Platform Credit, Advertising, and Customer Capital[*]

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Abstract

Advertising plays a crucial role in online marketplaces, where thousands of merchants offer similar products and compete for visibility and consumer attention. This study demonstrates theoretically and empirically that merchants underinvest in building customer capital due to financial constraints. By leveraging quasi-random variation in merchants' access to credit from a major platform lender, we establish that alleviating financial constraints leads to increases in advertising expenditures, enhanced shop visibility, and accelerated sales growth. The effects are especially pronounced among high-quality merchants with top ratings, suggesting that financial frictions may lead to misallocation of customer capital.

Keywords: platform credit, e-commerce, advertising, customer capital

JEL-Classification: G21, G23, L10, L81, M3

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1 Introduction

It is well documented that firm profitability and growth do not depend on productivity or technological efficiency alone (Foster et al., 2008). Demand-side fundamentals are equally crucial and can vary considerably among firms within the same market. For instance, young entrepreneurs typically trail behind their larger competitors regarding brand visibility, reputation, and customer base. Indeed, a lack of "customer capital" has been identified as a significant barrier to firm growth (Foster et al., 2016). Importantly, customer capital is not exogenous; firms can actively invest in advertising to enhance their visibility and customer base. In principle, advertising should enable small, high-quality firms to increase their market share. However, in practice, smaller firms tend to grow slowly and frequently exit the market, even when their productivity equals or surpasses that of larger, established competitors (Ferraz et al., 2015).

In this paper, we hypothesize that small firms often "underadvertise" or underinvest in customer capital because they are financially constrained. Having no or only limited access to capital markets, small firms must often rely on bank credit. Traditional banks often refuse to fund investments in customer capital because it cannot be used as collateral to secure loans. After all, a firm's visibility and reputation, as well as its customer base, are intangible and more difficult to value and sell than physical assets. Additionally, unsecured bank loans might be inaccessible due to asymmetric information, where banks fear potential adverse selection or moral hazard issues.

We argue that the rise of platform credit is particularly effective in addressing the financial constraints of small firms and, hence, key challenges related to the accumulation of customer capital. When we speak of platform credit, we consider credit from a company that simultaneously operates an e-commerce marketplace, for example, for retail consumer goods, and lends to merchants selling their goods on this platform. Such platform lenders can more accurately assess the quality and productivity of their borrowers by analyzing their detailed transaction histories and customer reviews, partially mitigating the issue of asymmetric information. Importantly, these lenders also have a greater ability to recover debt in cases of default, as they typically process and potentially have recourse to the payments between merchants and customers. Hence, compared to banks, platform lenders are in a better position to prevent defaulting borrowers from absconding with cash flows. Overall, these benefits should reduce the need for collateral and significantly enhance borrowers' ability to finance investments in customer capital.

We formalize these intuitions in a two-period model that features heterogeneous merchants who maximize expected utility from consumption and advertise to increase their visibility on an e-commerce marketplace. When a merchant's net worth is insufficient to cover advertising expenses, they must rely on credit from either a traditional bank or from the company that operates the e-commerce marketplace (the platform lender). Since advertising outcomes are uncertain, some merchants may default on their debt. In such cases, the platform lender can recover a larger fraction of the debt from the merchant's available cash than a traditional bank. We provide an analytical characterization of the optimal advertising, consumption, and borrowing decisions. We prove that when lenders have a stronger ability to recover debt from defaulting merchants—a scenario achievable through platform credit—advertising levels in equilibrium as well as sales growth increase. This effect is particularly pronounced for merchants with higher product quality or efficiency, i.e., for merchants with higher expected returns to advertising.

To test these theoretical predictions, we exploit a setting that features small firms that have large advertising needs but little collateral and that experience a quasi-random shock to their financial constraints: access to platform credit on Alibaba's e-commerce platform Taobao. Taobao is a Chinese online marketplace for consumer goods sold predominantly by small businesses and individual entrepreneurs (henceforth called merchants), who rarely manufacture themselves. Customers or buyers can choose from a large variety of differentiated products. While the depth of the market attracts customers, it also increases search costs and limits the visibility of each individual merchant, making its existing customer base and reputation its most valuable assets. To increase their visibility, merchants can buy advertisement space on Taobao, typically in the form of web banners that redirect customers to a merchant's shop page.

Alibaba provides small business credit to Taobao merchants through AntFinancial (Ant Group). Credit allocation is fully automated and relies on an algorithm that scores merchants' creditworthiness mostly based on transaction data from Taobao. Merchants do not observe their credit scores and do not know how they are calculated. They do not apply for a loan from AntFinancial themselves but receive automatic notification when they qualify for credit. AntFinancial has adjusted its credit eligibility criteria over time. For the purpose of this paper, we focus on the first half of the year 2015 when credit access is conditional on a credit score surpassing a certain threshold. Overall, platform credit from AntFinancial to Taobao merchants falls into the category of "BigTech credit", as it is supplied by a large technology company that makes use of the big data generated in its core business (i.e., data from Taobao) and employs an AI to manage credit scoring, loan approval, and monitoring of borrowers.

In our data set, we can measure merchants' performance as sales growth, their visibility as the number of customers' shop page visits, investments in customer capital as advertising expenses, and their reputation/quality as public customer ratings. We further observe each merchant's credit score, credit eligibility status, and credit uptake from AntFinancial. To test our hypothesis that financial constraints explain underinvestment in customer capital (i.e., underadvertising) by small firms (i.e., by Taobao merchants), we exploit the fact that access to platform credit from AntFinancial is discontinuous at a given credit score threshold. More specifically, we use quasi-random variation in credit eligibility for merchants with scores around the cutoff for causal identification in a regression discontinuity design (RDD).

Our empirical analyses show that (quasi-random) access to platform credit increases investment in customer capital. Consistent with our theoretical model, we find that merchants right above the credit score cut-off increase advertising by 0.024 RMB for each RMB in their sales. This accounts for a sizeable fraction of their new borrowings from AntFinancial: on average, these merchants use 17% of their new credit from AntFinancial to finance additional advertising expenses. We interpret this finding as evidence that merchants were financially constrained before qualifying for platform credit, in the sense that they could not finance advertising out of alternative funding sources or only at prohibitively higher costs. In other words, platform credit causes merchants to advertise more by relaxing their financial constraints.[1]

The effect of platform credit on advertising varies across Taobao merchants. We use past customer ratings for product quality, service, and delivery to distinguish between merchants of different quality or reputation. We find that only merchants with customer ratings above the median increase investment in customer capital after accessing credit from AntFinancial. These high-quality merchants use their new credit almost exclusively to fund an increase in advertising expenses. By contrast, merchants with below-median ratings do not increase advertising at all. One possible explanation would be that these low-quality merchants were not financially

[1]Assume that the opposite was true and that merchants were not financially constrained in the absence of platform credit. In that case, platform credit would have no effect on advertising as merchants could simply finance advertising out of other funding sources. In general, in the absence of financial frictions, financial policy is irrelevant, and investment policy (advertising) is independent of platform credit (Modigliani and Miller, 1958). The fact that platform credit has a positive effect on advertising allows us to reject this null hypothesis.

constrained beforehand and could already advertise in the absence of platform credit. However, we find that low-quality merchants borrow five times as much credit from AntFinancial as their high-quality counterparts. Hence, if anything, they seem to have been more and not less financially constrained ex ante. A more plausible explanation for the higher pass-through of credit to advertising by high-quality merchants, consistent with our model prediction, is that advertising is more profitable for merchants with high ratings. Specifically, when a new buyer clicks on an advertisement banner and is redirected to a shop page, he or she will be more likely to actually buy something if the shop page shows higher ratings by the merchant's past customers. Vice versa, bad customer ratings should depress the conversion of advertisement-directed shop visits into purchases.

Platform credit is useful because it solves or at least alleviates underinvestment in customer capital by financially constrained merchants. If this hypothesis were correct, we should observe that those merchants who use the new credit from AntFinancial to advertise become more visible among customers in subsequent months and manage to grow faster. Our empirical analysis confirms this prediction. We find that those (and only those) merchants that use their credit on advertising increase the number of shop page visits by potential buyers and grow their sales revenues over the next quarter. For example, high-quality (i.e., advertising) merchants grow the number of shop page visits about 10 times (0.143 vs. 0.015) faster than low-quality (non-advertising) merchants after receiving platform credit. As sales growth and the increase in shop page visits occur only for the high-quality merchants, who spend their new credit almost exclusively on advertising, we are confident that the positive effect of platform credit on customer capital and growth operates indeed through advertising and not through other investments.

Overall, we find that access to platform credit from AntFinancial increases advertising spending, particularly among high-quality merchants with strong customer ratings. Lower-rated merchants, despite borrowing more, do not invest in advertising, likely because it is less profitable for them. Only merchants who allocate credit to advertising experience significant growth in customer visits and sales, confirming that platform credit alleviates financial constraints and drives business expansion through increased visibility.

This paper contributes to the broader literature on FinTech credit (see surveys in Allen et al., 2021; Berg et al., 2022; Cornelli et al., 2023). More specifically, our analysis focuses on a subset of FinTech lenders that not only provide financial services but also operate e-commerce marketplaces—commonly referred to as BigTech or platform lenders. Several theoretical papers study this dual-role setting, including, for example, Bouvard et al. (2022), Huang (2023), Li and Pegoraro (2023), and Huang et al. (2025). These papers highlight how platform lenders can ease borrowers' financial constraints, either through better screening and monitoring, or because they internalize positive network externalities within the platform. Building on this literature, we adopt the notion of platform lenders' better loan enforcement technology relative to traditional banks, and study its implications for borrowers' advertising decisions in a product market characterized by search frictions. Cong et al. (2024) develop a general framework of FinTech platforms with asymmetric cross-side network effects and platform-level default risk, emphasizing user behavior and market dynamics. In contrast, we focus on the micro-level investment behavior of financially constrained merchants and the role of enforcement-based platform credit in facilitating customer capital formation.

In the empirical literature, the most closely related studies are Chen et al. (2021) and Hau et al. (2024), both of which examine FinTech credit on Alibaba's Taobao platform. Chen et al.

(2021) show that access to platform credit reduces firms' sales volatility and exit probability, and that credit recipients experience higher advertising-related revenues. However, their analysis centers on the output side—sales and volatility—without directly observing firms' advertising expenditures or the accumulation of customer capital. By contrast, our paper focuses on the input side. We trace how access to platform credit relaxes financing constraints, allowing merchants to increase advertising investment, build customer capital, and expand sales through greater visibility rather than through reduced risk exposure. Moreover, by documenting that these effects are concentrated among high-quality merchants with strong customer ratings, we uncover a novel allocation-efficiency dimension: platform credit channels funds toward firms with the highest marginal returns to advertising and thus improves the efficiency of intangible-capital formation within the platform economy.

Hau et al. (2024) focus on a different mechanism, financial inclusion in under-banked regions, and link the real effects of platform credit to inefficiencies in the credit allocation processes of state-owned banks in China. By contrast, our analysis centers on the role of platform credit in financing intangible assets and facilitating borrowers' accumulation of customer capital. In doing so, we contribute to a broader set of empirical studies on FinTech lending to small and medium-sized enterprises (SMEs) (e.g., Beaumont et al., forthcoming; Gambacorta et al., 2022; Gopal and Schnabl, 2022; Liu et al., 2022; Ghosh et al., forthcoming). A key insight from this literature is that FinTech lenders' privileged access to data enables them to lend to borrowers without collateral—an observation that aligns with our own findings. Relative to these papers, we causally identify the real effects of FinTech credit extended within the e-commerce marketplace of the lender, and we pin down the underlying mechanism as borrowers' accumulation of customer capital.

