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Investor Tax Breaks and Financing for Start-Ups: Evidence from China

Abstract

We examine how investor-level tax incentives affect financing for start-ups using the introduction of a generous tax deduction for qualified angel and VC investment in China as a quasi-natural experiment. We find that the tax incentive increases funding for eligible start-ups, with stronger responses from larger and more experienced investors. The tax incentive leads to substitution between eligible and non-eligible investments. There is no evidence that the tax incentive lowers investment quality. We further show that the investor-level tax incentive encourages firm entry into affected industries, especially in cities more exposed to venture capital funds.

JEL-Codes: G240, G320, H250, L260.

Keywords: venture capital, angel investment, tax incentives, entrepreneurship.

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1 Introduction

Venture capital (VC) and angel investment constitute an important source of financing for start-ups around the world, and the most drastic change in the global venture market during the last decade has been the rise of China. By 2019, China accounted for 38% of the global venture dollars invested while the US accounted for 42% (Lerner et al., 2024). We study the impact of tax incentives for early-stage financing in this fast-growing economy. Specifically, how do tax breaks for VC investment affect financing for start-ups? Recent studies have explored the impact of tax incentives in the form of capital gains tax reductions (Dimitrova and Eswar, 2023; Edwards and Todtenhaupt, 2020) or investment tax credits (Denes et al., 2023) that have been implemented in the United States. However, empirical evidence in this domain is still limited, especially outside the U.S.

China has emerged as a global hub for innovation and entrepreneurship (Chen et al., 2021; Zhou, Zhang and Sha, 2021*a*). We examine a Chinese tax incentive that is available to VC enterprises and individual business angels investing in qualified technology start-ups at the seed capital or start-up stage. The scheme started in 2017 and it is still in operation. Under the scheme, 70% of VCs' qualified investments can be used to offset incorporated VCs' corporate income tax (CIT), or for legal or individual partners in VC partnerships, the same percentage can be used to offset their corporate or personal income tax liabilities.[2] Angel investors can use 70% of their qualified investments to offset taxes on capital gains upon sale of eligible equities.[3]

The Chinese tax incentive is unique in the following ways: first, VC investors make deductions against their taxable income, which is not limited to capital gains and is not

[2]Generally, VCs in China can be organized as either a corporation or a partnership. According to the Chinese Asset Management Association, around 93% of VC enterprises were organized as partnerships in 2021, and around 3.7% were incorporated. The remaining VCs were either contractual-type funds or in other forms.

[3]Capital gains is generally applied to the profit generated from selling assets or investments in China, and is considered part of the individual's income tax .

contingent on making positive returns from a specific equity investment; second, unlike the US angel tax credit that only allows investors to offset their state-level income tax, the ceiling for the tax deduction is potentially much higher as the scheme allows investors to deduct against their total income tax;[4] and third, the Chinese tax incentive applies to both angel and VC investors simultaneously and thus has a much broader scope than the US angel tax credits that only target angel investors.

First, we use the introduction of the VC and angel tax incentive in China to identify the impact of the tax incentive on financing for start-ups, based on funding-rounds data provided by Crunchbase during 2014-2019. To qualify for the scheme, investee start-ups need to be "young technology" firms no more than 60 months old. We select eligible start-ups based on the "age" and "technology status" criteria to form the treatment group in our difference-in-difference (DID) estimations. We use non-technology start-ups that are no more than 60 months old to form the control group. Thus, for identification, we compare the funding round performance of treated firms against that of control firms before and after 2017. Using this strategy, we examine how the tax incentive affects qualified start-ups' financing activities. We also examine whether the tax incentive affects investment quality from two angles: first, we examine whether the tax incentive changes firms' ability to raise funds continuously, even when they pass the age threshold; and second, we check whether the tax incentive influences firms' probability of an IPO or being acquired subsequently.

Second, we use investor-level data to examine whether the tax incentive causes substitution between eligible and non-eligible investments. In particular, we test whether the tax incentive encourages investors to shift from mature investment to early-stage investment and to shift investment from non-technology to technology firms. For identification, we use hand-collected information about whether an equity investor is registered as a

[4]There is no state-level tax in China. The statutory corporate income tax rate is 25%. The dividend tax rate is 20% and the top marginal personal income tax rate for individual investors is 35%. In comparison, the average state-level income tax rate in the US, as documented by Denes et al. (2023), is around 5%.

"venture capital enterprise" with the Asset Management Association of China or the local Development and Reform Commission, a requirement set by the 2017 tax incentive.[5] We use registered VCs (thus eligible) as the treatment group and equity investors registered as other types (such as PEs) as the control group, and compare their investment before and after the implementation of the tax incentive.

Finally, we examine whether the investor-level tax incentive affects firms' entry decisions. We use the universe of Chinese business registration data from 2014-2019 for this exercise. Our identification relies on the assumption that different industries and different cities are exposed to the tax incentive to different degrees. Specifically, the tax incentive should have encouraged firms in high-tech industries to enter, with the expectation of better funding opportunities. Regions with greater exposure to VC activities would also be affected to a larger extent. We then use a triple DID setting to compare the entry of technology and non-technology firms in more or less exposed industries/regions.

Our key findings are as follows. First, we find that treated start-ups enjoy a significant increase in total capital raised per funding round following the implementation of the tax incentive. The magnitude of the increase in total funding for eligible technology start-ups is significant, around 20%. Eligible start-ups also attracted significantly more investors in each funding round after the tax incentive was implemented. These results are robust when we control for the effects of the national high-tech zones, and ad hoc tax incentives provided by local governments.

We find significant heterogeneity in responses. In particular, with the tax incentive, eligible start-ups became more likely to attract funding from larger or more experienced VC investors, and from older or more experienced angels. This finding is starkly different from the evidence provided by Denes et al. (2023), which shows that more sophisticated angel investors view the US angel tax credit as unimportant. There are several possible

[5] We exclude angel investors from this exercise.

explanations for this difference. First, the Chinese tax incentive for angel/VC investors is likely to be more generous than the US angel tax credit, in the sense that it has a much higher ceiling for deduction and a broader scope. Second, to utilize the tax deduction, investors must be making positive taxable income – unused deductions can be carried forward for up to five years but smaller investors would take longer to switch to the profitable position. Third, larger and more experienced investors should have better resources (e.g., can hire more tax experts) to comply with the tax code, such as preparing documents and claiming tax deductions, which can help them utilize the tax incentive (Cui, Hicks and Xing, 2022; Zwick, 2021).

Second, we find no evidence that the investor-level tax incentive lowers the quality of VC/angel investment. The investor-level tax incentive can reduce the quality of investment if investors have a targeted net-of-tax rate of return. However, it may increase the quality of investment if investors are incentivized to generate more taxable income to utilize the tax deduction, a view consistent with the theory by Keuschnigg and Nielsen (2004). Thus, the sign of the impact of the tax incentive on investment quality is theoretically ambiguous. If the tax incentive lowers the investment bar and leads to less cautious investment, investors may be less likely to continue financing these lower-quality firms, especially when they pass the age threshold. We thus use a Cox model to analyze firms' likelihood of receiving funding after passing the age limit. As another indicator for investment quality, we compare the successful exit (proxied by acquisition or IPO) probability of treatment and control firms in a DID setting. In both exercises, we do not find evidence for worsening investment quality.

Third, using the fund-level aggregated data, we find that qualified VC funds significantly increased the number of investments into high-tech start-ups younger than 60 months old, relative to non-qualified equity funds. Meanwhile, qualified VC funds significantly reduced the number of investments into firms more than 60 months old. Moreover, the tax incentive did not change the total number of investments by qualified VC funds. We find similar patterns when examining the extensive margin of investment at the fund level. Taken together, these results show that the tax incentive caused substitution between early and late-stage investment, and between funding for high-tech and non-high-tech firms.

Finally, we find a relative increase in the number of newly established firms in high-tech industries, compared with that in non-high-tech industries shortly after the implementation of the 2017 tax incentive. We further show that this positive effect on entry is larger for high-tech industries located in cities with greater exposure to venture capital before 2017. This suggests that the Chinese tax incentive is effective in encouraging more technology start-ups to be established. Our finding supports the positive role of venture capital on promoting entrepreneurship (Samila and Sorenson, 2011). However, this result is different from the findings of Denes et al. (2023) who show that the US angel tax credit does not generate new company formation. The implication is that when the tax incentive is generous enough to change the behavior of large investors, it can have a material impact on entrepreneurship.

We contribute to the literature on early-stage financing as follows. First, we analyze the impact of a new form of investor-level tax incentive. Three recent studies examine the impact of different tax incentives for early-stage investments in the US. Edwards and Todtenhaupt (2020) show that the exemption of capital gains tax for small firms under the 2010 Small Business Jobs Act (SBJA) led to a large increase in capital raised by eligible start-ups. Dimitrova and Eswar (2023) show that an increase in state-level capital gain tax rate negatively affects the quantity and quality of patents by start-ups. Denes et al. (2023) find that the US state-level angel tax credit leads to more angel investment, but has no impact on new business formation or local economic growth. Consistent with these studies, we find that the investor-level tax incentive in the form of investment-related tax deductions is effective in stimulating financing for start-ups. On the other hand, our results deviate from the existing literature in the following ways: we show that the Chinese tax incentive elicits more responses from larger and more experienced investors, and it leads to new business formation. We also present evidence on the caveat that the incentive causes a reallocation between ineligible start-ups and incentivized start-ups. Overall, our study helps researchers and policymakers assess the trade-offs in using tax instruments that aim to stimulate VC/angel funding for start-ups.

We also contribute to the literature on financing entrepreneurship in developing countries. Unlike more developed countries, early-stage financing remains more challenging in emerging markets due to weaker property rights protection and legal institutions (Cong et al., 2020). Studies have shown that in the Chinese context, programs like the government-initiated funding program *Innofund* (Guo, Guo and Jiang, 2016; Wang, Li and Furman, 2017), and location-based policies such as the establishment of high-tech zones (Tian and Xu, 2022), can be effective in promoting entrepreneurship. Relative to these other policy tools, studies on the effectiveness of the investor-level tax incentives on entrepreneurship are still limited, partly due to the lack of data in emerging markets (Chen, 2022). On the other hand, the effectiveness of complex tax incentives in developing countries may be limited due to the lack of tax expertise and inadequate tax information transmission (Cui, Hicks and Xing, 2022). Thus, our study contributes to the understanding of whether investor-level tax incentives can be an effective tool in encouraging financing entrepreneurship in less-developed markets.

The rest of the paper is structured as follows. In Section 2, we describe the institutional context and the reforms that enable our quasi-experimental identification strategy. In Section 3, we present our empirical specifications and research design. In Section 4, we describe our datasets and descriptive statistics. In Section 5, we present our results. We conclude in Section 6.

2 Policy background

2.1 Early-stage financing in China

The Chinese venture capital market has been growing rapidly in recent years. Currently, it represents the second-largest market in the world by aggregate deal value and number of unicorns, after the United States. As documented by Lerner et al. (2024), the rise of the Chinese VC market is also unique among developing countries—it contributes to a considerably higher share of global venture investment than other emerging economies. The rapid development of the Chinese VC industry is potentially driven by several factors: the fast-growing economy that brings an immense market demand and fuels entrepreneurship; the growing wealth of corporations and individuals that are crucial for the supply of VC funds; the increasing supply of talent due to the expansion of the country's higher education; and last but not least, the strong policy support from the government to nurture the research and innovation ecosystem as the country moves from "the world's factory" to a "high-tech innovator".

In contrast, China's angel investment market is relatively immature, and related statistics are hard to obtain. There is also limited empirical research on Chinese business angels. This reflects the still challenging situation for seed-stage financing in China (Cong et al., 2020). According to Zhou, Zhang and Sha (2021*b*), the average scale of Chinese angel investments is comparable to that of the US angel investors as of 2018, but the year-on-year growth of angel investment is much higher in China. This description is consistent with the common perception of the Chinese angel investment market, which is developing fast and becoming more institutionalized in recent years.

2.2 The 2017 VC tax incentive schemes

Table 1 illustrates the tax treatment of VC investment in China. A Chinese VC can be organized as a corporation or a limited partnership, which is subject to different tax codes.[6] Since 2006, however, the majority of VCs have taken the partnership form. The tax advantage of the partnership is that no tax is imposed at the fund level (pass-through). For legal person partners, their income derived from the VC fund is generally subject to a 25% corporate income tax. For individual partners, dividend income is taxed at the standard rate of 20%. Income from equity disposals is taxed either at 20%, or taxed according to the personal income schedule (3-35% progressively).[7]

We examine a tax incentive provided for VC and angel investors that permits generous deductions against investors' taxable income. The policy was issued by the Ministry of Finance (MOF) and State Taxation Administration (STA) on 28 April 2017 (Circular 38), and was applicable retroactively from 1 January 2017. Investments made in technology start-ups through equity investment and held for at least two years benefit from the incentive treatment. Specifically, if a VC takes the form of a partnership, the legal person and/or natural person partners of this VC partnership may offset 70% of the investment amount allocated to them from the partnership against their taxable income (CIT for legal persons and PIT for natural persons). The deduction can occur once the two-year holding period has elapsed. The balance of any deduction, not used immediately, may be carried forward into subsequent tax years, depending on the tax method the VC fund opts for. The majority of VCs in China are limited partnerships and therefore they benefit from the tax incentive as described above. For VCs taking the corporate form, 70% of the investment amount can offset their CIT liabilities.

[6] Chinese venture capital funds could be formed as partnerships only since 2006, following the passage of the Partnership Enterprise Law (PEL) in August 2006.

[7] If the VC opts for the fund-by-fund method, income from equity disposals is taxed at 20%. If the VC opts for the aggregation method, income from equity disposals is taxed progressively at 3-35%.

A similar tax incentive was also granted to angel investors. Specifically, 70% of the investment amount can be offset against the angel investor's taxable (personal) income arising from disposals of equities in invested technology start-ups. Any unused balance may be carried forward and used against future equity disposal gains from the same invested technology start-up. If the invested start-up is de-registered later on, any residual investment amount that has not been deducted can be used to offset the angel investor's taxable income from the transfer of equities in other invested technology start-ups within 36 months from the date of the de-registration.

Importantly, to enjoy the tax benefit, there are criteria set upon both the investees and the investors. Table A.1 in Appendix A lists the criteria in detail. For start-ups, they need to: 1) be a tax resident in mainland China; 2) be no more than 60 months old; 3) have no more than 200 employees, at least 30% of whom must have a university degree; 3) have assets and annual revenue no greater than 30 million RMB at the time of investment; 4) be non-listed within 2 years of the investment; and 5) have incurred at least 20% of total costs and expenses on research and development (R&D) in the year when the investment is made and in the following year. The tax incentive is implemented retroactively, so investments made as early as 2015 can be used for a tax deduction in 2017. This policy was first piloted in eight locations in mainland China in 2017 and rolled out nationwide in 2018. Certified investors can claim tax deductions on eligible investments once the equity investment is held for more than two years. While the 2017 tax incentive scheme imposes location restrictions on VC investors, it does not restrict the locations of the investees.[8]

For VCs to qualify for the tax incentive, they need to be tax residents in mainland China. The VC tax incentive scheme was first implemented in 2017 for VCs registered in eleven pilot locations, including the Beijing-Tianjin-Hebei area, Shanghai, Guangdong, Anhui, Sichuan, Wuhan, Xi'an, Shenyang, and Suzhou Industrial Park. The VC tax incentive was

[8]For angel investment, investees need to be in the pilot areas in 2017.

then rolled out nationwide in 2018. Note that there is no location restriction on the funded start-ups—a qualified VC in pilot regions can claim the tax deduction for its investment in a qualified technology start-up that is outside the pilot regions. Moreover, qualified investors must have been registered as a ”venture capital enterprise” either with the Asset Management Association of China or the local Development and Reform Commission. Qualified VCs need to hold equity interests in technology start-ups that are less than 50% of the share capital of the technology start-ups.

