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

Fangzhou Lu[a]

November 22, 2024

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 finding suggests that this growth can be attributed to a finance channel, wherein increased sales enhance small businesses' likelihood of opening online stores and subsequently accessing fintech credit.

JEL Codes: C93, D1, G30.

Keywords: Social media content creator, subsidy, fintech credit

*[a]HKU Business School, The University of Hong Kong. Please send correspondence to: lufz@hku.hk. We thank Maxime Couvert, Uta Schonberg, Maddalena Ronchi, Bohui Zhang and seminar participants at NYU and HKU for their helpful comments.

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). Among these interventions, access to finance plays a particularly crucial role by enabling micro-entrepreneurs to invest in growth strategies, including marketing efforts that are often prohibitively expensive. For instance, orange farmers frequently struggle to increase their product visibility, resulting in wholesalers collecting products directly from them. Similarly, a small doorbell seller may find it challenging to boost sales through extensive marketing campaigns. In this paper, we explore a novel approach to increasing the visibility and revenue of small enterprises: utilizing social media streaming or posting as a marketing strategy. This method not only enhances product visibility but also facilitates increased financing through fintech lenders (Berg, Burg, Gombović, and Puri, 2020; Chioda, Gertler, Higgins, and Medina, 2024). Consequently, small businesses acquire the necessary capital to scale their operations and improve their market presence.

Recent statistics highlight the rapid growth of social media platforms such as Instagram, Twitter, TikTok, WeChat Video, and Xiaohongshu, 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. 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 effective tools for advertising through live streaming, video posting, and photo posting. 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.

Our experiment provides the treatment group with a subsidy of 1,000 RMB, or around 140 USD, as a social media advertisement fee, such as the Dou+ services 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 receives nothing.[1] We also design a direct cash transfer of the same amount, unconditional, to serve as an alternative control group.

We identify and recruit 4,733 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, 2,741 businesses to the control group, and 1,000 businesses to the direct cash transfer group.[2] We collect detailed baseline data on the participating businesses'

[1]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.

[2]We assign 1,000 businesses to the treatment group, and 992 businesses eventually took up the subsidy.

characteristics, including business size, number of employees, annual revenue, access to bank and fintech credits, current marketing spending, and online presence. We administer a pre-intervention survey to gather information on business owners' perceptions of social media marketing and their expectations regarding the potential impact of the subsidy.

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 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.

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. Overall, the findings suggest that social media subsidies are more effective at promoting small business growth than direct cash transfers. This highlights the importance of targeted support through leveraging social

media platforms for business expansion and development.[3]

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. Therefore, we 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, 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 of merchants in real time. This capability allows them to assess creditworthiness more accurately and provide credit based on the observed

[3]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.

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.[4] At the same time, there should be no effect on bank credit.

Before the intervention, the treatment, control, and direct transfer groups had similar levels of online credit (3,156, 3,144, and 3,138 RMB, respectively) and bank loans (14,344, 14404, and 14,107 RMB, respectively). The percentage of small businesses with online stores was also relatively close between the groups at around 60%. After the treatment, the businesses in the treatment group experienced a significant increase in online credit, from three thousand to 20 thousand RMB, while the control and direct transfer groups saw only modest increases to around 10 thousand RMB, respectively. 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. Overall, our results suggest that sales growth can facilitate an accelerator effect if that growth enables entrepreneurs to gain access to 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. 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

[4]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.

a demand effect.

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 have valuable insights into a business's growth potential and creditworthiness. To verify this hypothesis, we categorize businesses into four subgroups based on their online store status one year after the intervention: those with exclusive Fintech lenders' stores, those with combined Fintech lenders and other stores, those with only other stores, and those with no online stores. The results of these subgroups are then compared to the control group to assess the impact of having an online store on a fintech lending platform.