Finally, our findings on the interplay between platform credit and the accumulation of customer capital inform a growing literature that highlights demand-side fundamentals as key drivers of firm growth. Gourio and Rudanko (2014) and Rob and Fishman (2005), for example, emphasize the importance of a merchant's customer base as a form of intangible capital that impacts firm valuation and growth.[2] Bian et al. (2025) document how firms' access to and sharing of customer data creates a network of intangible capital that influences firm performance and valuation across sectors. However, these papers do not consider cases in which the firms can face external borrowing constraints. Relative to this literature, we emphasize the role of financial frictions in the accumulation (or lack thereof) of customer capital and show that platform credit can address an important underadvertising problem that is most pertinent to small, collateral-constrained entrepreneurs. We do so by exploiting quasi-random variation in financial constraints on one of the largest e-commerce platforms worldwide.[3]

2 Theory

What market imperfections make it difficult for traditional banks to finance investments in intangible assets like brand visibility or customer base (henceforth, customer capital)? Why would companies that operate e-commerce platforms be in a better position to provide such funding? In Section 2.1, we review the answers that the literature has given to these questions. In Section 2.2, we then solve a two-period model with search frictions in the product market and financial frictions in the credit market and derive testable predictions.

[2]Further, see Foster et al. (2008, 2016) and Ferraz et al. (2015).

[3]This paper also contributes to the measurement of customer capital by leveraging merchant-level data from an online marketplace. Unlike public companies, where customer capital is one of several growth drivers (e.g., Crouzet et al. (2022); Dou et al. (2021); He et al. (2024)), the growth of online merchants depends exclusively on the expansion of their customer base.

2.1 Bank credit vs. platform credit in the literature

Traditional credit markets face challenges when lending to firms due to asymmetric information about borrower prospects. This information asymmetry can lead to two main problems: adverse selection and moral hazard. In the presence of adverse selection, lenders struggle to differentiate between high-risk and low-risk borrowers, which can result in credit rationing, where even creditworthy borrowers are denied loans (Stiglitz and Weiss, 1981). Moral hazard arises when lenders cannot observe the effort borrowers exert in pursuing their investments or whether they strategically default by misreporting realized cash flows (e.g., Aghion and Bolton, 1997; Holmström and Tirole, 1997; Townsend, 1979; Diamond, 1984; Gale and Hellwig, 1985; Williamson, 1986). The inability to fully monitor borrowers' behavior may lead to inefficient credit allocation and an increase in the cost of borrowing.

One mechanism to mitigate asymmetric information problems in credit markets is the use of collateral. Collateral serves as a screening device, enabling lenders to distinguish between riskier and safer borrowers (Bester, 1985, 1987; Besanko and Thakor, 1987; Chan and Kanatas, 1985). By requiring collateral, banks can induce self-selection, as safer borrowers are more willing to pledge assets to secure lower interest rates, while riskier borrowers opt for unsecured credit at higher rates. Moreover, collateral helps address moral hazard by reducing borrowers' incentives to default strategically and divert cash flows for personal use (Bester, 1994).

However, when firms seek credit to finance investments in intangible assets, such as brand visibility or customer acquisition, traditional collateral mechanisms can become ineffective. Unlike physical assets, intangible assets are difficult to value and often non-transferable, making them poor collateral. Merchants on platforms like Taobao, for instance, rely heavily on customer engagement and reputation, which are not easily collateralized. As a result, banks face substantial challenges in financing these firms, leading to credit constraints.

The literature has different reasons why e-commerce platform lenders could be able to overcome these credit market frictions even when collateral is unavailable. Several studies argue that platform lenders have superior monitoring capabilities, as they can observe merchants' sales, customer interactions, and reputation metrics in real time (e.g. Bouvard et al., 2022). Unlike banks, which may struggle to verify borrowers' cash flows, platform lenders can directly track sales and enforce repayment through automated deductions from merchants' platform revenue (Gambacorta et al., 2022; Huang, 2023; Li and Pegoraro, 2023). Additionally, the threat of banning defaulting merchants from the platform serves as an effective disciplinary tool, reducing the likelihood of strategic default. These enforcement advantages enable platform lenders to extend credit to collateral-constrained merchants, particularly for investments in intangible assets like advertising, which traditional banks might be reluctant to finance.

2.2 A simple model of advertising and credit

In this section, we develop a two-period model to illustrate how merchants on an e-commerce platform choose financing, advertising, and consumption under borrowing constraints. The model links the platform lender's enforcement advantage to merchants' optimal advertising decisions and provides a clear mechanism for the role of platform credit. Stronger enforcement increases merchants' ability to borrow and thus raises advertising investment, with the effect being especially pronounced for high-quality firms that have higher expected returns to advertising. These theoretical results form the structural foundation of the paper and yield the testable predictions that guide our empirical identification strategy.

At time 0, merchants allocate capital between early consumption and advertising, which increases their visibility on the platform and attracts potential customers (investment into customer capital). Merchants differ in their quality, which we model as their expected return to advertising (i.e., their ability to convert their visibility on the platform into actual sales). Consumption and advertising are in part funded with credit. If merchants default on their loans in period two, they abscond with part of their cash flow from sales. Platform lenders differ from traditional banks in that they can seize a larger fraction of this cash flow in default (e.g., Gambacorta et al., 2022; Huang, 2023; Li and Pegoraro, 2023). The model generates testable predictions about how platform credit increases merchants' customer capital and sales growth.

Merchants derive utility from consumption, with their expected utility expressed as:

$$\mathbb{E}[u(c_0) + \beta u(c_1)], \tag{1}$$

where $u(c)$ is the utility function, c_t denotes consumption in period $t = 0, 1$, and $\beta < 1$ represents the intertemporal discount factor, reflecting the merchant's time preference.

Advertising and Customer Acquisition At the beginning of the period 0, merchants are endowed with a net worth m_0, which they allocate between investment and consumption. Merchants operate an online shop that generates cash flows y_1 at the end of period 1. To acquire customers and to increase future sales, merchants invest in advertising at a cost $\kappa(l_0) = \kappa l_0$, where l_0 represents the number of advertising links posted on the platform and κ denotes the cost per link.

The number of customers that merchants acquire by posting an additional advertising link is called the click-through rate z_1. This rate is uncertain due to exogenous demand shocks, for example, caused by changing consumer preferences. We denote the distribution of z_1 as $\Phi(z_1)$, which is common knowledge among merchants and creditors.

Customer Base and Sales The deployment of l_0 links in period 0 generates a customer base of $n_1 = z_1 l_0$ in period 1. Once matched with customers, merchants generate sales, modeled as $y_1 = \gamma n_1$, where γ reflects the merchant's quality, reputation, or sales efficiency. The quality parameter γ is known in period 0 before advertising decisions are made.

External Financing Merchants rely on external financing to fund their investment, borrowing from traditional banks or the platform in period 0. The loan is repaid in period 1, with a face value b_1 and an interest rate R_1.

Default occurs if cash flows are insufficient to meet debt obligations, i.e., $y_1 = z_1 \gamma l_0 \leq b_1$. The threshold $\hat{z}_1$ for default is:

$$\hat{z}_1 = \frac{b_1}{\gamma l_0} = \frac{\alpha_1}{\gamma}, \tag{2}$$

where $\alpha_1 = \frac{b_1}{l_0}$ denotes the leverage ratio. Lenders set interest rates to break even:

$$\frac{b_1}{R_1} = \frac{\int_{\underline{z}}^{\hat{z}_1} \lambda y_1 d\Phi(z_1) + b_1 \int_{\hat{z}_1}^{\bar{z}} d\Phi(z_1)}{R_f} = \frac{\bar{b}(b_1, l_0)}{R_f}, \tag{3}$$

where R_f is the risk-free rate, and λ reflects the lender's ability to recover cash flows in default. The bounds $\underline{z}$ and $\bar{z}$ denote the support of z_1, and $\frac{\bar{b}(b_1,l_0)}{R_f}$ represents the borrowing proceeds.

Platform Credit vs. Bank Credit Upon loan repayment in period 2, lenders receive b_1. In default, the lender's ability to recover part of the face value depends on its ability to seize a share of the merchant's sales, i.e., to prevent the merchant from absconding with cash. We denote this recovery rate as λ, which could vary, for example, by lender type. A natural interpretation is that platform lenders have a larger λ than banks because these platforms fully observe and often process all payments between merchants and customers (e.g., Gambacorta et al., 2022; Huang, 2023; Li and Pegoraro, 2023).

Merchant's Optimization Problem: We summarize the merchant's problem as follows:

$$\max_{c_0,l_0,b_1,c_1} \quad : \quad u(c_0) + \beta \mathbf{E} u(c_1)$$

subject to:

$$c_0 = m_0 + \frac{b_1}{R} - \varphi(l_0) \geq 0 \tag{4}$$

$$c_1 = \max\{y_1 - b_1, 0\} \tag{5}$$

$$n_1 = z_1 l_0 \tag{6}$$

$$y_1 = \gamma n_1 = \gamma z_1 l_0 \tag{7}$$

$$\frac{b_1}{R_1} = \frac{\int_{\underline{z}}^{\hat{z}} \lambda y_1 d\Phi(z_1) + \int_{\hat{z}}^{\bar{z}} b_1 d\Phi(z_1)}{R_f} \tag{8}$$

Equation 4 is the budget constraint in period 0, under the assumption that consumption c_0 is nonnegative. Equation 5 specifies the budget constraint in period 1, which incorporates the limited liability condition for merchants. Equation 6 models the accumulation of the consumer base, while Equation 7 formalizes the sales generation process. Lastly, Equation 8 specifies the loan pricing condition, ensuring the lender's breakeven condition is met.

Solving the model analytically: To simplify the analytical proof, we assume that merchants are risk-neutral, with the utility function defined as $u(c) = c$. Then the merchant's optimization problem can be expressed as follows:

$$\max_{\alpha_1, l_0} \ : \ (1+\mu)\big(m_0 + f(\alpha_1)l_0 - \varphi(l_0)\big) + g(\alpha_1)l_0 \tag{9}$$

where μ is the Lagrangian multiplier of the non-negative consumption constraint $m_0 + f(\alpha_1)l_0 - \varphi(l_0) \geq 0$, and functions $f(\alpha_1)$ and $g(\alpha_1)$ are defined as follows

$$\begin{aligned} f(\alpha_1) &= \frac{1}{R_f}\Big(\lambda\gamma \int_{\underline{z}}^{\alpha_1/\gamma} z d\Phi(z) + \alpha_1 \int_{\alpha_1/\gamma}^{\bar{z}} d\Phi(z)\Big) \\ &= \frac{1}{R_f}\Big(\lambda\gamma \int_{\underline{z}}^{\alpha_1/\gamma} z\phi(z)dz + \alpha_1 \int_{\alpha_1/\gamma}^{\bar{z}} \phi(z)dz\Big) \end{aligned}$$

$$\begin{aligned} g(\alpha_1) &= \beta \int_{\alpha_1/\gamma}^{\bar{z}} (\gamma z - \alpha_1) d\Phi(z) \\ &= \beta\gamma \int_{\alpha_1/\gamma}^{\bar{z}} z\phi(z)dz - \beta\alpha_1 \int_{\alpha_1/\gamma}^{\bar{z}} \phi(z)dz \end{aligned}$$

Taking the first order conditions with respect to l_0 and α_1, we have:

$$(1+\mu)\big(f(\alpha_1) - \kappa\big) + g(\alpha_1) = 0 \tag{10}$$

$$(1+\mu)f'(\alpha_1) + g'(\alpha_1) = 0 \tag{11}$$

$$m_0 + f(\alpha_1)l_0 - \kappa l_0 = 0 \tag{12}$$

where,

$$f'(\alpha_1) = \frac{1}{R_f}\Big(\lambda\frac{\alpha_1}{\gamma}\phi(\frac{\alpha_1}{\gamma}) + \int_{\alpha_1/\gamma}^{\bar{z}}\phi(z)dz - \frac{\alpha_1}{\gamma}\phi(\frac{\alpha_1}{\gamma})\Big)$$

$$g'(\alpha_1) = \beta\Big(-\frac{\alpha_1}{\gamma}\phi(\frac{\alpha_1}{\gamma}) - \int_{\alpha_1/\gamma}^{\bar{z}}\phi(z)dz + \frac{\alpha_1}{\gamma}\phi(\frac{\alpha_1}{\gamma})\Big) = -\beta\int_{\alpha_1/\gamma}^{\bar{z}}\phi(z)dz$$

Equations 10–12 pin down the Lagrangian multiplier μ^* and the merchant's optimal choice of leverage α_1^* and advertising expense l_0^*. We derive the solution in closed form in Appendix A and B under the assumption that z_1 follows a uniform distribution. Finally, we do comparative statics of merchants' leverage α_1^*, advertising expense l_0^*, customer base n_1^*, and sales y_1^* with respect to the lender's recovery rate λ and with respect to merchant quality γ. For a sufficiently small advertising cost $\kappa < \frac{\gamma(\bar{z}+\underline{z})/2}{R_f}$ (ensuring that advertising has a positive NPV), Proposition 1 summarizes the following results:

Proposition 1.

