Fostering Social-Media Entrepreneurs: Evidence from A Field Experiment in China*

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Abstract

We conduct a field experiment in China to incentivize small business owners to become social media content creators. Our primary subsidy is provided as a social media advertisement subsidy for content boosting fees, directly given to the social media platform. This subsidy is conditional upon business owners creating new video, live stream, or photo posts to promote their business. Our findings indicate that after receiving the subsidy, business revenue grows by five thousand RMB per month, profit increases by two thousand RMB per month, and the number of employees grows by 0.66 within the one-year period after the intervention. These effects are significantly more pronounced than those observed with a direct cash transfer. Additionally, our findings suggest that this growth can be attributed to two channels: a finance channel, or "fintech accelerator," and a learning and feedback channel. In the finance channel, increased product ratings and sales enhance small businesses' likelihood of opening online stores and subsequently accessing fintech credit. The learning and feedback channel is unique to social media entrepreneurs, and boosts performance directly through learning and feedback, and indirectly through fintech credit.

JEL Codes: C93, D1, G30.

Keywords: Social media content creator, subsidy, fintech credit

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1 Introduction

Startups and small business owners often face challenges in growing their ventures into successful businesses due to limited access to essential resources. Interventions such as marketing, finance, management skills, in-kind transfers, and direct cash transfers have the potential to significantly enhance firm performance (Blattman, Fiala, and Martinez, 2014; Bruhn, Karlan, and Schoar, 2018; Cunha, De Giorgi, and Jayachandran, 2019; Anderson and McKenzie, 2022). However, both households and entrepreneurs typically need cues or small incentives to overcome present bias and adopt optimal financial planning strategies (Choi, Laibson, and Madrian, 2011; Choi, Haisley, Kurkoski, and Massey, 2017). In this paper, we explore a novel approach to increase the visibility and revenue of small enterprises: using in-kind transfers to promote social media streaming or posting as a growth strategy. This method not only enhances product visibility and sales through learning and feedback, but also facilitates increased financing from fintech lenders (Berg, Burg, Gombović, and Puri, 2020). As a result, small businesses acquire the capital necessary to scale their operations and improve their market presence. We use a combination of randomized controlled trials (RCTs) and surveys (Stantcheva, 2023) to investigate the effectiveness of this strategy in facilitating the growth of small and medium enterprises.

Recent statistics highlight the rapid growth of social media platforms such as Instagram, Twitter, TikTok, WeChat Video, and Xiaohongshu/Rednote, which have become key channels for content creators and business advertising. In China, online content creators numbered 50 million in 2020, with the market surpassing $20 billion. Social media has become an important tool for entrepreneurs in the new market economy model of China (Djankov, Qian, Roland, and Zhuravskaya, 2006) to achieve success without close government supervision. In the United States, the influencer marketing industry is projected to reach $13.8 billion in 2021, doubling in just three years. These trends show that social media content creation is a significant income source and advertising avenue for small businesses due to the vast audience reach. Social media platforms offer micro-entrepreneurs and SMEs cheap

and effective tools for advertising through live streaming, video posting, and photo posting, possibly because social media messages are shorter, simpler, and more emotionally charged (Zhuravskaya, Petrova, and Enikolopov, 2020). These methods provide real-time audience engagement, answering questions, and building rapport, which can increase customer loyalty and sales. They are also excellent for demonstrating products and services, making it easier for potential customers to understand their value.

To study the effect of empowering entrepreneurs with social media, we partnered with a Multi-Channel Network (MCN) firm for a field experiment.[1] The treatment group of small businesses received a subsidy of 1,000 RMB, or around 140 USD, as a social media advertisement fee for services such as Dou+ on TikTok. Social media services like Dou+ are designed to boost the reach and visibility of user-generated content on the TikTok platform by allowing content creators to pay for increased exposure. Essentially, more people are likely to see the business's video, streaming, or photo in their feed. This practice is also commonly observed across other social media platforms, where content creators leverage paid promotional tools to enhance user engagement and, consequently, their economic prospects. By providing households and small businesses with access to social media promotion services comparable to paid marketing services, we can evaluate the potential economic benefits and behavioral shifts resulting from increased online presence and exposure. According to TikTok's official website, one RMB of Dou+ reaches between 25 to 50 new viewers. Therefore, our 1,000 RMB subsidy allows small businesses to reach between 25,000 and 50,000 new views. Social media promoters on other platforms have a similar customer reach. This treatment is offered only on the condition that business owners create a new video, live stream, or photo post to promote their business. In the experiment, our control group

[1] A Multi-Channel Network (MCN) firm is a company that works with video platforms, such as YouTube, to offer assistance to content creators in areas such as audience development, content programming, creator collaborations, digital rights management, monetization, and sales. MCNs typically provide support to creators by helping them grow their channels, improve their content, and maximize their revenue opportunities. They may also offer technical support, access to production facilities, and opportunities for brand partnerships and sponsorships. In return, MCNs sometimes take a percentage of the revenue generated by creators' channels. However, in our experiment, our partner MCN does not require any such commission or compensation from the entrepreneurs.

receives nothing.[2] We also design a direct cash transfer of the same amount, unconditional, to serve as an alternative control group.[3]

We identify and recruit 5,741 small businesses in Guangdong, Zhejiang, Jiangsu, and Liaoning provinces in China. These businesses span various industries, such as electronic devices, cosmetic products, and toys. They are either already using, or are interested in using, social media platforms for marketing purposes. We randomly assign 1,000 businesses to the treatment group, 3,741 businesses to the control group, and 1,000 businesses to the direct cash transfer group.[4] We collect detailed baseline data on the participating businesses' characteristics, including business size, number of employees, revenue, access to bank and fintech credits, current marketing spending, online presence, and perceptions of social media marketing.

Six months and one year after the intervention period, we collect post-intervention data from all groups. This data includes updated revenue, employee numbers, business asset value, fintech credit amounts, marketing spending, online presence metrics, and profit. We also administer a follow-up survey to gather information on business owners' experiences and perceptions of the intervention, as well as any changes in their financing channels, marketing strategies, and social media usage behavior. We then estimate the causal effect of the subsidy on key outcome variables, such as revenue growth, fintech credits, marketing spending, and online presence metrics. Additionally, we investigate potential heterogeneous treatment effects by examining how the effects vary based on business size, geographic location, and

[2]We also use the subgroup that does not receive the in-kind subsidy but nevertheless tries to post on social media as an alternative control group. The results are qualitatively similar.

[3]Our partner MCN (Multi-Channel Network) firm also provides the following 3-page PDF brochure to the social media fee transfer treatment group and the cash transfer group: Showcase Success Stories, where the MCN firm shares case studies and testimonials from other small businesses that have successfully used social media to grow their revenue and customer base, highlighting the tangible benefits and the steps they took to achieve success; Content Creation Tools, where the MCN firm recommends apps that make content creation easier, such as graphic design software, video editing tools, and social media scheduling platforms; Templates and Guides, where the MCN firm offers templates for social media posts, content calendars, and guides on best practices for different platforms; and Data and Analytics, where the MCN firm demonstrates the potential impact and the number of consumers that social media can reach. The control group was not provided with the brochure.

[4]We assign 1,000 businesses to the treatment group, and 992 businesses eventually took up the subsidy as these are the ones that complied with the content creation requirement.

the gender of the business owner.

The treatment group, which received a social media advertisement subsidy of 1,000 RMB for content boosting fees, experienced a significant increase in revenue, 5620 RMB per month compared to the control group during the one year period after the intervention. Similarly, the increase in profit is 2000 RMB per month compared to the control group, and treated businesses hire 0.66 more employee than the control group. These results suggest that the social media advertisement subsidy had a considerable positive effect on the treated businesses.[5]

The direct cash transfer group did not show any significant improvement in revenue, profit, or labor one year after the intervention. This result indicates that the social media subsidy had a more significant impact on business growth. Moreover, three entrepreneurs in the treatment group received angel investment—defined as a capital infusion exceeding five million RMB—after the intervention, whereas no entrepreneurs in either the cash transfer group or the control group received similar investment. Overall, the findings suggest that social media subsidies are more effective at promoting small business growth than direct cash transfers, particularly in scenarios where businesses leverage the subsidy to achieve targeted outcomes, such as enhancing their online presence or expanding their online store operations. This highlights the importance of targeted support through leveraging social media platforms for business expansion and development.[6]

Per a one-time 1000 RMB targeted subsidy, a 2000 RMB increase in profit per month seems very large to be justified by this one-time subsidy alone. Although, some studies,

[5]There is a potential for spillover effects given that our sample of entrepreneurs is clustered around three common marketplaces. However, our evidence does not indicate significant negative local spillovers, as we find that the majority of revenue growth among treated businesses is driven by online sales. This suggests that any negative spillovers may be experienced by non-local stores that previously supplied these consumers, who may now be shifting their purchases to the online stores operated by our treated entrepreneurs. We are unable to measure the extent of this substitution or determine whether the online stores of treated entrepreneurs are generating entirely new demand. Therefore, our results should be interpreted with caution as reflecting partial equilibrium effects, rather than general equilibrium impacts.

[6]We also document how business use the money when it is an unconditional cash transfer. 55% of the money are used for daily consumption, 29% use the money to buy inventory for their business. 16% save the money.

such as Gertler, Higgins, Scott, and Seira (2023), show that a temporary incentive can have lasting impacts for years. We therefore hypothesize that businesses continue to invest in social media content booster fees after our one-time subsidy. Indeed, we find that, after the intervention, treated small businesses invest close to 700 RMB per month more in social media booster fees compared to the control group. Furthermore, treated small businesses spend an extra 170 RMB per month on outsourced marketing. Together, these results suggest that reinvestment in social media marketing appears to justify the large treatment effect.

Moreover, we investigated whether entrepreneurs who received the treatment became more active on social media. Our findings show that this is indeed the case. The treatment group had, on average, 1.62 more streaming days per month compared to the control group, while the direct transfer group had 0.08 fewer streaming days. Additionally, the treatment group posted 0.21 more videos per month, whereas the number of videos posted by the direct transfer group remained unchanged. Finally, the treatment group posted 0.36 more photos per month, while the direct transfer group posted only 0.04 more photos.

Furthermore, De Mel, McKenzie, and Woodruff (2008) and a large body of literature show that credit constraints are a major barrier for small businesses to achieve growth. Fintech creditors have emerged as an alternative source of credit for both households and small businesses alike. Hau, Huang, Shan, and Sheng (2017); Huang, Li, and Shan (2018) document that businesses with online stores, such as those on Alibaba and Ant Financial, are more likely to obtain fintech credit because these online store platforms serve both as marketplaces and fintech lending firms. Fintech lenders, particularly those operating as online marketplaces, have the advantage of observing the revenue streams and the product ratings of merchants in real time. This capability allows them to assess creditworthiness more accurately and provide credit based on the observed revenue of the merchants. Therefore, we hypothesize that the treated group is more likely to open online stores and thus more likely to obtain fintech credit.[7] At the same time, there should be no effect on bank credit.

[7]Alibaba grants fintech credit based on sales data (Hau et al., 2017; Huang et al., 2018). Being able to sell more also means qualifying for more credit, which in turn can lead to higher growth.

Before the intervention, the treatment, control, and direct transfer groups had similar levels of online credit (around 3,100 RMB) and bank loans (around 14,000 RMB). The percentage of small businesses with online stores was similar between the groups, with both having around 60%. After the treatment, businesses in the treatment group experienced a significant increase in online credit, from three thousand to close to sixty thousand RMB. In contrast, the control and direct transfer groups saw only modest increases compared to the treatment group. This suggests that the social media advertisement subsidy had a substantial impact on businesses' ability to access online credit. Furthermore, the treatment group showed a considerable increase in the percentage of businesses with online stores, from 61.5% to 95.8%, while the control and direct transfer groups had a relatively stable percentage of businesses during the treatment period, around 61.9%, respectively.

In contrast, the change in bank loans after the intervention was less pronounced across all groups. The treatment group experienced no increase in bank loans, and this is similarly true for the cash treatment group and the control group. This indicates that the effect of sales growth on access to bank loans is much weaker compared to online credit.

To further differentiate the supply effect of fintech credit from the demand effect, we find that when comparing the treatment and control groups, they have a similar rate of fintech credit application, but the approval rate for the treatment group is much higher. The control group's credit approval rate is around 37%. The intervention boosts the treatment group's credit approval rate to close to 80%, a 43% percent increase over the control group. For bank credit, both the application and approval rates are similar. This suggests that the increased access to fintech credit due to our treatment operates through a supply channel rather than a demand effect.

Taken together, we hypothesize that sales growth and increases in consumer ratings can facilitate a "fintech financial accelerator" effect; i.e., growth enables entrepreneurs to gain access to credit, which in turn leads to further growth in both sales and consumer ratings. Therefore, businesses opening an online store on a platform that also serves as a fintech lender

may experience a stronger treatment effect. This is because they can readily access more credit necessary for business growth. Fintech lenders have valuable insights into a business's growth potential and creditworthiness. To empirically test this hypothesis, we implement an interaction regression specification, where we define a variable $FinStore$ that equals one if a firm operated an online store on a fintech lending platform prior to the intervention. The results indicate that entrepreneurs who received the treatment and already operated such online stores before the intervention experienced an additional revenue gain of 2,600 RMB, hired 0.12 more workers, and achieved profit increases of 1,600 RMB, relative to the baseline treatment group, which has baseline coefficients of 4,500 RMB for revenue, 0.59 for labor, and 1,500 RMB for profit. Importantly, these estimates should be interpreted as a lower bound of the fintech accelerator effect, since 18% of entrepreneurs who did not previously have fintech-linked online stores established them following the treatment. Therefore, our estimated treatment effect is understated, because our definition of $FinStore$ excludes small businesses that began operating fintech online stores after the treatment.

In addition to the financial channel, we hypothesize that a learning and feedback channel also contributes to the success of these subsidies. Learning and feedback directly boost sales by improving entrepreneurs' understanding of consumers, and also indirectly increase sales through the financial accelerator channel, as fintech platforms consider product ratings when offering credit. Instant feedback is one channel that distinguish social media effort from traditional marketing. Entrepreneurs can gain insights from their consumers about their preferences and make necessary modifications to their products. They can also address any misunderstandings or concerns that consumers may have. Furthermore, entrepreneurs can learn from other social media content creators about how to improve their videos and understand their competitors' products (Lerner and Malmendier, 2013). Our findings indicate that, after the treatment, the treatment group experienced a significant increase in both learning from other bloggers (from 9% to 27%) and receiving feedback from consumers

(from 14% to 35%).[8] In contrast, the control and direct transfer groups showed little change in these learning and feedback channels, with percentages remaining low for both learning from other bloggers and receiving feedback from consumers. Additionally, we observed a significant increase in product ratings for the treatment group. These results suggest that the social media advertisement subsidy had a notable impact on the entrepreneurs' learning processes and feedback mechanisms. The increased engagement with other content creators and consumers can lead to a better understanding of consumer preferences and improved advertising strategies. Ultimately, this contributes to the growth and development of small businesses. Moreover, we also show that the financial accelerator effect is particularly more pronounced for those enterprenuers who benefit from this learning and feedback channel.

In summary, this study highlights the significant potential of social media platforms to serve as an effective growth channel for small businesses. Through a field experiment, we provided a social media advertisement subsidy to small business owners, which led to substantial increases in revenue, profit, and labor within one year of the intervention. The observed effects were considerably more pronounced than those achieved through direct cash transfers, highlighting the importance of leveraging social media platforms for business expansion and development. Furthermore, our analysis suggests that this growth can be attributed to a finance channel and a learning and feedback channel, where increased sales and product ratings enhance small businesses' likelihood of opening online stores and subsequently accessing fintech credit. These two channels together contribute to what we term a "fintech financial accelerator" effect; that is, growth enables entrepreneurs to gain access to credit, which in turn leads to further increases in both sales and consumer ratings. Overall, our study highlights the value of targeted transfers or nudges (Holz, List, Zentner, Cardoza, and Zentner,

[8]We also conducted an open-ended questionnaire. As Haaland, Roth, Stantcheva, and Wohlfart (2024) suggests, open-ended surveys can sometimes better reveal the mechanisms behind economic agents' behavior than the "revealed preference" approach, which is often limited. Our survey expanded beyond binary answers to include more questions regarding how merchants learn from consumers and other bloggers. Ultimately, we coded these responses into a learning and feedback score ranging from 0 to 10. Our conclusions remain similar: there is a significant increase in learning and feedback activities, which constitute the main channel facilitating SME growth in this paper.