For businesses that have online stores also functioning as fintech lenders, the fintech credit is 14,513 RMB higher, revenue is 7,072 RMB higher, labor is 0.61 higher, and profit is 3,065 RMB higher, all relative to the control group. For businesses hosting stores on both fintech lenders and other platforms, the fintech credit is 12,962 RMB higher, revenue is 5,493 RMB higher, labor is 1.09 higher, and profit is 1,734 RMB higher, all relative to the control group. For businesses that only host stores with no fintech lender affiliation, the fintech credit is 475 RMB higher, revenue is 4,261 RMB higher, labor is 0.28 higher, and profit is 805 RMB higher, all relative to the control group. For businesses without any online stores, the fintech credit is 1,417 RMB higher, revenue is 4,346 RMB higher, labor is -0.03 lower, and profit is 684 RMB higher, all compared to the control group. The 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.

In summary, this study demonstrates the significant potential of social media platforms as a marketing 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 con-

siderably 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, where increased sales enhance small businesses' likelihood of opening online stores and subsequently accessing fintech credit. Overall, our study underscores the value of utilizing social media platforms as a marketing tool for small businesses, as well as the potential benefits of targeted subsidies and support programs aimed at encouraging businesses to embrace these platforms.

This 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 entrepreneurial use in-kind subsidy induced credit to expand production.

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 accelerator that increase an entrepreneur's visibility but no 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 marketing, 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.

The rest of the paper is organized as following. Section two discusses the institutional details of social media content creating in China. Section three introduces our field experiment methodology. Section four shows the results of our field experiment. Section five concludes.

2 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 SMEs to advertise their products for several reasons. First, these platforms have a large and growing user base, providing businesses with access to a wide audience. For example, TikTok has more than 1 billion monthly active users worldwide, making it an attractive platform for businesses to reach potential customers. Second, short videos are highly engaging, as they can convey a message or showcase a product quickly and effectively. Users are more likely to watch and engage with a 15-second video than read a lengthy article or advertisement, increasing the chances of conversion. Third, advertising on social media platforms can be

more affordable than traditional advertising channels, making it an attractive option for small businesses and micro-entrepreneurs with limited marketing budgets.

Moreover, social media platforms offer advanced targeting options, allowing businesses to reach specific demographics, interests, and behaviors. This ensures that the advertisements are shown to users who are more likely to be interested in their products, increasing the chances of conversion. Furthermore, short videos on platforms like TikTok have the potential to go viral, reaching millions of users in a short period.[5] This can significantly boost brand exposure and drive sales for micro-entrepreneurs and SMEs. Last but not least, some social media platforms, like TikTok, are integrating e-commerce features, allowing users to discover and purchase products directly within the app. This seamless shopping experience can drive sales and make it easier for micro-entrepreneurs and SMEs to reach potential customers.

Recent statistics reveal the remarkable scale of this phenomenon. In China, the number of online content creators reached 50 million in 2020, with the market size surpassing $20 billion (iResearch, 2020). Similarly, in the United States, the influencer marketing industry is projected to reach $13.8 billion in 2021, doubling its size in just three years (Influencer Marketing Hub, 2021).

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.[6] 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.

[5]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

[6]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.

We identify and recruit 4,733 small businesses in Guangdong, Zhejiang, Jiangsu, and Liaoning provinces. 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 992 businesses to the treatment group, 2741 businesses to the control group, and 1000 businesses to the direct cash transfer group.[7] The randomization was stratified by sector and region and was conducted through a Stata program.[8] 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 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

[7]We assign 1000 businesses to the treatment group and 992 businesses eventually took up the subsidy.

[8]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.

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.[9] 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.[10] We also design a direct cash transfer of the same amount, unconditional, to serve as an alternative treatment/control group.

One year after intervention period, we collect 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.

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 7,871.90 RMB for the Treatment group to 7,901.40 RMB for the Cash Transfer group. The average monthly profit is around 1,785.52 RMB for the Treatment group, 1,835.18 RMB for the Control group, and 1,889.28 RMB for the Cash Transfer group. The average number of employees in a small business is about 1.5 across all groups. The

[9]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.

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

businesses spend on average around 295.22 RMB on advertisements excluding social media booster fees for the Treatment group, 291.77 RMB for the Control group, and 287.58 RMB for the Cash Transfer group. The average social media booster fee is around 81.48 RMB for the Treatment group, 77.34 RMB for the Control group, and 78.23 RMB for the Cash Transfer group. The mean social media booster fee is mainly driven by a small percentage of entrepreneurs who have used social media content booster fee before. The median value of these variables are zero.