1.1 Merchants advertise more if lenders can seize a larger share of merchants' cash flows in default: $\frac{\partial l_0^*}{\partial \lambda} > 0$

1.2 High-quality merchants increase advertising more than low-quality merchants when lenders' ability to seize cash flows in default increases: $\frac{\partial^2 l_0^*}{\partial \lambda \partial \gamma} > 0$

1.3 Conditional on not defaulting, merchants' customer base and sales increase in lenders' ability to seize cash flows in default: $\frac{\partial \int_{\hat{z}}^{\bar{z}} n_1^* d\Phi(z_1)}{\partial \lambda} > 0$ *and* $\frac{\partial \int_{\hat{z}}^{\bar{z}} y_1^* d\Phi(z_1)}{\partial \lambda} > 0$

Proof: See Appendix A and B.

Proposition 1 summarizes how lenders' ability λ to seize merchants' cash flows in default affects their advertising, their build-up of customer capital, and ultimately sales growth. In our empirical setting, we test these predictions for merchants that gain (random) access to platform credit, i.e., access to a lender with a higher λ than traditional banks.

3 Empirical setting and predictions

Next, we describe the technical and advertising solutions of Alibaba's e-commerce platform Taobao (Section 3.1), the automated (and discontinuous) credit allocation of Alibaba's lending arm AntFinancial (Section 3.2), and a set of predictions that follow from Proposition 1 and that can be tested in our empirical setting (Section 3.3).

3.1 Matching customers and merchants on Alibaba's platform Taobao

Taobao is a Chinese e-commerce platform that belongs to Alibaba Group and matches buyers and sellers in the market for consumer goods like clothing, cosmetics, etc. While Taobao offers merchants the possibility to auction off (second-hand) articles, almost all merchandise is new and sold at fixed prices. Merchants are small businesses and individual entrepreneurs that essentially act as retailers and rarely manufacture merchandise themselves. As such, they have few tangible assets apart from inventory (working capital). In terms of market size, Taobao was China's leading shopping app with nearly 650 million monthly active users as of November 2024.[4] Gross merchandise volume was reported as RMB 1.597bn in 2015 and grew to RMB 3.387bn in 2020.[5]

The large number of products and merchants helps the platform attract customers who value

[4] https://www.statista.com/statistics/1044676/china-leading-shopping-apps-monthly-active-users/?utm_source=chatgpt.com (February 20, 2025)

[5] https://www.statista.com/statistics/959633/china-taobao-gross-merchandise-volume/ (February 20, 2025)

choosing from a range of different products. At the same time, the sheer breadth of supply reduces the visibility of each individual merchant and increases customers' search cost. The platform provides different technical solutions that help match customers with merchants. First, the platform features a search engine that suggests products based on customers' keyword search and their past shopping behavior. Second, to increase the visibility of their product listings, merchants can buy advertising space on the platform from Taobao, typically in the form of banners that redirect customers to the merchants' shop page or product listing if customers click on them.[6] Third, the platform invites customers to evaluate service and product quality after completed transactions and aggregates and communicates these ratings on the merchant's shop page and product listings.[7] Fourth, Taobao features an instant messaging tool that allows customers and merchants to exchange about a product or service. Hence, the platform reduces frictions in the product market by enabling direct product search (search engine), increasing product visibility (advertising), and removing asymmetric information between merchants and customers (customer ratings and instant messaging).

As a byproduct of matching customers with merchants, Taobao collects large amounts of data. For example, a merchant's visibility among customers is known to Taobao as the number of customers that visit the merchant's shop page or its individual product listings either after searching for the merchant/product directly in the search engine or after clicking on an advertisement banner. As a signal for a merchant's reputation, the platform observes customer ratings of product quality and service. The size of a merchant's customer base can be measured by the total number of customers who have not just visited the merchant's shop page but actu-

[6] More recently, Taobao has started to offer additional advertising formats, including Pay-for-Performance (P4P) ads, which allow merchants to bid for higher placement in search results, and AI-driven personalized recommendations known as Super Recommendations.

[7] Beyond customer ratings, Taobao provides additional trust signals, such as detailed product reviews with images and videos, and AI-generated summaries of customer sentiment.

ally bought one or several of its products in the recent past. Finally, Taobao has full visibility of a merchant's financial performance as it manages (via its affiliate payment service Alipay, in a function similar to an escrow agent) all transactions between merchants and customers and, in fact, directly deducts any platform fees before releasing the cash flow to the merchants.

3.2 Platform credit from Alibaba's AntFinancial (Ant Group)

Alibaba's AntFinancial, nowadays known as Ant Group, provides small business credit to merchants on the e-commerce platform Taobao. The credit allocation process is fully automated and encompasses credit scoring, loan approval decision, borrower communication, and loan monitoring. Credit scoring is based on a model that considers a vast range of different variables, including information on past sales as the main input, the merchant's customer base, historical defaults, and other transaction data collected by Alibaba's Taobao. Credit scores range from 380 to 680. Before June 2015, merchants needed to surpass a threshold of 480, motivated by a value-at-risk model, to qualify for a credit line. Additional exclusion criteria were also considered, such as previous defaults on bank or trade credit (obtained from national sources), poor customer service on the platform, and instances of fraud (e.g., suspicion of selling counterfeit goods).

AntFinancial automatically computes and updates a credit score for each merchant at a monthly frequency. When their score exceeds the threshold of 480 and they meet none of the exclusion criteria, merchants receive an automated notification informing them that they qualify for credit. Upon notification, the eligible merchant is prompted to complete a contract form, which typically takes around 3 minutes. After submitting the form, merchants gain access to a credit line whose terms are similar to those of a credit card. Borrowers are subject to continuous monitoring, and if their credit score falls below 480, their credit line is withdrawn in the following month. They have a period of 12 months to repay any outstanding balance.

In our empirical analyses, we exploit the discontinuity at the credit-score cut-off point of 480 to draw causal inference. As we elaborate in Section 4.2.1, this discontinuity provides us with an opportunity to investigate the effect of quasi-random access to platform credit on merchants' investments in customer capital. We note that AntFinancial removed the discontinuity of credit eligibility at a credit score of 480 after June 2015, which is the reason why our sample includes only the first half of 2015. The credit allocation process described above is the one that AntFinancial used during this sample period, but it may have changed since.

3.3 Empirical predictions

Our empirical setting can be mapped to our model in Section 2.2. In particular, we can exploit the variation in lenders' ability λ to seize the cash of defaulting merchants. Initially, merchants on Taobao only borrow from traditional lenders who do not observe (and have no direct recourse to) their platform sales. After receiving access to credit from Alibaba, merchants can borrow from a platform lender who processes all financial transactions with customers. This shock to creditors' enforcement technology allows us to restate Proposition 1.1 as a testable prediction:

Hypothesis 1. ***Advertising and platform credit***

Platform credit increases investments into customer capital. Merchants on the e-commerce platform Taobao increase advertising after they receive quasi-random access to credit from Ant-Financial.

The null hypothesis to Hypothesis 1 is that merchants are able to finance all profitable investments, including advertisement, even in the absence of platform credit. Under this null hypothesis, merchants are financially unconstrained ex ante and access to a lender with a better enforcement technology is irrelevant (Modigliani and Miller, 1958). Vice versa, a positive effect of platform credit on advertisement (Hypothesis 1) implies that merchants were unable to unlock funding from traditional lenders who lack full recourse to merchants' platform sales.

Our model explains the positive effect of platform credit on advertising (Hypothesis 1) with platforms' superior ability to seize the cash flows of defaulting merchants (Proposition 1.1). However, as discussed in Sections 1 and 2.1, alternative explanations are conceivable. For example, the competitive advantage of platforms relative to traditional lenders could come from privileged access to more data (better screening of borrowers' risk types) or from positive network externalities that make it profitable to lend to more merchants than banks would lend to (e.g., Li and Pegoraro, 2023). Our identification strategy mutes those alternative explanations because we study *quasi-random* access to platform credit. I.e., merchants with and without access are comparable with respect to their risk type or platform externalities. The only thing that changes for the randomly selected merchants is that they gain access to a lender with superior enforcement technology.

Variation in merchants' product and service quality is another important feature that we can map into our model. In the model, merchants' quality γ determines the expected return to advertising and, hence, the effect of platform credit on merchants' advertisement investments. In our empirical setting, merchants' shop pages and product listings show their customer ratings from past transactions. Stronger ratings should increase the probability that new customers make a purchase after clicking merchants' advertisement links.[8] Consistent with Proposition

[8] This prediction depends on buyers' consideration for a merchant's ratings. For example, if buyers expect the customer ratings to be manipulated, they would pay them less attention. Nevertheless, as long as ratings are somewhat informative, we expect that access to platform credit will especially boost advertising by merchants with high customer ratings.

1.2, we predict that quasi-random access to platform credit from Alibaba has a larger effect on advertising for merchants with better ratings.[9]

Hypothesis 2. ***Merchant quality and platform credit***

Especially high-quality merchants with strong customer ratings increase their investments into intangible customer capital and advertise more following quasi-random access to credit from AntFinancial.

While Hypothesis 2 follows naturally from the assumption that high-quality merchants find advertisement more profitable, alternative explanations leading to the same prediction are also conceivable. In particular, high- and low-quality merchants could be financially constrained to different degrees, ex-ante. Under some conditions, adverse selection in traditional credit markets could entail that high-quality merchants benefit more from access to platform credit and, hence, increase investment (advertising) more (Stiglitz and Weiss, 1981). In general, the heterogeneous effects of platform credit on investment can be due to differences in merchants' financial constraints or due to differences in their investment opportunities. Disentangling both channels is the topic of a large literature.[10] We leave this question open for now but will return to it in the empirical analysis (see Section 5.2).

Proposition 1.3 posits that lenders' ability λ to seize cash flows in default increases merchants' customer base and sales as a result of an increase in advertising. In our empirical setting, featuring quasi-random access to a platform lender with superior enforcement technology, we restate this prediction in Hypothesis 3:

[9] We note that *quasi-random* access to platform credit does not mean that all merchants have identical quality (ratings). It means that the distribution of quality is identical among the merchants with and without access.

[10] The challenge of disentangling the effects of investment opportunities and financial constraints on investment has been discussed, for example, in the literature on cash flow-sensitivities of investment (Fazzari et al., 1988; Kaplan and Zingales, 1997; Erickson and Whited, 2000; Faulkender and Petersen, 2012).

Hypothesis 3. ***Platform visibility, sales growth, and platform credit***

Merchants borrowing from the platform to finance advertising perform better in terms of customer visibility on the platform and sales subsequently.

As especially high-quality merchants are predicted to advertise (Hypothesis 2), we also expect that especially high-quality merchants improve their sales performance and customer acquisition ex post. However, some papers predict that platforms find it optimal to subsidize (for example, through cheap funding) low-quality merchants because this practice increases product range and generates positive network externalities (e.g., Li and Pegoraro, 2023). A priori, it is unclear how the performance of these low-quality merchants should evolve compared to that of high-quality merchants.[11] Our empirical setting does not speak to this prediction. As explained in Section 4.2, we study quasi-random access to platform credit. As such, credit supply by the platform is not conditional on merchant quality or any network externalities that different merchants might generate. Of course, demand for platform credit might still vary across different merchants that gain access, but we predict (Hypothesis 2) and show empirically (Section 5.2) that mostly high- and not low-quality merchants increase investment.

4 Data and methodology

In Section 4.1, we explain the origin and construction of our regression sample. In Section 4.2, we show validity checks for our RDD estimation and describe the regression specification. Section 4.3 provides summary statistics for our main variables

[11] Performance will depend jointly on quality and on the subsidies from the platform.