2023) in helping small businesses overcome investment hurdles, as well as the important role a fintech financial accelerator can play in supporting small businesses.

2 Literature Review

Our paper contributes to the literature on external intervention in order improve micro-entrepreneurs and small and medium enterprises outcome. We find that entrepreneurs only realize the benefit of social media after the the subsidy, consistent with Duflo, Kremer, and Robinson (2011) that enterpreneurs suffer from bias and uncertainty in terms of making investment decision to promote their products. Moreover, De Mel, McKenzie, and Woodruff (2008) find that micro-enterprenuerial experience and wealth affect the eventual outcome of subsidy to entrepreneurs. McKenzie (2017) show that business plan competition cash prize help to overcome the rule-of-thumb ten employee hurdle of business in developing countries. Bruhn and Love (2014) show that access to bank loan improves labor outcome. Consistent with Banerjee and Duflo (2014), we find that the entrepreneurial use of in-kind subsidies induces credit expansion to support increased production.

This paper contributes to the extensive literature on the effects of social media on social, economic, and political behavior, as well as the overall welfare of economic agents. Bailey, Cao, Kuchler, and Stroebel (2018) show that social media can transmit valuations in the housing market. Chen, De, Hu, and Hwang (2014) demonstrate that the aggregation of social media messages can predict future stock returns. Allcott, Braghieri, Eichmeyer, and Gentzkow (2020) find that stopping the use of social media can improve individual welfare. Enikolopov, Makarin, and Petrova (2020) show that social media helps solve coordination problems in political protests. Zhuravskaya, Petrova, and Enikolopov (2020) provide a comprehensive summary of the influence of social media on politics. One key question raised by Zhuravskaya, Petrova, and Enikolopov (2020) is whether social media's "shorter, simpler, and more emotionally charged messages" are inherently linked to the distribution of

extreme content. Our results offer a different perspective, showing that the "shorter, simpler, and more emotionally charged" nature of social media can explain the rapid growth of entrepreneurs when they use social media for advertising.

Anderson, Chandy, and Zia (2018) show that marketing practice is equally important as finance practice in terms of improving SMEs' profitability. González-Uribe and Reyes (2021) show that business accelerators, which increase an entrepreneur's visibility without providing cash, can help a firm with its growth. Ittner and Larcker (1998); Huang (2018) show that customer satisfaction can eventually predict the financial performance of a firm. Consistent with Lieber and Lockwood (2019), we find that targeting transfer is better for entrepreneurial growth as unconditional cash transfer leads to consumption increase (Broda and Parker, 2014) instead of entrepreneurial capital investment (Jayachandran, 2021).

Last but not least, our research contributes to how fintech credits improve the results of entrepreneurs. By highlighting the interplay between fintech credit and social media's unique learning and feedback channel, this paper contributes to the broader literature on the role of financial innovation in supporting small business development. Berg, Fuster, and Puri (2022) show that there has been rapid growth in fintech credit over the last decade. Hau, Huang, Lin, Shan, Sheng, and Wei (2021) and Chen, Huang, Lin, and Sheng (2022) demonstrate that fintech credits facilitate entrepreneurial growth, and small businesses spend their credit on marketing expenses. Different from Hau et al. (2021) and Chen et al. (2022), where their research focuses on the intensive margin of fintech credit, our research also shows the extensive margin in addition to the intensive margin. Moreover, we show that entrepreneurs' self-marketing leads to more fintech credits, which leads to higher growth, while the previous literature shows that fintech credits lead to higher marketing expenses, which leads to higher growth. Most importantly, we show that soft information such as product ratings also play an important role in securing more fintech credit, which the literature has not documented.

3 Institutional Background and Methodology

Social media streaming and short video platforms such as Twitter, Instagram, TikTok, Bilibili, and Kuaishou have become increasingly popular channels for micro-entrepreneurs and small businesses to advertise their products. These platforms offer access to large and rapidly growing audiences—TikTok alone has over a billion monthly users—and allow businesses to engage potential customers with quick, captivating videos that are often more affordable than traditional ads. Advanced targeting options help businesses reach specific groups, and the viral nature of short videos may rapidly boost brand exposure and sales, as seen with trends such as the Stanley Cup.[9] Additionally, features such as integrated e-commerce make it easier for users to discover and purchase products directly within the apps. Reflecting this shift, China had 50 million online content creators and a market size over 20 billion in 2020, while the U.S. influencer marketing industry reached 13.8 billion in 2021, doubling in just three years.

The rapid expansion of online marketing and commerce has also transformed the broader digital ecosystem in which small businesses operate. As entrepreneurs increasingly leverage social media and e-commerce to reach customers and drive sales, online sales platforms such as Alibaba have evolved beyond their initial roles as digital marketplaces to become comprehensive ecosystems that integrate commerce, payment, and credit services. In particular, a key innovation has been the seamless embedding of fintech credit within the operational infrastructure of these platforms. Merchants who set up online stores on Alibaba, for example, automatically generate a rich stream of transactional and behavioral data—such as sales volume, customer ratings, and inventory turnover—that is leveraged by affiliated fintech arms like Ant Financial to perform real-time credit assessments and offer tailored financing products.

This integration of sales, product ratings, and credit services offers several advantages

[9]For example, the recent case of Stanley Cup serves as a great example: https://www.cnbc.com/2023/12/23/how-a-40-ounce-cup-turned-stanley-into-a-750-million-a-year-business.html

for small businesses and micro-entrepreneurs. First, it lowers the barriers to accessing working capital, as credit decisions are based on actual business performance recorded on the platform rather than solely on historical credit scores or physical collateral. Second, credit products are often disbursed rapidly and flexibly, enabling entrepreneurs to respond to market opportunities and manage cash flow more effectively. Finally, by linking credit access directly to sales performance, platforms like Alibaba create a virtuous cycle: as businesses grow and demonstrate success through increased sales, their access to credit expands, which in turn supports further investment in inventory, marketing, and operational upgrades. This seamless integration of fintech credit thus plays a critical role in fostering the growth and resilience of small enterprises in the digital economy.

3.1 Data Collection

The field experiment was conducted in partnership with a MCN firm specializing in investing in small businesses and nurturing the growth of social media content creators.[10] This collaboration allowed us to leverage the expertise and resources of the MCN firm to design and implement a well-structured intervention that targeted the specific needs of small businesses and aspiring content creators. Furthermore, this partnership facilitated the seamless integration of our research goals with the practical implementation of the subsidy program, ensuring that the experiment's objectives were effectively met.

We identify and recruit 5,741 small businesses in Guangdong, Zhejiang, Jiangsu, and Liaoning provinces. For our sample inclusion criteria, note the MCN firm is part of nearly 200 mobile messaging groups that include entrepreneurs across these three regions. These mobile messaging groups contain close to 35,000 entrepreneurs. We also complement these groups with 4,000 small businesses from business registries in the marketplaces.[11] We send

[10]MCN firm, or multi-channel network firm, is a company that supports video content creators by providing resources for content production, audience growth, monetization, rights management, analytics, and technical support. The firm essentially serves as angel investors and run seed accelerators (Cohen and Hochberg, 2014; Hochberg, 2016). But in this particular experiment, the firm agree and promise to run unconditional social-media subsidy and cash transfer.

[11]In an unreported table, we find that the economic magnitude of the treatment effects for businesses

invitations to participate in our RCT through mobile messages and physical pamphlets. Eventually, 5,741 businesses showed interest in participating. These businesses span various industries (e.g., electronic products, clothes and shoes, or cosmetic products) and are either inactively or actively using, or are interested in using social media platforms for marketing purposes. We randomly assign 1000 businesses to the treatment group, 3741 businesses to the control group, and 1000 businesses to the direct cash transfer group.[12] The randomization was stratified by sector and region and was conducted through a Stata program.[13] We administer a pre-intervention survey to gather information on business owners' perceptions of social media marketing and their expectations regarding the subsidy's potential impact. We collect detailed baseline data on participating businesses' characteristics, such as business size, number of employees, annual revenue, current marketing spending, and online presence. We start to offer the social media subsidy in 2023 February. All participating businesses are compensated 50 RMB per business for completing the survey, and they understand that there won't be a second round of treatment either in terms of in-kind subsidy or cash regardless of their performance.

In our field experiments, social media promoters such as Dou+ have been employed as in-kind subsidy treatments for households and small businesses to examine the economic implications of increased social media engagement through paid marketing strategies. Taking Dou+ as an example, it serves as a video promotion tool designed to boost user-generated

recruited through message groups and those recruited through business registries are similar. However, the results for the former are much more statistically significant, likely due to the much larger sample size.

[12]We built trust with the entrepreneurs by informing them that the experiment was supported by our university, a well-known public institution sponsored by the government. Additionally, we signed a brief contract with the entrepreneurs to reassure them that the subsidy would be provided as promised. We assigned 1,000 businesses to the treatment group, and 992 businesses eventually took up the subsidy.

[13]We closely follow the procedure as Bruhn et al. (2018). We use the Stata code automatically to re-randomized as follows. We first allocated small businesses to the treatment and control groups on the basis of a randomly generated number. Using this allocation, we then calculated the maximum and the average t-statistics on the differences in averages across the treatment and control groups for the following variables: Entrepreneur age, gender, years of schooling, business age, total asset value, business revenue/sales, If the maximum t-statistic for these variables was higher than 1.25 or the average t-statistic was higher than 0.35, we drew a new random number and allocated firms to the treatment and control groups on the basis of this new number. We repeated this process until the maximum t-statistic was 1.25 or lower and the average t-statistic was 0.35 or lower.

content's reach and visibility on the TikTok platform by allowing content creators to pay for increased exposure. This practice is commonly observed across other social media platforms, where content creators leverage paid promotional tools to enhance user engagement and, consequently, their economic prospects. By providing households and small businesses with access to Dou+ or other comparable paid marketing services, we can evaluate the potential economic benefits and behavioral shifts resulting from increased online presence and exposure. According to TikTok's official website, for every one RMB spent on Dou+, it reaches between 25 to 50 new viewers.[14] This treatment is offered only on the condition that business owners create a new video, live stream, or photo post to promote their business. In the experiment, our control group receives nothing.[15] We also design a direct cash transfer of the same amount, unconditional, to serve as an alternative treatment/control group.

Our partner MCN firm also provides a 3-page PDF brochure to the social media fee transfer treatment group and the cash transfer group. The content is as following: Showcase Success Stories, where the MCN firm shares case studies and testimonials from other small businesses that have successfully used social media to grow their revenue and customer base, highlighting the tangible benefits and the steps they took to achieve success; Content Creation Tools, where the MCN firm recommends apps that make content creation easier, such as graphic design software, video editing tools, and social media scheduling platforms; Templates and Guides, where the MCN firm offers templates for social media posts, content calendars, and guides on best practices for different platforms; and Data and Analytics, where the MCN firm demonstrates the potential impact and the number of consumers that social media can reach. The control group was not provided with the brochure.[16]

[14]In terms of streaming, Wechat Streaming's video promoter function can help reach 1.6 to 5 online viewers per RMB spent. In terms of photo posting, Xiaohongshu's Shutiao function claims to lead to 100 clickers per RMB. We also collected the realized viewers for streaming, photo posting, and video posting after the experiment to double check that whether realized number is similar to the advertised number.

[15]Except for the 50 RMB incentive fees to complete to survey, which are offered to all entrepreneurs that completed the survey.

[16]The MCN firm and the authors' home institution jointly provide funding for this research. The MCN firm also recruited another 1,984 small businesses after we had conducted the randomization process to serve as an alternative control group. This group only received the 3-page educational brochure regarding how to become social media entrepreneurs. However, the results for this group were no different from the current

Six months and one year after the intervention period, we collect quarterly post-intervention data from both groups, including updated marketing spending, online presence metrics, and revenue. We also administer a follow-up survey to gather information on business owners' experiences and perceptions of the intervention, as well as any changes in their marketing strategies.[17]

Table 1 presents the summary statistics of the entrepreneurs before the intervention. The table is divided into three groups: Treatment, Control, and Cash Transfer. The Treatment group received a social media content booster fee of 1000 RMB, the Control group received no intervention, and the Cash Transfer group received a direct cash transfer of 1000 RMB.

The average age of entrepreneurs in the Treatment, Control, and Cash Transfer groups is approximately 36 years. The average number of years of education completed by the entrepreneurs is approximately 8.3 years across all groups. Around 35% of entrepreneurs are female, and about 31% are part of a couple in each group. On average, the businesses have been established for about 6.7 years across all groups. The average monthly revenue ranges from approximately 7,850 RMB for the Treatment group to 7,900 RMB for the Cash Transfer group. The average monthly profit is around 1,800 RMB for the Treatment group, 1,840 RMB for the Control group, and 1,889 RMB for the Cash Transfer group. The average number of employees in a small business is about 1.5 across all groups.[18] The businesses spend on average around 295 RMB on advertisements excluding social media booster fees for the Treatment group, 291 RMB for the Control group, and 287 RMB for the Cash Transfer group. The average social media booster fee is around 81 RMB for the Treatment group, 77 RMB for the Control group, and 78 RMB for the Cash Transfer group. The mean social media booster fee is mainly driven by a very small percentage of entrepreneurs who have used social media content booster fee before (less than 10%). The median value of these variables are zero.

control group that received nothing.

[17]We further discuss our data verification process in the Appendix A.2.

[18]Note that entrepreneurs may potentially underreport the number of their employees for tax-related reasons.

The average amount from bank loans or other bank-related channels is approximately 14,340 RMB for the Treatment group, 14,000 RMB for the Control group, and 14,100 RMB for the Cash Transfer group. About 61% of small businesses have an online store across all groups. The average total amount of online credit is approximately 3,150 RMB for the Treatment group, 3,140 RMB for the Control group, and 3,130 RMB for the Cash Transfer group. The average number of videos posted by the business per month to advertise its product is around 0.05 across all groups. The average number of days the business streamed per month to advertise its product is approximately 0.76 across all groups. The average number of photos posted by the business per month to advertise its product is about 0.24 across all groups. The table also includes the p-values of the mean differences between the Treatment and Control groups and between the Cash Transfer and Control groups. These difference are not significant across any pairs of comparisons.

We conduct our field experiments in three markets around China: Huaqiangbei in Shenzhen, Yiwu in Zhejiang, and Wuai in Shenyang. Huaqiangbei, situated in Shenzhen, is renowned as a major electronics marketplace. It is a bustling commercial area that specializes in electronic components, gadgets, and technology products. The market is a key player in the global electronics supply chain, providing an important platform for innovation and the latest tech trends. Conducting field experiments in Huaqiangbei offers insights into the electronics industry, consumer preferences, and the impact of technological advancements on market operations. The Yiwu Small Merchandise Market, located in Zhejiang province, is one of the largest wholesale markets in the world. Known for its vast variety of small commodities, it attracts buyers from all over the globe.[19] The market is a hub for international trade, offering everything from toys and jewelry to household goods and electronics. Its extensive network of suppliers and competitive pricing make it an ideal location for studying

[19]Most of our participants did not come from the Yiwu International Trade Center, which is the most famous merchandise market in Yiwu. Instead, they are from peripheral markets in Yiwu. The reason is that most merchants in Yiwu International Trade Center have very high annual revenues, ranging from a few million RMB to tens of millions of RMB. Technically speaking, these are not exactly small businesses or micro-entrepreneurs. These entrepreneurs also show little interest in our subsidies.

market dynamics and the behavior of small businesses. Wuai Market, located in Shenyang, is one of the largest markets in northeastern China. It features a wide array of products, including clothing, textiles, and home furnishings. The market serves both local and international buyers, making it a critical node in the regional economy.[20] Overall, these markets were chosen for field experiments due to their significant roles in their respective industries, diverse product offerings, and their influence on both local and global economies. They provide a rich context for understanding market behaviors, business strategies, and economic outcomes.