Angel investors qualifying for the tax incentive should not be the founders or employees of the invested technology start-ups, and should not supply staff to the start-ups. They should not hold more than 50% of the share capital in the technology start-ups within 2 years after the investment was made. The initial implementation of the tax incentive in 2017 did not impose any restriction on where the angel investors are located, but required the start-ups receiving angel investment to be located in one of the eleven pilot zones. In 2018, the angel tax incentive was rolled out nationwide.

It is helpful to compare China's tax incentive with the US angel tax credit (ATC). In Figure 1, we calculate tax savings for an investor with $250,000 taxable income, the same numerical exercise conducted by Denes et al. (2023). Following their approach, we assume the ATC rate to be 35%, and a typical US state tax rate to be 5%. We set the income tax rate to be 20% for a typical Chinese angel/VC investor. Note that the US ATC implies a much lower ceiling for tax savings. In this example, a US angel investor could save $12,500 at most. However, the ceiling for tax savings is $50,000 under the Chinese tax deduction scheme. Figure 1 shows that the US ATC generates more tax savings than the Chinese tax incentive before it hits the ceiling. With a larger investment amount, however, the Chinese tax deduction may lead to substantially more tax savings. More generally, since the US ATC only provides tax credits against investors' state-level income taxes, the Chinese tax incentive tends to be more generous as it allows deduction against investors' total income tax liability.

Several regulation changes may also affect the Chinese VC market in the past decade (Chen, 2022). For example, insurance companies have been allowed to invest in venture capital funds since 2010. Pension funds have been allowed to make equity investments since 2015. Moreover, banks have been encouraged to provide loans and equity for the same firm since 2016. These policies aim to broaden the funding sources for VCPE investors. However, there remain strong restrictions on the scope of participation by these institutions and their impact on the Chinese VCPE market is still limited. In 2019, China experimented with a new registration-based IPO system and introduced the STAR market. Still, the number of IPOs remains low in the STAR market by the end of 2019, which is the last year of our sample period. More importantly, none of these regulation changes target technology start-ups within a certain age limit. This helps us single out the impact of the 2017 investor-level tax incentive.

3 Research design

We begin our empirical analysis based on the funding-round data from Crunchbase. The advantage of the funding-round data is that it allows us to trace the funding activities of a certain start-up. We are also able to control for start-ups' characteristics and unobserved firm-level fixed effects in estimations based on the funding-round data.

The tax incentive is only applicable for investment into technology start-ups younger than 60 months old. This feature of the tax incentive provides us with an opportunity to use the DID approach. Specifically, the treatment group consists of funding rounds made by technology start-ups when they are no more than 60 months old. Funding rounds made by non-technology start-ups no more than 60 months old constitute the control group. In the DID estimations, we exclude funding rounds made when a firm is more than 60 months old. This allows us to abstract away from firm age effects. We estimate the following specification:

$$Y_{i,j,t} = \alpha + \beta \times Treated_j \times Post_t + \delta \times X'_{i,j,t} + \eta_t + \delta_j + \psi_i + \epsilon_{i,j,t} \tag{1}$$

where $Y_{i,j,t}$ is the outcome variable for funding round i of company j in year t. As outcome variables, we construct $Ln(Capital\ raised)$ which is the total capital raised in a certain founding round (in natural log), and $Ln(No.\ of\ investors)$ which is the number of investors per funding round (in natural log). $Treated_j$ is a dummy that equals 1 if firm j belongs to the treatment group, and 0 otherwise. While the tax incentive was only offered to VCs registered in certain pilot cities in 2017, there is no geographical restriction on firms they invest in. Thus, we set $Post_t$ to be 1 for years since 2017 in the funding-rounds estimations.

$X'_{i,j,t}$ is a set of firm-level and funding-round-level characteristics that serve as control variables in estimations. We report estimation results with and without control variables. Following the work by Edwards and Todtenhaupt (2020), we construct the variable $Ln(Rank)$, which is the natural logarithm of Crunchbase rank of the start-ups on the announcement day of each funding round. It reflects the relative placement of a firm among other firms, calculated by Crunchbase's own algorithm based on comprehensive firm-level information. This rank variable also varies over the funding rounds and hence, is not absorbed by firm-level fixed effects. In addition, existing research (Edwards and Todtenhaupt, 2020; Hellmann and Puri, 2002) suggests that firm age influences funding activities. We thus include $Ln(Age)$ in estimations, which is the natural logarithm of firm age at the time of a certain funding round.[9] Angel investors usually have unique investment preferences, especially for certain industries (Edwards and Todtenhaupt, 2020), leading

[9] We use the date of the funding rounds and a firm's establishment date to calculate its age at the time of each funding round.

to potential clustering. Therefore, we also control for $Angel$ which is a dummy that equals 1 if a funding round involves an angel investor, and 0 otherwise. In Equation 1, we also control for firm-level fixed effects (δ_j), funding-round fixed effects (ψ_i), and time fixed effects (η_t). We cluster the standard errors over each firm in all estimations.

Our identification strategy is based on the assumption that the outcome variables for the treated and control groups would have evolved in parallel in the absence of the treatment. We test this assumption using the event study methodology. Specifically, we estimate Equation 2:

$$Y_{i,j,t} = \alpha + \sum_{\kappa=-3}^{3} \beta_{i,\kappa} \mathbb{1}[t = \kappa] \times Treated_j + \delta \times X'_{i,j,t} + \eta_t + \delta_j + \psi_i + \epsilon_{i,j,t} \quad (2)$$

where $\mathbb{1}[t = \kappa]$ is a set of dummy variables that equal 1 in each of the κ years relative to the year in which the reform affected firm i. The coefficient on each of those dummies indicates the difference in each outcome variable between the two groups in that year relative to year $t-1$, omitted from the specification, which serves as a benchmark. We continue to control for firm, funding-round, and year fixed effects in this dynamic estimation.

One may also consider comparing technology firms just below the 60-month threshold with those just above, using the research discontinuity design (RDD). The advantage of the RDD approach is that we are comparing firms in more similar industries. However, the validity of the RDD estimation requires the tax incentive to have no impact on older technology firms. If the tax incentive causes investors to change their strategy and shift funds from mature technology firms towards eligible start-ups, the RDD estimation would generate an upward bias in the estimated treatment effect. We present a series of RDD estimations in Appendix F. Consistent with our argument, while the RDD estimations identify a positive treatment effect on funding activities of eligible start-ups, the point estimates tend to be larger than the corresponding DID estimates.

We explicitly examine whether the tax incentive causes substitution between different types of investments at the investor level, based on funding-round data aggregated to each fund level. We leverage the fact that the tax incentive was only provided for formally registered VC funds to conduct a staggered DID estimation. Specifically, VC funds formally registered with the China Asset Management Association or the local Development and Reform Commission form the treatment group, while funds registered as other types (including, for example, private equities funds) form the control group. Our staggered DID specification is as follows:

$$No.\ of\ Investments_{s,t} = \alpha + \beta \times Treated_s \times Post_{s,t} + \eta_t + \delta_s + \epsilon_{s,t} \tag{3}$$

where the outcome variable is the aggregated number of investments for investor s in year t.[10] The 2017 tax incentive was limited to VCs registered in 11 pilot regions and then rolled out nationwide in 2018. Thus, in the investor-level estimations, $Post_{s,t}$ equals 1 since an investor s is exposed to the tax policy, depending on its location. We further use an indicator that equals 1 if an investor makes a specific type of investment in a year as the outcome variable, and examine the effect of the tax incentive on the extensive margin of investment. Event studies are conducted to examine the pre-trend assumption.

To examine the impact of the 2017 tax incentive on firm entry, we utilize business registration data for each city-2-digit industry pair during 2014-2019. Specifically, we estimate the following equation:

$$Ln(No.\ of\ new\ firms)_{m,c,t} = \alpha + \beta \times Treated_{m,c} \times Post_t + \delta \times X'_{c,t-1} + \eta_{m,c} + \delta_t + \epsilon_{m,c,t} \tag{4}$$

where $Ln(No.\ of\ new\ firms)_{m,c,t}$ is the number of newly established firms in industry m,

[10] As we use the level variable as dependent variable, investors with 0 investments in a certain year are kept in the sample.

city c, and year t. $Treated_{m,c}$ equals 1 if industry m in city c is a high-tech industry, and 0 otherwise. $Post_t$ equals 1 since 2017, and 0 otherwise. We control for city-industry ($\eta_{m,c}$) and year-fixed effects (δ_t). In some specifications, we also control for $X'_{c,t-1}$, which is a set of city-level characteristics including the GDP growth rate, GDP per capita, and the population growth rate (with one year lag), all of which might affect firm entry.

We further use a triple DID setup to examine heterogeneity across cities in terms of their exposure to the VC industry before 2017. Specifically, we calculate the ratio of VC investors to the total number of start-ups for each city in 2016. We regard cities with a VC-startup ratio above the sample median as being more exposed and construct a dummy $HighExposure_c$, which equals 1 for city c with above-median exposure. Then we estimate the following triple DID model:

$$\begin{aligned} Ln(No.\ of\ new\ firms)_{m,c,t} = & \alpha + \beta_0 \times Treated_{m,c} \times Post_t + \beta_1 \times HighExposure_c \\ & \times Treated_{m,c} \times Post_t + \beta_2 \times HighExposure_c \times Post_t \\ & + \delta \times X'_{c,t-1} + \eta_{m,c} + \delta_t + \epsilon_{m,c,t} \end{aligned} \tag{5}$$

We hypothesize that the 2017 policy should have a bigger impact on firm entry in cities with a larger scale of VC activities. We expect the coefficient β_1 to be positive.

4 Data

4.1 Funding rounds data from Crunchbase

We use Crunchbase funding rounds data for Chinese start-ups for our baseline analysis. We collect funding rounds completed during the period Jan 2014-Dec 2019. The final year in our sample is 2019 because we want to avoid the impact of COVID-19, which broke out in China in early 2020. From Crunchbase, we obtain detailed information like the start-ups' names, industries, locations, and the year of establishment. For each funding round, we know the date of funding, the total amount of capital raised, and the number of investors. Following Edwards and Todtenhaupt (2020), we construct our funding-rounds dataset as follows.[11] First, we exclude non-equity funding rounds. We further exclude funding rounds without sufficient information on key control variables, or with irregular observations (for example, reporting negative firm age). We drop firms with only one funding round since we control for firm-level fixed effects. For our baseline estimation, we also select funding rounds that occurred when firms were no more than 60 months old.

One challenge is to define technology start-ups. The policy specifies that the annual R&D investment of the qualifying start-up needs to be at least 20% of the total costs. The start-up also must meet the size requirement defined in terms of total assets, operating revenue, and employment (see Table A.1). Unfortunately, Crunchbase does not provide financial information for firms, like R&D investment and total assets. It is also not feasible to match companies in Crunchbase with external data sources. More generally, financial information for private firms is difficult to obtain. Thus, we identify whether a start-up is a technology start-up based on the industry information provided by Crunchbase. Specifically, we believe that firms in industries listed by the Chinese government as "high and new technology" industries are more likely to satisfy the policy requirement. We list these industries and the corresponding 2-digit China Industry Classification (CIC) codes in Table B.1 of Appendix B. Note that Crunchbase only provides activity labels for each firm. Based on this information, we classify an activity in Crunchbase as "high and new technology" if it is mentioned by the official guidance. In Table B.2 of Appendix B, we provide the list of Crunchbase activity labels that are consistent with the description of the "high and new technology" industries, and the corresponding 2-digit CIC industry codes. Table

[11] Table C.1 illustrates the sample construction step by step.

B.3 provides the list of non-technology activity labels. One issue is that a firm can report multiple activities in Crunchbase, and we do not know the main industry the firm operates. Thus, we classify a company to be a qualified technology start-up if at least 50% of its activities reported in Crunchbase belong to the "high and new technology" industries. In our baseline estimations, we exclude start-ups with 0.01-50% of activities falling into the "high and new technology" category, for a cleaner identification.[12]

In the final funding rounds dataset for our benchmark DID estimations, we obtain 4,717 funding rounds for 1,932 start-ups during 2014-2019. Panel A of Table 2 illustrates the number of funding rounds, the average capital raised, and the average number of investors per funding round, year by year during our sample period. In terms of total capital raised and number of investors per funding round, there appears to be an upward trend during 2014-2019. By 2019, the levels of both variables have become substantially larger than those in 2014.

Panel B provides the summary statistics for key variables in our baseline DID estimations. [13] We differentiate between the treatment and control groups and report the mean, standard deviation, and t-test statistics for equal means for each variable. Among the various dimensions we examine, we observe that treated funding rounds tend to raise more capital and attract more investors on average. Treated start-ups also appear to be older when they receive funding and have a lower Crunchbase rank at the time of funding, relative to start-ups in the control group.

4.2 Alternative data: Zero2IPO

We use an alternative dataset called Zero2IPO for the investor-level estimations. Zero2IPO is the leading VC database in China which has better coverage of VC investment than alter-

[12]In Table E.2 of Appendix E, we report the estimation results when we relax this criterion.
[13]Appendix C provides the variable definitions.

native Chinese VC databases (such as CV Source) (Chen, 2022). Figure D.1 in Appendix D shows that the number and the overall trend of funding rounds recorded in Zero2IPO is comparable to that in Crunchbase. We use Crunchbase for our baseline DID and RDD analyses, mainly because it has a better coverage of two key variables. The first one is firm age. As shown in Table D.1 in Appendix D, only around 3% of firms fail to report age in Crunchbase. In comparison, this ratio is as high as 30% in Zero2IPO. Moreover, while around 17% of funding rounds in Crunchbase do not disclose the amount of investment, this ratio is as high as 40% in Zero2IPO.

Nevertheless, Crunchbase and Zero2IPO have similar coverage of investment events. Thus, both can be candidates for conducting investor-level estimations where we only examine the number of investments by each investor. However, our identification strategy requires us to know whether an investor is officially registered as a VC fund or not. The websites of the China Asset Management Association and the local Development and Reform Commissions only disclose the Chinese names of investors. We can match investors' registration information with Zero2IPO, which reports investors' Chinese names. In contrast, Crunchbase only reports investors' English names, making the matching more problematic. Thus, we choose Zero2IPO for the investor-level analysis.

4.3 Data on firm entry

We use the nationwide business registration data for China during 2014-2019 to study the impact of VC tax incentives on firm entry. In the business registration data, we observe the location of registration, year of establishment, and the 2-digit CIC industry code for the firm's main product. On the other hand, the business registration data only provides limited information on firms' financial status, including registered capital and employment. Using the business registration data, we construct the number of newly registered firms for each city-2-digit-industry pair during 2014-2019. Based on the industry classification of the newly registered firms, disclosed by the business registration data, we can measure firm entry into high-tech and non-high-tech industries, respectively.