4.1 Sample construction and data structure

The original database comprises the universe of merchants and their transactions on the e-commerce platform Taobao. Alibaba automatically collects and stores this data on a monthly basis. Initially, we were given access to data for the period from September 2014 to July 2015. During this timeframe, Taobao hosted approximately 3.5 million merchants, corresponding to more than 35 million merchant-month observations. However, the substantial size of this database, restrictions on software for statistical analysis, as well as other constraints, make it impractical to examine the entire database. Specifically, the discontinuity in credit eligibility, which we use for identification in this paper, was lifted in July 2015 and occasionally suspended in 2014. For these reasons, Alibaba provided us with a subsample that only includes observations from the first half of 2015, when the eligibility threshold was active. Additionally, we restrict the regression sample to observations with credit scores within a narrow bandwidth centered at the eligibility threshold of 480 and delete observations with scores below 460 or above 500. The resulting subsample concentrates on the relevant months and merchants necessary for empirical identification, reducing its size to a more manageable 658,311 observations. For confidentiality purposes, the sample is stored on a standalone computer located at Alibaba's headquarters and can only be accessed on-site.[12]

In the extracted subsample, one observation corresponds to a merchant-month pair (i, t). For the correct specification of our analyses, it is important to understand the structure of this panel. In particular, there is a one-month lag in the relation between a merchant's credit score and his or her eligibility for credit from Ant Financial. More precisely, whether merchant i has access to credit in month t depends on the score registered for $t-1$. The reason is that

[12] The computer has no internet connection nor interfaces with electronic media.

credit scores are normally reviewed at month's end, in which case any consequences for credit eligibility only take effect in the following month. Hence, in an RDD, the forcing variable for credit access would be the one-month lagged credit score.

Another important characteristic of our dataset is that although the sample frequency is monthly, some variables, notably our main variable of interest, merchants' advertising expenses, are only reported as rolling three-month aggregates. This is illustrated in Figure 1. For example, if t corresponds to January 2015, then the variable *Advertising expense past 3mth* reports the aggregate advertising expenses of merchant i in November, December, and January. Another variable *Advertising expense future 3mth* reports total advertising expenses in the subsequent three months: February, March, and April.

4.2 Methodology

4.2.1 Validity checks for regression discontinuity design

Hypotheses 1 to 3 in Section 3.3 make predictions about the effects of platform credit on merchants' investments in customer capital (advertising). To identify causality, we use a fuzzy RDD in our empirical analyses. In this section, we describe the discontinuity in the credit approval algorithm, provide evidence that the sorting of merchants slightly below or above this discontinuity is quasi-random, and show that there is no discernible difference in ex ante (i.e., lagged) advertising between merchants that stay below the discontinuity and merchants that will move across the threshold.

Figure 2 shows a regression-discontinuity plot presenting the average credit eligibility across nine bins below and above a credit score threshold of 480.[13] At the cutoff point, there is a

[13]As explained in Section 4.1, the forcing variable for credit access in month t is the credit score at month's end $t-1$. Hence, we construct the bins in Figure 2 with respect to merchants' lagged credit scores.

discrete jump of approximately 0.25 in the probability of being eligible for credit. However, the discontinuity is not entirely precise, as even some merchants with scores slightly below 480 are still eligible for credit, whereas some merchants with scores above 480 are denied credit access. The reasons for this can be attributed to two factors. First, as discussed in Section 3.2, AntFinancial employs additional credit exclusion criteria such as past defaults, poor service on Taobao, etc. Although we do not directly observe these criteria, they likely account for why a score above 480 does not guarantee credit access. Second, although AntFinancial normally updates credit scores at the end of each month, there are a few exceptions in which credit scores are calculated within the month, for example, when a recently listed merchant receives its credit score for the first time or when new information becomes available for a previously inactive merchant. It is possible that in some of these cases, the "within-month credit score" initially exceeds 480 but then falls below the cutoff by the end of the month. Importantly, although a score below 480 eventually renders the merchant ineligible for credit, AntFinancial withdraws credit access at the earliest in the next month. As a result, some merchants with a score below the threshold can still be credit-eligible at month's end. Given the lack of a sharp discontinuity in Figure 2, we will use a "fuzzy" RDD approach in our empirical analyses.

An important prerequisite for the validity of RDD is that agents do not manipulate the forcing variable. In our case, we have several reasons to believe that this condition is satisfied. First, merchants do not observe their credit scores and do not know how they are calculated. Hence, it seems highly unlikely that they are able to manipulate them. Second, Figure 3 shows a histogram depicting the credit scores of merchants close to the threshold of 480. The distribution exhibits a well-behaved and smooth pattern around the cutoff point, suggesting again that merchants are not manipulating their scores to gain credit access.

Finally, to identify the causal effect of platform credit on advertising in an RDD setting, we need to ensure that merchants that move across the cutoff of 480 and merchants that do not are comparable ex ante. In particular, we check whether switching and non-switching merchants already exhibit differences in advertising beforehand. Panel A of Figure 4 shows that this is not the case. Merchants that stay below 480 and merchants that switch from below to above 480 at the end of the month t have similar lagged advertising expenses throughout months $t-2$, $t-1$, and t. The Kernel densities are almost identical in both cases[14]. In Panel B of Figure 4, we plot a similar graph for merchant sales in $t-2$, $t-1$, and t. Again, the Kernel densities are almost identical for switching and non-switching merchants.

4.2.2 Regression specification

We implement the fuzzy RDD as a 2-stage instrumental variable (IV) regression in changes. In the first stage, we use changes in the credit score across the discontinuity to instrument changes in credit access. In the second stage, we regress changes in merchants' advertising expense on instrumented changes in credit access.

We ensure that the exact specification of the IV accounts for the particular structure of our data. As explained in Section 4.1, two aspects of our data are important. First, credit access in month t depends on the credit score at the end of month $t-1$. Second, advertising expenses are only reported as rolling three-months aggregates. Figure 5 illustrates how our IV model accounts for this setting, showing an example for $t =$ January 2015. As we only observe advertising expense aggregated over three months, we define the dependent variable in the second stage of the IV as a quarterly change. In the example depicted in Figure 5, this would be the difference between aggregated advertising expenses in February, March, and April

[14]The hump on the right tail is due to variable winsorization.

and expenses in November, December, and January, that is, *Advertising expense future 3mth* − *Advertising expense past 3mth*. To account for varying firm size, we standardize this quarterly change in advertising expenses by lagged sales. Alternative ways of standardizing changes in advertising would include the use of log growth rates or percentage growth rates. However, as advertising expenses are often zero, especially for merchants that do not qualify for credit yet, we would loose many observations. Standardizing by lagged sales avoids this issue. To ensure that the standardization by sales is not endogenous to changes in merchants' credit eligibility, we use the two-month lag of sales in $t-2$:

$$\Delta \textit{Advertising expense}_{i,t} = \frac{\textit{Advertising expense future 3mth}_{i,t} - \textit{Advertising expense past 3mth}_{i,t}}{3 \times \textit{Sales}_{i,t-2}}, \tag{13}$$

where we scale monthly sales in $t-2$ by factor 3 to be consistent with quarterly frequency. We use this same normalization by lagged sales also for the other dependent variables in our analysis to facilitate comparison of coefficient estimates.[15]

Since the dependent variable is defined as the quarterly change in advertising expenses, we also consider the quarterly change in credit access, which we calculate as the change in credit eligibility between quarter midpoints. In Figure 5, this would be the change in credit eligibility between December and March. For the credit score (i.e., our forcing variable or instrument), we proceed in the same way. However, we measure credit scores one month earlier than credit eligibility, due to the one-month lag in the relation between a merchant's credit score and his or her access to credit (see Section 4.1).

[15]For example in Figure 5, we would standardize *Advertising expense future 3mth* − *Advertising expense past 3mth* by sales in November.

The second stage of the IV is specified as in Equation (14):

$$\Delta Advertising\ expense_{i,t} = \beta\ Credit\ ineligible \rightarrow eligible_{i,t} + Controls + \epsilon_{i,t}\ , \tag{14}$$

where Δ*Advertising expense* is the quarterly change in advertising expenses defined in Equation (13). The binary variable *Credit ineligible* $\rightarrow$ *eligible* equals one if merchants' credit access switches from "ineligible" to "eligible" between quarters, and zero otherwise. The vector of *Controls* includes the continuous change in the credit score as well as industry and month fixed effects.[16] In keeping with Hypothesis 1, we predict that the coefficient estimate for β in Equation (14) is positive. Financially constrained merchants invest more into customer capital (advertise more) after receiving access to platform credit. In the first stage of the IV, we regress *Credit ineligible* $\rightarrow$ *eligible* on the instrument *CS below 480* $\rightarrow$ *above 480* and the same set of controls as in Equation (14):

$$Credit\ ineligible \rightarrow eligible_{i,t} = \gamma\ CS\ below\ 480 \rightarrow above\ 480_{i,t} + Controls + \mu_{i,t}\ , \tag{15}$$

where the binary variable *CS below 480* $\rightarrow$ *above 480* equals one if merchants' credit score switches from below 480 to above 480 between quarters, and zero otherwise. We cluster standard errors at the industry level.[17]

One concern about our methodology could be that we are using a monthly panel to estimate a regression model whose variables are measured at a rolling quarterly horizon and, hence, overlap across adjacent months (Figure 1). To address this concern, we also estimate the IV model as

[16] We use the proprietary industry classification used by Alibaba.

[17] Conventionally, a minimum of 50 clusters is considered as the threshold for clustering to be valid. The merchants in our regression sample are distributed across more than 100 industries, as defined by Alibaba. Note that the short length of the panel does not allow us to cluster by time.

a cross-sectional regression for each month separately. Specifically, we run Equations (14) and (15) in separate subsamples for $t =$ January 2015, $t =$ February 2015, $t =$ March 2015, etc. Each of these individual regressions only considers one cross-section of quarterly changes, and there is no overlap in rolling variables. As we will show in Section 5, the coefficient estimates and standard errors are similar in these subsample regressions and in the pooled panel estimation.

4.3 Summary statistics

Table 1 shows summary statistics for the regression sample studied in the empirical analysis. As explained in Section 4.1, our sample is restricted to merchants with credit scores ranging between 460 and 500. The sample mean and median of the credit score CS equal 483 and 485, respectively. Hence, the distribution of credit scores centers around the discontinuity of the credit allocation process at 480. *Credit eligibility* is a binary variable that equals one if a merchant qualifies for credit from AntFinancial in a given month and zero otherwise. Merchants with credit access account for 63% of all observations. The average stock of outstanding credit that merchants have not repaid yet equals RMB 14,413 and has a standard deviation of RMB 32,436. The small credit amounts can be attributed to the prevalence of small businesses and individual entrepreneurs among the merchants on Taobao. Indeed, average sales over last three months equal only RMB 96,302 and even the 90th percentile equals only RMB 232,100. Average advertising expense equals RMB 2,445, but the distribution is skewed with the median of advertising expense being zero. Shop visibility among customers is also distributed unevenly with a few merchants being visited much more often than the majority.

In Panel B of Table 1, we report the summary statistics for the variables in changes we use in the regressions. The quarterly change in the credit score has a mean of only -2.4 but a standard deviation of 19.82, which is sizeable considering that our sample is restricted to a bandwidth of scores between 460 and 500. A total of 16% of all observations correspond to cases in which merchants' credit scores transition from below to above the threshold of 480 between quarters. Likewise, 17% of the sample corresponds to cases in which AntFinancial grants credit access to previously ineligible merchants. The similar distributions of *CS below 480* $\rightarrow$ *above 480* and *Credit ineligible* $\rightarrow$ *eligible* highlight that the credit score threshold at 480 is indeed the primary determinant of credit access. Our dependent variable Δ *Advertising expense* has a mean close to zero but its standard deviation is much larger at 0.15. Like Δ *Advertising expense*, the variables Δ *Sales*, Δ *Shop visits*, and Δ *Credit amount* are defined as quarterly changes and standardized by lagged sales. Variables are winsorized at the 1% level.

5 Empirical Analysis

We now turn to the empirical analysis of Hypotheses 1 to 3. In Section 5.1, we establish that quasi-random access to platform credit leads Taobao merchants to invest more in customer capital through advertising. In Section 5.2, we show that this effect is stronger for high-quality merchants with better ratings. In Section 5.3, we provide evidence that platform-financed advertising improves merchants' visibility among customers and ultimately their sales performance.