The average amount from bank loans or other bank-related channels is approximately 14,344.20 RMB for the Treatment group, 14,004.87 RMB for the Control group, and 14,107.40 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 3,156.10 RMB for the Treatment group, 3,144.77 RMB for the Control group, and 3,138.40 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 t-statistics 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: Yiwu Small Merchandise Market in Zhejiang, Huaqiangbei in Shenzhen, and Wuai Market in Shenyang. 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. 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 market dynamics and the behavior of small businesses. Huaqiangbei, situated in Shenzhen, is renowned as a major electron-

ics 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. Wuai Market, located in Shenyang, is one of the largest wholesale 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. Studying Wuai Market provides valuable information on the wholesale trade, supply chain management, and the economic interactions between different regions. 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 2 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 190 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 243 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. Lastly, the Other sector includes 63 observations in the Treatment group, 219 in the Control group, and 54 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 (e.g., follower growth, engagement rate, and content frequency).

$$Y_{irs} = \alpha_i + \beta_i Treat_i + \gamma_i^F F_{rs} + \epsilon_{irs} \ , \tag{1}$$

Where Y are the dependent variables. $Treat$ is our intervention. F are the fixed effects we include. r represents one of the three regions we conduct the experiment, Yiwu, HuangQiang-Bei, or Wuai. s represents the industry of the small business. 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 Results

3.1 Baseline

Table 3 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 5,621 RMB, labor increased by 0.66, and profit increased by 2,039 RMB. All regressions control for strata dummies and re-randomization variables.

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.

In natural logarithm form, the treatment group experienced a significant increase in revenue and labor compared to the control group. The direct transfer group showed a significant increase in revenue but not in labor.

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 intervention may be more effective in promoting business growth than direct cash transfers.[11]

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 4 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 seems to justify the large treatment effect.

[11]These results are robust when we winsorize or censor the variables at 99% and 95% level. These results are also robust when we use a difference-in-differences approach.

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 4 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 transfer group showed no significant change in streaming days (-0.08 days) and no significant change in the number of videos posted per month (-0.00 videos). 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 transfer group 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 (Gertler, Higgins, Malmendier, and Ojeda, 2022). 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 5 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. The results suggest that a lack of knowledge about social media boosting was the 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.

3.2 Fintech Credit Channels

Table 6 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.

The treatment group experienced a significant increase in online credit from financial lenders (9,313 RMB, t=17.00) compared to the control group. The direct transfer group showed a smaller but still significant increase in online credit (1,023 RMB, t=1.94). The treatment group showed a small and not statistically significant increase in bank loans (411 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 (128 RMB, t=0.24). The

treatment group experienced a significant increase in the percentage of small businesses with online stores (2.16 percentage points, t=17.16) 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 (0.02 percentage points, t=0.36).

In summary, the results in Table 6 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 6 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. For bank credit, both the application and approval rates are similar.[12] This suggests a supply channel of fintech credit due to our treatment, rather than a demand effect.

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 verify this hypothesis, we categorize businesses into four subgroups based on their online store status a year after the intervention. 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 7 shows that for businesses that have online stores also functioning as fintech lenders, the Fintech credit is 14,513 higher (t-statistic = 16.91), revenue is 7,072 higher (t-statistic = 6.07), labor is 0.61 higher (t-statistic = 4.41), and profit is 3,065 higher (t-statistic = 3.56), all relative to the control group. For businesses hosting stores on both

[12]We show this result in Appendix Table A.9.

fintech lenders' marketplaces and other platforms, the Fintech credit is 12,962 higher (t-statistic = 15.73), revenue is 5,493 higher (t-statistic = 5.26), labor is 1.09 higher (t-statistic = 8.25), and profit is 1,734 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 475 higher (t-statistic = 0.48), revenue is 4,261 higher (t-statistic = 3.43), labor is 0.28 higher (t-statistic = 1.80), and profit is 805 higher (t-statistic = 0.75), all relative to the control group. For businesses without any online stores, the Fintech credit is 1,417 higher (t-statistic = 0.94), revenue is 4,346 higher (t-statistic = 2.30), labor is 0.03 lower (t-statistic = -0.13), and profit is 684 higher (t-statistic = 0.42), all compared to the control group. The 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.