In terms of industry distribution, the industries are divided into six sectors: Electronic Device, Cloth and Shoes, Jewelry/Handbag/Watch, Toys and Souvenirs, Cosmetic Product, and Other. Table A.1 shows that for the Electronic Device sector, there are 176 observations in the Treatment group, 611 in the Control group, and 165 in the Direct Transfer group. In the Cloth and Shoes sector, there are 195 observations in the Treatment group, 784 in the Control group, and 216 in the Direct Transfer group. The Jewelry/Handbag/Watch sector includes 175 observations in the Treatment group, 703 in the Control group, and 176 in the Direct Transfer group. The Toys and Souvenirs sector has 248 observations in the Treatment group, 953 in the Control group, and 270 in the Direct Transfer group. For the Cosmetic Product sector, there are 143 observations in the Treatment group, 471 in the Control group, and 119 in the Direct Transfer group.

We then use the following OLS regression similar to Bruhn et al. (2018) to estimate the causal effect of the subsidy on key outcome variables, such as revenue growth, business asset, employee number, marketing spending, and online presence metrics.

$$Y_{irs} = \alpha + \beta * Treat_i + \gamma_{r*s} + \mathbf{X}_i + \epsilon_{irs} \tag{1}$$

Where Y are the dependent variables. $Treat$ is our intervention. γ_{r*s} are the region-industry

[20]Similar to Yiwu, the Wuai Market features many wholesalers with very high revenues. The participants who show interest in our program are not major wholesalers in the Wuai Market. Instead, they are small businesses with much lower revenue levels.

strata dummies/fixed-effects. r represents one of the three regions we conduct the experiment, Yiwu, HuangQiangBei, or Wuai. s represents the industry of the small business. $\mathbf{X}_i$ are the characteristics (re-randomization variables) of the entrepreneurs and their business that we use as control variables. We also investigate potential heterogeneous treatment effects by stratifying the analysis by business size, geographic location, and gender of the business owner. Since we also collect the growth rate of all key variables before the intervention, an alternative approach is to use a difference-in-differences regression as our main specification. In the Appendix Table, we find the results to be similar in quality when we use a DiD approach.

3.2 Theoretical Motivation

We set up a toy model analyzing the investment decisions of entrepreneurs with quasi-hyperbolic discounting as they allocate effort to social media marketing across two periods. The framework incorporates a few central elements: present-biased preferences that lead to time-inconsistent choices (Laibson, 1997), uncertainty regarding the returns to social media promoting effort or investment returns in general, a learning and feedback channel generated by social media engagement, and the availability of fintech credit that is contingent upon both observed sales performance and feedback signals. Entrepreneurs face immediate disutility from exerting investment/social media effort, diminishing returns to this effort in generating sales, and the prospect of receiving credit from digital lenders based on realized sales and engagement feedback.[21] The model demonstrates that present bias and pessimistic beliefs about marketing productivity jointly suppress optimal investment relative to a first-best scenario, while feedback from consumers and peers can help update these beliefs.

The model further investigates the effects of policy interventions and yields three key predictions. First, a targeted subsidy that reduces the perceived cost of social media investment

[21] If we allow for increasing returns to marketing effort due to network effects, the model's core mechanisms are even more amplified. The impact of present bias, learning, and feedback becomes much more pronounced, as initial underinvestment or successful interventions can trigger out-sized, persistent effects through self-reinforcing dynamics.

effort is often more effective than an equivalent cash transfer, because it directly addresses present bias by making effort feel less costly and thus more attractive to entrepreneurs. Second, access to fintech credit acts as an accelerator: once initial investment/social media marketing effort generates observable results and engagement feedback, digital lenders expand credit, which amplifies both immediate and future investments. Third, the learning and feedback channel further magnifies this effect—entrepreneurs who receive more feedback and engagement not only update their beliefs about the productivity of marketing effort, but also become eligible for greater credit allocation from fintech platforms that value such engagement. As a result, targeted subsidies not only induce more persistent behavioral change than cash transfers, but their impact is further reinforced through belief updating and feedback-driven credit expansion. These predictions underscore the importance of designing interventions that reduce behavioral barriers, foster learning and engagement, and harness digital credit infrastructure, rather than merely alleviating liquidity constraints. For additional technical details, see Appendix B.

4 Results

4.1 Baseline

Table 2 presents the the impact of social media advertisement subsidies and direct cash transfers on the growth of revenue, labor, and profit one year after the intervention. The intervention consists of providing a 1,000 RMB social media advertisement subsidy for content boosting fees, directly provided to the social media platform, conditional on business owners creating a new video, live stream, or photo post to promote their business. Direct cash transfers are provided directly to the business owners. The table is divided into two panels: Panel A presents the raw value results, while Panel B presents the results in natural logarithm form.

The treatment group, which received the social media advertisement subsidy, experienced

a significant increase in revenue, labor, and profit one year after the intervention compared to the control group. The revenue increased by 5,620 RMB, labor increased by 0.66, and profit increased by 2,040 RMB. All regressions control for strata dummies and re-randomization variables.[22]

The direct transfer group, which received a cash transfer, showed a smaller and not statistically significant increase in revenue, a small and not statistically significant decrease in labor, and a not statistically significant increase in profit. This result also suggests that the 3-page educational PDF brochure was not very helpful when it was combined with a direct cash transfer, or another way to interpret it is that it was only helpful when it was combined with the cash transfer.[23]

In natural logarithm form[24], the treatment group experienced a significant increase in revenue and labor compared to the control group. The direct transfer group showed a slight increase in revenue but not in labor. Moreover, three entrepreneurs in the treatment group received angel investment—defined as a capital infusion exceeding five million RMB—after the intervention, whereas no entrepreneurs in either the cash transfer group or the control group received similar investment.

In summary, the social media advertisement subsidy appears to have a significant positive impact on revenue, labor, and profit for businesses one year after the intervention. The direct cash transfer has a smaller and less consistent impact, with a slight increase in revenue but no significant effects on labor and profit. These results suggest that the social media subsidy

[22]Viviano, Wuthrich, and Niehaus (2021) demonstrate that t-statistics can be artificially inflated in the context of multiple hypothesis testing, such as when conducting analyses across different subgroups or multiple variables within the same group. To address this concern, we implemented multiple hypothesis testing corrections in our analysis. As a result, the estimated effects were attenuated by approximately 5% to 20% on average; nevertheless, the results remained statistically significant.

[23]The MCN firm also provides the 3-page educational brochure to another 1,984 small businesses, but there is also no treatment effect among this group after matching the characteristics with the control group, given that the control group did not receive the 3-page brochure. Also, if we use this group in place of the control group, the treatment effect of the social media subsidies group and the direct cash transfer group will be very similar to our current results. Note that this group was recruited after we had already recruited the initial group and was not part of the randomization process.

[24]We convert observations with a value of 0 to 1 so that, after the log transformation, the new value becomes 0. We acknowledge the limitation of this approach; however, since less than 10% of our sample is affected, the baseline results remain largely unchanged.

intervention may be more effective in promoting business growth than direct cash transfers.[25]

Per a one-time 1000 RMB of targeted subsidy, a 2000 RMB increase in profit seems very large to be justified by this one time subsidy alone. Therefore, we hypothesize that businesses continue to invest in social media content booster fee after our one time subsidy. Table 3 Panel A shows that after the intervention, The treatment group, which received the social media advertisement subsidy, experienced a significant increase in self-financed social media fees (694 RMB) compared to the control group. The direct transfer group, which received a cash transfer, showed a small and not statistically significant increase in self-financed social media fees (32 RMB). For outsourced marketing expenses, the treatment group showed a small and not statistically significant increase (172 RMB), while the direct transfer group showed an even smaller and not statistically significant increase (19 RMB). Together, these results suggest that reinvestment in social media booster fee seems to justify the large treatment effect.

Moreover, we investigate whether our treatment has a long term effect on small business's social media presence. We hypothesize that our intervention should increase the long-run social media presence of the small business. Table 3 Panel B presents various variables related to the businesses' online presence and advertising activities after the intervention comparing the treatment and control groups.

The treatment group experienced a significant increase in the number of streaming days per month (1.62 days) and the number of videos posted per month (0.21 videos) compared to the control group. The direct cash transfer group showed no significant change in streaming days (-0.08 days) and no significant change in the number of videos posted per month. The treatment group also experienced a significant increase in the number of photos posted per month (0.36 photos) compared to the control group, while the direct cash transfer group

[25]These results are robust when we winsorize or censor the variables at 99% and 95% level (Table 10). These results are also robust when we use a difference-in-differences approach. We report these results in Appendix Table A.9, Appendix Table A.10, and Appendix Table A.11. These DiD regressions also satisfy the parallel trends assumption. As parallel trends test, we define January-June 2022 as the pre-treatment period and July 2022-Dec 2022 as the pseudo treatment period and we find no treatment effects.

showed a smaller but still significant increase in the number of photos posted per month (0.04 photos).

In summary, the social media advertisement subsidy appears to have a significant positive impact on self-financed social media expenses and social media presence for businesses one year after the intervention. The direct cash transfer has a smaller and less consistent impact on these outcomes. These results suggest that the social media subsidy intervention may be more effective in promoting business growth through increased social media marketing and presence than direct cash transfers, and reinvestment in social media booster fee is one channel that potentially justify the large treatment effect.

We also conducted a survey to understand why entrepreneurs did not invest in social media marketing before the intervention as it is important to study why entrepreneurs fail to take up profitable opportunities. The survey responses are divided into the treatment group, which received a social media advertisement subsidy, the control group, and the direct transfer group, which received a cash transfer. Table 4 presents these survey results. 33% of the treatment group, 36% of the control group, and 30% of the direct transfer group reported that they did not invest in social media due to capital constraints. A large majority in all groups (67% of the treatment group, 64% of the control group, and 70% of the direct transfer group) reported that they didn't know about social media boosting. 25% of the treatment group, 29% of the control group, and 17% of the direct transfer group said they simply hadn't considered investing in social media. 21% of the treatment group, 15% of the control group, and 19% of the direct transfer group did not think that marketing was important. A small percentage of each group (7% of the treatment group, 9% of the control group, and 6% of the direct transfer group) reported that they had tried social media marketing but failed. More than 50% of all participants acknowledged that they have a habit of procrastination when it comes to changing their business strategies.[26] The results suggest that a lack of knowledge about social media promotion, combined with procrastination, is the

[26]Appendix Section A.4 provides a detailed explanation of how we construct a binary variable to capture procrastination behavior based on survey responses.

most common reason for not investing in social media marketing across all groups. Capital constraints and underestimating the importance of marketing were also significant factors. Taken together, this evidence is largely consistent with our theoretical framework, which proposes that a nudge could help overcome present bias. This also echoes why it might be important to offer enterprenuers a bundle of the knowledge of social media (brochure) and the in-kind transfer (social media fee) because either intervention won't be sufficient when deploying alone.

4.2 Fintech Credit Channels

Table 5 Panel A examines the impact of the treatment (social media advertisement subsidy) and direct cash transfer on the small businesses' access to online credit, bank loans, and the presence of online stores. Online credit refers to the amount of credit that businesses obtain from financial lenders such as Ant Financial, and bank loan represents the amount of bank loans they receive. The presence of online stores is an important factor, as some fintech lenders provide credit based on sales data (Hau, Huang, Shan, and Sheng, 2017; Huang, Li, and Shan, 2018), which implies that higher sales can lead to more credit access and, consequently, higher growth. Appendix A.3 provides a detailed discussion of the eligibility rules associated with online platform presence. In the Appendix, we describe the typical fintech lenders, the criteria for credit approval, and whether participation on the platform can trigger access to credit.

The treatment group experienced a significant increase in online credit from financial lenders (48,100 RMB, t=19.24) compared to the control group. The direct transfer group showed a smaller but still significant increase in online credit (1,000 RMB, t=1.94). The treatment group showed a small and not statistically significant increase in bank loans (400 RMB, t=0.78) compared to the control group. The direct transfer group showed an even smaller and not statistically significant increase in bank loans (100 RMB, t=0.24). The treatment group experienced a significant increase in the percentage of small businesses with

online stores compared to the control group. The direct transfer group showed a negligible and not statistically significant increase in the percentage of small businesses with online stores.

In summary, the results in Table 5 panel A demonstrate that the social media advertisement subsidy had a substantial impact on small businesses' access to online credit and the presence of online stores, which in turn can lead to higher growth. The effect on bank loans was less significant, suggesting that online credit may be a more effective accelerator for small businesses.

To further differentiate the supply effect of fintech credit from the demand effect, Table 5 panel B shows that that when comparing the treatment and control groups, they have a similar rate of fintech credit application, but the approval rate for the treatment group is much higher. The control group's credit approval rate is around 37%. The intervention boosts the treatment group's credit approval rate to close to 80%, a 43% percent increase over the control group. For bank credit, both the application and approval rates are similar.[27] This suggests a supply channel of fintech credit due to our treatment, rather than a demand effect.[28]

We also hypothesize that businesses opening an online store on a platform that also serves as a fintech lender may experience a stronger treatment effect. This is because they can readily access more credit necessary for business growth. Fintech lenders are privy to valuable insights regarding a business's growth potential and creditworthiness. To test this hypothesis, we use an empirical strategy that identifies the fintech accelerator effect via an interaction term between *Treat* and *FinStore*, with *FinStore* defined as an indicator equal to one for businesses operating online stores that also served as fintech lenders before the

[27]We show this result in Appendix Table A.2.

[28]We also show in Appendix Table A.3 that before the treatment, the fintech credit application rate and approval rate are similar between the treatment and the control group. Moreover, the unconditional fintech credit approval rate is close to 22% for the treatment and 10% for the control group. The logistics regression comparing the two groups unconditionally is also significant with a Z-statistics of 7.37.

treatment.

$$Y_{irs} = \alpha + \beta_1 Treat_i + \beta_2 Treat_i * FinStores_i + \beta_3 FinStores_i + \gamma_{r*s} + \mathbf{X}_i + \epsilon_{irs} \quad (2)$$

β_1 is intended to capture the unconditional effect of social media, while β_2, the coefficient of central interest, represents the accelerator effect. Table 6 shows that this subtreatment group has significantly higher revenue, profit, and more labor hired. Specifically, entrepreneurs who received the treatment and already operated online stores that also functioned as fintech lenders before the treatment have revenues that are 2,600 RMB higher, hire 0.12 more workers, and have profits that are 1,600 RMB higher. These results are highly significant, given that the baseline treatment coefficients are 4,500 RMB for revenue, 0.59 for labor, and 1,500 for profit, respectively.

It should be noted that these estimates only serve as a lower bound for the effect of the Fintech accelerator, as 18% of entrepreneurs who previously did not own fintech online stores opened such stores after receiving our treatment. Therefore, our estimated treatment effect is understated, because our definition of $FinStore$ ignores small businesses that began owning fintech online stores after the treatment. As a result, in the regression analysis, the non-$FinStore$ treatment group may include businesses that should actually be classified as $FinStore$ treatment.

Therefore, as an alternative analysis, we categorize businesses into four subgroups based on their online store status one year after the intervention.[29] The results are then compared to the control group: exclusive Fintech lenders' stores, combined Fintech lenders and other stores, only other stores, and none. Table A.13 shows that for businesses that have online stores also functioning as fintech lenders, the Fintech credit is around 71,450 higher (t-statistic = 16.91), revenue is around 7,100 higher (t-statistic = 6.07), labor is 0.61 higher (t-statistic = 4.41), and profit is around 3,100 higher (t-statistic = 3.56), all relative to the

[29]One may argue that this analysis may suffer from endogeneity; however, we present the results to enrich and aid our understanding of the point estimates from the previous regression specifications.

control group. These estimates, which could arguably be biased due to endogeneity, are nevertheless very similar in economic magnitude to those from regression specification (2), where we define fintech-related online stores based on pre-treatment status. This evidence suggests that it is unclear whether sorting businesses according to their online store status after the intervention introduces endogeneity issues.