5.1 Advertising and platform credit

We begin by estimating the 2-stage IV regression model that was introduced in Section 4.2.2 as a test for Hypothesis 1. Table 2, Panels A and B show the first and second-stage regressions, respectively. In column 1, we estimate the IV in the full data set pooling all months from

January to May 2015. The coefficient of 0.255 in the first stage is positive and statistically significant. Merchants whose credit scores move across the threshold of 480 are 25% more likely to receive access to platform credit from AntFinancial. This regression estimate of 25% is similar to the discrete jump in credit-eligibility at a score of 480 observed in Figure 2. Hence, the first stage of our IV seems to model the discontinuity in the credit allocation process correctly.[18]

Panel B of Table 2 shows the corresponding second-stage regression for the effect of an instrumented change in credit access on merchants' advertising expenses. The coefficient estimate of 0.024 in column 1 is statistically significant and large compared to a sample mean and standard deviation of only 0.02 and respectively 0.15 for Δ *Advertising expense*. As this dependent variable is standardized by lagged sales, the coefficient implies that for each RMB in sales, merchants increase advertising by an additional RMB 0.024 in the next quarter. Consistent with Hypothesis 1, this result suggests that merchants were financially constrained initially and thus underinvested in customer capital before accessing platform credit.[19]

As explained in Sections 4.1 and 4.2.2, our regression model must account for the particular structure of our data. Whereas the sample frequency is monthly, advertising expenses are only reported as rolling three-month aggregates. Hence, the regression variables overlap between adjacent months when we use the full panel of merchant-month observations in column 1 of Table 2. To show that this particular structure does not have any undue effects on our estimation, we re-estimate the IV model as cross-sectional regressions for each month in our sample separately. These subsample regressions are shown in columns 2 to 6. We find that the

[18] See Section 4.2.1 for our validity checks of the RDD.

[19] Assume the opposite was true and merchants were financially *un*constrained initially. In that case, they would be able to finance advertising already before gaining access to platform credit. More generally, in the absence of financial frictions, merchants' investment decisions would be independent of access to platform credit (Modigliani and Miller, 1958). In particular, advertising would not depend on platform credit. The fact that platform credit boosts advertising in reality allows us to reject this null hypothesis (see Section 3.3).

estimation is largely robust across the different subsamples. Importantly, the effect of credit access on advertising (Panel B) is always positive and statistically significant in all subsamples except in the cross-section for January 2015 (column 2). In the subsamples for February to May 2015, the point estimates vary between 0.014 and 0.033 and are thus distributed around the panel estimate of 0.024 in column 1.

The increase in advertising expenses following credit access accounts for a sizeable part of the funds that merchants borrow from AntFinancial. In Table 3, column 1, we use the change in credit Δ *Credit amount* as the dependent variable in the second stage of the IV (Panel B). Unsurprisingly, (instrumented) credit access has a positive effect on merchants' borrowing. The second-stage coefficient of 0.145 is roughly six times as large as the coefficient of 0.024 in the original IV model for Δ *Advertising expense*, which is reproduced in column 2 of Table 3 for ease of comparison. In other words, merchants use 17% ($\approx 0.024/0.145$) of their platform credit to finance new advertising expenses. We note that we can compare the coefficients for Δ *Credit amount* and Δ *Advertising expense* in columns 1 and 2 because both variables are standardized identically (by lagged sales). Nevertheless, we also re-estimate the pass-through of credit to advertising in a single regression model. In column 3 of Table 3, we directly regress Δ *Advertising expense* on Δ *Credit amount*, which is itself instrumented by *CS below 480* $\rightarrow$ *above 480*. The second-stage coefficient of 0.168 again suggests that roughly 17% of credit passes through to advertising. In general, the results in column 3 are fully consistent with the first and the second stages in columns 1 and 2.[20]

Overall, the evidence in Tables 2 and 3 suggests that, consistent with Hypothesis 1, access

[20] In column 1, Δ *Credit amount* increases by on average 0.037 ($\approx 0.256 * 0.145$) when a merchant's credit score transitions from below to above 480. This number is identical to the first-stage coefficient in column 3. The pass through of credit to advertising of 16.8% in the second stage of column 3 is identical to the pass through implied by the stage-two coefficients in columns 1 and 2 (17% $\approx 0.024/0.145$).

to platform credit increases merchants' investments in customer capital, possibly by relaxing financial constraints that initially prevent merchants from advertising.

5.2 Merchant quality and platform credit

Next, we analyze how the effect of platform credit on advertising depends on the ex ante quality of Taobao merchants (Hypothesis 2). Table 4 shows an adjusted version of our IV model. In the second stage (column 3), we regress Δ *Advertising expense* on an additional interaction term *Credit ineligible* $\rightarrow$ *eligible* $\times$ *High quality*. The binary variable *High quality* equals one if the merchant's lagged customer rating for product quality, delivery, and service exceeds the sample median, and zero otherwise.[21] Column 2 shows the first stage for the new interaction term *Credit ineligible* $\rightarrow$ *eligible* $\times$ *High quality*. The IV model is just-identified, as we include one additional instrument, the interaction term *CS below 480* $\rightarrow$ *above 480* $\times$ *High quality*.

In column 3, the second stage shows a significant coefficient of 0.049 for the instrumented interaction term *Credit ineligible* $\rightarrow$ *eligible* $\times$ *High quality*, whereas the coefficient of -0.002 for the base variable *Credit ineligible* $\rightarrow$ *eligible* is essentially zero. As predicted by Hypothesis 2, platform credit only boosts advertising by high-quality merchants. In principle, there are two plausible explanations for this heterogeneous effect on high and low-quality merchants: (i) advertising is only profitable for high-quality merchants; (ii) only high-quality merchants are financially constrained before receiving platform credit. Explanation (i) is the one we also propose in our model in Section 2.2: When a potential buyer on Taobao clicks on an advertisement link and is redirected to a merchant's shop page, he or she will be more inclined to actually buy something if the shop page shows excellent ratings by the merchant's past

[21] *High quality* is based on the equally weighted average of three ratings for quality, delivery, and service.

customers. By contrast, the bad ratings of low-quality merchants likely deter the potential buyer. Hence, advertising could have a higher expected return for high-quality merchants, who therefore increase advertising when they receive platform funding.

Explanation (ii), on the other hand, states that access to platform credit only increases advertising by high-quality merchants because they are more financially constrained than low-quality merchants ex ante.[22] However, two arguments speak against this alternative explanation. First, a prerequisite for adverse selection is asymmetric information between borrowers and lenders. But in Table 4, our measure of merchant quality is based on customer ratings, which are publicly observable and available to traditional banks, too. Second, further evidence suggests that financial constraints are not stronger but in fact weaker for high-quality merchants: Table 5 reports a similar IV model as Table 4 but uses Δ *Credit amount* as the dependent variable in the second stage (column 3). The coefficient of -0.214 for the interaction term *Credit ineligible* $\rightarrow$ *eligible* $\times$ *High quality* shows that the uptake of platform credit is lower for high than for low-quality merchants. To be sure, total credit uptake of 0.051 ($= 0.265 - 0.214$) is still positive for high-quality merchants. However, the uptake by low-quality merchants is about 5 times larger ($5 \approx 0.265/0.051$). Considering their stronger credit uptake, low-quality merchants seem to have been more financially constrained than high-quality ones before qualifying for credit from AntFinancial.[23]

Importantly, the high-quality merchants use almost all their platform credit for advertising, as their uptake of 0.051 ($= 0.265 - 0.214$) closely matches their increase in advertising expenses

[22] As discussed in Section 3.3, high-quality borrowers can suffer from credit rationing due to adverse selection in bank credit markets (Stiglitz and Weiss, 1981). As a result, high-quality merchants would benefit more from platform credit and advertise more than low-quality merchants even if advertising profitability was identical.

[23] Our analysis remains agnostic about the reasons why low-quality merchants would be more financially constrained. One possible explanation could be that moral hazard is a larger concern for low-quality merchants, which thus struggle more to obtain bank funding in the absence of platform credit (see Section 3.3). For example, Bester (1994) predicts that traditional lenders worry more about strategic default for riskier borrowers.

by 0.047 ($= 0.049 - 0.002$) in Table 4.[24] Overall, we draw the following conclusions from Tables 4 and 5: After receiving quasi-random access to platform credit, both low and high-quality merchants borrow from AntFinancial, suggesting that both were financially constrained ex ante. However, the larger credit uptake by the low-quality merchants suggests that their financial constraints have been relatively tighter. Consistent with the hypothesis that advertising is more profitable for high-quality merchants with good customer ratings, we observe that the high-quality merchants use their platform credit almost exclusively for an increase in advertising, whereas advertising by low-quality merchants remains unchanged.

5.3 Platform visibility, sales growth, and platform credit

In Section 3.3, Hypothesis 3 predicts that platform-financed advertising allows merchants to build customer capital and ultimately to grow faster. Indeed, existing research has shown that customer capital is one of the most important determinants of firm profitability and growth, especially for small firms and entrepreneurs (Ferraz et al., 2015; Foster et al., 2008, 2016). If this narrative is correct, we should observe that merchants who use platform credit to increase advertising perform better in terms of customer visibility and sales in subsequent months.

Table 6 reports second-stage regression for quarterly changes in the number of buyers that visit a merchant's shop page (columns 1 and 2) and for quarterly changes in sales (columns 3 and 4).[25] Columns 1 and 3 show regressions without interaction terms. The positive and significant coefficient estimates for *Credit ineligible* $\rightarrow$ *eligible* reveal that shop visits and sales increase for the average Taobao merchant that gains access to credit from AntFinancial. Importantly, the

[24] We can compare the effects of platform credit on Δ *Credit amount* and Δ *Advertising expense* because both dependent variables are calculated as absolute changes in RMB standardized by lagged sales.

[25] As all previous dependent variables, Δ *Shop page visits* and Δ *Sales* are standardized by lagged sales in the month prior to when we measure any potential change in credit eligibility (see Section 4.2.2).

increase in shop page visits is concentrated among those merchants that were previously shown to increase advertising. In column 2, the effect of platform credit on Δ *Shop page visits* is only 0.015 for the low-quality merchants but 0.143 (= 0.015 + 0.128) for high-quality merchants. As high-quality merchants spend their platform credit almost exclusively on advertising (see Section 5.2), we are confident that the effect of platform credit on shop visits operates indeed through advertising and not through other investments. The increase in shop visits reflects an increase in visibility among customers, which seems to translate into higher revenues. Column 4 shows that only the high-quality (advertising) merchants manage to grow their sales in the months following access to platform credit. By contrast, the effect on Δ *Sales* is much smaller and statistically insignificant for the low-quality (non-advertising) merchants.

Consistent with Hypothesis 3, our findings suggest that platform credit relaxes financial constraints, thereby allowing high-quality merchants to build customer capital in the form of higher shop visibility and demand. By contrast, low-quality merchants experience no improvement in visibility or sales, consistent with our finding that they do not borrow to advertise.

6 Conclusion

Our analyses show that access to platform credit can play a significant role in overcoming financial constraints faced by small merchants on e-commerce platforms, enabling them to invest in customer capital through increased advertising. Studying quasi-random access to platform credit from Alibaba, we establish that financially constrained firms can use platform funding to boost visibility and drive sales growth. The impact of platform credit is particularly pronounced among high-quality merchants, who allocate a greater portion of their borrowing to advertising, resulting in the acquisition of more customers. Overall, our study suggests unique advantages of platform lenders in providing credit for intangible assets, such as customer capital, that are difficult to collateralize and may, hence, remain unfunded by traditional banks.

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Figure 1: **Data structure**

This figure illustrates our data structure. The sample frequency is monthly, but advertising expenses are reported as rolling three-months aggregates.

