_{c,t} + \varepsilon_{i,t}$, in which c is the subscript for cohort, i is the subscript for consumer, t is the subscript for calendar month, and $\delta_{c,t}$ represents month-cohort fixed effects. The dependent variable *Outcome* is either *Delinquent60Day* or *Delinquent90Day*. Variable definitions are in Appendix A. The coefficients are estimated using OLS regressions. We cluster standard errors by individual in all regressions. Standard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	**(2)**
Dependent Variable	*Delinquent60Day*	*Delinquent90Day*
HighSpendingEffect	0.000	-0.000
	(0.001)	(0.001)
Month-Cohort FE	YES	YES
Observations	520,645	520,645
Adjusted R-squared	0.006	0.006

Table 7. Identifying the Key Mechanism

Notes: This table compares the treatment effects between sub-groups of consumers. We perform a stacked cohort DDD analysis using the following specification: $Outcome_{i,t} = \beta_1 * Treated_i * Post_{c,t} * Group + \beta_2 * Treated_i * Post_{c,t} + \beta_3 * Group + \alpha_i + \delta_{c,t} + \varepsilon_{i,t}$, where c, i, and t is the subscript for cohort, consumer, and calendar month, respectively. α_i represents individual fixed effects, and $\delta_{c,t}$ represents month-cohort fixed effects. Panel A tests the mechanism of liquidity constraint, and uses *YoungAge* and *LowCreditScore* for *Group.* Panel B tests the mechanism of target marketing, and uses *HighVisit* and *HighOrder* for *Group.* The dependent variable *Outcome Spending, SpendingVolatility, or SKU.* Variable definitions are in Appendix A. The coefficients are estimated using OLS regressions. Group indicators and fixed effects are omitted for brifty. We cluster standard errors by individual in all regressions. Standard errors are presented in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Relaxation of Liquidity Constraint

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	*Spending*	*Spending*	*SpendingVolatility*	*SpendingVolatility*	*SKUs*	*SKUs*
*Treated * Post * YoungAge*	0.249***		-0.032***		0.314***	
	(0.020)		(0.005)		(0.055)	
*Treated * Post * LowCreditScore*		0.268***		-0.038***		0.289***
		(0.022)		(0.005)		(0.057)
*Treated * Post*	0.197***	0.204***	-0.041***	-0.045***	0.196***	0.216***
	(0.012)	(0.011)	(0.003)	(0.003)	(0.035)	(0.033)
Observations	2,562,426	2,562,426	2,024,658	2,024,658	190,087	190,087
Pseudo R-squared	0.377	0.377	0.0504	0.0505	0.288	0.289

Panel B. Targeted Marketing

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	*Spending*	*Spending*	*SpendingVolatility*	*SpendingVolatility*	*SKUs*	*SKUs*
*Treated * Post * HighVisit*	-0.212***		0.008*		-0.347***	
	(0.021)		(0.005)		(0.056)	
*Treated * Post * HighOrder*		-0.259***		0.005		-0.394***
		(0.022)		(0.005)		(0.056)
*Treated * Post*	0.437***	0.476***	-0.061***	-0.059***	0.560***	0.623***
	(0.018)	(0.019)	(0.003)	(0.003)	(0.046)	(0.046)
Observations	2,562,426	2,562,426	2,024,658	2,024,658	190,087	190,087
Pseudo R-squared	0.378	0.380	0.0505	0.0507	0.290	0.295