For businesses hosting stores on both fintech lenders' marketplaces and other platforms, the Fintech credit is 50,200 higher (t-statistic = 15.73), revenue is around 5,500 higher (t-statistic = 5.26), labor is 1.09 higher (t-statistic = 8.25), and profit is around 1,700 higher (t-statistic = 1.94), all relative to the control group. For businesses that only host stores with no fintech lender affiliation, the Fintech credit is 1300 higher (t-statistic = 0.48), revenue is 4,300 higher (t-statistic = 3.43), labor is 0.28 higher (t-statistic = 1.80), and profit is 800 higher (t-statistic = 0.75), all relative to the control group. For businesses without any online stores, the Fintech credit is 1,400 higher (t-statistic = 0.94), revenue is 4,300 higher (t-statistic = 2.30), labor is 0.03 lower (t-statistic = -0.13), and profit is 2500 higher (t-statistic = 0.42), all compared to the control group. These results suggest that businesses with online stores operating on platforms that also serve as fintech lenders tend to experience the most significant growth, with higher credit, revenue, labor, and profit relative to the control group.

There is also no evidence that fintech credit imposes a burden on these entrepreneurs; rather, it appears to function as a growth accelerator. First, our measure of profit explicitly accounts for the cost of servicing credit liabilities. The MCN firm ensured that entrepreneurs were fully informed about debt service costs and instructed them to include these expenses when reporting profits. Second, we observe no increase in bank credit among the treatment group, suggesting that the additional debt is facilitating business growth and that the uptake of fintech credit is a voluntary decision, not one driven by financial distress. Third, we find no indication of financial distress in the treatment group. If anything, the bankruptcy rate is higher in the control group, as evidenced by a greater incidence of businesses whose revenues dropped to zero.

4.3 Learning and feedback

We also test if there is a learning and feedback channel, which are process variables that describe how entrepreneurs improve their service quality to the consumers after the social media subsidy. As our model suggests, the learning and feedback channel not only increases product rating which directly boost sales, but also increases fintech credit which indirectly boost the revenue. The results presented in Table 7 illustrate the effects of a social media advertisement subsidy on various dimensions of learning and feedback among small businesses. The analysis examines two key areas: learning from other bloggers and feedback from consumers. Lerner and Malmendier (2013) show that learning from peers is a key channel for entrepreneurs to avoid failures. Therefore, we study this specific response from the entrepreneurs. Additionally, we assess the impact on product rating, service rating, delivery rating, and product variety.

Table 7 Panel A highlights the significant role of the social media advertisement subsidy in facilitating learning and feedback. Specifically, businesses that received the social media advertisement subsidy are much more likely to learn from other bloggers compared to the control group. This effect is highly significant, improving the percentage from 9% to 27%, indicating a strong positive impact of the subsidy on learning from peers in the blogging community. In contrast, the direct cash transfer group shows no significant difference from the control group.

Similarly, businesses in the treatment group are much more likely to receive feedback from consumers compared to the control group. This finding is also highly significant, improving the percentage from 14% to 35%, suggesting that the subsidy effectively encourages consumer engagement and feedback. The direct cash transfer group again shows no significant effect.

As Stantcheva (2023) and Haaland, Roth, Stantcheva, and Wohlfart (2024) suggest, open-ended surveys can sometimes reveal the mechanisms behind economic agents' behavior more effectively than the "revealed preference" approach, which is often limited. Therefore, we also conducted an open-ended questionnaire. Our survey expanded beyond binary answers

to include additional questions regarding how merchants learn from consumers and other bloggers, as documented in Appendix A.1, questions 61 to 70. Ultimately, we coded these responses into a learning and feedback score ranging from 0 to 10 (see Appendix A.5). Our conclusions remain similar: there is a significant increase in the learning and feedback channel for the treatment group.[30]

Together, these results suggest that the social media advertisement subsidy significantly enhances the likelihood of businesses engaging in valuable learning experiences from both consumers and other bloggers. This is likely because the subsidy increases the businesses' online presence and visibility, facilitating greater interaction and feedback.

Table 7 Panel B further examines the impact of the interventions on product rating, service rating, delivery rating, and product variety. The results reveal that the treatment group experiences a significant increase in product rating by 0.75 points compared to the control group. This effect is significant at the 1% level, with a t-statistic of 3.48, indicating that the subsidy positively influences consumers' perception of product quality. The direct transfer group shows no significant change in product rating, with a coefficient of 0.07 and a t-statistic of 0.40.

Furthermore, the subsidy also leads to a significant improvement in service rating by 0.54 points compared to the control group, with a t-statistic of 2.80. This suggests that the increased online presence and interaction facilitated by the subsidy enhance the perceived quality of service. The direct transfer group shows no significant effect on service rating, with a coefficient of -0.14 and a t-statistic of -0.63.

In terms of delivery rating, the treatment group sees a significant increase by 0.35 points, significant at the 5% level (t-statistic of 2.18), indicating that the subsidy also positively impacts the efficiency and reliability of product delivery. The direct transfer group again shows no significant effect, with a coefficient of -0.11 and a t-statistic of -0.20. When examining product variety, neither the treatment group nor the direct transfer group show significant

[30]For brevity, we omit this result from the main analysis, but the results are available upon request.

changes. This suggests that while the subsidy improves product quality and service, it does not necessarily lead to an expansion in the range of products offered.[31]

In Table 8, we also show that the fintech accelerator effect is particularly pronounced among entrepreneurs who believe that feedback and learning are important. Specifically, we use an empirical design similar to a triple difference-in-differences regression, in which we identify the direct and indirect effects of learning and feedback through a triple interaction term and a double interaction term among *Treat*, *FinStore*, and *Learn*. Here, *Learn* is defined as an indicator variable equal to one for businesses that, prior to the treatment, considered customer feedback or learning from other merchants to be important.

$$\begin{aligned} Y_{irs} = \alpha &+ \beta_1 \,\text{Treat}_i + \beta_2 \,\text{Treat}_i \cdot \text{FinStore}_i + \beta_3 \,\text{Treat}_i \cdot \text{FinStore}_i \cdot \text{Learn}_i \\ &+ \beta_4 \,\text{FinStore}_i + \beta_5 \,\text{Learn}_i + \beta_6 \,\text{FinStore}_i \cdot \text{Learn}_i + \beta_7 \,\text{Treat}_i \cdot \text{Learn}_i \\ &+ \gamma_{r*s} + \mathbf{X}_i + \epsilon_{irs} \end{aligned} \tag{3}$$

This evidence further supports our theoretical motivation that both increased sales and greater customer satisfaction contribute to the fintech accelerator effect and the eventual growth of these businesses. Specifically, the learning and feedback channel directly contributes to a greater treatment effect, which is captured by β_7 in the regression, while also indirectly contributes to a greater treatment effect through the fintech credit channel, captured by β_3 in the regression. Both coefficients are economically and statistically significant.

Overall, the findings underscore the effectiveness of the social media advertisement subsidy in enhancing business learning and feedback mechanisms. The subsidy significantly increases the likelihood of businesses learning from other bloggers and receiving feedback from consumers, which in turn positively impacts product and service ratings, as well as delivery ratings. However, the subsidy does not appear to significantly affect product variety. These results suggest that by increasing online presence and visibility, the social media

[31]Note that the number of businesses with these ratings represents only a subset of those that have online stores, since not all online stores feature such ratings.

advertisement subsidy effectively facilitates valuable interactions that lead to improvements in perceived product and service quality.

4.4 Heterogeneous Treatment Effect

4.4.1 Region and Industry

Table 9 provides a breakdown of the treatment effects on revenue, labor, and profit for different regions and industries one year after the intervention. Panel A shows that in Yiwu, the treatment significantly increased revenue by around 7300 (t=4.66), labor by 0.73 (t=3.76), and profit by around 3000 (t=2.21). In Wuai, the treatment significantly increased revenue by around 4700 (t=3.96) and labor by 0.65 (t=4.58), while the increase in profit was not statistically significant. In Huangqiangbei, the treatment significantly increased revenue by around 5500 (t=4.71), labor by 0.60 (t=4.40), and profit by around 2100 (t=2.03).

Panel B shows that in the electronic device industry, the treatment significantly increased revenue by around 7100 (t=4.32), labor by 0.91 (t=4.36), and profit by around 3200 (t=2.26). In the cloth/shoes industry, the treatment significantly increased revenue by around 5100 (t=2.96) and labor by 0.74 (t=3.67), while the increase in profit was not statistically significant. In the jewellery/handbag/watch industry, the treatment significantly increased labor by 0.77 (t=3.57), while the increases in revenue and profit were not statistically significant. In the toys/souvenirs/accessories industry, the treatment significantly increased revenue by around 9900 (t=6.10), labor by 0.45 (t=2.63), and profit by around 6200 (t=4.42). In the cosmetic product industry, the treatment significantly increased revenue by around 4700 (t=2.58), while the increases in labor and profit were not statistically significant. In the other merchandise industry, the treatment significantly increased labor by 0.80 (t=2.27), while the increases in revenue and profit were not statistically significant.

Overall, the treatment generally had positive effects on revenue, labor, and profit across different regions and industries. The results also suggest that the treatment had a more pronounced effect on industries where products require more effective demonstrations from

sellers and those with a lower unit price. The electronics and toys/souvenirs/accessories industries, which often involve products that require effective demonstrations to increase sales, showed significant increases in revenue, labor, and profit. This suggests that the intervention, which may have improved marketing or presentation strategies, was particularly beneficial for these industries.

On the other hand, the jewellery/handbag/watch industry, which also relies on effective product demonstration but typically involves higher unit prices, showed less significant treatment effects. This suggests that while effective product demonstration is important, the unit price of products could be a crucial factor in determining the efficacy of such interventions.

5 Further Tests

5.1 Collateral Channel

We conduct some further tests understand the heterogeneity and channels of our results. We first test the collateral channel. The collateral channel is that if entrepreneurs are credit constrained, those that don't have collateral should have larger treatment effects. The results presented in Table A.4 indeed highlight the heterogeneous treatment effects based on whether the entrepreneur owns property, specifically focusing on revenue growth, labor, and profit. The analysis reveals that the treatment effect is significantly higher for entrepreneurs who do not own property, suggesting that property ownership plays a crucial role in accessing traditional credit and the fact that entrepreneurs are credit constrained.

Firstly, the coefficient for revenue growth indicates that entrepreneurs without commercial property, home property, or both types of property experience substantially more increases in revenue when receiving the social media advertisement subsidy. Specifically, the treatment effect of the revenue growth for those without commercial property is 280 RMB higher (t-statistic = 1.87), which is significant at the 10% level. This effect is more pronounced for those without home property (670 RMB higher, t-statistic = 2.82) and those

without both types of property (930 RMB higher, t-statistic = 3.12), both significant at the 1% level. These findings suggest that entrepreneurs without property collateral benefit more from the subsidy in terms of revenue growth, likely because they face greater challenges in obtaining traditional bank credit and thus rely more on alternative financing channels like fintech credit.

In terms of labor, the treatment effects also show significant positive impacts for entrepreneurs without property. The increase in labor for those without commercial property is 0.08 employees higher (t-statistic = 1.24) than other treated enterprenuers, significant at the 10% level. For those without home property, the increase is 0.13 employees higher (t-statistic = 2.18), significant at the 5% level. The most substantial increase is observed for those without both types of property, with an additional 0.15 employees higher (t-statistic = 2.35), significant at the 5% level. These results indicate that the subsidy not only boosts revenue but also enables businesses to expand their workforce, particularly for those lacking property collateral.

Overall, the findings underscore the importance of property ownership in accessing traditional credit and highlight the effectiveness of the social media advertisement subsidy in providing alternative financing for entrepreneurs without property collateral. By leveraging fintech credit and increasing online visibility, these entrepreneurs can achieve significant growth in revenue and labor.

5.2 Store locations

We also conduct heterogeneity tests by hypothesizing that entrepreneurs with worse store locations would experience a higher treatment effect because the increase in revenue potentially comes more from online stores rather than onsite shopping. Based on the heterogeneous treatment effects indicated in Table A.5, we indeed observe that our treatment has a more significant impact on stores that are potentially located in areas with less foot traffic and less prime locations. This suggests that our social media advertisement subsidy is particularly

beneficial for businesses that do not benefit from high visibility or prime real estate locations within a shopping center or mall.

More specifically, our analysis reveals that for stores located in prime locations such as outside facing, near escalators, and near entrances, the positive treatment effects are reduced relatively to the baseline. For instance, the coefficient for stores that are outside facing (Prime_Outside_Facing*Treat) is -234 with a T-statistic of -3.42, indicating a significant reduction in the positive treatment effect on revenue for businesses in these prime locations. Similarly, stores near escalators (Prime_Near_Escalator*Treat) and near entrances (Prime_Near_Entrance*Treat) show negative coefficients of -125 and -310 for revenue, respectively, both statistically significant with T-statistics of -3.09 and -3.95.

In contrast, the treatment effect is significantly more positive for stores in non-prime locations. The coefficient (Non_Prime*Treat) is around 520 with a T-statistic of 4.82, indicating a substantially more increase in revenue for these businesses. This pattern is consistent across other key outcome variables such as labor and profit. For labor, the coefficient is 0.35 (T-statistic of 2.78), while for profit, it is around 280 (T-statistic of 2.41), both of which are statistically significant and positive.

These results suggest that stores in less prime locations, which typically experience lower foot traffic, benefit more from the social media advertisement subsidy. This could be due to the fact that these businesses have more to gain from the increased visibility and engagement provided by social media platforms, as they are not naturally benefiting from high foot traffic and prime real estate positioning. By leveraging social media to reach a broader audience, these businesses can overcome some of the limitations imposed by their physical location, resulting in significant improvements in revenue, labor, and profit.

Overall, our findings highlight the importance of targeted interventions that consider the specific circumstances of small businesses. Social media subsidies appear to be particularly effective for businesses in less advantageous locations, providing them with the tools to enhance their online presence and drive growth.

5.3 Transaction number as robustness checks

We also use the number of transactions as a robustness check in addition to the profit and revenue results we already show. Based on the results shown in Table A.6, we perform a robustness check by analyzing the impact of the social media subsidy and direct cash transfer on the number of transactions per month, in addition to the previously examined dependent variables such as labor, revenue, and profit.

Panel A of Table A.6 presents the raw values of the number of transactions one year after the intervention. The "treatment" group, which received a social media advertisement subsidy of 1,000 RMB for content boosting fees, shows a substantial increase in the number of transactions with a coefficient of 248 and a t-statistic of 5.10. This indicates a significant positive effect on the number of transactions due to the social media subsidy. In contrast, the "direct transfer" group, which received an unconditional cash transfer, exhibits a smaller increase in the number of transactions with a coefficient of 35 and a t-statistic of 1.01, which is not statistically significant. The control group, which did not receive any intervention, has a mean of 61 transactions with a standard deviation of 182. These results suggest that the social media subsidy is more effective in boosting the number of transactions compared to a direct cash transfer.

Panel B of Table A.6 displays the results using the natural logarithm of the number of transactions as the dependent variable. The treatment group again shows a significant positive effect, with a coefficient of 0.63 and a t-statistic of 4.19. This indicates a substantial growth in the number of transactions due to the social media subsidy when considering the percentage change. On the other hand, the direct transfer group shows a negligible increase with a coefficient of 0.05 and a t-statistic of 0.24, which is statistically significant but much smaller in magnitude compared to the treatment group. The R-squared values for the treatment and direct transfer groups are 0.04 and 0.01, respectively, indicating that the model explains a small but meaningful portion of the variance in the number of transactions.

These results reinforce our earlier findings that the social media advertisement subsidy

has a more significant and positive impact on business performance metrics compared to a direct cash transfer. Specifically, the subsidy not only increases revenue, labor, and profit but also significantly boosts the number of transactions. This further highlights the efficacy of leveraging social media platforms for business growth and development, particularly for small businesses seeking to enhance their online presence and customer engagement.