3.3 Heterogeneous Treatment Effect

3.3.1 Region and Industry

Table 8 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 7328 (t=4.66), labor by 0.73 (t=3.76), and profit by 2971 (t=2.21). In Wuai, the treatment significantly increased revenue by 4726 (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 5525 (t=4.71), labor by 0.60 (t=4.40), and profit by 2063 (t=2.03).

Panel B shows that in the electronic device industry, the treatment significantly increased revenue by 7155 (t=4.32), labor by 0.91 (t=4.36), and profit by 3183 (t=2.26). In the cloth/shoes industry, the treatment significantly increased revenue by 5059 (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 9893 (t=6.10), labor by 0.45 (t=2.63), and profit by 6232 (t=4.42). In the cosmetic product industry, the treatment significantly increased revenue by 4652 (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.

4 Further Tests

4.1 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 282 RMB higher (t-statistic = 1.87), which is significant at the 10% level. This effect is more pronounced for those without home property (671 RMB higher, t-statistic = 2.82) and those without both types of property (926 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 leverag-

ing fintech credit and increasing online visibility, these entrepreneurs can achieve significant growth in revenue and labor.

4.2 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. The results presented in Table A.2 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. Additionally, it assesses the impact on product rating, service rating, delivery rating, and product variety.

Table A.2 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 2.64 times more likely to learn from other bloggers compared to the control group. This effect is highly significant, with a Z-statistic of 9.92, 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, with an odds ratio of 1.03 and a Z-statistic of 0.26.

Similarly, businesses in the treatment group are 1.94 times more likely to receive feedback from consumers compared to the control group. This finding is also highly significant, with a Z-statistic of 7.47, suggesting that the subsidy effectively encourages consumer engagement and feedback. The direct cash transfer group again shows no significant effect, with an odds ratio of 1.01 and a Z-statistic of 0.18.

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 A.2 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 (-0.21, t-statistic of -0.35) nor the direct transfer group (0.12, Z-statistic of 0.17) show significant 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.

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 advertisement subsidy effectively facilitates valuable interactions that lead to improvements

in perceived product and service quality.

4.3 Store locations

We also conducted heterogeneity tests by hypothesizing that entrepreneurs with worse store locations would experience a higher treatment effect. 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 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 for Non_Prime*Treat is 521 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 for Non_PrimeTreat is 0.35 (T-statistic of 2.78), while for profit, it is 276 (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.

4.4 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 performed 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 4.01, 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.

4.5 Intensive Margin

We next investigate the intensive margin of our treatment effect. Table A.3 displays the heterogeneous treatment effects conditional on various pre-existing conditions: already having access to bank credit, already using social media to advertise products, already using online platforms to sell products, and already using online platforms that are also fintech lenders. The dependent variables examined are business revenue, labor, and profit. The results are derived from regressions that incorporate robust standard errors, with t-statistics provided in parentheses. All regressions control for strata dummies and re-randomization variables.

The treatment effect on revenue for businesses already having access to bank credit is statistically significant, with a coefficient of 5832 (t-statistic = 4.69), indicating a substantial revenue increase. For businesses already using social media for advertising, the revenue coefficient is 5582 (t-statistic = 3.85), also showing a significant positive effect. Businesses

already using online platforms to sell products experience a significant revenue increase with a coefficient of 5739 (t-statistic = 2.46). The highest revenue increase is observed in businesses already using online platforms that are also fintech lenders, with a coefficient of 6289 (t-statistic = 2.24), which is statistically significant.

The treatment effect on labor for businesses already having access to bank credit is significant, with a coefficient of 0.55 (t-statistic = 2.91). For businesses already using social media for advertising, the labor coefficient is 0.74 (t-statistic = 2.74), indicating a significant positive effect. Businesses already using online platforms to sell products show a significant increase in labor with a coefficient of 0.60 (t-statistic = 2.35). The labor increase is also significant for businesses using online platforms that are fintech lenders, with a coefficient of 0.68 (t-statistic = 2.46).