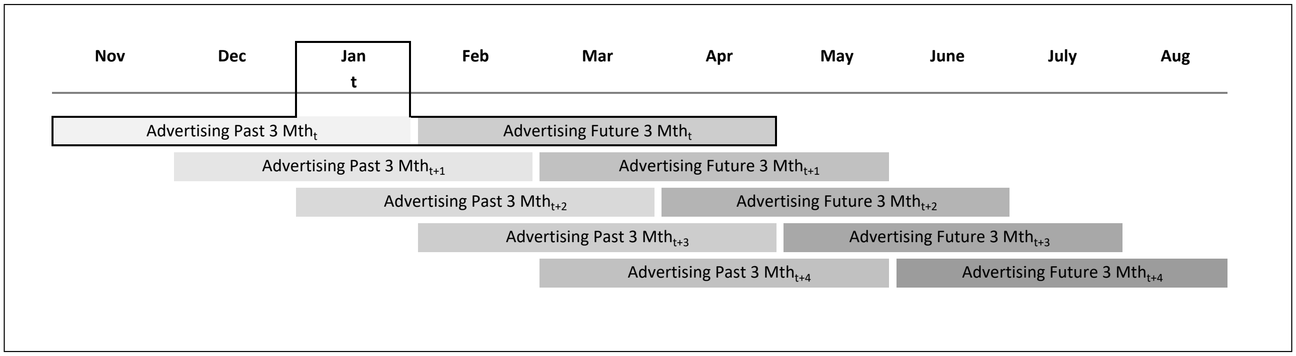


Figure 2: **Discontinuity graph**
This figure shows average credit eligibility (vertical axis) across bins of credit scores around the cutoff at 480 in the credit allocation process (horizontal axis).

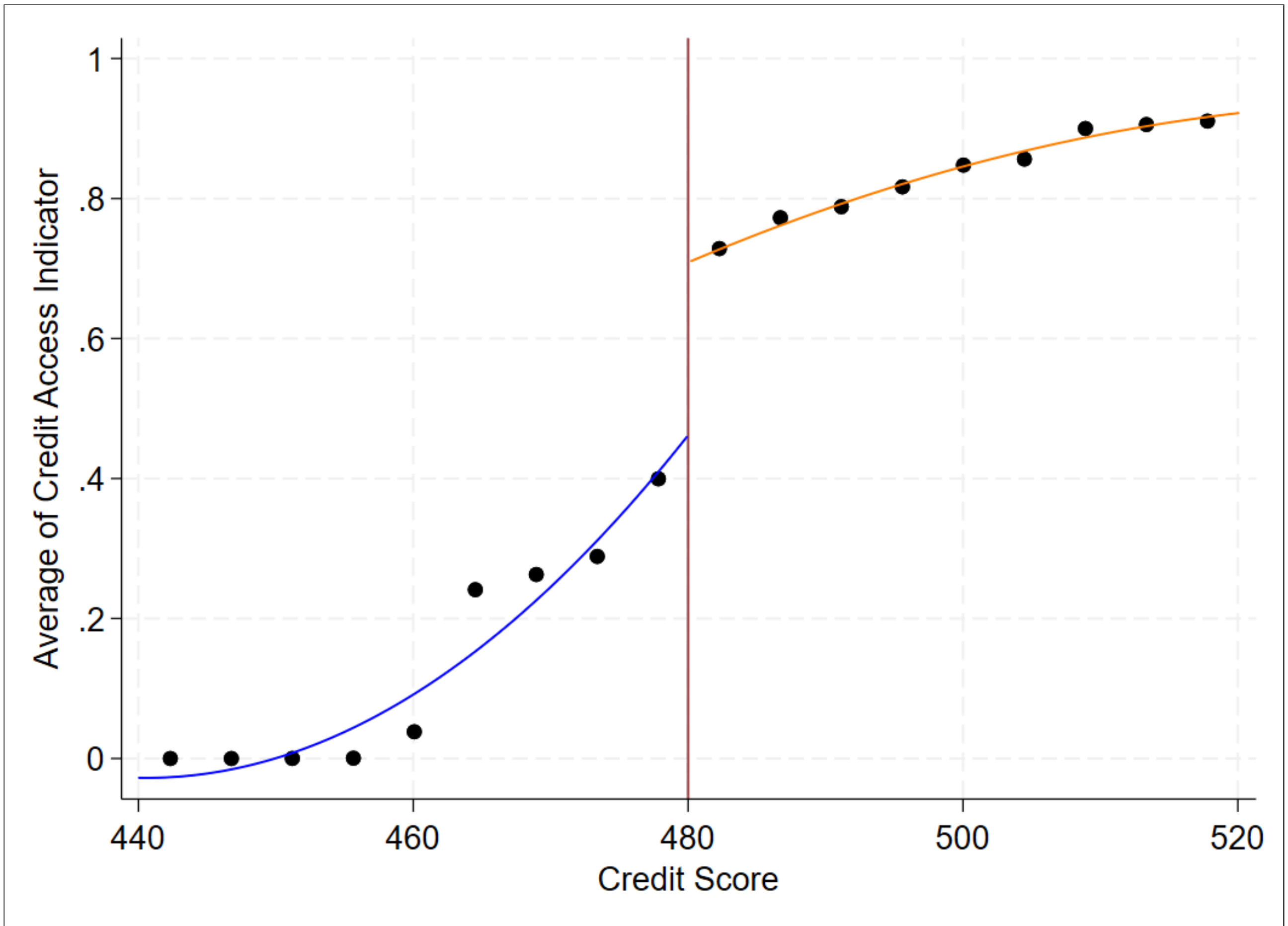


Figure 3: **Histogram of credit scores**
This figure shows the distribution of credit scores between 460 and 500.

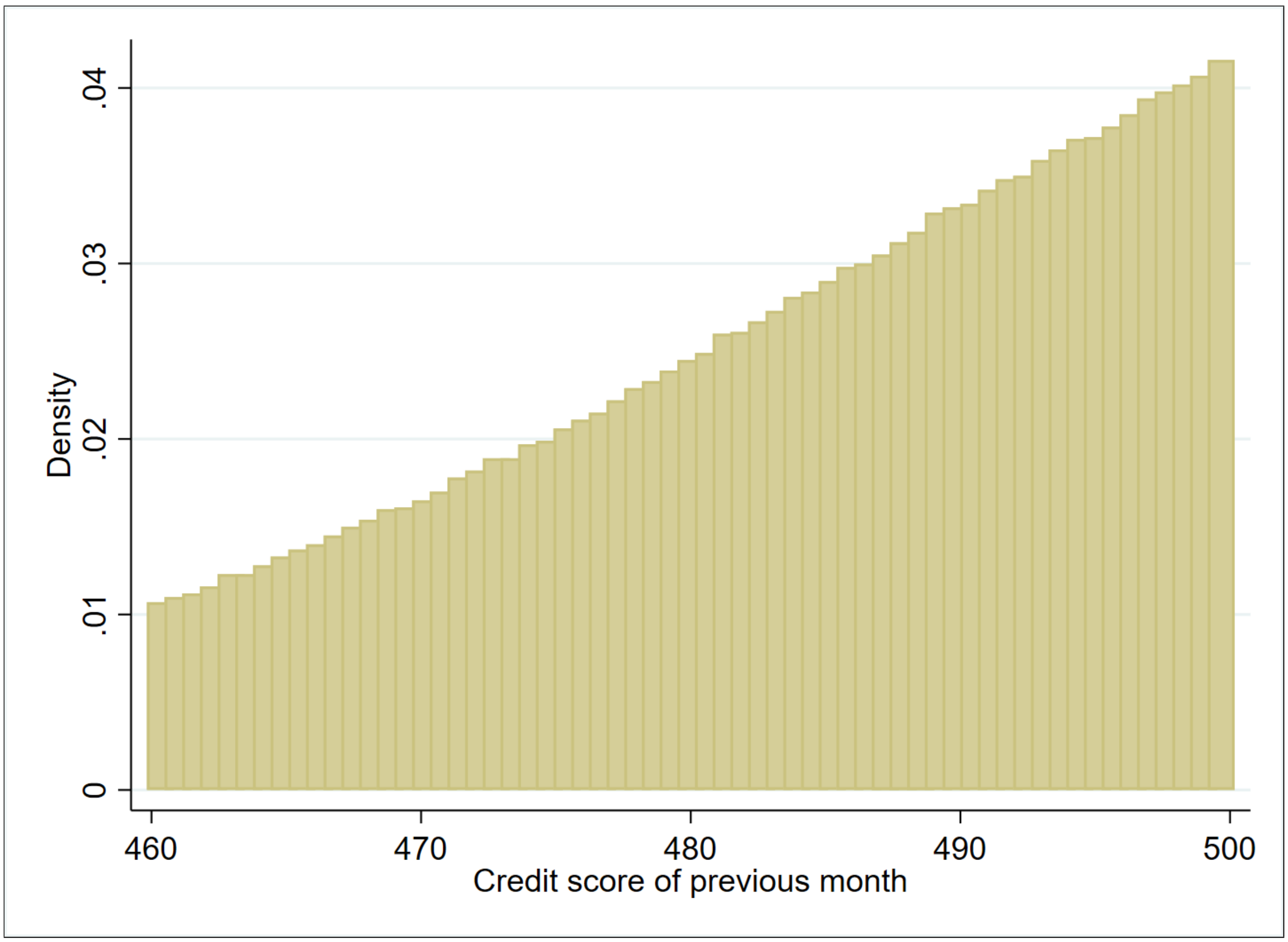
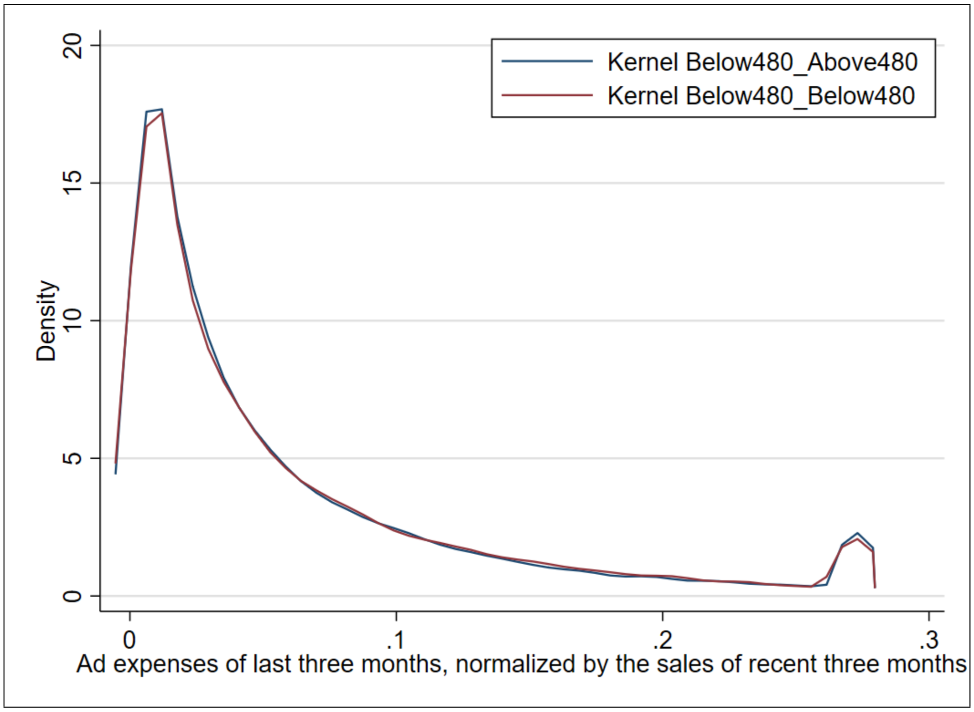


Figure 4: **Panel A (Distribution of lagged advertising expense)**
This figure shows Kernel desnisities of lagged advertising expense standardized by lagged sales for merchants with an initial credit score below the cutoff at 480 that either transition above a score of 480 (blue line) or remain below 480 (red line). The Kernels are drawn for merchants with strictly positive advertising expense; the hump on the right tail is due to variable winsorization.



Panel B (Distribution of lagged sales)
This figure shows sales of the recent three months for merchants with an initial credit score below the cutoff at 480 that either transition above a score of 480 (blue line) or remain below 480 (red line); outliers in the right tail are not plotted.