5.4 Online vs Onsite Revenue

We further hypothesize that our treatment effect should come more from online revenue than onsite revenue. The results from Table A.7 indicate that the primary revenue growth for businesses comes from online revenue rather than onsite revenue. Businesses that received the social media subsidy experienced a significant increase in online revenue, growing by 4576 RMB on average, with a t-statistic of 5.39, indicating strong statistical significance. In contrast, the direct cash transfer did not have a significant impact on online revenue, as evidenced by a t-statistic of -0.80. On the other hand, the impact of the social media subsidy on onsite revenue is positive but much smaller, with an increase of 1048 RMB on average and a t-statistic of 1.78, which is less statistically significant. The direct cash transfer also showed a positive but non-significant effect on local revenue, with an increase of 1064 RMB and a t-statistic of 1.20.

Furthermore, the results from Table A.8 support the finding that the main growth in business activity occurs online. The social media subsidy significantly increased the number of online transactions by 205 on average, with a t-statistic of 4.78, indicating strong statistical significance. In contrast, the direct cash transfer had no significant impact on online transactions, as shown by a t-statistic of -0.75. The impact of the social media subsidy on local transactions is minimal and not significant, with an increase of 48 transactions on average and a t-statistic of 1.18. Similarly, the direct cash transfer showed a non-significant increase in local transactions, with an increase of 53 transactions and a t-statistic of 1.01.

In conclusion, the results from both Table A.7 and Table A.8 indicate that the primary

growth in revenue and transactions for businesses receiving the social media subsidy comes from online sources rather than local sources. The social media subsidy substantially boosts online revenue and transactions, whereas its impact on local revenue and transactions is relatively minor. This suggests that incentivizing small business owners to create social media content effectively drives online business growth.

5.5 Spillover Effect: SUTVA

There is a potential for spillover effects given that our sample of entrepreneurs is clustered around three common marketplaces. However, our evidence does not indicate significant negative local spillovers, as we find that the majority of revenue growth among treated businesses is driven by online sales. This suggests that any negative spillovers may be experienced by non-local stores that previously supplied these consumers, who may now be shifting their purchases to the online stores operated by our treated entrepreneurs. We are unable to measure the extent of this substitution or determine whether the online stores of treated entrepreneurs are generating entirely new demand. Therefore, our results should be interpreted with caution as reflecting partial equilibrium effects, rather than general equilibrium impacts.

6 Conclusion

Our study has provided evidence of the potential of social media platforms to significantly boost small business growth. By conducting a field experiment in China, we found that providing small businesses with a social media advertisement subsidy led to substantial increases in business revenue, profit, and employment. This impact was notably greater than the effects observed from direct cash transfers, underscoring the powerful role of social media in driving business expansion and development.

Our findings also suggest that this growth is facilitated by a fintech accelerator channel

wherein increased sales from social media advertising enhance small businesses' likelihood of establishing online stores and accessing fintech credit. The most pronounced growth was observed among businesses that sell on online stores with platforms that also serve as fintech lenders. Moreover, we find a learning and feedback channel that reimforce with the fintech accelerator channel. Overall, our study contributes to the literature on external interventions aimed at improving outcomes for micro-entrepreneurs and small and medium enterprises. It highlights the significance of mitigating biases and uncertainties in investment decisions, while also demonstrating the general value of targeted subsidies and support initiatives.

While our field experiment is conducted among small businesses in three major provinces in China, spanning diverse industries and implemented within real business settings, several aspects of our design support the external validity of our results. Our sample reflects the growing global trend of small businesses leveraging social media platforms for business growth, and the mechanisms we document, such as improved access to fintech credit and learning through digital engagement, are increasingly relevant worldwide as digital ecosystems expand. At the same time, the extent to which our results apply to businesses in countries with limited access to mobile phones or fintech lenders, remains an open question. Overall, our study provides evidence on the effectiveness of targeted social media subsidies for a substantial and representative segment of SMEs, and offers insights that are likely relevant for small businesses globally as social media becomes an ever more integral part of entrepreneurship and growth.

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Table 1: Summary Statistics

This table shows the summary statistics of entrepreneurs and their businesses before the intervention. *Age* refers to the age of the entrepreneur. *Education* represents the number of years of education that the entrepreneur has completed. *Female* denotes the percentage of female entrepreneurs, and *Couple* indicates the percentage of entrepreneurs who run the stores together with their partners (male entrepreneurs are the omitted category). *Years* represents the number of years the business has been established. *Employee* refers to the number of employees in a given small business. *Revenue* is the average monthly sales figure for a business. *Profit* represents the average monthly net profit of a business. *Advertisement* is the average monthly spending on commercial purposes (excluding social media booster fees). *Social Media Fee* is the average spending on social media booster fees. *Bank Loan* is the total amount of loans from banks or other bank-related channels. *Online Credit* is the total amount of online credit. *Video* is the number of videos posted by the business per month to advertise its product. *Streaming* refers to the number of days the business streamed per month to advertise its product. *Photo* is the number of photos posted by the business per month to advertise its product. *Treatment* is the sample that receives a social media content booster fee valued at 1,000 RMB. *Cash Transfer* is the sample that receives a cash transfer of 1,000 RMB. *N_initial* denotes the number of observations in each group according to the treatment allocation. *N_summ* denotes the number of observations in each group that provided summary statistics in January 2023, before the intervention. *N_endline* denotes the number of observations in each group that provided business operation information in February 2024, after the intervention. P values of mean differences are also reported and the results are marked with *, **, and *** to signify statistical significance at different levels.

	Treatment		Control		Cash Transfer		Mean Difference	
	(1)		(2)		(3)		(1-2)	(3-2)
	Mean	SD	Mean	SD	Mean	SD		
Age	36.26	9.71	36.23	9.46	36.13	9.59	0.91	0.76
Educations	8.38	5.30	8.36	5.39	8.30	5.37	0.88	0.76
female	0.35	0.48	0.35	0.48	0.35	0.48	0.88	0.83
Couple	0.31	0.46	0.31	0.46	0.31	0.46	0.88	0.78
Years	6.70	2.78	6.72	2.90	6.71	2.78	0.87	0.90
Revenue	7871.90	4834.35	7895.51	5906.39	7901.40	5764.29	0.89	0.97
Profit	1785.52	4817.72	1835.18	5915.53	1889.28	5854.32	0.78	0.79
Employee	1.53	1.81	1.52	1.81	1.49	1.80	0.90	0.66
Advertisement	295.22	438.85	291.77	416.44	287.58	390.31	0.82	0.76
Social Media Fee	81.48	415.45	77.34	235.22	78.23	217.75	0.76	0.90
Bank Loan	14344.20	14818.11	14004.87	14755.53	14107.40	15622.76	0.51	0.85
OnlineStore	0.61	0.49	0.60	0.49	0.60	0.49	0.91	0.94
Fintech Credit	3156.10	1888.32	3144.77	1880.25	3138.40	1942.19	0.86	0.92
Video	0.05	0.23	0.05	0.22	0.06	0.23	0.68	0.60
Streaming	0.76	1.27	0.76	1.35	0.77	1.36	0.96	0.90
Photo	0.24	0.54	0.24	0.52	0.23	0.51	0.80	0.77
N_endline	784		2,805		759			
N_summ	992		3,387		1,000			
N_initial	1,000		3,741		1,000			

Table 2: Impact of Social Media Subsidy and Cash Transfer on Profit

Panel A shows the growth of revenue, labor, and profit one year after the intervention. The term "treatment" refers to a social media advertisement subsidy of 1,000 RMB for content boosting fees, which is directly provided to the social media platform. This treatment is offered only on the condition that business owners create a new video, live stream, or photo post to promote their business. "Direct Transfer" refers to an unconditional cash transfer made directly to the business owner. Panel B shows the separate treatment effects of the social media subsidy and direct cash transfer on the natural logarithm of revenue and labor using OLS regressions. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. *N_endline* is the number of observation with endline response in each subgroup. N_Angel denotes the number of entrepreneurs who have received angel investment after the intervention, defined as a capital infusion exceeding 5 million RMB.

Panel A Raw value			
	Treatment	Direct Transfer	Control (Mean and SD)
Revenue	5621***	816	13091
T-statistics	(7.63)	(1.19)	(18285)
Controls	Y	Y	
R^2	0.01	0.00	
Labor	0.66***	-0.06	1.89
T-statistics	(7.50)	(-0.74)	(2.34)
Controls	Y	Y	
R^2	0.01	0.00	
Profit	2039***	491	5948
T-statistics	(3.22)	(0.82)	(15807)
Controls	Y	Y	
R^2	0.01	0.00	
N_endline	784	759	2805
N_Angel	3	0	0

Panel B Natural logarithm		
	Treatment	Direct Transfer
Revenue	0.70***	0.27***
T-statistics	(11.89)	(4.83)
Controls	Y	Y
R^2	0.04	0.01
Labor	0.12***	0.02
T-statistics	(5.32)	(1.05)
Controls	Y	Y
R^2	0.02	0.00

Table 3: Impact of Social Media Subsidy and Cash Transfer on Social Media Presence

Panel A presents results where the dependent variables are self-financed social media expenses and outsourced marketing expenses, measured one year post-intervention. Panel B presents the separate treatment effects of the social media subsidy and direct cash transfer on the number of days per month the business conducts video-streaming to sell its products, the number of videos per month the business posts advertising its products, and the number of photos posted per month advertising its products, using OLS regressions. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. *N_endline* is the number of observation with endline response.

Panel A Social media marketing	Treatment	Direct Transfer	Control (Mean and SD)
Self-financed social media fee	694***	32	169
T-statistics	(3.18)	(0.21)	(555)
Controls	Y	Y	
R^2	0.06	0.01	
Outsourced marketing	172	19	299
T-statistics	(1.27)	(0.15)	(427)
Controls	Y	Y	
R^2	0.03	0.01	
N_endline	784	759	2805
Panel B Social media presence	Treatment	Direct Transfer	Control (Mean and SD)
Streaming days	1.62***	-0.08	0.92
T-statistics	(22.68)	(-1.60)	(1.52)
Controls	Y	Y	
R^2	0.10	0.00	
Video Posted	0.21***	-0.00	0.04
T-statistics	(21.75)	(-0.11)	(0.20)
Controls	Y	Y	
R^2	0.09	0.01	
Photo Posted	0.36***	0.04**	0.22
T-statistics	(16.65)	(2.32)	(0.51)
Controls	Y	Y	
R^2	0.06	0.00	
N_endline	784	759	2805

Table 4: Survey of Why the Entrepreneur Did Not Invest in Social Media in the First Place

This table reports survey results on reasons businesses did not invest in social media prior to the intervention. Respondents could select multiple reasons. The survey was conducted in January 2023, one month before the intervention. *N_summ* denotes the number of observations in each group that provided summary statistics in January 2023, before the intervention.

	Treatment	Control	Direct Transfer
Before Treatment			
Capital Constraints	33%	36%	30%
Didn't know social media booster	67%	64%	70%
Habbit of Procrastination	55%	53%	58%
Simply hadn't considered it	25%	29%	17%
Think marketing is not important	21%	15%	19%
Tried social media but failed	7%	9%	6%
N_summ	992	3,387	1,000

Table 5: Fintech Credit vs. Traditional Bank Credit: The Supply Channel

This table presents the separate treatment effects of the social media subsidy and direct cash transfer, using the following dependent variables: *Online Credit* is the total amount of credit obtained from fintech lenders, excluding credit from traditional lenders such as banks; *Bank Loan* is the amount of bank loan received by the business; *Online Stores* is a dummy variable equal to one if the small business has an online store; *Credit Application Rate* is a dummy variable equal to one if the entrepreneur applied for fintech credit in the treatment year; *Credit Approval Rate* is a dummy variable equal to one if the entrepreneur successfully obtained fintech credit in the treatment year, conditional on application; *Credit Interest Rate* is the interest rate of the loan, conditional on successful fintech credit approval in the treatment year. T-statistics are reported in parentheses for OLS regressions and Z-statistics are reported for logistic regressions. For logistic regressions, the regression coefficients, or the logarithm of odds ratios, are reported.

Panel A:Fintech vs. Traditional Bank				
	Treatment	Direct Transfer	Control (Mean and SD)	Regression Types
Online Credit	48131***	1023*	11551	OLS
T-statistics	(19.24)	(1.94)	(14663)	
Controls	Y	Y		
R^2	0.06	0.00		
Bank Loan	411	128	14055	OLS
T-statistics	(0.78)	(0.24)	(14754)	
Controls	Y	Y		
R^2	0.00	0.00		
Online Stores	2.16***	0.02	0.59	Logistic
Z-statistics	(17.16)	(0.36)	(0.49)	
Controls	Y	Y		
$Pseudo_R^2$	0.08	0.00		
$N_endline$	784	759	2805	
Panel B: Fintech Credit				
	Treatment	Direct Transfer	Control (Mean and SD)	
Application Rate	-0.05	-0.11	0.27	Logistic
Z-statistics	(-0.16)	(-0.20)	(0.45)	
Controls	Y	Y		
$Pseudo_R^2$	0.01	0.00		
Approval Rate	1.96***	0.10	0.37	Logistic
Z-statistics	(3.08)	(0.31)	(0.49)	
Controls	Y	Y		
$Pseudo_R^2$	0.15	0.00		
Interest Rate	-0.83	0.13	8.14	OLS
T-statistics	(-0.60)	(0.28)	(6.12)	
Controls	Y	Y		
R^2	0.01	0.00		
$N_endline$	784	759	2805	

Table 6: Fintech Accelerator

This table presents the heterogeneous treatment effect based on the indicator variable *FinStore*, which equals one if the entrepreneur is only using online platforms that are simultaneously fintech lenders before the treatment, and zero otherwise. The dependent variables are the revenue, labor, and profit of a business.

$$Y_{irs} = \alpha + \beta_1 Treat_i + \beta_2 Treat_i * FinStore_i + \beta_3 FinStore_i + \gamma_{r*s} + \mathbf{X}_i + \epsilon_{irs} \ ,$$

Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. $N_treat_FinStore$ is the number of observations in the social media treatment group with an endline response and $FinStore_i = 1$. N_k is the number of observation in the regression.

	Coefficient	T-statistics
(1) Revenue		
β_1 (Treat)	4587***	(3.71)
β_2 (FinStore*Treat)	2621**	(2.39)
β_3 (FinStore)	-425	(-0.83)
(2) Labor		
β_1 (Treat)	0.59***	(3.10)
β_2 (FinStore*Treat)	0.12**	(2.18)
β_3 (FinStore)	-0.02	(-0.79)
(3) Profit		
β_1 (Treat)	1532**	(2.41)
β_2 (FinStore*Treat)	1629**	(2.17)
β_3 (FinStore)	-76	(0.34)
$N_treat_FinStore$ =143		
N_k =3589		

Table 7: Learning and Feedback

This table shows the results when the dependent variables are the learning and feedback variables one year after the intervention. *Feedback from consumers* is a dummy variable equal to one if the business ever learns from consumers about product quality. *Learn from other bloggers* is a dummy variable equal to one if the business learns from other social media content creators how to advertise. Other dependent variables include product rating, service rating, delivery rating, and product variety. These four variables are only applicable to entrepreneurs with an online store and are displayed on each store's page. To ensure comparability across stores, product, service, and delivery ratings are normalized to a 0–5 scale; these ratings are provided voluntarily by consumers. Product variety is measured as the number of distinct products offered by the store. *N_endline* is the number of observation with endline response. T-statistics are reported in parentheses for OLS regressions and Z-statistics are reported for logistic regressions. For logistic regressions, the regression coefficients, the logarithm of odds ratios, are reported. All regressions control for strata dummies and re-randomization variables.