The treatment effect on profit for businesses already having access to bank credit is significant, with a coefficient of 2024 (t-statistic = 3.12). For businesses already using social media for advertising, the profit coefficient is 2052 (t-statistic = 2.35), indicating a significant positive effect. Businesses already using online platforms to sell products experience a significant profit increase with a coefficient of 2150 (t-statistic = 2.31). The profit increase is significant for businesses using online platforms that are fintech lenders, with a coefficient of 1931 (t-statistic = 2.16).

The results indicate that the treatment, in the form of a social media advertisement subsidy, is effective across various subsamples. Businesses that already have some form of digital engagement or financial access benefit significantly in terms of revenue, labor, and profit. This underscores the efficacy of targeted social media subsidies in fostering business growth compared to direct cash transfers.

4.6 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 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 finance 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. 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 importance of overcoming biases and uncertainties in investment decisions and demonstrates the value of targeted subsidies and support programs designed to encourage businesses to leverage social media platforms.

References

Anderson, S. J., Chandy, R., Zia, B., 2018. Pathways to profits: The impact of marketing vs. finance skills on business performance. Management Science 64, 5559–5583.

Anderson, S. J., McKenzie, D., 2022. Improving business practices and the boundary of the entrepreneur: A randomized experiment comparing training, consulting, insourcing, and outsourcing. Journal of Political Economy 130, 157–209.

Banerjee, A. V., Duflo, E., 2014. Do firms want to borrow more? testing credit constraints using a directed lending program. Review of Economic Studies 81, 572–607.

Berg, T., Burg, V., Gombović, A., Puri, M., 2020. On the rise of fintechs: Credit scoring using digital footprints. The Review of Financial Studies 33, 2845–2897.

Berg, T., Fuster, A., Puri, M., 2022. Fintech lending. Annual Review of Financial Economics 14, 187–207.

Blattman, C., Fiala, N., Martinez, S., 2014. Generating skilled self-employment in developing countries: Experimental evidence from Uganda. The Quarterly Journal of Economics 129, 697–752.

Broda, C., Parker, J. A., 2014. The economic stimulus payments of 2008 and the aggregate demand for consumption. Journal of Monetary Economics 68, S20–S36.

Bruhn, M., Karlan, D., Schoar, A., 2018. The impact of consulting services on small and medium enterprises: Evidence from a randomized trial in mexico. Journal of Political Economy 126, 635–687.

Bruhn, M., Love, I., 2014. The real impact of improved access to finance: Evidence from mexico. The Journal of Finance 69, 1347–1376.

Chen, T., Huang, Y., Lin, C., Sheng, Z., 2022. Finance and firm volatility: Evidence from small business lending in china. Management Science 68, 2226–2249.

Chioda, L., Gertler, P., Higgins, S., Medina, P., 2024. Fintech lending to borrowers with no credit history. Working Paper .

Cohen, S., Hochberg, Y. V., 2014. Accelerating startups: The seed accelerator phenomenon .

Cunha, J. M., De Giorgi, G., Jayachandran, S., 2019. The price effects of cash versus in-kind transfers. The Review of Economic Studies 86, 240–281.

De Mel, S., McKenzie, D., Woodruff, C., 2008. Returns to capital in microenterprises: evidence from a field experiment. The Quarterly Journal of Economics 123, 1329–1372.

Duflo, E., Kremer, M., Robinson, J., 2011. Nudging farmers to use fertilizer: Theory and experimental evidence from kenya. American economic review 101, 2350–2390.

Gertler, P., Higgins, S., Malmendier, U., Ojeda, W., 2022. Why small firms fail to adopt profitable opportunities. Working Paper .

González-Uribe, J., Reyes, S., 2021. Identifying and boosting "gazelles": Evidence from business accelerators. Journal of Financial Economics 139, 260–287.

Hau, H., Huang, Y., Lin, C., Shan, H., Sheng, Z., Wei, L., 2021. Fintech credit and entrepreneurial growth. The Journal of Finance .

Hau, H., Huang, Y., Shan, H., Sheng, Z., 2017. Techfin in china: Credit market completion and its growth effect. SSRN Working Paper .