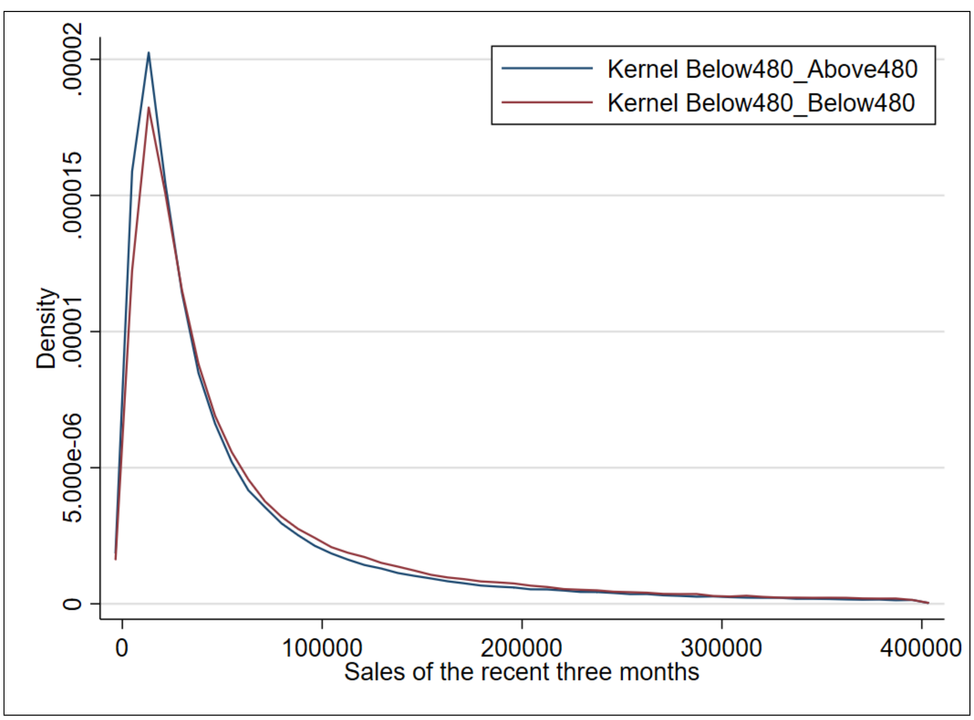


Figure 5: **Timing of credit eligibility**
This figure illustrates when we measure (changes in) merchants' credit scores and credit eligibility status for the example of t = January 2015.

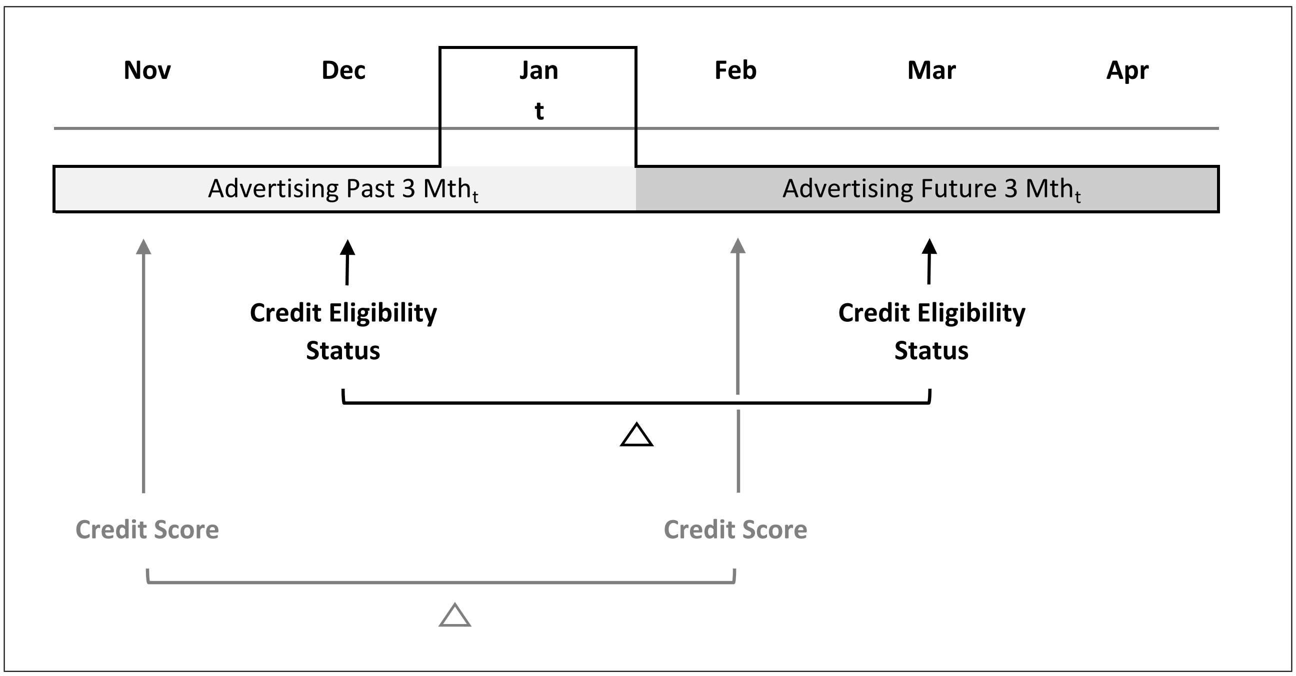


Table 1: **Summary statistics**

This table reports summary statistics for the variables used in our regression analysis. The sample comprises merchants with a credit score (*CS*) between 460 and 500 and the period from January to May 2015. Panels A and B report variables in levels and in changes, respectively. The variables in changes, Δ *Advertising expense*, Δ *Sales*, Δ *Shop visits*, and Δ *Credit amount*, are standardized by lagged sales as shown in Equation (13). All variables are winsorized at 1%.

	Obs. (1)	Mean (2)	S.D. (3)	P10 (6)	P25 (7)	P50 (8)	P75 (9)	P90 (10)
Panel A: Variables in levels								
CS	658,311	483.49	10.38	468.16	475.70	484.70	492.15	496.63
Credit eligible	658,311	0.63	0.48	0.00	0.00	1.00	1.00	1.00
Credit amount	658,311	14,412.61	32,435.86	0	5,000	10,000	11,000	21,450
Sales	658,311	96,301.74	163,430.04	8,200	16,700	38,600	97,100	232,100
Advertising expense	658,311	2,445.26	8,007.30	0	0	0	700	5,400
Shop visits (per month)	658,311	495.55	4,074.06	0	100	100	300	800
Customer rating	658,311	4.68	0.49	4.47	4.64	4.75	4.86	4.96
Panel B: Variables in changes								
Δ *CS*	658,311	–2.40	19.82	–27.79	–14.42	–1.59	10.18	21.71
CS below 480 → *above 480*	658,311	0.16	0.37	0.00	0.00	0.00	0.00	1.00
Credit ineligible → *eligible*	658,311	0.17	0.37	0.00	0.00	0.00	0.00	1.00
Δ *Advertising expense*	658,311	0.02	0.15	–0.02	0.00	0.00	0.00	0.04
Δ *Sales*	646,350	0.68	4.63	–1.05	–0.56	–0.26	0.40	2.32
Δ *Shop visits*	648,190	–0.01	0.64	–0.33	–0.14	–0.05	0.02	0.27
Δ *Credit amount*	648,192	–0.09	0.99	–0.55	–0.10	0.00	0.02	0.35

Table 2: **Effect of platform credit on advertising**

This table shows coefficient estimates from 2-stage least squares instrumental variable (IV) regressions. Panels A and B report the first and second stage, respectively. In the first stage, *Credit ineligible → eligible* equals one if merchants' credit access switches from "ineligible" to "eligible" between quarters, and zero otherwise. It is instrumented with *CS below 480 → above 480*, which equals one if merchants' credit score switches from below 480 to above 480. Δ *Advertising expense* is the quarterly change in advertising expenses normalized by lagged sales. All columns control for industry fixed effects and the continuous change in the credit score. Column 1 additionally controls for time fixed effects. The sample is restricted to merchants with a credit score between 460 and 500. In column 1, we estimate the IV in the full data set pooling all months from January to May 2015. In columns 2 to 6, we estimate the IV model as cross-sectional regressions for each month in our sample separately. Robust standard errors are clustered at the industry level. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First-stage regressions						
			Credit ineligible → eligible			
CS below 480 → above 480	0.255***	0.173***	0.329***	0.333***	0.312***	0.119***
	(0.006)	(0.008)	(0.008)	(0.011)	(0.011)	(0.004)
Panel B: Second-stage regressions						
			Δ *Advertising expense*			
Credit ineligible → eligible (instrumented)	0.024***	0.004	0.021***	0.033***	0.014**	0.033***
	(0.003)	(0.008)	(0.005)	(0.004)	(0.007)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample period:	All months	Jan 2015	Feb 2015	Mar 2015	Apr 2015	May 2015
Obs.	658,304	129,903	133,220	137,774	132,744	124,646
F-stat of excluded instrument	1,859.8	475.2	1520.1	989.8	770.9	948.5
Bandwidth (CS)	[460;500]	[460;500]	[460;500]	[460;500]	[460;500]	[460;500]

Table 3: **Pass-through of platform credit to advertising**
This table shows coefficient estimates from 2-stage least squares instrumental variable (IV) regressions. Panels A and B report the first and second stages, respectively. In columns 1 and 2, we instrument *Credit ineligible* $\rightarrow$ *eligible* with *CS below 480* $\rightarrow$ *above 480*. In the second stage, the dependent variables are Δ *Credit amount* and Δ *Advertising expense* in columns 1 and 2, respectively. In column 3, we directly instrument Δ *Credit amount* by *CS below 480* $\rightarrow$ *above 480* in Panel A to explain Δ *Advertising expense* in Panel B. Δ *Credit amount* is defined as the quarterly change in outstanding credit normalized by lagged sales. All other variables and controls are identical to those in column 1 of Table 2. The sample is restricted to merchants with a credit score between 460 and 500 and the month January to May 2015. Robust standard errors are clustered at the industry level. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
Panel A: First-stage regressions			
	Credit ineligible $\rightarrow$ *eligible*	*Credit ineligible* $\rightarrow$ *eligible*	Δ *Credit amount*
CS below 480 $\rightarrow$ *above 480*	0.255***	0.255***	0.037***
	(0.006)	(0.006)	(0.006)
Panel B: Second-stage regressions			
	Δ *Credit amount*	Δ *Advertising expense*	Δ *Advertising expense*
Credit ineligible $\rightarrow$ *eligible*	0.145***	0.024***	
	(0.026)	(0.003)	
Δ *Credit amount*			0.168***
			(0.026)
Controls	Yes	Yes	Yes
Obs.	648,184	658,304	648,184
F-stat of excluded instrument	1,844.2	1,859.8	36.29
Bandwidth (CS)	[460;500]	[460;500]	[460;500]

Table 4: **Merchant quality, platform credit, and advertising**

This table shows coefficient estimates from 2-stage least squares instrumental variable (IV) regression. The IV model is similar to the one in Table 2 except that the second stage, reported in column 3, further includes the regressor *High quality* and its interaction *Credit ineligible → eligible × High quality*. The model has two first stages reported in columns 1 and 2 and is just-identified by the instruments *CS below 480 → above 480* and *CS below 480 → above 480 × High quality*. *High quality* is a binary variable that equals one if the merchant's lagged customer rating exceeds the median, and zero otherwise. All other variables and controls are identical to those in column 1 of Table 2. The sample is restricted to merchants with a credit score between 460 and 500, and the months January to May 2015. Robust standard errors are clustered at the industry level. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
	First stages		Second stage
	Credit ineligible → eligible	*Credit ineligible → eligible × High quality*	*Δ Advertising expense*
CS below 480 → above 480 × High quality	−0.005	0.324***	
	(0.007)	(0.005)	
CS below 480 → above 480	0.257***	−0.042***	
	(0.009)	(0.005)	
Credit ineligible → eligible × High quality			0.049***
			(0.005)
Credit ineligible → eligible			−0.002
			(0.003)
High quality	0.035***	0.132***	0.001
	(0.002)	(0.003)	(0.001)
Controls	Yes	Yes	Yes
Obs.	658,304	658,304	658,304
F-stat of the excluded instruments	1,615.4	2,885.8	–
Bandwidth (CS)	[460;500]	[460;500]	[460;500]