4.4 Hand-collected data

We also utilize several hand-collected data for the empirical analyses. First, to analyze how investors change their investment portfolios, we manually check the websites of the China Asset Management Association and the local Development and Reform Committees, and collect the list of registered VC investors from these sources. Second, we manually search the internet to gather information about the national high-tech Zones and local tax incentives for VC and PE investors. We use these information to conduct robustness checks of the baseline funding-rounds estimations.

5 Results

5.1 Did eligible start-ups receive more funding?

5.1.1 Baseline analysis using difference-in-differences

We first report DID estimation results where we compare funding rounds made by technology start-ups (treated) with those by non-technology (control) start-ups. We obtain funding rounds from Crunchbase when the start-up is no more than 60 months old. Our DID estimation strategy relies on the assumption that there would have been a parallel trend between treated and control groups in the absence of the policy intervention. We check the plausibility of this assumption by examining parallel trends between the treatment and control groups before the policy reform in Figure 2, where we consider two outcome variables: total capital raised and the number of investors (both in logs), for each funding round. The dynamic estimation is based on Equation 2. The dot represents the point estimates, while the shadow represents the 95% confidence intervals. Figure 2 shows that for both outcome variables, there is no significant divergence between the treatment and control groups before the reform. After the reform, for both outcome variables, we observe a jump for the treatment group after 2017, attributable to the introduction of the tax incentive.

Table 3 reports the DID estimation results based on Equation 1, where we restrict the sample size to be the same across columns. Column 1 shows that the treatment group enjoyed a 21% increase in total capital raised since 2017, relative to the control group. Column 2 shows that relative to the control group, treated firms attract on average 9 percent more investors after the implementation of the tax incentive. In Columns 3-4, we include the set of control variables as discussed in Section 3. The estimated treatment effects on total capital raised and the number of investors are similar to those in columns 1 and 2. In Table E.1, we report estimation results analogous to Table 3 without controlling for funding-round fixed effects.[14] The results there are qualitatively similar to those in Table 3.

5.1.2 Robustness checks for the baseline analysis

A larger treatment group. In our baseline estimations, we restrict the treated group to funding rounds from start-ups that are most likely to be in the high-tech industries. Specifically, we require that at least half of the activities of a treated start-up, as reported in Crunchbase, be in the officially acknowledged high-tech industries. Start-ups with less than half of their activities in the high-tech industries are excluded from estimations for a cleaner identification. In Table E.2, we relax this restriction and classify a start-up to be a qualified technology start-up as long as one of its Crunchbase activity labels belongs to the "high and new technology" industry list. Generally speaking, while the estimated treat-

[14] We have a slightly larger sample for this exercise since we exclude funding-rounds with unknown sequence numbers in Table 3.

ment effects are of the same signs based on this alternative larger sample, the magnitudes tend to be smaller and the point estimates tend to be less significant.

The earlier tax incentive. The 2017 tax incentive scheme is an extension and generalization of earlier tax schemes. The Chinese government provided a similar tax deduction scheme for qualified investment, albeit on a much narrower basis, for a few incorporated VCs since 2008. This early scheme was then applied to VCs formed in partnerships in 2015. However, substantial differences exist between the earlier schemes (in particular the 2015 policy) and the 2017 initiative. First, the earlier schemes were rather restrictive in terms of the eligibility of investees—those need to be officially certified high-tech enterprises, while the 2017 scheme does not require official certification. This effectively expands the scope of eligible investees. Second, the 2015 tax incentive scheme did not apply to individual investors of VC firms or angel investors, while the 2017 policy covers both legal and individual investors. Thus, the 2017 tax scheme also increases the scope of potential incentive beneficiaries. For these two reasons, it has been commented that the 2017 tax scheme has much broader coverage than the previous ones (KPMG, 2017). Third, the earlier schemes tend to target more matured high-tech firms, as there is no age limit and the size ceiling is also higher (see, Table A.1 in Appendix A). In comparison, the 2017 tax incentive scheme puts a specific age limit on eligible start-ups and the size ceiling is considerably lower. Thus, the 2017 tax incentive especially targets young start-ups.

In Table E.3, we conduct a placebo test to examine whether the 2015 VC tax incentive has any material impact on the funding of technology start-ups, based on Crunchbase funding-rounds data. The hypothesis is that the impact of the earlier scheme should be rather limited since it imposes stricter requirements on firms, and also does not provide tax incentives for individual investors. To test this, we use the year 2015 as the policy year and compare funding rounds for technology and non-technology start-ups (no more than 5 years old by the time of funding) completed during 2012-2016. We do not find any difference in the total capital raised or the number of investors between high-tech and non-high-tech start-ups in this DID estimations. This is consistent with our conjecture that the earlier VC tax incentive scheme had limited impact on funding activities, due to its restrictiveness.

National high-tech zones. Another potential confounding policy is the establishment of high-tech zones, as documented by Tian and Xu (2022). Various incentives, including preferential tax treatments, may be given to firms located in high-tech zones.[15] It has also been shown that the establishment of high-tech zones increases VC funding in the zone area. In our empirical analysis using the funding-rounds data, we control for firm-level fixed effects. Therefore, our approach should have controlled for the impact of the high-tech zones, unless the start-up is located in a high-tech zone that was established during our sample period. As a robustness check, we exclude from our empirical analysis funding rounds for start-ups located in national high-tech zones that have been established since 2014. Only 8.5% of funding rounds are excluded. Based on the smaller sample, we obtain similar results as our baseline estimations (see Table E.5). Therefore, our benchmark results are unlikely to be confounded by the establishment of national high-tech zones.

Local investment incentives. Finally, we examine the interaction between the 2017 tax incentive and local investment benefits for VC investors. Many Chinese local governments provide tax incentives for VCPE investors, even before 2017. The timing, scale, and content of these special benefits vary across regions, which makes the comparison difficult. Nevertheless, local tax incentives are usually provided in the form of tax rebates as a fixed percentage of tax paid to the local governments.[16] Importantly, these local tax incentives

[15] In Table E.4, we provide the list of national high-tech zones established during 2014-2019 in China.

[16] While Chinese local governments do not tax businesses or individuals separately, they share the tax

for VC investors are generally not limited to investment into high-tech start-ups. Even though the scale of these local tax incentives is small, such local tax benefits may crowd out the 2017 tax incentive.

To examine whether there might be such an effect, we hand-collect the list of cities offering VC tax incentives, as well as the implementation and end years of the local tax incentives. We find that around 16% of our funding rounds sample would be affected by the existence of local VC tax incentives. We then interact a dummy indicating the presence of local VC tax incentives with $Post \times Treated$. Table E.6 reports the triple DID estimation results. The estimated coefficient on the triple DID term is statistically insignificant, while that on $Post \times Treated$ remains similar to the baseline estimate. Therefore, we do not find evidence of crowding out between local tax incentives and the 2017 tax deduction benefit.

5.1.3 Heterogeneity across investor types

We examine whether technology start-ups are more likely to attract a certain type of investors after 2017. We consider heterogeneity across VC investors of different sizes and ages in Table 4. For this exercise, we use the Crunchbase classification to differentiate VCs from other investor types. We use the total number of investments by the end of 2019 to measure the size of each VC investor. We regard a VC with the number of investments above the sample median as being large. Investor age is calculated based on the establishment date for each investor. A VC is considered to be old if its age is above the sample median.

We construct dummies indicating the presence of a certain type of VC investor for each funding round. We report the OLS estimation results where we use these dummies as the dependent variable in columns 1-4 of Table 4.[17] We find that after the tax incentive

revenue with the central government based on a fixed percentage. For the corporate income tax, for example, the sharing ratio for local governments is 40%.

[17]We use the OLS estimator in the first four columns so that we can control for firm-level fixed effects.

was implemented, the likelihood of treated start-ups receiving funding from larger VCs significantly increased, relative to the control group (column 1). In contrast, there is no evidence that eligible start-ups are more likely to receive funding from smaller VCs (column 2). We also observe that older VCs are more likely to invest in treated startups after 2017 (column 3), while there is no difference between eligible and non-eligible startups in attracting investment from younger VCs (column 4).

Columns 5-8 report the DID estimation results where the outcome variable is the number of a certain type of VC investors in a certain funding round. At this margin, we find that the treated firms tend to attract more larger and older VCs in a typical funding round since the reform, relative to the control group (columns 5 and 7). In contrast, there is no significant difference between the treatment and control firms in terms of the number of smaller or younger VC investors they attract after the policy change.

One possible explanation for the contrast between investors of different sizes and experiences is that larger/more experienced investors should be more likely to generate positive taxable income than smaller/younger investors, all else equal. Since the Chinese tax incentive is a deduction against investors' taxable income, the tax incentive is likely to be less important for investors making less profit, or even losses. Besides, larger investors may have better resources (e.g., administrative personnel, tax experts, and better connection with the tax authorities) to comply with the tax code, and also assist their investees to comply. On the other hand, given the generosity of the Chinese tax incentive, it proves to be sufficient to affect the behavior of large and experienced investors.

As a separate heterogeneity analysis, in Table G.2 in Appendix G, we examine whether the tax incentive induces more investment into earlier-stage start-ups. We do not find differential effects at this margin.

We obtain similar results when we use the Probit estimator. However, we cannot control for firm-level fixed effects in Probit estimations due to non-convergence of the algorithm.

5.1.4 Quality of investment

The tax incentive may lower the investor's required rate of return before tax, which may lead them to invest in lower-quality projects. On the other hand, Keuschnigg and Nielsen (2004) suggests that a lower tax on investors should increase the level of VC support for start-ups, likely increasing the performance and success probability of start-ups. How the tax incentive affects investment quality is thus an empirical issue, which we examine in this section.

Continuity in fundraising. One measure of investment quality is the ability of the investee to continue to raise funds after the policy-induced increase in funding. If the incentive lowers the bar for the quality of VC investments, we may see a reduction in the investee's probability to receive financing after it ceases to be eligible for the VC incentive. To see if the investee firms continue to be successful in attracting non-incentivized funding, we test whether there is any change in the likelihood of receiving funding once a firm passes the 60-month age threshold, conditional on having received funding when it is below the age threshold. Specifically, we compare technology and non-technology firms and estimate the following Cox model:

$$h(J|t,x) = \lambda(t)exp(\alpha_0 Post + \alpha_1 Treated + \beta Treated \times Post + \gamma z') \tag{6}$$

where $h(J|t,x)$ is the hazard rate of receiving funding post the age threshold, t days since the last funding within the age threshold. $\lambda(t)$ is a common function of the time-at-risk. In some estimations, we include z', which is a vector of observable characteristics for the start-up. The estimated coefficient β captures the difference-in-differences between the hazard rates of the treated and control groups, before and after the 2017 tax incentive was implemented. The exponentiated coefficient $exp(\beta)$ provides an estimate for the hazard ratio. For this exercise, we only retain the firms that received at least one round of funding when they were under 60 months between January 2014 and December 2021. The start date for our survival analysis is the date when a firm received its last batch of funding while under 60 months from establishment. For firms that received funding post the age threshold by December 2021, the end date is the date when the firm received first post-age-limit funding. For firms that did not receive funding after they exceeded the age threshold during our sample period, the end date is set to be December 31, 2021.

We use the full sample of firms for the hazard model estimation in the first two columns of Table 5. In columns 3 and 4, we conduct a nearest neighbor one-on-one propensity score matching between technology and non-technology firms, based on firms' age and rank at the beginning of the sample period. Throughout different columns, Table 5 shows that since 2017, relative to the control group (non-tech firms), the treated group (tech firms) has a similar likelihood to receive subsequent funding when they grew older, conditional on having received funding below the age threshold. This is because the coefficient on the interaction term $Post \times Treated$ is not statistically different from 0, even though the point estimate is positive. This evidence does not support the view that the tax incentive lowers the investment bar.

Successful exits. Another indicator of the quality of investment is successful exits, via either acquisition or IPO. If the tax incentive leads to a lower average quality of investments, we might expect to observe a lower probability of a successful exit for the treated group after the reform. On the other hand, if the tax incentive increases VC support or leads investors to choose better targets, we may observe a higher exit probability for start-ups in VC portfolios. We construct a dummy $Exit$ that equals 1 if a startup was either acquired or went through an IPO by the end of 2021, and 0 otherwise. Table 6 reports the Cox model estimation results where we use $Exit$ as the outcome variable. In columns 1-4, we compare technology and non-technology start-ups that received their first round of funding after January 2017. We use either the full sample (columns 1-2) or a smaller sample of start-ups matched on their age and Crunchbase $Rank$ (columns 3-4). These columns show that relative to non-technology start-ups, there is no significant difference in the likelihood of exit between treated and control groups, although the point estimate for $Treated$ is positive. In columns 5-8, we repeat the Cox model estimation where we consider start-ups that received at least one funding after January 2017. Again, we obtain positive estimates for $Treated$, but none of these estimates are statistically significant. Thus, we do not find that the tax incentive lowers the investment quality.

5.2 Does the policy generate new funding or do VCs merely substitute between ineligible and eligible projects?

We have shown that the investor-level tax deduction led to increased funding for technology startups. One remaining question is whether the tax incentive increases the supply of total funding for startups, or investors simply shift funding from non-eligible firms towards eligible ones. We shed light on this issue in this section. For identification, we utilize the fact that the tax code requires investors to formally register their funds as "venture capital funds", either with the China Asset Management Association, or the local Development and Reform Committee. Funds registered as other types (e.g., private equity) cannot claim the tax deduction. We thus compare registered VC funds with non-VC funds before and after 2017 in a DID setup.

To classify funds into different types, we use their Chinese names as reported in Zero2IPO to match the list of qualified VC funds disclosed by the government authorities. We cannot use Crunchbase for this exercise since it only provides fund names in English, making the matching problematic. To obtain the list of certified VC funds, we manually check the websites of the China Asset Management Association and the local Development and Reform Committees.

For our investor-level analysis, we have focused predominantly on the number of investments as the dependent variable. Aggregation of investment amount data for each VC fund is challenging using the available data sources. In both Crunchbase and Zero2IPO, there are a large number of funding rounds with multiple investors, where disaggregated investment by each investor is not disclosed. This makes aggregation of the total investment amount at the fund level problematic. This problem is aggravated by the large number of missing observations for the actual investment amount in both datasets, particularly in Zero2IPO. However, we can more accurately calculate the number of investments for each fund during 2014-2019, year by year, based on Zero2IPO. We also classify the number of investments by each fund into different types: early-stage (no more than 60 months) high-tech, early-stage non-high-tech, late-stage (>60 months) high-tech, and late-stage non-high-tech, based on investees' age and industry.[18]

We conduct a propensity score matching to achieve better comparability between registered VC funds and other funds. Appendix H illustrates the PSM approach we use in more detail. Specifically, we matched VC funds and non-VC funds based on the number of investments between 2013-2016, as well as fund age in 2019. Based on this matched sample of investors, in Figure 3, we plot the dynamic effects of the tax incentive on certified VCs' investment into different types of startups during the sample period 2014-2019, relative to that by other equity investors. In this estimation, we control for investor-level fixed effects and year-fixed effects. Each dot in Figure 3 indicates the corresponding point estimates, while the shadow indicates the associated 95% confidence intervals. Across the set of sub-figures, we show that the parallel trend is largely satisfied. Certified VCs increase the number of investments in early-stage technology firms gradually from 2017 (Panel A). There is no significant change in investment into early-stage non-tech firms (Panel B). Combining both types of early-stage investments, Panel C shows a gradual and

[18]Since around 34% of investees in Zero2IPO did not disclose information on age, our aggregates are potentially biased downward.

significant increase in early-stage investment by certified VCs since the policy change, relative to other equity investors. In comparison, investments in late-stage firms appear to shift downward since 2017, for both tech and non-tech firms. This provides some graphical evidence that the tax incentive may have caused a substitution between early-stage and late-stage investments.