Hochberg, Y. V., 2016. Accelerating entrepreneurs and ecosystems: The seed accelerator model. Innovation policy and the economy 16, 25–51.

Huang, J., 2018. The customer knows best: The investment value of consumer opinions. Journal of Financial Economics 128, 164–182.

Huang, Y., Li, Y., Shan, H., 2018. Fintech and firm selection: Evidence from e-commerce platform lending. SSRN Working Paper .

Ittner, C. D., Larcker, D. F., 1998. Are nonfinancial measures leading indicators of financial performance? an analysis of customer satisfaction. Journal of Accounting Research 36, 1–35.

Jayachandran, S., 2021. Microentrepreneurship in developing countries. Handbook of labor, human resources and population economics pp. 1–31.

Lieber, E. M., Lockwood, L. M., 2019. Targeting with in-kind transfers: Evidence from medicaid home care. American Economic Review 109, 1461–1485.

McKenzie, D., 2017. Identifying and spurring high-growth entrepreneurship: Experimental evidence from a business plan competition. American Economic Review 107, 2278–2307.

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 are part of a couple (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 from bank loans 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* denotes the number of observations. T statistics of mean differences are also reported.

	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	992		3,741		1,000			

Table 2: 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	190	784	216
Jewelry, Handbag, Watch	175	703	176
Toys and souveniors	243	953	270
Costmetic product	143	471	119
Other	63	219	54

Table 3: 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" indicates a 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.

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	

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 4: Impact of Social Media Subsidy and Cash Transfer on Social Media Presence

Panel A shows the results when dependent variables are self-financed social media expenses and outsourced marketing expenses one year after the 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.

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	
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	

Table 5: Survey of Why the Entrepreneur Did Not Invest in Social Media in the First Place

This table shows the survey results regarding why businesses think they did not invest in social media before the intervention. The survey respondents could provide multiple reasons.

	Treatment	Control	Direct Transfer
Before Treatment			
Capital Constraints	33%	36%	30%
Didn't know social media booster	67%	64%	70%
Simply hadn't considered it	25%	29%	17%
Think marketing is not important	21%	15%	19%
Tried social media but failed	7%	9%	6%

Table 6: Online Stores and Online Credit from Fintech Lender: The Finance 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 amount of credit the business gets from financial lenders such as Ant Financial. *Bank Loan* is the amount of bank loan the business gets. *Online Stores* is the percentage of small businesses that have an online store. *Credit Application Rate* is a dummy variable that equals one if the entrepreneur has applied for fintech credit in the past year. *Credit Approval Rate* is a dummy variable that equals one if the entrepreneur has successfully obtained fintech credit in the past year conditional on the application. *Credit Interest Rate* is the interest rate of the loan if the entrepreneur has successfully obtained fintech credit in the past year. 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:Fintech vs. Traditional Bank			
	Treatment	Direct Transfer	Control
			(Mean and SD)
Online Credit	9313***	1023*	11551
T-statistics	(17.00)	(1.94)	(14663)
Controls	Y	Y	
R^2	0.06	0.00	
Bank Loan	411	128	14055
T-statistics	(0.78)	(0.24)	(14754)
Controls	Y	Y	
R^2	0.00	0.00	
Online Stores	2.16***	0.02	0.59
Z-statistics	(17.16)	(0.36)	(0.49)
Controls	Y	Y	
$Pseudo_R^2$	0.08	0.00	
Panel B: Fintech Credit			
	Treatment	Direct Transfer	Control
			(Mean and SD)
Application Rate	-0.09	0.01	0.27
Z-statistics	(-0.86)	(0.15)	(0.44)
Controls	Y	Y	
$Pseudo_R^2$	0.01	0.00	
Approval Rate	1.74***	0.03	0.53
Z-statistics	(9.26)	(0.53)	(0.50)
Controls	Y	Y	
$Pseudo_R^2$	0.05	0.00	
Interest Rate	-0.83	0.13	8.14
Z-statistics	(-0.60)	(0.28)	(6.12)
Controls	Y	Y	
R^2	0.08	0.00	

Table 7: 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. "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. "Others Only" refers to the subsample where the treated stores own online marketplaces that are not fintech lenders. "None" refers to the subsample where the treated stores do not own an online marketplace. 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.