Panel A:				
	Treatment	Direct Transfer	Control (Mean and SD)	Regression Types
Learn from other bloggers	1.32***	0.11	0.09	Logistics
Z-statistics	(12.70)	(0.84)	(0.28)	
$Pseudo_R^2$	0.06	0.00		
Feedback from consumers	1.20***	0.08	0.14	Logistics
Z-statistics	(12.91)	(0.69)	(0.34)	
$Pseudo_R^2$	0.05	0.00		
N_endline	784	759	2805	
Panel B:				
Product Rating	0.75***	0.07	3.73	OLS
T-statistics	(3.48)	(0.40)	(1.28)	
R^2	0.02	0.00		
Service Rating	0.54***	-0.14	4.09	OLS
T-statistics	(2.80)	(-0.63)	(1.07)	
R^2	0.02	0.00		
Delivery Rating	0.35**	-0.11	3.91	OLS
T-statistics	(2.18)	(-0.20)	(0.75)	
R^2	0.02	0.00		
Product Variety	-0.21	0.12	21.21	OLS
T-statistics	(-0.35)	(0.17)	(7.84)	
R^2	0.00	0.00		
N_endline	291	275	989	

Table 8: Fintech Accelerator and Learning/Feedback

This table shows the heterogeneous treatment effects based on whether the entrepreneur is only using online platforms that are simultaneously fintech lenders before the treatment, denoted as *FinStore*, and whether entrepreneurs consider customer feedback or learning from other merchants important prior to the treatment, denoted as *Learn*. Specifically, *Learn* is a dummy variable that equals one if either *Feedback from consumers* or *Learn from other bloggers* equals one prior to the intervention. The dependent variables are business revenue, labor, and profit. We report regression coefficients and t-statistics.

$$\begin{aligned} Y_{irs} = \alpha &+ \beta_1 Treat_i + \beta_2 Treat_i * FinStore_i + \beta_3 Treat_i * FinStore_i * Learn_i \\ &+ \beta_4 FinStore_i + \beta_5 Learn_i + \beta_6 FinStore_i * Learn_i + \beta_7 Treat_i * Learn_i \\ &+ \gamma_{r*s} + \mathbf{X}_i + \epsilon_{irs} \ , \end{aligned}$$

Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. N_k is the number of observation in the regression.

	Coefficient	T-statistics
(1) Revenue		
β_3 (FinStore*Treat*Learn)	1131*	(1.89)
β_7 (Treat*Learn)	1229**	(2.01)
β_2 (Treat*FinStore)	1935**	(2.35)
(2) Labor		
β_3 (FinStore*Treat*Learn)	0.05	(1.37)
β_7 (Treat*Learn)	0.03	(0.87)
β_2 (Treat*FinStore)	0.12**	(2.04)
(3) Profit		
β_3 (FinStore*Treat*Learn)	737*	(1.81)
β_7 (Treat*Learn)	831*	(1.90)
β_2 (Treat*FinStore)	948**	(1.98)
N_k =3589		

Table 9: Treatment Effects by Region and Industry

Panel A shows the treatment effects separately for Yiwu, Wuai, and Huangqiangbei. The dependent variables are the revenue, labor, and profit of the business. Panel B shows the treatment effects separately for electronic devices; clothing and shoes; jewelry, handbags, and watches; toys, souvenirs, and accessories; cosmetic products; and other merchandise. *N_treat* is the number of observation in the social media treatment group with endline response. *N_control* is the number of observation in the social media control group with endline response. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. We perform a Wald test to assess the equality of coefficients across different subgroups.

	Revenue	Labor	Profit	*N_treat*	*N_control*
Panel A: Regions					
Yiwu	7328***	0.73***	2971**	272	970
T-statistics	(4.66)	(3.76)	(2.21)		
Wuai	4726***	0.65***	1469	105	371
T-statistics	(3.96)	(4.58)	(1.44)		
Huangqiangbei	5525***	0.60***	2063**	407	1464
T-statistics	(4.71)	(4.40)	(2.03)		
Wald χ^2	1.86	0.30	0.84		
P-value	0.31	0.86	0.40		
Panel B: Industries					
Electronic	7155***	0.91***	3183**	138	461
T-statistics	(4.32)	(4.36)	(2.26)		
Cloth	5059***	0.74***	1582	154	580
T-statistics	(2.96)	(3.67)	(1.06)		
Jewellery	1296	0.77***	-2038	133	503
T-statistics	(0.71)	(3.57)	(-1.30)		
Toys	9893***	0.45***	6232***	190	709
T-statistics	(6.10)	(2.63)	(4.42)		
Cosmetic	4652***	0.35	1066	112	351
T-statistics	(2.58)	(1.44)	(0.71)		
Other	1568	0.80**	-1901	57	68
T-statistics	(0.80)	(2.27)	(-1.15)		
Wald χ^2	8.81	4.58	22.26		
P-value	0.12	0.47	0.00		

Table 10: Impact of Social Media Subsidy and Cash Transfer on Profit (Winsorized)

Panel A shows the growth of revenue, labor, and profit one year after the intervention, with all dependent variables winsorized at either the 99% or the 95% level. The term "treatment" refers to a social media advertisement subsidy of 1,000 RMB for content boosting fees, which is directly provided to the social media platform. This treatment is offered only on the condition that business owners create a new video, live stream, or photo post to promote their business. "Direct Transfer" indicates an unconditional cash transfer made directly to the business owner. Panel B shows the separate treatment effects of the social media subsidy and direct cash transfer using quantile regressions (50 percentile). Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables.

Panel A OLS	99% winsorized		95% winsorized	
	Treatment	Direct Transfer	Treatment	Direct Transfer
Revenue	5219***	748	4730***	706
T-statistics	(6.37)	(0.97)	(5.92)	(0.85)
Controls	Y	Y	Y	Y
Labor	0.62***	-0.05	0.60***	-0.05
T-statistics	(6.92)	(-0.63)	(6.85)	(-0.59)
Controls	Y	Y	Y	Y
Profit	1802***	473	1529**	442
T-statistics	(2.90)	(0.76)	(2.37)	(0.69)
Controls	Y	Y	Y	Y

Panel B Quantile Regression		
	Treatment	Direct Transfer
Revenue	3400***	550
T-statistics	(4.19)	(0.62)
Controls	Y	Y
Profit	950*	250
T-statistics	(1.81)	(0.49)
Controls	Y	Y

A Online Appendix

Table A.1: Industry Classification

This Table shows the number of observation in each industry.

	Treatment	Control	Direct Transfer
Sector:			
Electronic Device	176	611	165
Cloth and Shoes	195	784	216
Jewelry, Handbag, Watch	175	703	176
Toys and souveniors	248	953	270
Cosmetic product	143	471	119
Other	63	219	54

Table A.2: Credit from Traditional Banks

This Table presents the treatment effects of the social media subsidy and direct cash transfer separately using the following dependent variables. *Credit Application Rate* is a dummy variable that equals one if the entrepreneur has applied for bank credit in the treatment year. *Credit Approval Rate* is a dummy variable that equals one if the entrepreneur has successfully obtained bank credit in the treatment year conditional on the application. *Credit Interest Rate* is the interest rate of the loan if the entrepreneur has successfully obtained bank credit in the treatment year. T-statistics are reported in parentheses for OLS regressions and Z-statistics are reported for logistic regressions. For logistic regressions, the regression coefficients, the logarithm of odds ratios, are reported. All regressions control for strata dummies and re-randomization variables. *N_endline* is the number of observation with endline response.

Bank Credit After Treatment				
	Treatment	Direct Transfer	Control (Mean and SD)	Regression Types:
Application Rate	-0.12	0.04	0.41	Logistics
Z-statistics	(-0.43)	(0.14)	(0.49)	
Controls	Y	Y		
$Pseudo_R^2$	0.00	0.00		
Approval Rate	-0.16	-0.27	0.12	Logistics
Z-statistics	(-0.23)	(-0.39)	(0.33)	
Controls	Y	Y		
$Pseudo_R^2$	0.00	0.00		
Interest Rate	0.12	0.09	6.83	OLS
T-statistics	(0.25)	(0.13)	(5.04)	
Controls	Y	Y		
R^2	0.00	0.00		
N_endline	784	759	2805	

Table A.3: Credit from Fintech Lenders before Treatment

This Table presents the treatment effects of the social media subsidy and direct cash transfer separately using the following dependent variables. *Credit Application Rate* is a dummy variable that equals one if the entrepreneur has applied for fintech credits in the past year before our internvention. *Credit Approval Rate* is a dummy variable that equals one if the entrepreneur has successfully obtained fintech credits in the past year conditional on the application before our intervention. *Credit Interest Rate* is the interest rate of the loan if the entrepreneur has successfully obtained fintech credits in the past year before the intervention. T-statistics are reported in parentheses for OLS regressions and Z-statistics are reported for logistic regressions. For logistic regressions, the regression coefficients, the logarithm of odds ratios, are reported. All regressions control for strata dummies and re-randomization variables. *N_endline* is the number of observation with endline response.

Fintech Credit Before Treatment				
	Treatment	Direct Transfer	Control (Mean and SD)	Regression Types:
Application Rate	-0.10	0.09	0.29	Logistics
Z-statistics	(-0.31)	(0.30)	(0.46)	
Controls	Y	Y		
N_endline	784	2805	759	
$Pseudo_R^2$	0.00	0.00		
Approval Rate	-0.25	-0.20	0.31	Logistics
Z-statistics	(-0.42)	(-0.38)	(0.47)	
Controls	Y	Y		
N_endline	784	2805	759	
$Pseudo_R^2$	0.00	0.00		
Interest Rate	-0.26	0.09	8.45	OLS
T-statistics	(-0.19)	(0.12)	(6.30)	
Controls	Y	Y		
N_endline	784	759	2805	
R^2	0.00	0.00		

Table A.4: Collateral Channel

This table shows the heterogeneous treatment effect based on whether the entrepreneur owns property. The dependent variables are the revenue, labor, and profit of a business. We only report the coefficients and t-statistics of the interaction terms (β_2) in the regressions.

$$Y_{irs} = \alpha + \beta_1 Treat_i + \beta_2 Treat_i * Property_Ownership_i + \beta_3 Property_Ownership_i + \gamma_{r*s} + \mathbf{X}_i + \epsilon_{irs} ,$$

Non_Commercial_Property is a dummy variable that equals one if an entrepreneur does not own the store. *Non_Home_Property* is a dummy variable that equals one if an entrepreneur does not own an apartment or house. We only consider the entrepreneur to own a store or apartment if they have fully repaid the mortgage, if any. *Non_Both_Property* is a dummy variable that equals one if the entrepreneur does not own either an apartment or store. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. *N_treat* is the number of observation in the social media treatment group with endline response that also satisfy the specific filter listed above ($Non_Commercial_Property = 1$, $Non_Home_Property = 1$, or $Non_Both_Property = 1$ in the corresponding regression).

	Coefficient	T-statistics	*N_treat*
Revenue			
β_2 (Non_Commercial_Property*Treat)	282*	(1.87)	527
β_2 (Non_Home_Property*Treat)	671***	(2.82)	171
β_2 (Non_Both_Property*Treat)	926***	(3.12)	165
Labor			
β_2 (Non_Commercial_Property*Treat)	0.08*	(1.24)	527
β_2 (Non_Home_Property*Treat)	0.13**	(2.18)	171
β_2 (Non_Both_Property*Treat)	0.15**	(2.35)	165
Profit			
β_2 (Non_Commercial_Property*Treat)	75	(1.07)	527
β_2 (Non_Home_Property*Treat)	164	(1.14)	171
β_2 (Non_Both_Property*Treat)	226	(1.48)	165

Table A.5: Store Location

This table shows the heterogeneous treatment effect based on store locations of the entrepreneurs. The dependent variable is the revenue growth of a business, labor, and profit. We only report the coefficients and t-statistics of the interaction terms (β_2) in the regressions.

$$Y_{irs} = \alpha + \beta_1 Treat_i + \beta_2 Treat_i * Store_Locations_i + \beta_3 Store_Locations_i + \gamma_{r*s} + \mathbf{X}_i + \epsilon_{irs} \ ,$$

Prime_Outside_Facing is a dummy variable that equals one if the store is outside facing. *Prime_Near_Escalator* is a dummy variable that equals one if the store is located near an escalator. *Prime_Near_Entrance* is a dummy variable that equals one if the store is located near the entrance. *Non_Prime* is a dummy variable that equals one if the store is located in none of the three prime locations. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. N_treat is the number of observation in the treatment group with endline response that also satisfy the specific filter listed above N_treat is the number of observation in the social media treatment group with endline response that also satisfy the specific filter listed above ($Prime_Outside_Facing = 1$, $Prime_Near_Escalator = 1$, $Prime_Near_Entrance = 1$, or $Non_Prime = 1$ in the corresponding regression).

	Coefficient	T-statistics	N_treat
Revenue			
β_2 (Prime_Outside_Facing*Treat)	-234***	(-3.42)	54
β_2 (Prime_Near_Escalator*Treat)	-125***	(-3.09)	120
β_2 (Prime_Near_Entrance*Treat)	-310***	(-3.95)	72
β_2 (Non_Prime*Treat)	521***	(4.82)	538
Labor			
β_2 (Prime_Outside_Facing*Treat)	-0.12**	(-2.77)	54
β_2 (Prime_Near_Escalator*Treat)	-0.20***	(-3.05)	120
β_2 (Prime_Near_Entrance*Treat)	-0.08**	(-2.25)	72
β_2 (Non_Prime*Treat)	0.35***	(2.78)	538
Profit			
β_2 (Prime_Outside_Facing*Treat)	-75	(-1.10)	54
β_2 (Prime_Near_Escalator*Treat)	-60	(-1.15)	120
β_2 (Prime_Near_Entrance*Treat)	-163*	(-1.90)	72
β_2 (Non_Prime*Treat)	276**	(2.41)	538

Table A.6: Impact of Social Media Subsidy and Cash Transfer (Transactions)

Panel A shows the growth in the number of transactions one year after the intervention. The term "treatment" refers to a social media advertisement subsidy of 1,000 RMB for content boosting fees, which is directly provided to the social media platform. This treatment is offered only on the condition that business owners create a new video, live stream, or photo post to promote their business. "Direct Transfer" indicates an unconditional cash transfer made directly to the business owner. Panel B shows the treatment effect of the social media subsidy and direct cash transfer on the natural logarithm of the number of transactions using OLS regressions. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. *N_endline* is the number of observation with endline response.

Panel A: Raw value			
	Treatment	Direct Transfer	Control (Mean and SD)
Transactions	248***	35	1061
T-statistics	(5.10)	(1.01)	(1382)
Controls	Y	Y	
R^2	0.01	0.00	
N_endline	784	759	2805
Panel B Natural logarithm			
	Treatment	Direct Transfer	
Transactions	0.63***	0.05	
T-statistics	(4.19)	(0.24)	
Controls	Y	Y	
R^2	0.04	0.01	
N_endline	784	759	2805

Table A.7: Impact of Social Media Subsidy and Cash Transfer (Online vs. Onsite Revenue)

This table shows the results when the dependent variables are the online and onsite revenue of a small business one year after the intervention. The term "treatment" refers to a social media advertisement subsidy of 1,000 RMB for content boosting fees, which is directly provided to the social media platform. This treatment is offered only on the condition that business owners create a new video, live stream, or photo post to promote their business. "Direct Transfer" indicates an unconditional cash transfer made directly to the business owner. Robust standard errors are calculated for the corresponding regressions and t-statistics are reported in the parenthesis. All regressions controls for strata dummies and re-randomization variables. *N_endline* is the number of observation with endline response.

	Treatment	Direct Transfer	Control (Mean and SD)
Online Revenue	4576***	-175	6430
T-statistics	(5.39)	(-0.80)	(11947)
Controls	Y	Y	
R^2	0.01	0.00	
N_endline	784	759	2805
Onsite Revenue	1048*	1064	7549
T-statistics	(1.78)	(1.20)	(12854)
Controls	Y	Y	
R^2	0.01	0.00	
N_endline	784	759	2805

Table A.8: Impact of Social Media Subsidy and Cash Transfer (Online Vs. Onsite Transactions)

This table shows the number of online transactions and onsite transactions one year after the intervention. The term "treatment" refers to a social media advertisement subsidy of 1,000 RMB for content boosting fees, which is directly provided to the social media platform. This treatment is offered only on the condition that business owners create a new video, live stream, or photo post to promote their business. "Direct Transfer" indicates an unconditional cash transfer made directly to the business owner. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. *N_endline* is the number of observation with endline response.