Table 5: **Merchant quality and credit uptake**
This table shows coefficient estimates from 2-stage least squares instrumental variable (IV) regression. The IV model is identical to the one in Table 4 except that the dependent variable in the second stage is Δ *Credit amount*. The sample is restricted to merchants with a credit score between 460 and 500, and the months January to May 2015. Robust standard errors are clustered at the industry level. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
	First stages		Second stage
	Credit ineligible → eligible	*Credit ineligible → eligible × High quality*	Δ *Credit amount*
CS below 480 → above 480 × High quality	−0.005	0.324***	
	(0.007)	(0.005)	
CS below 480 → above 480	0.257***	−0.042***	
	(0.009)	(0.005)	
Credit ineligible → eligible × High quality			−0.214***
			(0.036)
Credit ineligible → eligible			0.265***
			(0.025)
High quality	0.035***	0.132***	−0.089***
	(0.002)	(0.003)	(0.006)
Controls	Yes	Yes	Yes
Obs.	658,304	658,304	648,184
F-stat of the excluded instruments	1,634.1	2,908.4	–
Bandwidth (CS)	[460;500]	[460;500]	[460;500]

Table 6: **Platform visibility, sales growth, and platform credit**
This table shows coefficient estimates from 2-stage least squares instrumental variable (IV) regression. Only the second-stage regressions are reported. The dependent variables are Δ *Shop page visits* in columns 1 and 2 and Δ Sales in columns 3 and 4. Both are defined as quarterly changes and measure the number of customers that visit a merchant's shop page and its sales normalized by lagged sales. All other variables and controls are identical to those in previous tables. The IV models in columns 1 and 3 each have one first stage, which is identical to the first stage in column 1 of Table 2. The IV models in columns 2 and 4 each have two first stages, which are defined as in Tables 4 and 5. The sample is restricted to merchants with a credit score between 460 and 500, and the months January to May 2015. Robust standard errors are clustered at the industry level. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Second-stage regressions	(1)	(2)	(3)	(4)
Dependent variable:	Δ *Shop page visits*		Δ *Sales*	
Credit ineligible → eligible	0.085***	0.015	1.266***	0.081
	(0.027)	(0.015)	(0.134)	(0.081)
Credit ineligible → eligible × High quality		0.128***		2.202***
		(0.033)		(0.087)
High quality		0.038***		0.150***
		(0.004)		(0.031)
Controls	Yes	Yes	Yes	Yes
Obs.	648,182	648,182	646,342	646,342
Bandwidth (CS)	[460;500]	[460;500]	[460;500]	[460;500]

A Analytical Proof of Proposition H1

We begin with the following first–order conditions:

$$(1+\mu)\Big[f(\alpha)-k\Big]+g(\alpha)=0, \tag{FOC 1}$$

$$(1+\mu)f'(\alpha)+g'(\alpha)=0, \tag{FOC 2}$$

$$m_0+f(\alpha)l-kl=0, \tag{FOC 3}$$

where

$$\begin{aligned}
f(\alpha) &= \frac{1}{R_f}\left[\lambda\gamma\int_{\underline{z}}^{\alpha/\gamma} z\,d\Phi(z)+\alpha\int_{\alpha/\gamma}^{\overline{z}} d\Phi(z)\right] \\
&= \frac{1}{R_f}\left[\lambda\gamma\int_{\underline{z}}^{\alpha/\gamma} z\,\phi(z)\,dz+\alpha\int_{\alpha/\gamma}^{\overline{z}} \phi(z)\,dz\right], \\
g(\alpha) &= \beta\int_{\alpha/\gamma}^{\overline{z}}(\gamma z-\alpha)\,d\Phi(z) \\
&= \beta\gamma\int_{\alpha/\gamma}^{\overline{z}} z\,\phi(z)\,dz-\beta\alpha\int_{\alpha/\gamma}^{\overline{z}}\phi(z)\,dz,
\end{aligned}$$

and

$$\begin{aligned}
f'(\alpha) &= \frac{1}{R_f}\left[\lambda\,\frac{\alpha}{\gamma}\,\phi\!\left(\frac{\alpha}{\gamma}\right)+\int_{\alpha/\gamma}^{\overline{z}}\phi(z)\,dz-\frac{\alpha}{\gamma}\,\phi\!\left(\frac{\alpha}{\gamma}\right)\right], \\
g'(\alpha) &= \beta\left[-\frac{\alpha}{\gamma}\,\phi\!\left(\frac{\alpha}{\gamma}\right)-\int_{\alpha/\gamma}^{\overline{z}}\phi(z)\,dz+\frac{\alpha}{\gamma}\,\phi\!\left(\frac{\alpha}{\gamma}\right)\right]=-\beta\int_{\alpha/\gamma}^{\overline{z}}\phi(z)\,dz.
\end{aligned}$$

Assumption on the Distribution

Assume that z follows a uniform distribution on $[\underline{z}, \overline{z}]$ with probability density function (PDF)

$$p = \frac{1}{\overline{z} - \underline{z}}.$$

Then, the functions $f(\alpha)$ and $f'(\alpha)$ simplify to

$$f(\alpha) = \frac{1}{R_f} \left[\frac{\lambda \gamma p}{2} \left(\frac{\alpha^2}{\gamma^2} - \underline{z}^2 \right) + \alpha p \left(\overline{z} - \frac{\alpha}{\gamma} \right) \right],$$

and

$$f'(\alpha) = \frac{p}{R_f} \left[\frac{\alpha}{\gamma} (\lambda - 2) + \overline{z} \right].$$

Similarly, we have

$$g(\alpha) = \frac{\beta p}{2\gamma} (\gamma \overline{z} - \alpha)^2, \quad g'(\alpha) = \frac{\beta p}{\gamma} (\alpha - \gamma \overline{z}).$$

A.1 Derivation of the Optimal Advertising Threshold α^*

By combining equations (FOC 1) and (FOC 2), we obtain

$$f'(\alpha)\, g(\alpha) = g'(\alpha) \Big[f(\alpha) - k \Big],$$

evaluated at $\alpha = \alpha^*$. After substituting the expressions for $f(\alpha)$, $f'(\alpha)$, $g(\alpha)$, and $g'(\alpha)$ and simplifying, we arrive at

$$\frac{1}{2} (\alpha - \gamma \overline{z}) \left[\frac{\alpha}{\gamma} (\lambda - 2) + \underline{z} \right] = \frac{\lambda \gamma}{2} \left(\frac{\alpha^2}{\gamma^2} - \underline{z}^2 \right) + \alpha \left(\overline{z} - \frac{\alpha}{\gamma} \right) - \frac{k R_f}{p}.$$

Solving this equation yields the optimal threshold

$$\alpha^* = \frac{\gamma\big(\overline{z}\,\underline{z} - \lambda\,\underline{z}^2\big) - \dfrac{2kR_f}{p}}{\underline{z} - \lambda\,\overline{z}}.$$

The derivative of α^* with respect to λ is given by

$$\frac{\partial \alpha^*}{\partial \lambda} = \frac{\gamma \underline{z}\,(\overline{z}^2 - \underline{z}^2) - 2kR_f\,\overline{z}(\overline{z} - \underline{z})}{\Big(\underline{z} - \lambda\overline{z}\Big)^2}.$$

After further simplification, we can write

$$\frac{\partial \alpha^*}{\partial \lambda} = \frac{(\overline{z} - \underline{z})\Big[\gamma\underline{z}(\overline{z} + \underline{z}) - 2k\overline{z}R_f\Big]}{\Big(\underline{z} - \lambda\overline{z}\Big)^2}.$$

Since $\overline{z} > \underline{z}$ and if γ is sufficiently large so that

$$2k\overline{z}R_f < \gamma\underline{z}(\overline{z} + \underline{z}),$$

we have $\frac{\partial \alpha^*}{\partial \lambda} > 0$, meaning that α^* increases with λ.

From (FOC 3), the resource constraint binds:

$$l^* = \frac{m_0}{k - f(\alpha^*)}.$$

Calculation of $f'(\alpha^*)$

We have

$$f'(\alpha^*) = \frac{p}{R_f}\left[\frac{\alpha^*}{\gamma}(\lambda - 2) + \overline{z}\right].$$

After substituting the expression for α^* and performing algebraic manipulations (details omitted for brevity), we obtain an equivalent expression:

$$f'(\alpha^*) = \frac{\gamma\,\overline{z}^2\,p\,(\lambda-1) + (\lambda-2)\Big(2R_f\,k + \gamma\,p\big(\lambda\,\underline{z}^2 - \overline{z}^2\big)\Big)}{R_f\,\gamma\,\overline{z}\,(\lambda-1)}.$$

Under our model assumptions (i.e., $p > 0$, $R_f > 0$, $\gamma > 0$, $\overline{z} > 0$, and $\lambda < 1$), each term in the numerator and denominator is positive. Consequently,

$$f'(\alpha^*) > 0.$$

It follows that

$$\frac{\partial l^*}{\partial \lambda} = \frac{f'(\alpha^*)}{(k - f(\alpha^*))^2} \cdot \frac{\partial \alpha^*}{\partial \lambda} > 0,$$

so that the optimal advertising expenditure l^* increases with λ.

B Analytical Proof of Proposition H2

We now analyze the sensitivity of the optimal threshold with respect to the merchant quality parameter γ. In particular, note that

$$\frac{\partial}{\partial \gamma}\left(\frac{\partial \alpha^*}{\partial \lambda}\right) = \frac{\underline{z}\,(\overline{z}^2 - \underline{z}^2)}{\Big(\underline{z} - \lambda\overline{z}\Big)^2} > 0.$$

To prove that the cross–partial derivative of l^* with respect to λ and γ is positive, we write

$$\frac{\partial^2 l^*}{\partial \lambda \partial \gamma} = \frac{\partial}{\partial \gamma}\left(\frac{f'(\alpha^*)}{(k - f(\alpha^*))^2} \cdot \frac{\partial \alpha^*}{\partial \lambda}\right).$$

By the product rule, this expression can be decomposed into:

$$\frac{\partial^2 l^*}{\partial\lambda\partial\gamma} = \underbrace{\frac{\partial}{\partial\gamma}\left(\frac{f'(\alpha^*)}{(k-f(\alpha^*))^2}\right)\cdot\frac{\partial\alpha^*}{\partial\lambda}}_{\text{Term 1}} + \underbrace{\frac{f'(\alpha^*)}{(k-f(\alpha^*))^2}\cdot\frac{\partial^2\alpha^*}{\partial\lambda\partial\gamma}}_{\text{Term 2}}.$$

Term 1: Since we already have $\frac{\partial\alpha^*}{\partial\lambda} > 0$, we need only analyze

$$\frac{\partial}{\partial\gamma}\left(\frac{f'(\alpha^*)}{(k-f(\alpha^*))^2}\right).$$

A direct calculation yields

$$\frac{\partial}{\partial\gamma}\left(\frac{f'(\alpha^*)}{(k-f(\alpha^*))^2}\right) = \frac{f''(\alpha^*)\cdot\frac{\partial\alpha^*}{\partial\gamma}\cdot(k-f(\alpha^*))^2 + 2f'(\alpha^*)\cdot\frac{\partial\alpha^*}{\partial\gamma}\cdot(k-f(\alpha^*))}{(k-f(\alpha^*))^4}.$$

Under our assumptions, $k-f(\alpha^*) > 0$, $\frac{\partial\alpha^*}{\partial\gamma} > 0$, and $f'(\alpha^*) > 0$. Moreover, since

$$f''(\alpha^*) = \frac{p}{R_f\,\gamma}(\lambda-2),$$

and $\lambda < 1$ implies $f''(\alpha^*) > 0$, we conclude that Term 1 is positive.

Term 2: From previous results,

$$\frac{\partial^2\alpha^*}{\partial\lambda\partial\gamma} = \frac{\overline{z}^2 - \underline{z}^2}{\overline{z}(1-\lambda)} > 0.$$

Since $f'(\alpha^*) > 0$ and $k-f(\alpha^*) > 0$, Term 2 is also positive.

Thus, we have

$$\frac{\partial^2 l^*}{\partial\lambda\partial\gamma} > 0,$$

which proves that high–quality merchants (with higher γ) exhibit a larger sensitivity of advertising expenditure l^* to the credit parameter λ.