	Fintech Credit	Revenue	Labor	Profit
Subsamples:				
Fintech lenders' store only	14513***	7072***	0.61***	3065***
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	12962***	5493***	1.09***	1734*
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	475	4261***	0.28*	805
T-statistics	(0.48)	(3.43)	(1.80)	(0.75)
Controls	Y	Y	Y	Y
R^2	0.00	0.00	0.00	0.00
None	1417	4346**	-0.03	684
T-statistics	(0.94)	(2.30)	(-0.13)	(0.42)
Controls	Y	Y	Y	Y
R^2	0.00	0.00	0.00	0.00

Table 8: 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. 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.

	Revenue	Labor	Profit
Panel A: Regions			
Yiwu	7328***	0.73***	2971**
T-statistics	(4.66)	(3.76)	(2.21)
Wuai	4726***	0.65***	1469
T-statistics	(3.96)	(4.58)	(1.44)
Huangqiangbei	5525***	0.60***	2063**
T-statistics	(4.71)	(4.40)	(2.03)
Panel B: Industries			
Electronic	7155***	0.91***	3183**
T-statistics	(4.32)	(4.36)	(2.26)
Cloth	5059***	0.74***	1582
T-statistics	(2.96)	(3.67)	(1.06)
Jewellery	1296	0.77***	-2038
T-statistics	(0.71)	(3.57)	(-1.30)
Toys	9893***	0.45***	6232***
T-statistics	(6.10)	(2.63)	(4.42)
Cosmetic	4652***	0.35	1066
T-statistics	(2.58)	(1.44)	(0.71)
Other	1568	0.80**	-1901
T-statistics	(0.80)	(2.27)	(-1.15)

A Online Appendix

Table A.1: Treatment Effects Across Different Social Media Platforms

This table shows the heterogeneous treatment effects based on different social media platforms. We categorize the social media platforms based on the platform that entrepreneurs chose for the subsidy. 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.

	Coefficient	T-statistics
Revenue		
Streaming	7045***	(5.15)
Video	4654**	(2.40)
Photo	4380**	(2.31)
Labor		
Streaming	0.96***	(4.02)
Video	0.40**	(2.38)
Photo	0.44**	(2.41)
Profit		
Streaming	4175***	(3.82)
Video	1164**	(2.08)
Photo	1109**	(1.98)

Table A.2: 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 that equals one if the business ever learns from their consumers regarding their product quality. *Learn from other bloggers* is a dummy variable that equals one if the business also 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 conditional on the entrepreneurs already having an online 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.

Panel A: Logistic Regression	Treatment	Direct Transfer	Control (Mean and SD)
Learn from other bloggers	2.64***	1.03	0.09
Z-statistics	(9.92)	(0.26)	(0.28)
Controls	Y	Y	
$Pseudo_R^2$	0.03	0.00	
Feedback from consumers	1.94***	1.01	0.14
Z-statistics	(7.47)	(0.18)	(0.34)
Controls	Y	Y	
$Pseudo_R^2$	0.01	0.00	
Panel B: OLS regressions			
Product Rating	0.75***	0.07	3.73
T-statistics	(3.48)	(0.40)	(1.28)
Controls	Y	Y	
R^2	0.02	0.00	
Service Rating	0.54***	-0.14	4.09
T-statistics	(2.80)	(-0.63)	(1.07)
Controls	Y	Y	
R^2	0.02	0.00	
Delivery Rating	0.35**	-0.11	3.51
T-statistics	(2.18)	(-0.20)	(0.75)
Controls	Y	Y	
R^2	0.02	0.00	
Product Variety	-0.21	0.12	21.21
T-statistics	(-0.35)	(0.17)	(7.84)
Controls	Y	Y	
R^2	0.00	0.00	

Table A.3: Treatment Effects in Subsamples: Intensive Margin

This table shows the heterogeneous treatment effect conditional on already having access to bank credit, already using social media to advertise their products, already using online platforms to sell their products, or already using online platforms that are also fintech lenders to sell their products. The dependent variables are the revenue, labor, and profit of a business. 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.