	Treatment	Direct Transfer	Control (Mean and SD)
Online Transactions	205***	-18	468
T-statistics	(4.78)	(-0.75)	(865)
Controls	Y	Y	
R^2	0.01	0.00	
N_endline	784	759	2805
Onsite Transactions	48	53	583
T-statistics	(1.18)	(1.01)	(805)
Controls	Y	Y	
R^2	0.01	0.00	
N_endline	784	759	2805

Table A.9: Impact of Social Media Subsidy and Cash Transfer (DiD)

This table shows the growth of revenue, labor, and profit one year after the intervention using difference-in-differences regressions. The term "treatment" refers to a social media advertisement subsidy of 1,000 RMB for content boosting fees, which is directly provided to the social media platform. This treatment is offered only on the condition that business owners create a new video, live stream, or photo post to promote their business. "Direct Transfer" indicates an unconditional cash transfer made directly to the business owner. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. N_k is the number of observation in the difference-in-differences regression.

	Treatment	Direct Transfer
Revenue		
Treat*Post	6259***	-174
T-statistics	(5.15)	(-0.37)
Controls	Y	Y
R^2	0.02	0.00
Labor		
Treat*Post	1.17***	-0.15
T-statistics	(6.18)	(-0.48)
Controls	Y	Y
R^2	0.01	0.00
Profit		
Treat*Post	2184***	392
T-statistics	(3.22)	(0.62)
Controls	Y	Y
R^2	0.01	0.00
N_k	7178	7128

Table A.10: Impact of Social Media Subsidy and Cash Transfer (DiD)

This table shows enterprenuers' social media presence one year after the intervention using difference-in-differences regressions. The term "treatment" refers to a social media advertisement subsidy of 1,000 RMB for content boosting fees, which is directly provided to the social media platform. This treatment is offered only on the condition that business owners create a new video, live stream, or photo post to promote their business. "Direct Transfer" indicates an unconditional cash transfer made directly to the business owner. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. N_k is the number of observation in the difference-in-differences regression.

Social media presence	Treatment	Direct Transfer
Streaming days		
Treat*Post	1.95***	-0.14
T-statistics	(4.30)	(-1.10)
Controls	Y	Y
R^2	0.05	0.00
Video Posted		
Treat*Post	0.42***	-0.02
T-statistics	(4.17)	(-0.16)
Controls	Y	Y
R^2	0.03	0.01
Photo Posted		
Treat*Post	0.53***	0.02
T-statistics	(4.28)	(1.06)
Controls	Y	Y
R^2	0.03	0.00
N_k	7178	7128

Table A.11: Online Stores and Online Credit from Fintech lender: The Finance Channel (DiD)

This table shows financing outcomes using difference-in-differences regressions. "Online Credit" refers to the total amount of credit the business receives from fintech lenders, while "Bank Loan" refers to the amount of loan the business receives from banks. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. N_k is the number of observation in the difference-in-differences regression.

	Treatment	Direct Transfer
Online Credit		
Treat*Post	52105***	373
T-statistics	(5.13)	(0.85)
Controls	Y	Y
R^2	0.06	0.00
Bank Loan		
Treat*Post	-275	209
T-statistics	(-0.38)	(0.73)
Controls	Y	Y
R^2	0.00	0.00
N_k	7178	7128

Table A.12: Treatment Effects Across Different Social Media Formats

This table shows the heterogeneous treatment effects based on different social media formats. We categorize the social media platforms based on the platform that entrepreneurs chose for the subsidy (1000 RMB). The dependent variables are revenue, labor, and profit. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. N_k is the number of observation in the regression analysis. We perform a Wald test to assess the equality of coefficients across different subgroups.

	Coefficient	T-statistics	N_k
Revenue			
Streaming	7045***	(5.15)	3096
Video	4654**	(2.40)	3013
Photo	4380**	(2.31)	3090
Wald χ^2	1.74		
P-value	0.58		
Labor			
Streaming	0.96***	(4.02)	3096
Video	0.40**	(2.38)	3013
Photo	0.44**	(2.41)	3090
Wald χ^2	4.08		
P-value	0.13		
Profit			
Streaming	3038***	(3.82)	3096
Video	1301**	(2.08)	3013
Photo	1296**	(1.98)	3090
Wald χ^2	3.61		
P-value	0.16		

Table A.13: Online Stores and Online Credit from Fintech Lender: The Finance Channel

This table reports regression results similar to Table 3 but for four different subsamples. "Fintech Lenders' Store Only" refers to the subsample where the treated stores have opened an online marketplace that is also a fintech lender during the intervention period. "Fintech Lenders + Others" refers to the subsample where the treated stores have opened an online marketplace that is a fintech lender, and they also have an online marketplace that is not a fintech lender during the intervention period. "Others Only" refers to the subsample where the treated stores own online marketplaces that are not fintech lenders during the intervention period. "None" refers to the subsample where the treated stores do not own an online marketplace during the intervention period. The control group remains the same. Robust standard errors are calculated for the corresponding regressions, and t-statistics are reported in parentheses. All regressions control for strata dummies and re-randomization variables. N_k is the number of observation in the regression analysis. We perform a Wald test to assess the equality of coefficients across different subgroups.

	Fintech Credit	Revenue	Labor	Profit	N_k
Subsamples:					
Fintech lenders' store only	71451***	7072***	0.61***	3065***	3063
T-statistics	(16.91)	(6.07)	(4.41)	(3.56)	
Controls	Y	Y	Y	Y	
R^2	0.07	0.01	0.01	0.01	
Fintech lenders+ Others	50219***	5493***	1.09***	1734*	3031
T-statistics	(15.73)	(5.26)	(8.25)	(1.94)	
Controls	Y	Y	Y	Y	
R^2	0.06	0.01	0.02	0.00	
Others only	1294	3261**	0.28*	405	3040
T-statistics	(0.48)	(2.41)	(1.80)	(0.75)	
Controls	Y	Y	Y	Y	
R^2	0.00	0.00	0.00	0.00	
None	2513	3346**	-0.03	384	2880
T-statistics	(0.94)	(2.45)	(-0.13)	(0.42)	
Controls	Y	Y	Y	Y	
R^2	0.00	0.00	0.00	0.00	
Wald χ^2	179.89	9.10	28.43	8.50	
P-value	0.00	0.03	0.00	0.04	

A.1 Sample Pre and after intervention Questionnaire

Business and Owner Demographics

1. **Age of Business Owner:** _____ (Enter your age)
2. **Education Level:**

   High School

   Associate Degree

   Bachelor's Degree

   Master's Degree

   Doctorate

   Other (Please specify): _____

3. **Sex:**

   Male

   Female

   Other

4. **Do you co-run the business as a couple:**

   Yes

   No

5. **Do you co-run the business with other people:**

   No

   Yes (Please specify): _____

Business Information

6. **Years of Business Establishment:** _____ (Enter number of years)
7. **Monthly Revenue (in local currency):** _____ (Enter monthly revenue)

8. **Monthly Number of Transactions:** _____ (Enter number of transactions)
9. **Monthly Profit (in local currency):** _____ (Enter monthly profit)
10. **Number of Employees:** _____ (Enter number of employees)
11. **Monthly Advertisement Expense (in local currency):** _____ (Enter advertisement expense)
12. **Monthly Social Media Booster Fee Expense (in local currency):** _____ (Enter expense)
13. **Outstanding Bank Loan:**

    Yes

    No

    The amount

14. **Did you apply for a new bank loan this year?**

    Yes

    No

    The amount

15. **Was your loan approved?**

    Yes

    No

16. **What is the interest rate of the loan?**

    Interest Rate

Online Presence

17. **Do you have an online store?**

    Yes

    No

18. **Which kind of online store?**

    Personal Website

    Online Marketplace (e.g., Taobao) (Please specify): _____

    Social Media Store (e.g., Xiaohongshu Shop) (Please specify): _____

    Other (Please specify): _____

19. **Do you have big fintech firm credits?**

    Yes

    No

20. **Did you apply for a new fintech loan this year?**

    Yes

    No

    The amount

21. **Was your loan approved?**

    Yes

    No

22. **What is the interest rate of the loan?**

    Interest Rate

Social Media Activity

23. **Number of Videos Posted per Month:** _____ (Enter number of videos)
24. **Streaming Days per Month:** _____ (Enter number of streaming days)
25. **Number of Photos Posted per Month:** _____ (Enter number of photos)

Learning and Feedback

26. **Do you learn from other bloggers?**

    Yes

    No

27. **Do you get feedback from consumers?**

    Yes

    No

Ratings

28. **Product Rating:** _____ (Enter rating out of 5)
29. **Delivery Rating:** _____ (Enter rating out of 5)
30. **Service Rating:** _____ (Enter rating out of 5)
31. **Product Variety Rating:** _____ (Enter rating out of 5)

Subsidies and Ownership

32. **Do you get any other forms of subsidies from the government or other entities?**

    Yes

    No

33. **Do you own an apartment or house?**

    Yes

    No

34. **Do you own the shop you have?**

    Yes

No

Location and Revenue Breakdown

35. **Is your store outside facing or on an upper floor in a shop?**

    Outside facing

    Upper floor in a shop

    Near an escalator

    Near an entrance

36. **What portion of revenue comes from online sales?** _____ (Enter percentage)
37. **What portion of revenue comes from onsite sales?** _____ (Enter percentage)
38. **What portion of transactions are conducted online?** _____ (Enter percentage)
39. **What portion of transactions are conducted onsite?** _____ (Enter percentage)

Procrastination and Present Bias in Business Strategy

40. **In the past month, how often have you delayed important business tasks (such as posting on social media, updating your online store, or applying for credit) even though you knew they could help your business in the long run?**

    Never

    Rarely

    Sometimes

    Often

    Always

41. **How often do you postpone starting new business strategies because they feel too time-consuming or difficult right now?**

Never

Rarely

Sometimes

Often

Always

42. **Imagine you have the opportunity to invest 1,000 RMB in marketing today, which is likely to increase your revenue next month. How likely are you to make this investment now versus waiting until next month?**

    Very likely

    Somewhat likely

    Not sure

    Somewhat unlikely

    Very unlikely

43. **When considering business investments, do you focus more on:**

    Immediate costs/effort

    Potential future benefits

    Both equally

44. **How much do you agree with the statement: "I prefer immediate rewards, even if waiting could bring greater benefits to my business."**

    Strongly disagree

    Disagree

    Neutral

    Agree

    Strongly agree

45. **How often do you plan to create content for your business's social media, but end up postponing or forgetting to do it?**

Never

Rarely

Sometimes

Often

Always

46. **What are the main reasons you delay posting on social media for your business? (Select all that apply)**

    Lack of time

    Uncertainty about effectiveness

    Dislike of content creation

    Immediate business needs take priority

    Forgetfulness

    Other (please specify): _____

47. **Would you find it helpful to receive reminders or small incentives to help you follow through with your marketing or content creation plans?**

    Yes

    No

48. **In the past, have you set business goals (such as posting weekly on social media) but failed to follow through? If yes, what usually prevented you?**

    Yes (please specify reasons): _____

    No

49. **Suppose you could receive a 500 RMB cash reward for posting a new product video today, or a 1,000 RMB reward if you post it one month from now. Which would you choose?**

    500 RMB today

    1,000 RMB in one month

50. **Over the past three months, how many times did you intend to execute a new business strategy (e.g., starting a livestream, launching a promotion), but did not do so until later than planned?**

    Never

    1-2 times

    3-5 times

    More than 5 times

Open-Ended Questions: Fintech Offers

51. **First offer moment.** In your own words, describe the first time you saw a credit offer on the platform (where it appeared; exact wording if you recall). What had changed in the previous 30–60 days for your shop?
52. **Perceived triggers.** What are the top three signals you believe the platform uses to decide who gets an offer (e.g., 30-day sales, average rating, return rate, delivery delays, account age, disputes)? Why these?
53. **Before/after narrative.** Tell us about a time your credit offer or limit increased/decreased. What events, metrics, or customer ratings changed in the weeks just before that happened?
54. **Binding constraint.** If only one metric is the bottleneck for you right now, what is it? What evidence would convince you that a different metric actually matters more?
55. **Controllable vs. not.** Which of the signals you listed are under your control, and how do you try to influence each one? Which are not under your control?
56. **False positives/negatives.** Describe a time you expected to get (or keep) an offer but didn't (or it was reduced)—or you got one unexpectedly. What do you think the algorithm "saw" differently from you?
57. **Freeze flags.** What behaviors or events do you think can freeze or suspend offers

(e.g., spikes in refunds/chargebacks, policy violations)? How do you prevent these?

58. **Eligibility recipe (your guess).** If the platform published a short "eligibility recipe," what would it say about thresholds and windows? (e.g., "rating $\geq$ 4.6 over 60 days, return rate $\leq$ 3%, on-time shipping $\geq$ 95%, monthly sales $\geq$ _____ for 2 months").
Explain why.
59. **Evidence you'd show.** If you could attach one screenshot or dashboard view that best proves you're eligible, which would you choose and why?
60. **Tiny action plan (next week).** Name one specific change you'll make next week to cross or protect a threshold (what, where, how often). What simple check will tell you it worked?

Researcher note: The bold labels (e.g., ***First offer moment.****) are instrument headings for authors and are* not *shown to respondents.*

Learning and Feedback

61. **Why post/stream (or not).** In your own words, what are the first two reasons you do (or do not) post or live stream about your products?
62. **Most recent iteration.** Think of the last time you changed your product, price, or pitch because of audience reactions (comments, views, likes, direct messages, live chat).
    - What exactly did people say or do?
    - What one change did you make?
    - What happened afterwards?
63. **Which feedback matters.** When you look at responses to your posts/streams, which signals do you pay attention to first, and why? (e.g., specific comments, view time, saves, inquiries, ratings, returns)

64. **Learning from peers.** In your own words, describe one thing you learned from another seller/creator in the last 3 months and how you applied it.
65. **Bottlenecks to using feedback.** What are the top two obstacles that make it hard to use feedback to improve (e.g., time, skills, uncertainty, negative comments)? Please explain.
66. **Mind-change test.** What one fact or example about customers or content would most likely change your mind about how often you should post or what you should show?
67. **Quality & ratings link.** In your own words, how do comments and ratings translate (or fail to translate) into sales for you?
68. **Tiny action plan (next week).** Name one specific post or live stream you will do next week to test something you learned (what will you show, what outcome will tell you it worked?).
69. **When learning did not work.** Tell us about a time a change you made based on feedback did not improve results. What do you think went wrong, and what will you try next?
70. **Reliable vs. noisy signals.** Which feedback signals do you consider reliable and which are noisy? How do you filter or verify them before making a change?

Researcher note: The bold labels (e.g., ***Most recent iteration.****) are instrument headings for authors and are* not *shown to respondents.*

A.2 Verification of self-report data

To ensure the accuracy of our research data, we asked entrepreneurs to prepare financial records, such as sales and expense ledgers, and any other relevant documents that record revenue and costs associated with running their business. We assured entrepreneurs of the confidentiality and security of their financial information. During face-to-face interviews, we began by explaining the need to verify the data and how it would help ensure the accuracy of the research. We reinforced the confidentiality of their data and emphasized that it would be used solely for research purposes.

We requested several types of financial documents to verify the monthly revenue reported by entrepreneurs. Examples of such documents include sales ledgers, invoices and receipts, and bank statements, which can be used to cross-verify sales deposits. We compared the monthly revenue reported in the survey with the figures in these financial documents and verified consistency across different months whenever possible.

If there were discrepancies between the survey data and financial records, we discussed them openly with the entrepreneurs. For example, if the revenue recorded in the sales ledger for February was 45,000 RMB but the survey response indicated 55,000 RMB, we would ask the entrepreneur to help us understand the difference. Possible reasons for discrepancies include misreporting or misunderstanding in the survey, timing differences in recording revenue, and unrecorded cash transactions. When such discrepancies were identified, we corrected them in the dataset.

We also cross-checked the number of transactions through the sales ledger or POS (Point of Sale) system reports and verified the number of transactions reported in the survey with actual transaction records. Additionally, we double-checked advertisement expenses by asking for invoices and comparing these expenses with the survey responses. We compared reported monthly revenue, profit, and expenses with actual financial documents and verified social media activity (e.g., number of posts, streaming days) with analytics from their social media accounts. Employee count was also cross-checked with internal records.

Consistency tests were constructed to ensure logical coherence in the data. For instance, the age of the business owner should logically increase by the duration of the intervention period, and the years of business establishment should similarly increase. We verified that demographic information remained consistent and checked for logical consistency in business information, such as revenue trends.