More formally, we conduct DID estimations based on Equation 4 on the matched sample. The results are reported in Table 7. In column 1 of Table 7, we find that relative to the unregistered investors, registered VCs significantly increased the number of investments into young high-tech start-ups by 12 percentage points after the 2017 policy change. In column 2, we find no significant difference between treated and control groups in terms of the number of investments into young non-high-tech start-ups. Adding up the two types of investments, we find that registered VCs' total number of investments into early-stage start-ups increased by around 12.5 percentage points, which is statistically significant (column 3. In columns 4-6, we examine investment into older firms ($>$60 months). Relative to non-VC investors, registered VCs significantly cut the number of investments into mature firms, significantly so for both mature high-tech and non-high-tech firms (columns 4 and 5). The total number of investments into mature firms declined by around 5 percentage points, as shown by column 6. In column 7, we use the total number of investments, across all types, as the outcome variable in the DID estimation. While we find a positive coefficient, it is not statistically significant. This suggests that the tax incentive leads to some substitution between investments into different types of firms, most significantly between young high-tech start-ups and mature firms.

In Table G.3, we report the impact of the 2017 tax incentive on the likelihood of making a certain type of investment at the investor level. To obtain the result in column 1 of this supplementary appendix table, we construct a dummy that equals 1 if an investor makes at least one investment into technology start-ups no more than 60 months old in a certain year. We show that relative to the control group, registered VC investors are significantly more likely to invest in qualified technology start-ups, as the estimated treatment effect is positive and strongly significant. In column 2, we construct another dummy that equals 1 if an investor makes at least one investment into non-technology start-ups (no more than 60 months old) in a certain year, and we find a null impact of the policy there. Shifting to mature firms, we find that registered VCs became significantly less likely to invest in mature firms (columns 4 and 5). Overall, at the intensive margin, we find similar patterns of substitution as that observed from Table 7.

5.3 The impact of the tax incentive on firm entry

We have shown that the 2017 tax incentive lead to increasing funding for eligible start-ups. One related question is that with the perceived better funding opportunities, does the angel/VC tax incentive lead to the entry of more start-ups? To answer this question, we use the nationwide business registration data and calculate the number of newly established independent companies for each city-2-digit-industry pair. There are 102,032 city-industry-year observations in total. In this exercise, we regard high-tech industries as being treated, and non-high-tech industries as the control group. We also use a triple DID approach to explore heterogeneity across cities in terms of their exposure to the VC industry before 2017.

Table 8 reports the results based on Equation 4. In columns 1-2, the dependent variable is the number of new firms at the city-industry level (in logs). We do not include control variables in column 1, and control for city-level GDP (in logs), GDP growth rate, and population (in logs), all lagged by one year, in column 2. In both columns, we find that the number of new firms in high-tech industries has increased by around 17% since 2017, compared with that in non-high-tech industries. In column 3, the dependent variable is an indicator that equals 1 if a city-industry pair has any new firm entry in a particular year, and 0 otherwise. We find that relative to the control group, there are more likely to be new firms established in high-tech industries after 2017. This further supports the hypothesis that the angel/VC tax incentive encourages firm entry. Figure 4 provides the event plot for our entry analysis, which supports the parallel trend assumption. The event plot lends further support to the DID estimation results.

We report the triple DID estimation results based on Equation 5 in the next three columns in Table 8. The literature suggests that VC and angels tend to have a bias towards local firms (Cumming and Dai, 2010). Thus, the tax incentive should have a larger impact on firm entry where the local VC/angel investment is more active. Consistent with our conjecture, we find that the impact of the 2017 policy on firm entry is more prominent for high-tech industries located in cities with a larger exposure to the VC industry before the policy change. In all three columns, the estimated coefficient on $HighExposure_i \times Treated_{i,j} \times Post_t$ are positive and statistically significant. In unreported exercises, we instead measure a city's exposure to the VC industry before 2017 as the number of VC investors in and around that city. We continue to find qualitatively similar results as those in the last three columns of Table 8.[19]

Taken together, results from our entry analyses indicate a positive and significant impact of the 2017 investor-level tax incentive on entrepreneurship. Moreover, we find that the impact on entrepreneurship is heterogeneous across different regions, depending on how active the local VC/angel market is.

6 Conclusion

We examine how investor-level tax incentives for angel and venture capital investors affect financing for start-ups, utilizing the implementation of the 2017 Chinese angel/VC

[19]These results are available upon request.

tax scheme as a natural experiment. We find that the tax incentive leads to improved financing for eligible start-ups. The tax policy also encourages investors to shift late-stage investment into early-stage projects, which is in line with the policymakers' goal and could have contributed to the surge of China's venture capital market in recent years.

Further analyses indicate that larger and more experienced investors appear to be more responsive to tax incentives. There is also evidence that the tax incentive helps larger investors to crowd out smaller ones in the early-stage financing market. Our finding suggests that the benefit of the investor-level tax incentive is not equally distributed across investors, which may in turn affect the venture capital market structure.

On the other hand, we show that when tax incentives are sufficiently generous, larger and more experienced investors would take up the tax benefit. Consequently, this leads to a real impact on the economy as we observe more firm entry. Start-ups are often associated with new jobs or new ideas (Haltiwanger, Jarmin and Miranda, 2013). If so, the Chinese investor-level tax incentive may positively impact employment and innovation in the economy and potentially influence its long-run growth. We leave this important issue for future research.

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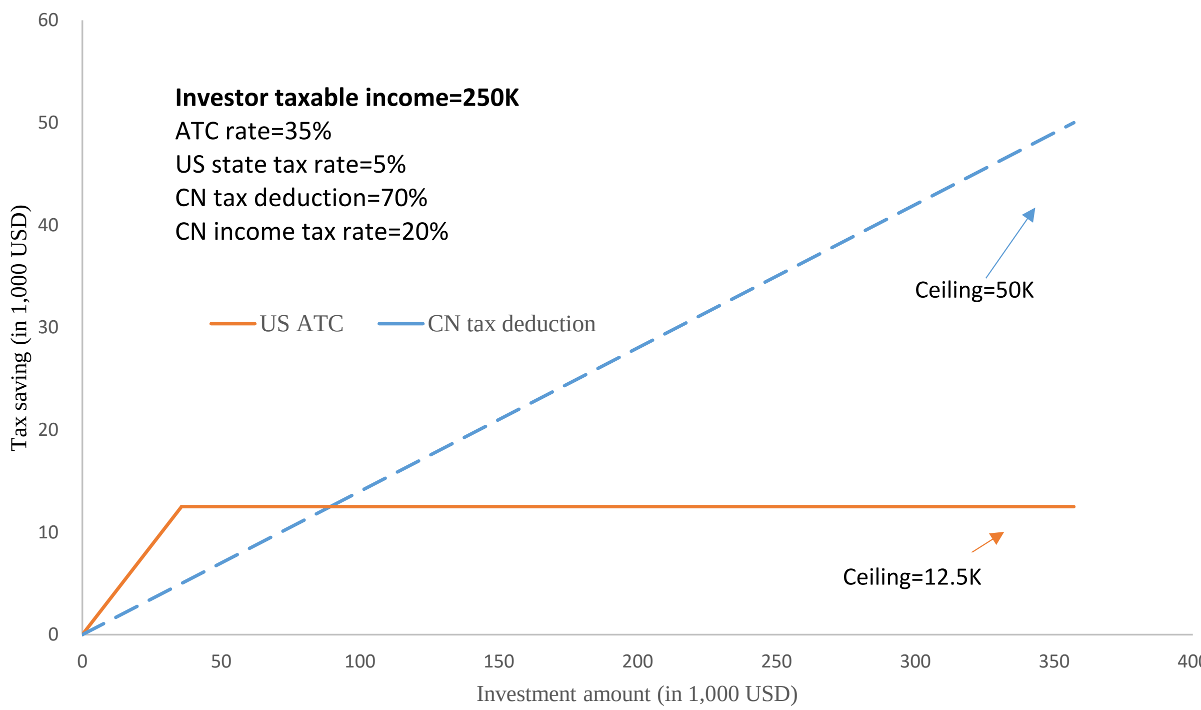
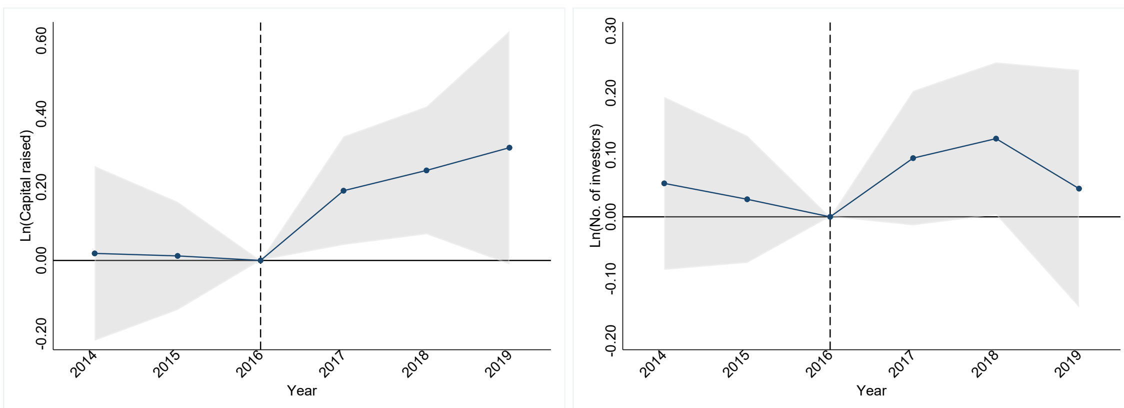
Figure 1: Comparing with the US ATC



Note: In this figure, we calculate tax savings for an investor with 250,000 USD taxable income under different tax schemes. We assume the angel tax credit (ATC) rate to be 35%, and a typical US state tax rate to be 5%. We set the income tax rate to be 20% for a typical Chinese angel/VC investor, and the tax deduction rate to be 70%.

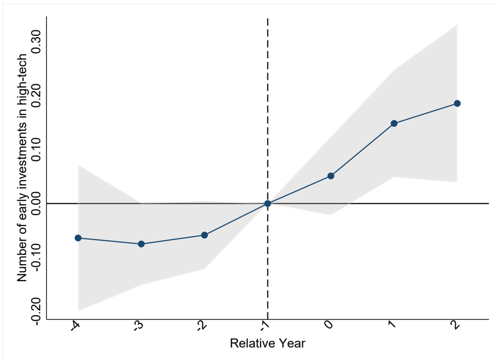
Figure 2: Dynamic effects of the investor tax incentive: funding rounds estimations



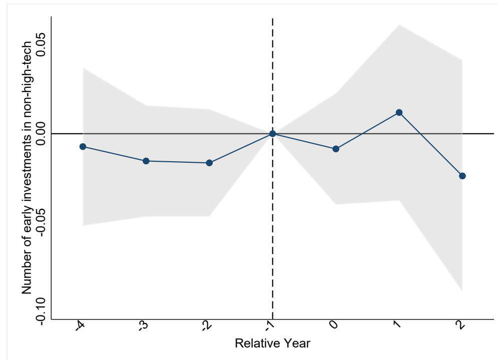
(a) Ln(Capital raised) (b) Ln(No. of investors)

Note: These figures plot the dynamic effects of the tax-incentive policy on capital raised and the number of investors. We set one year before the policy (year=2016) as the benchmark. We perform dynamic DID estimations by equation 2. For each outcome variable, we plot the point estimates (blue dots) and the 95% confidence intervals (the gray shaded area). We control for firm, funding-round and year fixed effects in dynamic DID regressions. Standard errors are robust and clustered at the firm level.

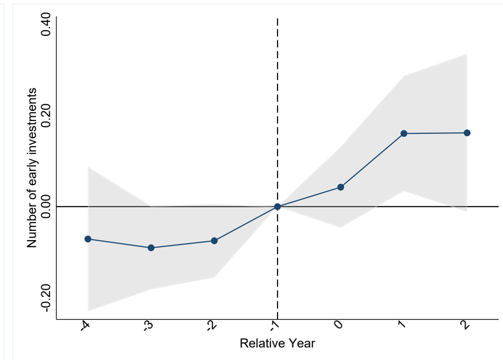
Figure 3: Investor-level evidence: number of investments



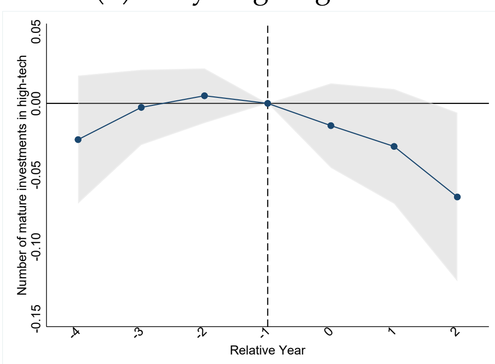
(a) Early-stage high-tech



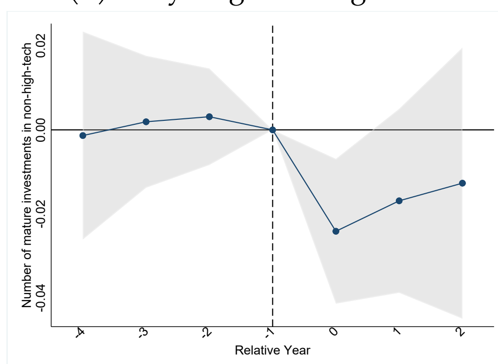
(b) Early-stage non-high-tech



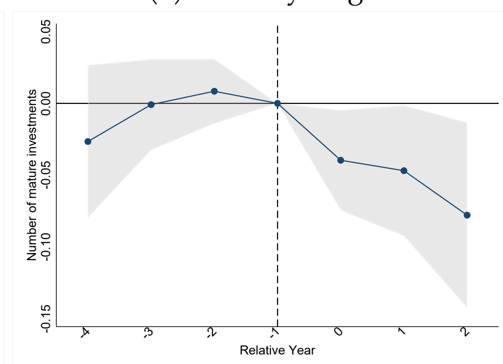
(c) All early-stage



(d) Late-stage high-tech



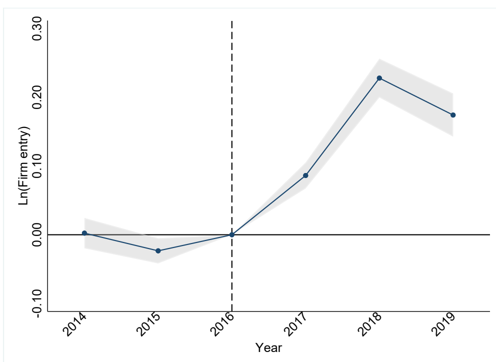
(e) Late-stage non-high-tech



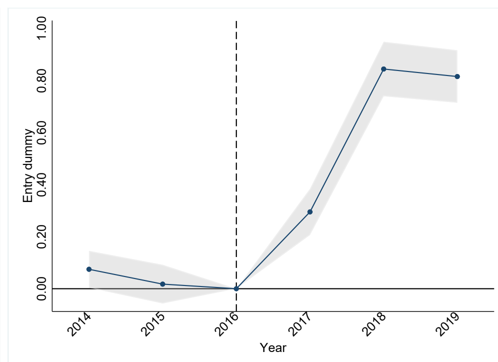
(f) All late-stage

Notes: This figure plots the dynamic effects of the tax incentive on the number of investments made by VC funds, relative to non-VC funds. Each dot displays the point estimate and the gray shaded area represents the 95% confidence interval. We control for investor-level and year-fixed effects in dynamic DID estimations. Standard errors are robust and clustered at the investor level.