	Coefficient	T-statistics
Revenue		
Bank Credit Already	5832***	(4.69)
Social Media Already	5582***	(3.85)
Online Store Already	5739**	(2.46)
Online Store/Fintech Lenders Already	6289**	(2.24)
Labor		
Bank Credit Already	0.55***	(2.91)
Social Media Already	0.74***	(2.74)
Online Store Already	0.60***	(2.35)
Online Store/Fintech Lenders Already	0.68**	(2.46)
Profit		
Bank Credit Already	2024***	(3.12)
Social Media Already	2052**	(2.35)
Online Store Already	2150**	(2.31)
Online Store/Fintech Lenders Already	1931**	(2.16)

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 in the regressions.

$$Y_{irs} = \alpha_i + \beta_i Treat_i + \beta_2 Treat_i * Property_Ownership + \beta_3 Property_Ownership + \gamma_i^F F_{rs} + \epsilon_{irs} ,$$

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.

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

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 in the regressions.

$$Y_{irs} = \alpha_i + \beta_i Treat_i + \beta_2 Treat_i * Store_Locations + \beta_3 Store_Locations + \gamma_i^F F_{rs} + \epsilon_{irs} \ ,$$

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.

	Coefficient	T-statistics
Revenue		
Prime_Outside_Facing*Treat	-234***	(-3.42)
Prime_Near_Escalator*Treat	-125***	(-3.09)
Prime_Near_Entrance*Treat	-310***	(-3.95)
Non_Prime*Treat	521***	(4.82)
Labor		
Prime_Outside_Facing*Treat	-0.12**	(-2.77)
Prime_Near_Escalator*Treat	-0.20***	(-3.05)
Prime_Near_Entrance*Treat	-0.08**	(-2.25)
Non_Prime*Treat	0.35***	(2.78)
Profit		
Prime_Outside_Facing*Treat	-75***	(-2.60)
Prime_Near_Escalator*Treat	-60**	(-2.15)
Prime_Near_Entrance*Treat	-163***	(-3.02)
Non_Prime*Treat	276**	(2.41)

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 a 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.

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	
Panel B Natural logarithm			
	Treatment	Direct Transfer	
Transactions	0.63***	0.05	
T-statistics	(4.19)	(4.01)	
Controls	Y	Y	
R^2	0.04	0.01	

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 a 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.

	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	
Onsite Revenue	1048*	1064	7549
T-statistics	(1.78)	(1.20)	(12854)
Controls	Y	Y	
R^2	0.01	0.00	

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 a 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.

	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	
Onsite Transactions	48	53	583
T-statistics	(1.18)	(1.01)	(805)
Controls	Y	Y	
R^2	0.01	0.00	

Table A.9: Credit from Traditional Banks

This Table presents the separate treatment effects of the social media subsidy and direct cash transfer 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 past year. *Credit Approval Rate* is a dummy variable that equals one if the entrepreneur has successfully obtained bank credit in the past 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 past year. 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.

Bank Credit			
	Treatment	Direct Transfer	Control (Mean and SD)
Application Rate	-0.09	0.01	0.27
Z-statistics	(-0.86)	(0.15)	(0.44)
Controls	Y	Y	
$Pseudo_R^2$	0.01	0.00	
Approval Rate	-0.42	0.03	0.53
Z-statistics	(-1.03)	(0.53)	(0.50)
Controls	Y	Y	
$Pseudo_R^2$	0.05	0.00	
Interest Rate	-0.83	0.13	8.14
Z-statistics	(-0.60)	(0.28)	(6.12)
Controls	Y	Y	
R^2	0.08	0.00	

Table A.10: 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 a 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.

	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

Table A.11: Impact of Social Media Subsidy and Cash Transfer (DiD)

This table shows self-financed social media expenses and outsourced marketing expenses 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 a 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.

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

Table A.12: 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 amount of credit the business receives from financial 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.

	Treatment	Direct Transfer
Online Credit		
Treat*Post	10748***	373
T-statistics	(4.71)	(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

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)

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.