To further verify their data, we asked entrepreneurs additional questions such as, "Can you walk me through how you calculate your monthly revenue and profit?" and "How do you track the number of transactions each month?" We also inquired, "Can you show me examples of your social media activity?" and "How do you gather feedback from consumers, and how do you use it?" By following these steps, we aimed to ensure that our questionnaire accurately captured the necessary data and that the responses were reliable and valid.

A.2.1 Cross-Validation The Revenue Data

For small businesses in Huaqiangbei, Shenzhen, we further cross-validate the revenue data with tax filing records from the Shenzhen Tax Authority database. We find that 89% of the revenue figures fall within 90% to 110% of the officially reported amounts. This alleviates concerns about experimenter demand effects, specifically the possibility that revenues may be overreported due to the presence of external researchers.

A.3 Eligibility Rules for Fintech Credit Triggered by Online Platform Participation

In China, leading e-commerce platforms such as Taobao (Alibaba), Tmall, and JD.com are vertically integrated with fintech lenders (e.g., Ant Financial/Ant Group, JD Finance), who use merchants' real-time operational data to algorithmically assess creditworthiness. Opening an online store on these platforms is a necessary first step for credit eligibility. Once a merchant has established an active store, the platform automatically collects transactional and behavioral data—including sales volume, product inventory, and customer interactions.

Fintech lenders then use this data to dynamically assess eligibility and extend credit offers. In practice, merchants who reach certain sales thresholds and maintain good standing may receive unsolicited credit offers directly through their merchant dashboards.

Importantly, credit assessment is based not only on quantitative factors such as sales and transaction frequency, but also on qualitative metrics including product ratings, service ratings, and delivery ratings. High ratings across these categories signal customer satisfaction, business reliability, and operational excellence, all of which reduce perceived lender risk and can result in higher credit limits or more favorable loan terms. Conversely, low ratings or frequent complaints may flag a merchant as higher risk, reducing eligibility or tightening credit conditions. Platforms incorporate these ratings into their proprietary credit scoring algorithms and risk models; trends and consistency in ratings are also monitored, with sudden drops potentially triggering credit reassessment.

Thus, platform participation is a necessary but not always sufficient condition for credit access; active sales growth and consistently high operational ratings jointly trigger the dynamic extension of fintech credit. This institutional context aligns with our empirical finding that sales growth and platform presence substantially increase the likelihood of accessing fintech credit, supporting the "fintech accelerator" mechanism hypothesized in our study. Below are the criteria summarized as bullentin points.

- **Automatic Credit Pre-qualification:**
  - **Opening an Online Store:** Registering and operating a store on e-commerce platforms (e.g., Taobao, Tmall, JD.com) may make a business eligible for pre-screening for credit products.
  - **Data Access:** The platform collects real-time data, including sales volume, product/service/delivery ratings, customer feedback, inventory turnover, and transaction history.
  - **Algorithmic Approval:** Fintech lenders (e.g., Ant Financial, JD Finance) use proprietary, confidential algorithms to assess creditworthiness based on multi-

dimensional operational data.

  - **Automatic Offers:** Merchants may receive pre-approved credit lines or loan offers directly via their merchant dashboards upon reaching certain sales or operational milestones, sometimes with no formal application required.

- **Main Eligibility Criteria (based on public information):**
  - **Active Store Status:** Store must be active and in good standing (not suspended or under investigation).
  - **Minimum Sales Volume:** Public sources report a typical minimum monthly sales threshold ranging from 3,000–10,000 RMB; however, exact thresholds are proprietary and may change dynamically.
  - **Store Tenure:** Some platforms require 3–6 months of operating history before extending credit offers.
  - **Compliance:** Merchant must comply with platform rules, with no record of serious violations or fraud.
  - **Verification:** Full completion of Know-Your-Customer (KYC) processes, including business license and owner identity verification.

- **Credit Approval Process:**
  - **No Separate Application Needed:** Credit may be extended automatically based on the merchant's ongoing performance data.
  - **Dynamic Credit Limits:** Credit limits are adjusted over time as sales and risk profiles evolve; both increases and decreases are possible.
  - **Platform Exclusivity:** Credit products are typically tied to the merchant's activity on the specific platform and may be withdrawn if the merchant leaves or is delisted.

- **Holistic Data Assessment:**
  - Fintech lenders use a wide array of data, both quantitative (e.g., sales, trans-

action frequency) and qualitative (e.g., ratings, customer feedback), for credit assessment.

  - Algorithms are confidential and updated regularly to reflect changes in the platform ecosystem.

- **Importance of Ratings:**
  - **Product Rating:** High product ratings (typically above 4.5/5) increase credit eligibility; platforms may require minimum average ratings (e.g., 4.0/5 or above) but exact thresholds are not publicly disclosed.
  - **Service Rating:** Good after-sales and customer service ratings reflect merchant reliability.
  - **Delivery Rating:** Fast, reliable delivery ratings signal operational efficiency.
- **How Ratings Impact Credit Offers:**
  - High and stable ratings across categories improve merchant scores, resulting in higher credit limits and better loan terms.
  - Low ratings or a pattern of negative feedback may flag merchants as higher risk, leading to reduced eligibility or stricter terms.
  - Time series dynamics are critical: sudden rating drops or persistent negative trends can trigger credit reassessment or reduction.
- **Confidentiality and Dynamics:**
  - Exact credit thresholds, algorithmic weights, and minimum rating requirements are confidential and subject to change; platforms do not publicly disclose the full details of their scoring or approval processes.
  - Credit assessment models are updated frequently to reflect new data and changing market conditions.
- **Public Statements and Documentation:**

- Ant Group's IPO prospectus and official statements highlight the use of "multi-dimensional data," including customer feedback and ratings, in credit scoring.
- JD Finance and others publicly state that both quantitative and qualitative data are used for dynamic, ongoing risk profiling.

A.4 Binary Classification of Present Bias and Procrastination

To construct a unified binary indicator for procrastination or present bias among small business owners, we first operationalize the concept using their responses to a series of survey questions designed to capture both self-reported behaviors and attitudes related to the postponement of business tasks and the preference for immediate rewards. Each survey item is coded as either indicative (1) or non-indicative (0) of procrastination or present bias, based on the content of the response.

For questions assessing the frequency of delaying important business tasks, postponing the initiation of new strategies, or postponing social media content creation, a response of "sometimes," "often," or "always" is coded as 1, reflecting the presence of procrastinatory behavior, whereas "never" or "rarely" is coded as 0. Questions that probe the likelihood of making investments with future benefits are coded as 1 if the respondent expresses uncertainty or reluctance to invest immediately ("not sure," "somewhat unlikely," "very unlikely"), and as 0 if the respondent is "very likely" or "somewhat likely" to invest now.

When asked about their focus in business decision-making, respondents who prioritize "immediate costs/effort" are assigned a value of 1, while those who focus on "potential future benefits" or "both equally" are assigned 0. Similarly, agreement with the statement preferring immediate rewards over greater future benefits is considered indicative of present bias, with responses of "agree" or "strongly agree" coded as 1 and other responses as 0.

For the multi-select question regarding reasons for delaying social media posts, selection of any option that reflects procrastination or present bias—such as "lack of time," "immediate business needs take priority," or "forgetfulness"—results in a value of 1; otherwise, the value

is 0. Responses indicating the need for reminders or incentives to follow through with plans are also coded as 1, reflecting a reliance on external cues to overcome present bias, with "no" responses coded as 0. If the respondent admits to setting business goals but failing to follow through, this is likewise coded as 1.

The hypothetical choice between an immediate smaller reward and a delayed larger reward is a standard measure of present bias; choosing the immediate reward is coded as 1, while selecting the delayed reward is coded as 0. Finally, for questions on the historical frequency of delaying the execution of business strategies, any response indicating one or more instances of delay is coded as 1, while "never" is coded as 0.

After coding each individual item, we construct a summary binary variable for each respondent. If the respondent exhibits procrastination or present bias on more than three of these questions—then the summary variable is coded as 1. Otherwise, the overall responses are coded as 0. This approach ensures that the indicator captures even a single instance of procrastination or present bias, providing a conservative measure of the behavioral tendency in the sample.

A.5 Coding of Learning and Feedback Open-Ended Responses

We transform a subset of open-ended answers into a 0–10 *Learning & Feedback Practice Score* (LFPS). The score captures whether merchants (i) use specific audience signals, (ii) implement concrete changes, (iii) measure outcomes over a time window with recent evidence, (iv) adjust sequentially using simple decision rules, and (v) adopt practices learned from peers.

Items used. Content is coded from five prompts: most recent iteration (Q2), which feedback matters (Q3), learning from peers (Q4), how comments/ratings translate into sales (Q7), and when learning did not work (Q9).

Rubric (0, 1, or 2 points per dimension).

i) **Specific signals (Q3, Q7).**

- 0 = only generic mentions (e.g., "comments", "likes").
- 1 = at least one actionable signal named (e.g., direct messages/inquiries, saves/bookmarks, average view duration, product page visits, click-through rate, add-to-cart rate, conversion/purchase rate, star rating level/trend, return/chargeback rate, themes in review text).
- 2 = at least two distinct actionable signals, or a signal accompanied by a quantitative threshold.

ii) **Specific action (Q2).**

- 0 = no concrete change.
- 1 = one concrete change to product/price/creative/operations (e.g., added size chart; introduced a bundle; instituted faster reply policy).
- 2 = two or more concrete changes across different areas, with brief detail.

iii) **Measured result with time window and recency (Q2, Q7).**

- 0 = no outcome beyond impressions.
- 1 = reports a metric *or* a time window; or reports both but clearly more than 60 days old; or timing unstated.
- 2 = reports a numeric change *and* a time window, and the episode occurred within the past 60 days.

iv) **Sequential adjustment and decision rule (Q2, Q9).**

- 0 = one-off tweak; no follow-up logic.
- 1 = at least one follow-up adjustment *or* a simple keep/revert rule tied to an observed outcome.
- 2 = stepwise process with an explicit decision threshold (e.g., "keep if purchases rise by $\geq 20\%$ over one week or return rate stays $\leq 3\%$; otherwise revert").

v) **External learning applied (Q4).**

- 0 = no learning from others.

- 1 = learned from another seller/creator but not applied.
- 2 = learned and applied (what was adopted and how).

Score construction. Let $s_{id} \in \{0, 1, 2\}$ denote respondent i's subscore on dimension $d \in \{1, \ldots, 5\}$. Define

$$\text{LFPS}_i \;=\; \sum_{d=1}^{5} s_{id}\,,$$

so $\text{LFPS}_i \in [0, 10]$, with higher values indicating stronger practice of learning-and-feedback.

B Model Setup

Consider entrepreneurs with quasi-hyperbolic discounting (Laibson, 1997) making social media marketing investment decisions over two periods. The model captures four key elements: (1) time-inconsistent preferences, (2) uncertain returns to marketing effort, (3) learning and feedback effects, and (4) fintech credit contingent on observed performance and feedback.

B.1 Preferences

We assume that agents exhibit present-biased preferences characterized by:

$$U_t = u_t + \beta \sum_{k=1}^{T-t} \delta^k u_{t+k} \tag{B-1}$$

where $\beta \in (0, 1)$ represents the present-bias factor (immediate gratification overweighting) and $\delta \in (0, 1)$ is the standard exponential discount factor.

B.2 Production Technology

Entrepreneurs face several key technological relationships:

- **Effort Cost**: Immediate disutility from marketing effort M_t (e.g., time creating content): $c(M_t) = \phi M_t$ where $\phi > 0$ is the marginal disutility
- **Sales Generation**: Social media marketing converts effort to sales through: $S_t = \theta M_t^{\alpha}$ with $\alpha \in (0, 1)$ capturing diminishing returns
- **Feedback Generation**: Marketing effort also generates consumer and peer feedback:

$$F_t = \psi M_t^{\omega} \tag{B-2}$$

  where $\psi > 0$ and $\omega \in (0, 1)$ represent the productivity and diminishing returns of feedback generation.

- **Fintech Credit**: Digital lenders provide credit proportional to observed sales *and* feedback:

$$C_{t+1} = \gamma_1 S_t + \gamma_2 F_t \tag{B-3}$$

where $\gamma_1 > 0$ and $\gamma_2 > 0$ are the multipliers for sales and feedback, respectively.

B.3 Behavioral Frictions

B.3.1 Present Bias

Period-1 utility perception combines immediate costs and discounted future benefits:

$$U_1 = -\phi M_1 + \beta\delta\mathbb{E}[\theta]M_1^{\alpha} \tag{B-4}$$

Maximizing this leads to suboptimal investment due to $\beta < 1$:

$$M_1^* = \left(\frac{\beta\delta\alpha\mathbb{E}[\theta]}{\phi}\right)^{\frac{1}{1-\alpha}} < M^{FB} \tag{B-5}$$

where $M^{FB} = \left(\frac{\delta\alpha\theta^*}{\phi}\right)^{\frac{1}{1-\alpha}}$ is the first-best effort with $\beta = 1$ and perfect information.

B.3.2 Uncertainty and Learning

Entrepreneurs initially underestimate true social media marketing productivity:

$$\mathbb{E}_1[\theta] = \mu_\theta < \theta^* \tag{B-6}$$

After observing feedback F_1, beliefs are updated according to:

$$\mathbb{E}_2[\theta] = \mu_\theta + \lambda F_1 \tag{B-7}$$

where $\lambda > 0$ measures how feedback from consumers and peers influences beliefs about marketing productivity.

B.3.3 Policy Intervention

A subsidy τ reduces effective marketing costs by directly offsetting effort disutility:

$$\phi \to \phi - \tau \tag{B-8}$$

This targeted intervention increases optimal effort to:

$$M_1^{sub} = \left(\frac{\beta\delta\alpha\mu_\theta}{\phi - \tau}\right)^{\frac{1}{1-\alpha}} \tag{B-9}$$

Unlike cash transfers (which enter utility additively), subsidies specifically alleviate the present-bias distortion by making effort feel less costly at the margin.

B.4 Fintech and Feedback Accelerator Mechanism

Realized sales and feedback data enable credit expansion in Period 2:

$$C_2 = \gamma_1\theta^*(M_1^{sub})^\alpha + \gamma_2 F_1 \tag{B-10}$$

The entrepreneur's Period-2 problem incorporates both direct sales, feedback-enhanced beliefs, and credit-enhanced profits:

$$U_2 = -\phi M_2 + \delta\left[\mathbb{E}_2[\theta]M_2^\alpha + \eta C_2\right] \tag{B-11}$$

$$M_2^* = \underbrace{\left(\frac{\delta\alpha\mathbb{E}_2[\theta]}{\phi}\right)^{\frac{1}{1-\alpha}}}_{\text{Direct SM marketing (now belief-adjusted)}} + \underbrace{\frac{\eta}{\phi}C_2}_{\text{Fintech leverage via sales \& feedback}} \tag{B-12}$$

where $\eta > 0$ captures returns to borrowed capital.

B.5 Empirical Predictions

- **Social Media Subsidy > Cash**: The subsidy's τ directly reduces ϕ in FOC, while cash grants don't affect the marginal effort decision
- **Persistence**: $\frac{\partial M_2^*}{\partial M_1^{sub}} > 0$ shows self-reinforcing effects
- **Fintech and Feedback Dependence**: $\frac{\partial M_2^*}{\partial \gamma_2} = \frac{\eta}{\phi} F_1$ quantifies treatment effects that operate via the feedback/learning channel, not just sales
- **Learning/Feedback Amplifies Accelerator**: Interventions that increase F_1 (engagement, ratings, peer learning) will have outsize effects on belief updating and credit access.

This model illustrates how temporary nudges create persistent effects through three channels: (1) overcoming present bias via cost reduction, (2) resolving uncertainty through forced experimentation and learning, and (3) activating fintech credit multipliers through both sales and feedback signals.

The results suggest subsidy should:

1. Target behavioral parameters (β, μ_θ) rather than just liquidity constraints
2. Use data generated by entrepreneurs' activities and feedback on digital marketing platforms to inform policy and improve credit allocation
3. Coordinate with fintech lenders' monitoring technologies (γ_1, γ_2) for both sales and engagement/feedback measures