Figure 4: Investor tax incentive and firm entry



(a) Ln(Newly registered firms)



(b) Entry dummy

Note: These figures plot dynamic effects on the entry of independent corporations. We set one year before the policy (year=2016) as the benchmark. Each dot displays the point estimate and the gray shaded area displays the 95% confidence intervals. Panel A plots the dynamic effects on the number of newly registered corporations (in logs) after controlling for city-year and city-industry fixed effects. Panel B plots the dynamic effects on firm entry at the extensive margin after controlling for GDP per capita, GDP growth, population and year fixed effects. Standard errors are robust and clustered at the city-industry pair level.

Table 1: Tax treatments of VC enterprises

Panel A: Tax treatments for incorporated VCs

		Dividends	Equity disposals
Fund level		Exempted	25%
Shareholders	Legal person	Exempted	25%
	Natural person	20%	20%

Panel B: Tax treatments for VC partnerships

		Dividends	Equity disposals
Fund level		N.A.	N.A.
General partners*		25%	25%
Limited partners	Legal person	25%	25%
	Natural person	20%	20% or 5%-35% **

Notes: This table describes the tax treatment for venture capital enterprises in China, organized as corporations (Panel A) or partnerships (Panel B).*: GPs are usually incorporated fund managers, and all of their income (dividends, capital gains, management fees, consulting fees, etc.) are subject to the standard corporate income tax rate. **: If a VC partnership elects to tax its investment returns on a fund-by-fund basis, a flat 20% tax rate is applied to the individual partners' capital gains. If a VC partnership elects to tax its investment returns on an annual enterprise income basis, income derived by an individual partner through the VC enterprise is calculated as a proportion of the VC enterprise's aggregate income—this is determined by deducting (from gross income and gains) the allowable costs, expenses and losses related to the business, allowing for aggregation and offset of all the different income streams arising to the VC enterprise. The taxable income of the individual partners is then subject to an income tax at a progressive rate from 5% to 35%

Table 2: Summary statistics

Panel A: Summary statistics of key variables by year

Year	Number of funding rounds	Capital raised per round (USD) Mean	Capital raised per round (USD) Median	Number of investors Mean	Number of investors Median
2014	437	9,397,079	1,307,618	1.56	1
2015	938	8,313,443	1,540,556	1.74	1
2016	1145	16,362,030	1,522,002	1.91	1
2017	1005	11,757,252	2,470,362	1.96	1
2018	792	40,850,380	3,122,438	2.23	2
2019	400	48,749,108	4,297,866	2.14	2

Panel B: Treated group v.s. Control group: two-sample t tests with equal means

Variables	Treated group Obs.	Treated group Mean	Treated group S.D.	Control group Obs.	Control group Mean	Control group S.D.	Mean Difference	T-Value
Ln (Capital raised)	2,025	14.782	1.637	2,692	14.666	1.550	0.116	2.490**
Ln (No. of Investors)	2,025	0.492	0.575	2,692	0.461	0.542	0.031	1.884*
Ln (Age)	2,025	0.86	0.544	2,692	0.79	0.561	0.070	4.270***
Ln (Rank)	2,025	7.805	0.508	2,692	7.84	0.464	-0.035	2.464**
Angel dummy	2,025	0.041	0.198	2,692	0.042	0.200	-0.001	0.105

Notes: This table reports summary statistics for the baseline funding-rounds estimation sample. The sample period is 2014-2019. Panel A reports summary statistics of key variables year by year. Table C.1 provides the sample construction details and Table C.2 provides the variable definitions. Panel B reports summary statistics for the treated (funding rounds by technology firms no more than 5 years old) and control group (funding rounds by non-technology firms no more than 5 years old), separately. The last two columns in Panel B present the difference in means between the treated and control groups and the associated T-test statistics.

Table 3: The impact of the investor-level tax incentive on funding activities: baseline results

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Capital raised)	(4) Ln(No. of investors)
Post × Treated	0.208***	0.089**	0.208***	0.088**
	(0.065)	(0.044)	(0.065)	(0.043)
Ln (Age)			0.285***	0.122**
			(0.076)	(0.050)
Ln (Rank)			0.030	0.014
			(0.035)	(0.023)
Angel dummy			0.126	0.378***
			(0.080)	(0.043)
Firm FE	Yes	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,717	4,717	4,717	4,717
R-squared	0.884	0.560	0.884	0.570

Notes: This table reports the estimated effect of the investor-level tax incentive on the total amount of capital raised per funding round (columns 1 and 3) and the number of investors (columns 2 and 4), both in logs. The treated group consists of funding rounds made by technology firms that are no more than 5 years old. The control group consists of funding rounds made by non-technology firms no more than 5 years old. We restrict the sample to funding rounds completed during 2014-2019, as reported by Crunchbase. Standard errors are clustered at the firm level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table 4: Heterogeneity across VC investors

	Indicator for each type of investor				Number of investors			
Dep. Var.:	(1)Large	(2)Small	(3)Old	(4)Young	(5)Large	(6)Small	(7)Old	(8)Young
Post × Treated	0.085**	-0.009	0.092**	-0.042	0.134*	-0.004	0.144***	-0.038
	(0.040)	(0.015)	(0.037)	(0.031)	(0.070)	(0.018)	(0.053)	(0.037)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,717	4,717	4,717	4,717	4,717	4,717	4,717	4,717
R-squared	0.563	0.489	0.605	0.554	0.597	0.488	0.617	0.567

Notes: In this table, we examine the effects of the tax incentive on VC investors of different sizes and ages, using funding rounds data during 2014-2019. The treated group consists of funding rounds by technology firms that are no more than 5 years old. The control group consists of funding rounds by non-technology firms no more than 5 years old. In Columns 1-4, we report OLS estimation results where the dependent variable is a dummy indicating the presence of a certain type of VC investors. In Columns 5-8, the dependent variable is the number of a certain type of VC investors for each funding round. We use the total number of investments as reported in Crunchbase to proxy investor size. Investor age is calculated as the number of years since an investor is founded. We then use the median value of these variables to define whether an investor is large, small, old or young. Standard errors are clustered at the firm level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table 5: The effect of the tax incentive on the hazard rate of continuous funding

	(1)	(2)	(3)	(4)
	Full sample		Matched sample	
Post × Treated	0.214	0.318	0.274	0.324
	(0.209)	(0.210)	(0.223)	(0.223)
Treated	0.548***	0.197	0.316	0.215
	(0.195)	(0.195)	(0.207)	(0.207)
Post	-0.326**	-0.781***	-0.405**	-0.783***
	(0.150)	(0.151)	(0.169)	(0.169)
Ln(Rank)		-0.670***		-0.677***
		(0.041)		(0.042)
Ln(Age)		2.536***		2.586***
		(0.116)		(0.127)
exp(β)	1.239	1.374	1.315	1.383
Observations	10,291	10,058	8,090	8,090
# of treated firms	3,093	3,038	3,038	3,038
# of control firms	4,509	4,423	3,038	3,038
χ^2	107.5	1284	58.23	1103

Notes: This table shows the semi-parametric hazard rate estimates of receiving follow-up funding. In the sample, we retain those firms that received at least one round of funding when they were under 60 months between 2014 and 2021, thereby entering our treatment group. The start date for our survival analysis is the last funding date when a firm is under 60 months, and the end date is the first funding date when the company exceeds the age threshold (if applicable), or if the company does not receive any further funding, the end of December 31, 2021. $Treated$ is a dummy indicating whether a firm is categorized as a technology firm for the purpose of the policy. $Post$ is a dummy for the period after January 1, 2017. We control for the age and rank of a firm at the last funding date when it is under 60 months. Samples in columns 1 and 2 include all firms in Crunchbase that received at least one funding while under 60 months, between 2014 and 2019. In columns 3 and 4, we conduct a nearest neighbor 1:1 propensity score matching on firm age and rank (measured at the beginning of the sample period) between technology and non-technology firms, and report the Cox model estimation results based on this matched sample. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table 6: Impact of the tax incentive on exit through IPO or acquisition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Startups receiving first funding after Jan 2017				Startups receiving at least one funding after Jan 2017			
	Full sample		Matched sample		Full sample		Matched sample	
Treated	-0.022	0.041	0.039	0.041	0.144	0.179	0.102	0.106
	(0.392)	(0.398)	(0.427)	(0.427)	(0.227)	(0.229)	(0.241)	(0.241)
Ln(Rank)		-0.013		-0.079		0.141		0.129
		(0.362)		(0.374)		(0.206)		(0.211)
Ln(Age)		0.178		0.329		-0.294*		-0.267
		(0.249)		(0.291)		(0.164)		(0.178)
exp(β)	0.978	1.042	1.040	1.042	1.155	1.196	1.107	1.112
Observations	3,524	3,453	2,949	2,949	4,729	4,658	4,046	4,046
# of treated firms	1504	1473	1473	1473	2054	2023	2023	2023
χ^2	0.00293	0.531	0.00821	1.425	0.398	3.991	0.180	2.686

Notes: This table reports the semi-parametric estimates of the Cox model for the hazard rate of exit through IPO or acquisition, based on Crunchbase. In columns 1-4, we restrict the sample to be firms that received first funding while being no more than 5 years old after January 2017. The start date for this survival analysis is the first funding date, and the end date is the day when the firm had an exit (IPO or being acquired, if applicable), or the end of December 31, 2021. In columns 5-8, we restrict the sample to be firms that received at least one funding while being no more than 5 years old after January 2017. The start date for this survival analysis is the date of establishment, and the end date is the day when the firm had a successful exit (if applicable), or the end of the sample period. $Treated$ is a dummy indicating whether it is a technology firm. In columns 3-4 and columns 7-8, we conduct a nearest neighbor 1:1 propensity score matching between the technology and non-technology firms based on their initial age and Crunchbase rank. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table 7: Effects of the tax incentive on investors: Intensive margin

Dep. Var.: Number of investments	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Early-stage investments			Mature investments			All investments
	High-tech	Non-high-tech	Total	High-tech	Non-high-tech	Total	
Treated×Post	0.123***	0.003	0.125***	-0.026**	-0.022***	-0.048***	0.077
	(0.035)	(0.015)	(0.044)	(0.013)	(0.007)	(0.015)	(0.048)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,417	13,417	13,417	13,417	13,417	13,417	13,417
R-squared	0.471	0.373	0.488	0.328	0.282	0.357	0.501
# of investors	2946	2946	2946	2946	2946	2946	2946
# of treated investors	1473	1473	1473	1473	1473	1473	1473
# of control investors	1473	1473	1473	1473	1473	1473	1473

Notes: In this table, we examine the effect of the 2017 tax incentive on fund-level outcomes. The regression sample is composed of annual fund-level data, aggregated based on funding rounds reported by Zero2IPO. We select investors who have had at least one investment during 2014 and 2019, and exclude investors established after 2017 for a more balanced sample. For each investor, the start year is 2014 or its establishment year, whichever is later. The end year of the panel data is the year when the last investment was made. If the last investment occurred after 2019, we set the end year as 2019. The treated group consists of VC funds, and the control group consists of non-VC funds. Before the staggered DID estimations, we performed the nearest neighbor 1:1 propensity score matching on the pre-reform characteristics (including the number of investments before 2013,the number of investments in 2014, the number of investments in 2015, the number of investments in 2016, investor age, and city fixed effects) of the treated and control groups. *Post* equals 1 since 2017 for investors locates in 8 pilot cities. For investors in other cities, *Post* equals 1 since 2018. Standard errors are clustered at the investor-level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 8: Impact of the investor-level tax incentive on firm entry

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Ln(Entry)	Ln(Entry)	Entry dummy	Ln(Entry)	Ln(Entry)	Entry dummy
Treated×Post	0.170***	0.170***	0.574***	0.141***	0.140***	0.559***
	(0.011)	(0.011)	(0.036)	(0.015)	(0.015)	(0.045)
Treated×Post×HighExposure				0.058***	0.058***	0.057
				(0.022)	(0.022)	(0.076)
Post×HighExposure				0.035**	0.029*	-0.229***
				(0.016)	(0.016)	(0.049)
Treated×HighExposure						0.282***
						(0.046)
Treated			0.049**			-0.056**
			(0.022)			(0.028)
HighExposure						0.143***
						(0.034)
Ln(GDP per capita)$_{t-1}$		0.104***	0.600***		0.095***	0.589***
		(0.024)	(0.016)		(0.024)	(0.017)
GDP growth rate$_{t-1}$		-0.052	-0.084		-0.050	-0.093
		(0.045)	(0.129)		(0.045)	(0.129)
Ln(Population)$_{t-1}$		0.234***	0.636***		0.218***	0.627***
		(0.068)	(0.011)		(0.067)	(0.011)
City×Industry FE	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,032	102,032	102,032	102,032	102,032	102,032
# of city-industry	17,061	17,061	17,061	17,061	17,061	17,061
R-squared	0.897	0.897	0.078	0.897	0.897	0.080

Notes: This table reports the effects of the tax incentive on firm entry based on business registration data during 2014-2019. To increase the comparability between the two types of industry-city pairs, we match them using the 1:1 nearest neighbor propensity score matching, based on the number of newly established firms before 2017. $Treated_{m,c}$ equals 1 if industry m in city c is an high-tech industry, and 0 otherwise. $Post$ equals 1 since 2017. The dependent variable in columns 1-2 and columns 4-5 is the number of newly established firms in city c, industry m and year t (in logs). The dependent variable in columns 3 and 6 is a dummy that equals 1 if there is at least one firm birth in a city-industry pair in year t, and 0 otherwise. We further construct a dummy variable $HighExposure_c$, based on whether the number of VC investors in a certain city before 2017 is above the national median. Standard errors are clustered at the city-industry level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Appendices

ONLINE APPENDIX

A Policy comparison

Table A.1: Comparison with the 2015 tax incentive

		2015	2017
Is it applicable to VC?		Yes, but only legal person investors	Yes, both legal person and individual investors
Is it applicable to angels?		No	Yes
Restriction on investees	Development stage	Non-listed when the investment is made or in the following two years	1. <=60 months at the time of investment; 2. Non-listed when the investment is made or in the following 2 years.
	Degree of innovation	Certified high-tech enterprises	R&D expenses no less than 20% of total costs and expenses when the investment is made and in the following fiscal year
	Employment	$<= 500$ employees	$<= 200$ employees, at least 30% of whom must have a university degree.
	Operating conditions	Annual revenue/total asset $<= 200$ million RMB at the time of investment	Annual revenue/total asset $<= 30$ million RMB at the time of investment (increased to 50 million RMB in 2018)

Notes: This table compares the key features of the 2015 and 2017 tax incentives for VC/angel investors.

B Industry classification based on Crunchbase activity labels

Table B.1: High-tech industries and the corresponding 2-digit CIC codes

Industry code(CIC)	Industry name
25	Petroleum, coal and other fuel processing
26	Chemical raw materials and chemical products manufacturing
27	Medicine manufacturing
28	Chemical fiber manufacturing
30	Non-metallic mineral products manufacturing
32	Non-ferrous metal smelting and calendering
34	General equipment manufacturing
35	Special equipment manufacturing
36	Automotive manufacturing
37	Railway, ship, aerospace and other transportation equipment manufacturing
38	Electrical machinery and equipment manufacturing
39	Computer, communications and other electronic equipment manufacturing
40	Instrumentation manufacturing
41	Other manufacturing
42	Comprehensive utilization of resources
44	Electricity, heat, gas and water production and supply
46	Water production and supply
63	Telecommunications, broadcast television and satellite transmission services
64	Internet and related services
65	Software and information technology services
73	Research and development services
74	Professional technical services
75	Technology promotion and application services
76	Water conservancy management
77	Ecological protection and environmental governance industry

Notes: This table shows the industry name and the 2-digit CIC code for high-tech industries that meet the official guidance, based on the industry classification standard GB/T 4754-2017.

Table B.2: Activity labels in Crunchbase and corresponding CIC codes: high-tech

3D Printing [75]	Communications Infrastructure [39]	Geospatial [65]	Pharmaceutical [27]
3D Technology [75]	Computer [39]	Green Tech	Pollution Control [77]
Advanced Materials [28]	Computer Vision [65]	Health Diagnostics [27]	Presentation Software [65]
Aerospace [37]	Consumer Software [65]	Human Computer Interaction [39]	Printing [75]
Ag Tech [75]	Cyber Security [64]	ISP [64]	Private Cloud [64]
Air Transportation [37]	Cycling [77]	IT Infrastructure [64]	RFID [63]
Alternative Medicine [27]	DSP [39]	IT Management [64]	Recycling [77]
Android [65]	Data Center [64]	IaaS [34]	Renewable Energy [75]
Application Specific Integrated Circuit [39]	Data Center Automation [64]	Image Recognition [65]	Robotics [34]
Artificial Intelligence [39]	Data Integration [64]	Industrial Automation [34]	SEM [35]
Augmented Reality [39]	Data Mining [64]	Information Services [65]	SEO [65]
Automotive [39]	Data Storage [64]	Information Technology [65]	SaaS [65]
Autonomous Vehicles [39]	Data Visualization [64]	Information and Communications Technology [63] [65]	Satellite Communication [63]
Battery [38]	Database [64]	Intelligent Systems [39]	Search Engine [64]
Big Data [64]	Drone Management [39]	Laser [63]	Semantic Web [64]
Biofuel [25]	Drones [39]	Life Science [27]	Semiconductor [35]
Bioinformatics [65]	E-Commerce [64]	Linux [65]	Sensor [39]
Biometrics [65]	E-Commerce Platforms [64]	Logistics [74]	Smart Cities [75]
Biopharma [27]	E-Learning [64]	Machine Learning [75]	Social CRM [74]
Biotechnology [27]	Electric Vehicle [36]	Management Information Systems [65]	Software [65]
Broadcasting [63]	Electrical Distribution [38]	Mapping Services [65]	Software Engineering [65]
Business Information Systems [65]	Electronic Design Automation (EDA) [34]	Marine Technology [74]	Solar [25]
Business Intelligence [65]	Embedded Software [65]	Marine Transportation [37]	Space Travel [74]
CAD [64]	Embedded Systems [65]	Medical [27]	Speech Recognition [75]
CMS [64]	Emergency Medicine [73]	Medical Device [27]	Telecommunications [63]
CRM [64]	Energy [25]	Meeting Software [65]	Text Analytics [75]
Clean Energy [44][77]	Energy Efficiency [25]	Nanotechnology [41]	Virtual Reality [75]
Clean Tech [77]	Energy Management [75]	Navigation [63]	Virtualization [75]
Cloud Computing [64]	Energy Storage [25]	Network Hardware [39]	VoIP [63]
Cloud Data Services [64]	Enterprise Software [65]	Network Security [64]	Waste Management [77]
Cloud Infrastructure [64]	Environmental Engineering [77]	Neuroscience [73]	Water Purification [76]
Cloud Management [64]	Facial Recognition [65]	Nuclear [41]	Wind Energy [25]
Cloud Security [64]	GPS [63]	Operating Systems [65]	Wired Telecommunications [63]
Cloud Storage [64]	GPU [39]	Optical Communication [63]	Wireless [63]
Communication Hardware [39]	Genetics [27]	PaaS [64]	iOS [65]

Notes: This table displays the activity labels of high-tech firms that we classify based on Crunchbase. The corresponding 2-digit CIC codes are reported in the square brackets.

Table B.3: Activity labels in Crunchbase: non-high-tech

Accounting	E-Books	Local	Reservations
Ad Network	EdTech	Local Business	Residential
Adult	E-discovery	Local Shopping	Resorts
Adventure Travel	Education	Location Based Services	Restaurants
Advertising	Elder Care	Loyalty Programs	Retail
Advertising Platforms	Elderly	MMO Games	Retail Technology
Advice	EHR	Machinery Manufacturing	Risk Management
Affiliate Marketing	Email Marketing	Made to Order	STEM Education
Agriculture	Emerging Markets	Management Consulting	Sales
American Football	Employee Benefits	Manufacturing	Sales Automation
Amusement Park and Arcade	Employment	Market Research	Same Day Delivery
Angel Investment	Enterprise	Marketing	Scheduling
Animal Feed	Enterprise Applications	Marketing Automation	Seafood
Animation	ERP	Marketplace	Secondary Education
App Discovery	Environmental Consulting	Media and Entertainment	Self-Storage
App Marketing	Event Management	Men's	Serious Games
Application Performance Management	Event Promotion	Messaging	Service Industry
Apps	Events	Micro Lending	Sex Industry
Aquaculture	Eyewear	Military	Sex Tech
Architecture	Facilities Support Services	Mining	Sharing Economy
Art	Facility Management	Mining Technology	Shipping
Asset Management	Family	Mobile	Shoes
Association	Fantasy Sports	Mobile Advertising	Shopping
Auctions	Farmers Market	Mobile Apps	Shopping Mall
Audio	Farming	Mobile Devices	Skiing
Audiobooks	Fashion	Mobile Payments	Skill Assessment
Auto Insurance	Fast-Moving Consumer Goods	Motion Capture	Small and Medium Businesses
B2B	Fertility	Museums and Historical Sites	Smart Building
B2C	Field Support	Music	Smart Home
Baby	File Sharing	Music Education	Snack Food
Bakery	Film	Music Label	Soccer

Banking	Film Distribution	Music Streaming	Social
Beauty	Film Production	Musical Instruments	Social Assistance
Billing	FinTech	Natural Language Processing	Social Entrepreneurship
Bitcoin	Finance	Natural Resources	Social Impact
Blockchain	Financial Exchanges	News	Social Media
Blogging Platforms	Financial Services	Nightclubs	Social Media Advertising
Boating	First Aid	Nightlife	Social Media Management
Brand Marketing	Fitness	Non-Profit	Social Media Marketing
Brewing	Flowers	Nursing and Residential Care	Social Network
Broadcasting	Food Delivery	Nutrition	Social News
Building Maintenance	Food Processing	Office Administration	Social Recruiting
Building Material	Food and Beverage	Oil and Gas	Sporting Goods
Business Development	Forestry	Online Auctions	Sports
Business Travel	Franchise	Online Forums	Staffing Agency
Call Center	Fraud Detection	Online Games	Stock Exchanges
Car Sharing	Freelance	Online Portals	Subscription Service
Career Planning	Freight Service	Organic	Supply Chain Management
Casual Games	Fruit	Organic Food	Sustainability
Catering	Funding Platform	Outdoor Advertising	TV
Celebrity	Funerals	Outdoors	TV Production
Charter Schools	Furniture	Outsourcing	Task Management
Chemical	Gambling	PC Games	Tea
Child Care	Gamification	Packaging Services	Technical Support
Children	Gaming	Paper Manufacturing	Test and Measurement
Civil Engineering	Gift	Parenting	Textbook
Coffee	Gift Card	Parking	Textiles
Collaboration	Gift Exchange	Parks	Theatre
Collaborative Consumption	Golf	Payments	Therapeutics
Collectibles	Government	Peer to Peer	Ticketing
Collection Agency	Green Consumer Goods	Performing Arts	Timber

College Recruiting	Grocery	Personal Branding	Tobacco
Comics	Group Buying	Personal Development	Tour Operator
Commercial	Guides	Personal Finance	Tourism
Commercial Insurance	Handmade	Personal Health	Toys
Commercial Lending	Hardware	Personalization	Trade Shows
Commercial Real Estate	Health Care	Pet	Trading Platform
Communities	Health Insurance	Photo Editing	Training
Concerts	Higher Education	Photo Sharing	Transaction Processing
Console Games	Home Decor	Photography	Translation Service
Construction	Home Health Care	Physical Security	Transportation
Consulting	Home Improvement	Plastics and Rubber Manufacturing	Travel
Consumer	Home Renovation	Play-station	Travel Accommodations
Consumer Applications	Home Services	Podcast	Travel Agency
Consumer Electronics	Home and Garden	Point of Sale	Tutoring
Consumer Goods	Homeland Security	Precious Metals	Universities
Consumer Lending	Hospital	Presentations	Vacation Rental
Consumer Research	Hospitality	Price Comparison	Vending and Concessions
Consumer Reviews	Hotel	Primary Education	Venture Capital
Content	Housekeeping Service	Privacy	Veterinary
Content Creators	Human Resources	Private Social Networking	Video
Content Delivery Network	Impact Investing	Procurement	Video Advertising
Content Marketing	Incubators	Product Design	Video Chat
Continuing Education	Independent Music	Product Management	Video Conferencing
Cooking	Indoor Positioning	Product Research	Video Editing
Corporate Training	Industrial	Product Search	Video Games
Cosmetic Surgery	Industrial Manufacturing	Productivity Tools	Video Streaming
Cosmetics	Infrastructure	Professional Networking	Video on Demand
Coupons	Innovation Management	Professional Services	Virtual Assistant
Courier Service	Insure-Tech	Project Management	Virtual Currency
Coworking	Insurance	Property Development	Virtual Goods
Craft Beer	Intellectual Property	Property Insurance	Virtual Reality
Creative Agency	Interior Design	Property Management	Virtual Workforce

Credit	Internet Radio	Psychology	Vocational Education
Credit Cards	Jewelry	Public Relations	Warehousing
Crowdfunding	Journalism	Public Safety	Water
Crowdsourcing	Knowledge Management	Public Transportation	Water Transportation
Cryptocurrency	LGBT	Publishing	Wealth Management
Customer Service	Landscaping	Q&A	Wearables
Dating	Language Learning	Quality Assurance	Web Apps
Delivery	Last Mile Transportation	RFID	Web Browsers
Delivery Service	Laundry and Dry-cleaning	Racing	Web Development
Dental	Law Enforcement	Railroad	Wedding
Diabetes	Lead Generation	Reading Apps	Wellness
Dietary Supplements	Lead Management	Real Estate	Wholesale
Digital Entertainment	Leasing	Real Estate Investment	Wine And Spirits
Digital Marketing	Legal	Recipes	Winery
Digital Media	Legal Tech	Recreation	Women's
Digital Signage	Leisure	Recreational Vehicles	Wood Processing
Direct Marketing	Lending	Recruiting	Young Adults
Direct Sales	Life Insurance	Rehabilitation	eSports
Document Management	Lifestyle	Religion	mHealth
Document Preparation	Lighting	Rental	
Domain Registrar	Lingerie	Rental Property	
E-Signature	Livestock	Reputation	

Notes: This table displays the activity label of the control group reported in Crunchbase.

C Sample construction and variable definition

Table C.1: Sample selection

No.	Sample Selection	Number of observations
(1)	Equity-only funding-round observations recorded in Crunchbase 2014–2019, China	24110
(2)	Excluding firms above 5 years old at funding-round announcement date	17674
(3)	Excluding firms with only one funding round	12025
(4)	Excluding funding rounds without sufficient information on control variables	11903
(5)	Excluding firms with unclear industry classification	10808
(6)*	Excluding firms with less than 50% of industry descriptions are high-tech industry.	7673
(7)	Excluding observations with funding type reported as ”Unknown” or “Private Equity” in Crunchbase.	7459
(8)	Excluding observations with any missing variables (including dependent variables and control variables).	4717

Notes: This table presents the sample selection process. We show step by step how we construct the benchmark funding-rounds regression sample based on Crunchbase.

Table C.2: Variable definitions

Variable	Definition	Data source
Ln(Capital raised)	The natural logarithm of the amount of capital raised (in USD) in a funding round.	Crunchbase
Ln(No. of investors)	The natural logarithm of the number of investors in a funding round.	Crunchbase
Ln(Age)	The natural logarithm of difference between the announcement date of a funding round (measured in years) and the establishment date of the firm	Crunchbase
Angel dummy	A dummy variable that equals 1 if a funding round involves an angel investor, and 0 otherwise	Crunchbase
Ln(Rank)	The natural logarithm of Crunchbase's rank of a funding round, which is based on Crunchbase's own algorithms.	Crunchbase
Exit dummy	A dummy variable that equals 1 since a firm was acquired or had an IPO, and 0 otherwise.	Crunchbase
Acquired dummy	A dummy variable that equals 1 since a firm was acquired, and 0 otherwise.	Crunchbase
IPO dummy	A dummy variable that equals 1 since a firm had an IPO, and 0 otherwise.	Crunchbase
Ln (No. of investments)	The natural logarithm of the number of investments by a certain investor in a certain year.	Zero2IPO
Ln (Firm entry)	The natural logarithm of the number of newly established firms in a city-industry pair in a certain year.	Business registration data
Entry dummy	A dummy variable that equals 1 if there is at least one new firm entry in a city-industry pair in a certain year, otherwise 0.	Business registration data

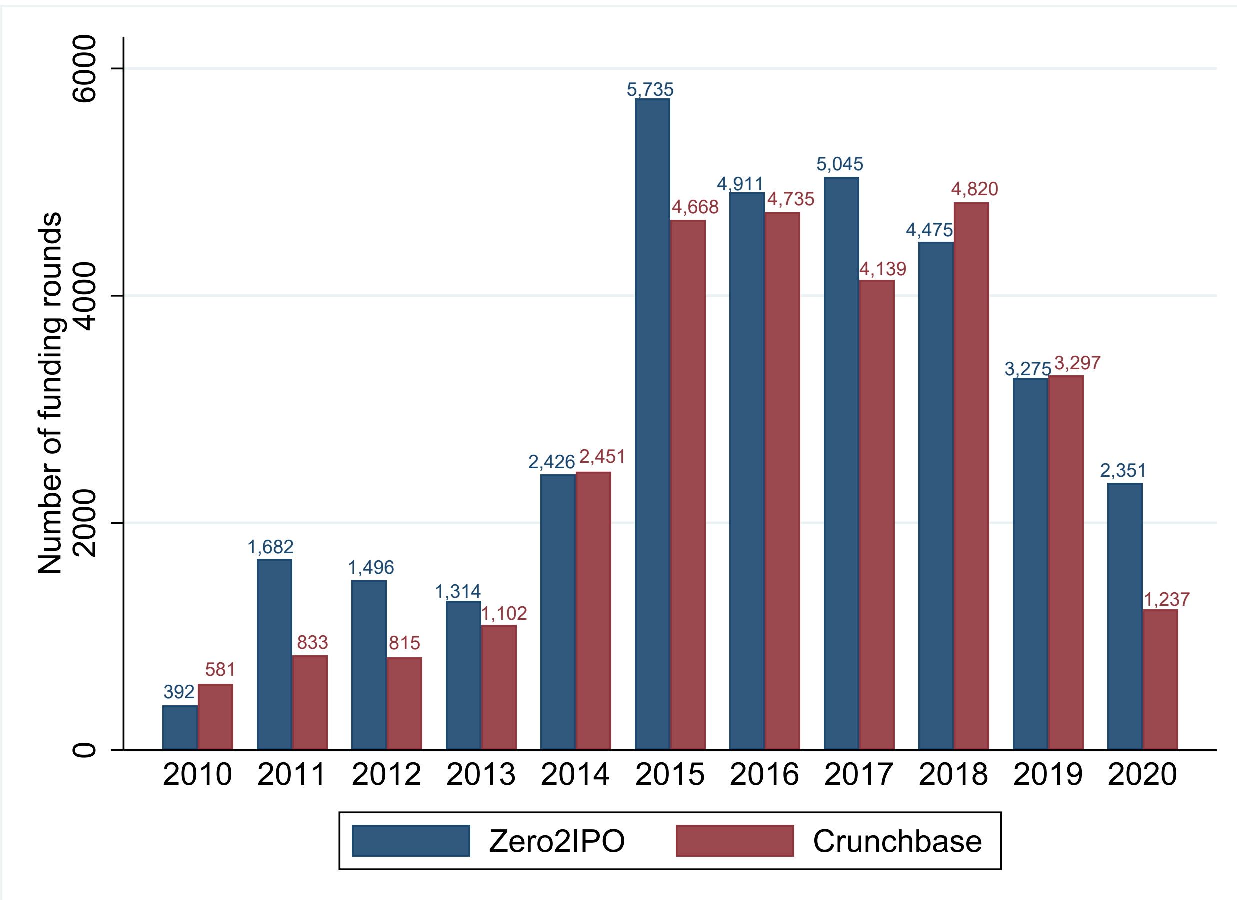
D Comparison between Crunchbase and Zero2IPO

Table D.1: Funding round coverage under different selection criteria

	Crunchbase	Zero2IPO
(1) Total funding rounds	24,110 (raised by 14,540 firms)	25,867 (raised by 17,740 firms)
(2) No. of funding rounds with firm age	23,526	18,266
(3) No. of funding rounds with total investment amount	19,973	15,745
(4) No. of funding rounds satisfying criteria (2)+(3)	19,847	9,535
–No. of funding rounds with multiple investors	7,715 (38.9%)	2,381(24.9%)

Notes: In this table, we compare funding rounds reported by Crunchbase and Zero2IPO under different selection criteria.

Figure D.1: Funding rounds coverage



Note: This figure compares the number of funding rounds reported in Crunchbase and Zero2IPO from 2010-2020. This table covers funding rounds for firms across all ages and industries.

E Robustness checks for the funding-rounds estimations

Table E.1: Baseline results without controlling for funding-round fixed effects

	(1)	(2)	(3)	(4)
Dep. Var.:	Ln(Capital raised)	Ln(No. of investors)	Ln(Capital raised)	Ln(No. of investors)
Post × Treated	0.251***	0.089**	0.244***	0.087**
	(0.073)	(0.044)	(0.072)	(0.043)
Ln (Age)			0.748***	0.140***
			(0.090)	(0.048)
Ln (Rank)			0.050	0.017
			(0.039)	(0.023)
Angel dummy			0.075	0.381***
			(0.087)	(0.044)
Firm FE	Yes	Yes	Yes	Yes
Funding-round FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Observations	4,717	4,717	4,717	4,717
R-squared	0.849	0.556	0.855	0.566

Notes: In this table, We re-conduct the baseline estimations in Table 3 and do not control for funding-round fixed effects.

Table E.2: Baseline results based on a broader treatment group

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Capital raised)	(4) Ln(No. of investors)
Post × Treated	0.120**	0.047	0.123**	0.047
	(0.054)	(0.037)	(0.054)	(0.036)
Ln (Age)			0.257***	0.141***
			(0.060)	(0.038)
Ln (Rank)			-0.004	-0.012
			(0.028)	(0.018)
Angel dummy			0.040	0.346***
			(0.068)	(0.041)
Firm FE	Yes	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	7,432	7,432	7,432	7,432
R-squared	0.881	0.563	0.882	0.571

Notes: In this table, we examine the effect of the tax incentive on total capital raised and the number of investors for each funding round, using a broader treatment group in the DID estimations. The treatment group consists of firms with at least one activity label that belongs to the high-tech industry list. The control group is the same as that in Table 3. Standard errors are clustered at the firm-level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table E.3: The effect of the earlier policy

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Capital raised)	(4) Ln(No. of investors)
Post × Treated	-0.053	0.061	-0.043	0.065
	(0.106)	(0.065)	(0.104)	(0.064)
Ln (Age)			0.453***	0.047
			(0.098)	(0.061)
Ln (Rank)			0.028	-0.006
			(0.050)	(0.032)
Angel dummy			0.164	0.376***
			(0.105)	(0.058)
Firm FE	Yes	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,366	2,366	2,366	2,366
R-squared	0.875	0.575	0.878	0.585

Notes: In this table, we examine the effect of 2015 tax incentive. We restrict the sample to be funding rounds completed during 2012-2016, reported by Crunchbase. The treated group consists of funding rounds made by technology firms that are no more than 5 years old . The control group consists of funding rounds made by non-technology firms no more than 5 years old. Standard errors are clustered at the firm-level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table E.4: List of national high-tech zones since 2014

No.	Zone Name	Year Certified	Province	City	No.	Zone Name	Year Certified	Province	City
1	Zhenjiang High-Tech Zone	2014	Jiangsu	Zhenjiang	28	Bishan High-tech Zone	2015	Chongqing	Chongqing
2	Changzhi High-Tech Zone	2015	Shanxi	Changzhi	29	Luzhou High-tech Zone	2015	Sichuan	Luzhou
3	Jinzhou High-Tech Zone	2015	Liaoning	Jinzhou	30	Panzhihua High-tech Zone	2015	Sichuan	Panzhihua
4	Yancheng High-Tech Zone	2015	Jiangsu	Yancheng	31	Deyang High-tech Zone	2015	Sichuan	Deyang
5	Lianyungang High-Tech Zone	2015	Jiangsu	Lianyungang	32	Ankang High-tech Zone	2015	Shanxi	Ankang
6	Yangzhou High-Tech Zone	2015	Jiangsu	Yangzhou	33	Ordos High-tech Zone	2017	Neimenggu	Eerduosi
7	Changshu High-Tech Zone	2015	Jiangsu	Changshu	34	Suqian High-tech Zone	2017	Jiangsu	Suqian
8	Xiaoshan Linjiang High-Tech Zone	2015	Zhejiang	Hangzhou	35	Huaian High-tech Zone	2017	Jiangsu	Huaian
9	Huzhou Moganshan High-Tech Zone	2015	Zhejiang	Huzhou	36	Tongling Lion Rock High-tech Zone	2017	Anhui	Tongling
10	Jiaxing High-Tech Zone	2015	Zhejiang	Jiaxing	37	Huanggang High-tech Zone	2017	Hubei	Huanggang
11	Sanming High-Tech Zone	2015	Fujian	Sanming	38	Xianning High-tech Zone	2017	Hubei	Xianning
12	Longyan High-Tech Zone	2015	Fujian	Longyan	39	Changde High-tech Zone	2017	Hunan	Changde
13	Fuzhou High-Tech Zone	2015	Jiangxi	Fuzhou	40	Shantou High-tech Zone	2017	Guangdong	Shantou
14	Ji'an High-Tech Zone	2015	Jiangxi	Ji'an	41	Neijiang High-tech Zone	2017	Sichuan	Neijiang
15	Ganzhou High-Tech Zone	2015	Jiangxi	Ganzhou	42	Anshun High-tech Zone	2017	Guizhou	Anshun
16	Zaozhuang High-Tech Zone	2015	Shandong	Zaozhuang	43	Huainan High-tech Zone	2018	Anhui	Huainan
17	Dezhou High-Tech Zone	2015	Shandong	Dezhou	44	Komsomolsk High-tech Zone	2018	Jiangxi	Jiujiang
18	Laiwu High-Tech Zone	2015	Shandong	Laiwu	45	Yichun Fengcheng High-tech Zone	2018	Jiangxi	Yichun
19	Yellow River Delta Agricultural High-tech Zone	2015	Shandong	Dongying	46	Jingzhou High-tech Zone	2018	Hubei	Jingzhou
20	Pingdingshan High-tech Zone	2015	Henan	Pingdingshan	47	Yellowstone Daye Lake	2018	Hubei	Huangshi
21	Jiaozuo High-tech Zone	2015	Henan	Jiaozuo	48	Qianjiang High-tech Zone	2018	Hubei	Qianjiang
22	Xiantao High-tech Zone	2015	Hubei	Xiantao	49	Huaihua High-tech Zone	2018	Hunan	Huaihua
23	Suizhou High-tech Zone	2015	Hubei	Suizhou	50	Zhanjiang High-tech Zone	2018	Guangdong	Zhanjiang
24	Chenzhou High-tech Zone	2015	Hunan	Chenzhou	51	Maoming High-tech Zone	2018	Guangdong	Maoming
25	Yuancheng High-tech Zone	2015	Guangdong	Yuancheng	52	Rongchang High-tech Zone	2018	Chongqing	Chongqing
26	Qingyuan High-tech Zone	2015	Guangdong	Qingyuan	53	Yongchuan High-tech Zone	2018	Chongqing	Chongqing
27	Beihai High-tech Zone	2015	Guangxi	Beihai	54	Chuxiong High-tech Zone	2018	Yunnan	Chuxiong

Notes: This table displays the national high-tech zones in China established since 2014. $Year\ certified$ shows the year when the zone was approved by the central government to become a national high-tech zone.

Table E.5: Excluding high-tech zones

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Capital raised)	(4) Ln(No. of investors)
Post × Treated	0.210***	0.085*	0.215***	0.089**
	(0.069)	(0.046)	(0.069)	(0.045)
Ln (Age)			0.292***	0.120**
			(0.080)	(0.053)
Ln (Rank)			0.025	0.026
			(0.036)	(0.024)
Angel dummy			0.134*	0.391***
			(0.081)	(0.047)
Firm FE	Yes	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,282	4,282	4,282	4,282
R-squared	0.885	0.557	0.886	0.567

Notes: In this table, we re-examine the effect of the 2017 investor-level tax incentive while excluding funding rounds that occurred in high-tech zones from the baseline sample. Standard errors are clustered at the firm-level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table E.6: The role of local tax benefits

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Capital raised)	(4) Ln(No. of investors)
Post × Treated	0.187***	0.093**	0.188***	0.093**
	(0.070)	(0.047)	(0.070)	(0.047)
Post × Treated×	0.115	-0.020	0.113	-0.029
Local tax benefit	(0.124)	(0.070)	(0.123)	(0.069)
Ln (Age)			0.285***	0.122**
			(0.076)	(0.050)
Ln (Rank)			0.029	0.014
			(0.035)	(0.023)
Angel dummy			0.125	0.378***
			(0.080)	(0.043)
Firm FE	Yes	Yes	Yes	Yes
Funding-round FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,717	4,717	4,717	4,717
R-squared	0.884	0.560	0.885	0.570
% of obs. to receive the local tax benefit	16.53%	16.53%	16.53%	16.53%

Notes: This table examines whether the existence of local tax benefits affect the impact of the 2017 investor-level tax incentive. *Local tax benefit* is a dummy variable that equals one when a city provides tax benefits for investors, and zero otherwise. We use the same sample as in Table 3. Standard errors are clustered at the firm-level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

F Regression discontinuity design

The 2017 tax incentive specifies an age limit for eligible start-ups: they need to be no greater than 60 months old at the time of receiving funding. We thus employ a sharp regression discontinuity design (RDD) to examine funding activities just below and above this age threshold. The RDD estimation results, however, need to be interpreted with caution, because any substitution from older firms to younger firms will manifest in an amplified treatment effect in the RDD analysis. We therefore only report the RDD estimation results in this Appendix.

We use the following regression specification:

$$Y_{ijt} = \alpha + \beta Below_{ijt} + f(t) + g(t) + \phi_i + \epsilon_{ijt} \tag{7}$$

where the running variable t measures the number of months relative to the age threshold (60 months). $Below_{ijt}$ is a dummy variable that equals 1 if a funding round occurs when the start-up is younger than 60 months old, and 0 otherwise. $f(t)$ and $g(t)$ are second-order polynomial functions of the running variable. We employ the algorithm developed by Calonico, Cattaneo and Titiunik (2014) to select optimal bandwidth non-parametrically to implement the RDD estimations.

To conduct the RDD estimations, we collect funding rounds by technology firms made during 2017-2019 (reported by Crunchbase), if a firm is between 20-100 months old by the time of a certain funding event. We divide the sample into 30 bins, with 15 bins on each side of the cutoff (60 months). We then plot in Figure F.1 the amount of total funding and the number of investors averaged across funding rounds in each bin. Figure F.1 shows a clear drop in funding activities once the firm passes the age threshold. In comparison, when we analyze non-technology firms during the same sample period (right-hand side panels in Figure F.1), we do not observe such discontinuity. We report the RDD estimation results based on Equation 7 in Table F.1. Consistent with Figure F.1, the first two columns show a significant jump in total funding and the number of investors for technology start-ups below the age threshold. Columns 3-4 show that non-technology start-ups did not benefit from the tax incentive. In fact, we obtain a negative coefficient in column 3.

As another placebo test, in Figure F.2, we report the RDD plots for all firms and technology firms during 2014-2016, seperately. The age limit was initiated in the 2017 tax code and hence, we should not observe discontinuity around 60 months before 2017. Indeed, for both samples, we do not observe significant discontinuity. Formal estimation results in Table F.2 further reinforce our conclusion.

Table F.1: Regression discontinuity design estimations

	(1)	(2)	(3)	(4)
	Technology firms: 2017-2019		Non-technology firms: 2017-2019	
Dep. Var.:	Ln(Capital raised)	Ln(No. of investors)	Ln(Capital raised)	Ln(No. of investors)
$Below_{ijt}$	0.976***	0.313**	-0.805**	-0.024
	(0.357)	(0.124)	(0.406)	(0.094)
Bandwidth	24.558	21.937	18.891	27.733
Order of polynomial	2	2	2	2
N(effective)	1,029	1,025	935	1,734

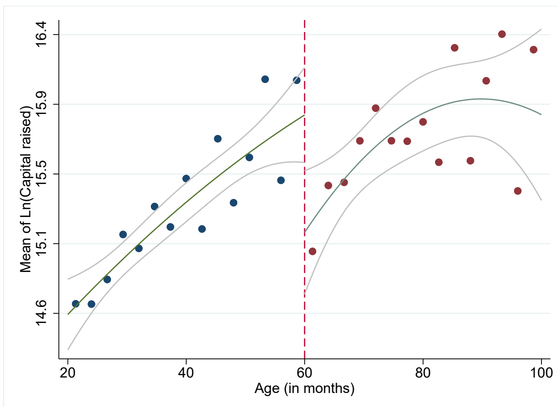
Notes: This table reports the RDD estimation results where we use 60 months as the cut-off point. Estimates reported are obtained using a local quadratic RD estimator with bandwidth selection as per Calonico et al. (2014). The sample for columns 1-2 consists of funding rounds for all technology firms between 2017 and 2019. The sample for columns 3-4 consists of funding rounds for all non-technology firms between 2017 and 2019. The standard errors are clustered at firm level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

Table F.2: RDD estimation results: placebo tests

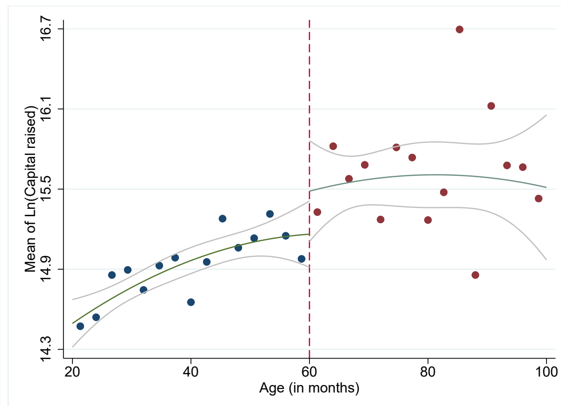
	(1)	(2)	(3)	(4)
	Technology firms: 2017-2019		Non-technology firms: 2017-2019	
Dep. Var.:	Ln(Capital raised)	Ln(No. of investors)	Ln(Capital raised)	Ln(No. of investors)
$Below_{ijt}$	0.303	0.033	0.319	–0.051
	(0.204)	(0.053)	(0.368)	(0.117)
Bandwidth	27.120	41.754	29.132	35.699
Order of polynomial	2	2	2	2
N(effective)	2,627	4,669	773	961

Notes: This table reports placebo tests for RDD estimations using funding rounds that occurred between 2014 and 2016.The point estimators are constructed using local quadratic polynomial estimators with a uniform kernel function. The bandwidth are obtained from optimal bandwidth selection approach proposed by Calonico et al. (2014). The sample for columns 1-2 consists of funding rounds from all firms (including technology firms and non-technology firms) between 2014 and 2016. The sample for columns 3-4 consists of funding rounds for all technology firms between 2014 and 2016. The standard errors are clustered at firm-level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

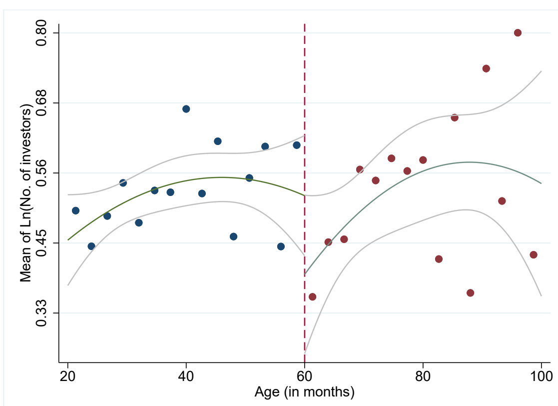
Figure F.1: Regression discontinuity design: technology and non-technology firms during 2017-2019



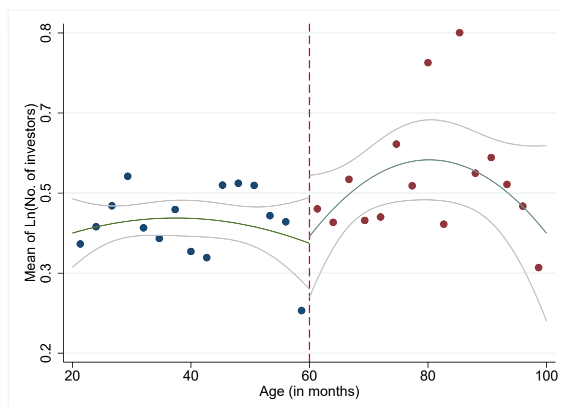
(a) Ln(Capital raised): technology firms



(b) Ln(Capital raised):non-technology firms



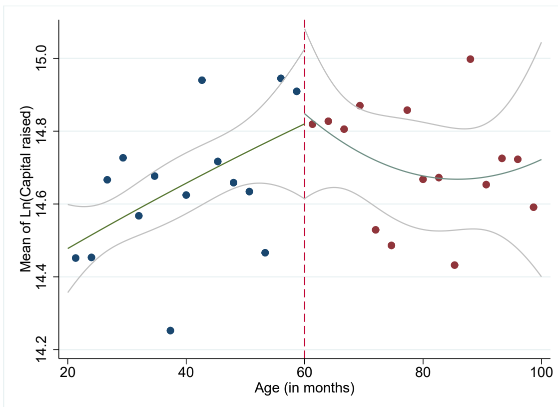
(c) Ln(No. of investors):technology firms



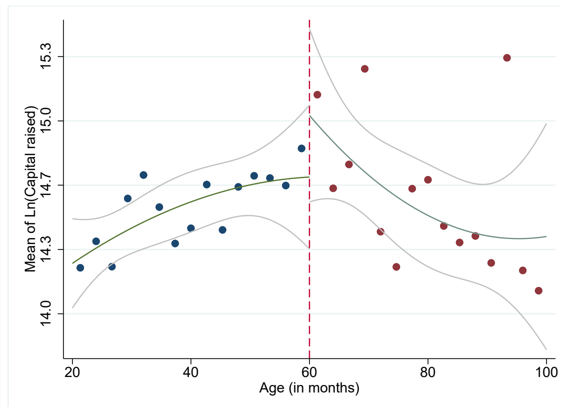
(d) Ln(No. of investors):non-technology firms

Note: These figures plot the distribution of each dependent variable across different bins. We set 60 months as the cutoff for firm age. We divide the sample into 30 bins, with 15 bins on each side of the cutoff. The solid dots represent the mean of each variable within each bin. The green line represents the quadratic best-fitted curve of each variable, and the gray lines represent the 95% confidence intervals of the fitted curve. The sample for panels (a) and (c) consists of funding rounds for technology firms from 2017-2019. The sample for panels (b) and (d) consists of funding rounds of non-technology firms from 2017-2019.

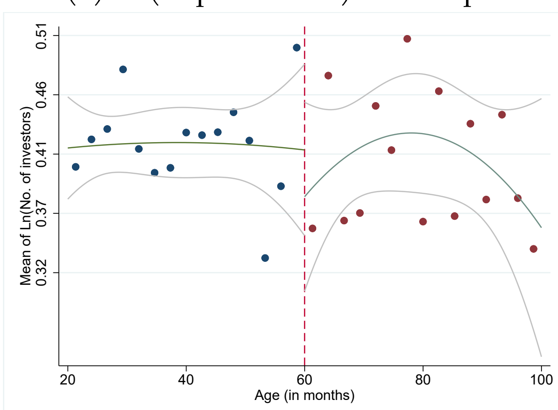
Figure F.2: RDD figures: placebo tests



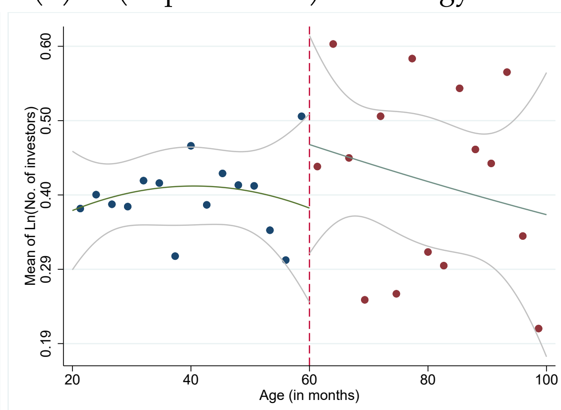
(a) Ln(Capital raised):full sample



(b) Ln(Capital raised):technology firms



(c) Ln(No. of investors):full sample



(d) Ln(No. of investors):technology firms

Note: These figures plot the distribution of each dependent variable across different bins. We set 60 months as the cutoff for firm age. Here, we divided the sample into 30 bins, with 15 bins on each side of the cutoff. The solid dots represent the mean of each variable within each bin. The green line represents the quadratic best fitted curve of each variables, and the gray line represent the 95% confidence interval of the fitted curve. The sample for panels (a) and (c) consists of funding rounds for all firms from 2014-2016. The sample for panels (b) and (d) consists of funding rounds for technology firms from 2014-2016.

G Supplementary analyses

Table G.1: The effect of the presense of VC and/or angel investors

	(1)	(2)
Dep. Var.:	Ln(Capital raised)	
Post × Treated	0.046	0.049
	(0.089)	(0.089)
Post × Treated×VC-angel dummy	0.268**	0.264**
	(0.118)	(0.118)
Post×VC-angel dummy	-0.090	-0.087
	(0.076)	(0.076)
Treated×VC-angel dummy	-0.071	-0.072
	(0.087)	(0.087)
VC-angel dummy	0.131**	0.129**
	(0.054)	(0.054)
Ln (Age)		0.278***
		(0.076)
Ln (Rank)		0.026
		(0.035)
Firm FE	Yes	Yes
Funding-round FE	Yes	
Year FE	Yes	Yes
Observations	4,717	4,717
R-squared	0.885	0.885

Notes: We examine whether the baseline DiD estimation results in Table 3 are driven by VC and/or angel investors. We construct a dummy to indicate the presence of at least one VC or angel investor in a certain funding round. We then interact the VC-angel dummy with Post×Treated, and perform a triple DID analysis. Standard errors are clustered at the firm level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Heterogeneity across funding rounds. Investing in younger firms is more likely to provide future tax benefits for the investor, compared with investing in a firm closer to the age threshold. If so, we would observe a larger positive effect of the tax incentive on earlier-stage funding rounds. However, investing in younger firms is riskier, which may moderate the effect of the tax incentive. To examine this issue, we construct a dummy *Pre-A* that equals 1 for funding rounds with sequence numbers of "Angel", "Seed" or "Pre-seed".[20] In this way, we classify around 35% of funding rounds in our baseline sample as pre-A. We then include *Pre-A* and its interaction with $Treated$, $Post$, and $Treated \times Post$ in the DID estimations. We do not find any difference between *Pre-A* and *non-Pre-A* investments in either total capital raised (columns 1 and 3) or the number of investors (columns 2 and 4). Overall, Table G.2 shows that while the tax incentive encourages more equity financing into eligible firms, it does not generate a greater positive effect on financing earlier-stage firms. If anything, the estimated coefficients in all four columns in Table G.2 are negative, although not statistically significant.

Table G.2: Heterogeneity across different funding rounds

Dep. Var.:	(1) Ln(Capital raised)	(2) Ln(No. of investors)	(3) Ln(Capital raised)	(4) Ln(No. of investors)
Post×Treated	0.292*** (0.083)	0.134** (0.055)	0.290*** (0.083)	0.127** (0.055)
Post×Treated×Pre-A	-0.091 (0.138)	-0.053 (0.089)	-0.080 (0.137)	-0.037 (0.088)
Post×Pre-A	0.207** (0.098)	0.004 (0.058)	0.191* (0.099)	-0.011 (0.057)
Treated×Pre-A	0.144** (0.073)	0.070 (0.048)	0.141* (0.073)	0.061 (0.047)
Ln(Age)			0.280*** (0.076)	0.123** (0.050)
Ln(Rank)			0.029 (0.035)	0.014 (0.023)
Angel dummy			0.121 (0.080)	0.377*** (0.043)
Firm FE	Yes	Yes	Yes	Yes
Funding round FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,717	4,717	4,717	4,717
R-squared	0.884	0.560	0.885	0.570

Notes: In this table, we examine the heterogeneity effects of the tax incentive on different stages of funding. We construct a dummy *Pre-A* that indicates "Angel", "Seed" or "Pre-seed" in Crunchbase. The sample used in this table is the same as the one used in Table 3. Standard errors are clustered at the firm level and are presented in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

[20] In unreported exercises, we instead classify funding rounds made when the firm is under 24 months as being earlier-stage investments, and we continue to find similar results.

Table G.3: Effects of the tax incentive on investors: Extensive margin

Dep. Var.:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Indicator for each	Early-stage investments			Mature investments			
type of investment	High-tech	Non-high-tech	Total	High-tech	Non-high-tech	Total	All investments
Treated×Post	0.040***	-0.008	0.015	-0.027**	-0.021***	-0.049***	-0.052***
	(0.013)	(0.009)	(0.014)	(0.011)	(0.007)	(0.012)	(0.014)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,417	13,417	13,417	13,417	13,417	13,417	13,417
R-squared	0.440	0.333	0.472	0.330	0.278	0.350	0.548
# of investors	2946	2946	2946	2946	2946	2946	2946
# of treated investors	1473	1473	1473	1473	1473	1473	1473
# of control investors	1473	1473	1473	1473	1473	1473	1473

Notes: In this table, we examine the effect of the 2017 tax incentive on fund-level outcomes at extensive margin. The sample used in this table is the samples as the one used in Table 7. The dependent variable is a dummy that equals 1 if a fund makes at least one investment of a certain type in a particular year (aggregated to each investor from the funding round data in Zero2IPO), and 0 otherwise. Standard errors are clustered at the investor-level and are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

H Propensity score matching

In this section, we illustrate the propensity score matching we conducted for the investor-level estimations (as reported in Table 7). To make the treated and control investors more comparable, we matched VC invetsors and non-VC investors based on the number of investments before 2014 and during 2014-2016, as well as investor age as in 2016. Specifically, we estimate the following probit model:

$$Treated_i = \alpha_0 + \alpha_1 \times X_i^{'} + \theta_c + \varepsilon_i \tag{8}$$

where $Treated_i$ equals 1 if investor i is a formal registered VC investor, and 0 otherwise. $X_i^{'}$ is a vector of investor-level pre-reform characteristics as discussed above. We also control for the city fixed effects θ_c. ε_i is the error term. The predicted probabilities from this regression- propensity scores -are used to construct the matched sample of VC and non-VC investors. We use the 1:1 nearest neighbor matching. Table H.1 reports the regression results based on equation 8. Table H.2 reports the means of key variables for the treated and the control groups before and after our matching procedure, as well as the pairwise t-tests and the associated bias reduction that results from the matching.

Table H.1: Probit regression results for PSM

Dep.Var.: Treated	
No. of investments before 2014	0.804***
	(0.156)
No.of invesrments in 2014	0.419***
	(0.152)
No. of invesrments in 2015	0.297***
	(0.089)
No. of invesrments in 2016	-0.051
	(0.077)
Investor's age in 2014	-0.072***
	(0.017)
City FE	Yes
No. of investors	3,241
Pseudo R-squared	0.024

Table H.2: Comparison of investor characteristics before and after propensity score matching

Variable	Group	Mean Treated	Mean Control	T-value	%bias	%bias reduction
No. of investments before 2014	Unmatched	0.043	0.022	3.460	12.000	20.700
	Matched	0.043	0.026	2.510	9.500	
No. of invesrments in 2014	Unmatched	0.031	0.021	1.740	6.100	37.200
	Matched	0.031	0.025	1.000	3.800	
No. of invesrments in 2015	Unmatched	0.092	0.074	1.940	6.800	53.100
	Matched	0.092	0.084	0.850	3.200	
No. of invesrments in 2016	Unmatched	0.092	0.118	-2.400	-8.500	81.700
	Matched	0.092	0.096	-0.440	-1.600	
Investor's age in 2019	Unmatched	2.963	3.014	-0.810	-2.800	-18.900
	Matched	2.963	2.903	0.910	3.400	

Notes: This table reports the matching properties for the list of matching variables we use. % bias reduction is calculated as (% bias of unmatched sample-% bias of matched sample)/(% bias of unmatched sample).